ISIGrowth

INNOVATION-FUELLED, SUSTAINABLE, INCLUSIVE GROWTH

Working Paper

How to achieve the green transition

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Report: Green transition

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How to achieve the green transition

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ISIGrowth is a 3-year EC Horizon 2020 funded project aimed at offering comprehensive diagnostics on the relationship between innovation, employment dynamics and growth in an increasingly globalized and financialized world economy. The project will provide a coherent policy toolkit to achieve the Europe 2020 objectives of smart, sustainable and inclusive growth. The theoretical foundation is based on the dynamic link between Schumpeterian economics of innovation and Keynesian demand policies. Analytical tools include agent-based modelling, non-parametric statistics, and detailed case studies of business and industry histories.

The present deliverable provides an ample overview of the main issues, drivers and threats behind the transition towards a pattern of sustainable growth. In the present context, sustainable development indicates a trajectory of self-sustained growth, fueled by increasing shares of renewable energies, produced through constantly ameliorating technologies, helping reduce the adversarial impacts of climate change, both through mitigation and adaptation. Moving away from fossil fuel and current business-as-usual practices is not immune to risks, and requires a coherent mix of policy interventions and societal transformation.

The deliverable is composed by three papers that – together – offer a comprehensive assessment of the policies, the infrastructural and societal requirements that a green transition would need. Further, an analysis of transitions in presence and absence of climate change and its impacts is proposed.

Lamperti et al (2018) propose an integrated assessment agent based model to explore the likelihood of a green transition under business as usual. The model comprises heterogeneous fossil-fuel and renewable plants, capital- and consumption-good firms and a climate box linking greenhouse gasses emission to temperature dynamics and microeconomic climate shocks affecting labour productivity and energy demand of firms. Hence, the model allow studying the conditions behind sustainable transition both in absence and presence of climate damages. Simulation results show that the economy possesses two statistical equilibria: a carbon-intensive lock-in and a sustainable growth path characterized by better macroeconomic performances. Once climate damages are accounted for, the likelihood of a green transition depends on the damage function employed. To move the economy away from fossil fuels, a complex sets of policies encompassing any mix of carbon (fossil fuel) taxes and green subsidies is considered and explored through counterfactual simulation experiments. The results point to a general lack of effectiveness of these incentive-based tools, unless their size grows substantially with respect to the actual levels. In general, the paper envisions and discusses complementarities between incentive and regulation policies to foster a green transition.

As green transitions necessarily pass through a strong increase in the share of renewables in total final energy mix, many challenges emerges from the need of safely integrating novel energy producers in current energy markets. **Ciarli et al (2018)** tackle these issues by building a simple agent based model to assess the likelihood of the alternative effects that distributed storage systems might have on aggregate energy demand volatility, under different parametrizations of the power generation storage systems. In particular, the paper tests weather such systems act as a buffer and smooth the intra-daily variation in electricity flows or, by contrast, they may increase volatility, if a large number of distributed generators simultaneously use the network. The results suggest that distributed storage systems reduce fluctuations, and are thus beneficial at a systemic level, rejecting the volatility increase hypothesis.

The third paper that composes this deliverable focuses on the demand side and then examines under which conditions the diffusion of sustainable goods among consumers is favored by the economic and institutional environment. **Pasimeni and Ciarli (2018)** build a stylized yet insightful agent based model to investigate the process of coalition formation conditioning the common decision to adopt a shared (sustainable) good, which is too expensive for an average consumer, who would also not be able to exhaust its use. Coalitions formation sets the conditions for adoption, while diffusion influences the consequent formation of coalitions. Results show that both coalitions and diffusion are subject to network effects, which also have an impact on the information flow though the population of consumers. Consumers prefer to form large coalitions in order to buy expensive goods and share ownership and use, rather than establishing smaller coalitions. In larger groups the individual cost is lower, although it increases if higher quantities are purchased collectively.

Main policy implications from Deliverable 6.6

- Under business-as-usual, the likelihood of transition is remarkably low. We find that endogenous transitions towards the equilibrium where green energy technology dominates the market are possible but, in the absence of policy intervention, the likelihood of such an event does not exceed 18%. This result is based on assuming zero climate damages.

- The presence of climate damages can potentially increase or reduce the likelihood of transitions. We consider climate damages in two different ways. Firstly, we take the standard aggregate perspective embraced by the majority of IAMs. Secondly, heterogeneous climate damages that target labour productivity or energy efficiency are considered. In the first case, the likelihood of transition is exactly the same as the case of no damages, since they only affect aggregate potential output. In the second case, we find that labour productivity shocks might increase the likelihood of transitions (with respect to the case of aggregate damages), while the opposite happens for energy efficiency shocks. The main channel of these effects is represented by the size of the final demand for energy (see Annex IV for details).

- The price of fossil fuels non-linearly influences the likelihood of transition. We find that an increase in the initial price of fossil fuels might increase the likelihood of a transition. However, such an effect is largely non-linear. Given the initial backwardness of clean technologies' productivity and the cumulative nature of the technical change process, small variations of the fossil fuel price have a surprisingly low impact on inducing the transition, while for moderate/high increases the likelihood increases substantially. This result supports the idea that policy intervention, in this case aimed at increasing the cost of fossil fuels, needs to be substantial in order to significantly affect the environmental sustainability of the production system.

- Within the energy sector and with particular reference to distributed energy storage, increasing the size of the systems and their share in the population of energy users reduces the aggregate electricity volatility of the network load. Therefore, that there are only gains, at the systemic level, from improving battery technology, and promoting their diffusion among users.

- The total number of users is a key determinant of the diffusion success of large scale sustainable goods (e.g. near zero-energy buildings) enforcing a green transition. Policies should aim at maximizing users' awareness, engagement as well as their connections.

And Then He Wasn't a She:
Climate Change and Green Transitions in an Agent-Based Integrated Assessment Model

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Abstract

In this work, we employ an agent-based integrated assessment model to study the likelihood of transition to green, sustainable growth in presence of climate damages. The model comprises heterogeneous fossil-fuel and renewable plants, capital- and consumption-good firms and a climate box linking greenhouse gasses emission to temperature dynamics and microeconomic climate shocks affecting labour productivity and energy demand of firms. Simulation results show that the economy possesses two statistical equilibria: a carbon-intensive lock-in and a sustainable growth path characterized by better macroeconomic performances. Once climate damages are accounted for, the likelihood of a green transition depends on the damage function employed. In particular, aggregate and quadratic damage functions overlook the impact of climate change on the transition to sustainability; to the contrary, more realistic micro-level damages are found to deeply influence the chances of a transition. Finally, we run a series of policy experiments on carbon (fossil fuel) taxes and green subsidies. We find that the effectiveness of such market-based instruments depends on the different channels climate change affects the economy through, and complementary policies might be required to avoid carbon-intensive lock-ins.

Keywords: climate change; agent based models; transitions; energy policy; growth.
JEL: C63, Q40, Q50, Q54.

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1 Introduction

How does climate change impact on the transition from fossil-fuel to low carbon technologies? According to our results, quite a lot. While the literature analysing transitions is large and variegate, there is a gap on how climate change can affect the likelihood and speed of decoupling economic growth from fossil fuels and the ensuing macroeconomics effects. In the present work, we fill this gap relying on an agent-based integrated assessment model where energy transitions are endogenous and co-evolve with climate change and can be possibly affected by policy interventions.

Economic growth must be sustained by energy production. Different portfolio of energy sources can support the same rate of growth at different costs, which change over time according to the technological evolution. However, once the possible impacts of climate change are taken into account, economic growth ought to be *sustainable*, i.e. it must be decoupled from greenhouse gas (GHG) emissions. Indeed, as pointed out by the literature on high-end scenarios, the environmental, health, and physical damages triggered by climate change may outpace any adaptation effort, hampering long-term growth prospects and ultimately treating the very existence of life as we know it. Thus, long-term economic growth cannot be a credible objective without treating the green transition as an unavoidable goal of public policy-making. And as climate change, technical change and economic growth co-evolve over time, increasing research efforts are required to understand if the speed of transition implicitly defined by the international climate agreements is fast enough, and whether policies are effective.

Against this background, traditional integrated assessment models (IAMs) are badly equipped to study the role of firm and energy plant heterogeneity and the sources and direction of technical change triggering successful energy transition towards sustainability. Further, climate damages are often measured in percentages of GDP losses, under the implicit assumption that, due to linearity in the economic system, the aggregate shock is plainly the sum of microeconomic shocks. While being empirically questionable, such a perspective does not allow policy-makers to identify from where in the economic system the risks and costs of climate change originate and propagate, thus affecting the transition to sustainable growth. More generally, the microeconomic analysis of energy transitions has little to say about the ensuing macroeconomic dynamics (Stirling, 2014; Mazzucato and Semieniuk, 2017).

The Dystopian Schumpeter meeting Keynes (DSK; Lamperti et al., 2018b) agent-based model constitutes a viable platform to analyze the energy transition while dealing with all the above mentioned issues.[1] In particular, DSK accounts for endogenous technical change in the three sectors it comprises, namely capital goods, consumption goods, and energy. Technical change is the outcome of boundedly rational R&D decisions by heterogeneous agents, who finance R&D through retained earnings and (rationed) credit, and whose effect is stochastic. Firms also engage in technological diffusion as they adopt or imitate new vintages of machinery, characterized by heterogenous levels of labor productivity, energy efficiency, and environmental friendliness.

In the energy sector, firms can choose between fossil-fuel and renewable plants. Brown energy plants have higher production costs than green one, but have zero installation costs, while firms has to pay a fixed cost to expand their renewable energy capacity. Energy firms invest in R&D

[1] Agent based models are flexible computational environments simulating the behaviour of complex systems, nowadays widespread in different areas of the social sciences (Bonabeau, 2002; Tesfatsion and Judd, 2006; Haldane and Turrell, 2018). The interested reader might want to look at Fagiolo and Roventini (2012) and Fagiolo and Roventini (2017) for two surveys on macro agent based models and to Balint et al. (2017) and Lamperti et al. (2018a) for agent based applications to the issue of climate and environmental change.

a fraction of its past sales in order to develop the green and dirty technologies. Industrial and energy productions generate GHG emissions, whose effect on climate is modelled in a climate box. Once temperatures change, the economy is hit by microeconomic climate shocks affecting, labor productivity or energy efficiency of machines, and in turn macroeconomic dynamics.

The DSK model is able to account for a wide range of micro and macro stylized facts concerning economic dynamics and the evolution of climate change (e.g. self-sustained growth punctuated by endogenous crises, co-integration of energy and output dynamics, increasing frequency of extreme events). Simulation results show that, even without considering climate damages, the model produces a non-ergodic behaviour characterized by two statistical equilibria: a carbon-intensive lock-in, wherein the share of renewable energy plants approaches zero; and an equilibrium wherein the transition to green energy technologies is successful. In the latter case, GDP growth is faster,and unemployment lower than in the carbon-intensive lock-in, suggesting that sustainable growth can improve macroeconomic dynamics.

Once climate damages are accounted for, the likelihood of green transition depends on the damage function employed. When climate shocks are modelled as aggregate output losses, as commonly done in the majority of general-equilibrium IAMs (Nordhaus and Sztorc, 2013; Nordhaus, 2014), climate shocks do not affect the probability of carbon decoupling. However, when one focuses on the different channels through which microeconomic climate damages hit firms, the results are more complex. More specifically, negative shocks to energy efficiency are found to slow down the transition, whereas shocks reducing labor productivity accelerate it. Both effects interact with the dynamics of energy demand and prices, which affect the investment of energy firm in green and dirty technologies. Finally, the success of policies supporting sustainable growth such as carbon tax and green subsidies depends on the different channels through which climate damages affect the economy, and complementary command-and-control interventions are often required to avoid carbon-intensive lock-ins

The paper is structured as follows. After a brief review of the relevant literature in Section 2, we describe the model in Section 3. The model is empirically validated in Section 4. Simulation results focused on transition to sustainable growth are presented in Section 5. Finally, Section 6 concludes.

2 A critical review of the literature

The literature on transitions to sustainable production modes is large and variegate (Frantzeskaki and Loorbach, 2010; Markard et al., 2012). From a theoretical perspective, four main frameworks have been developed to analyse the issue. These include transition management (Rotmans et al., 2001; Loorbach, 2010), strategic niche management (Kemp et al., 1998), the multi-level perspective on socio-technical transitions (Geels, 2002), and technological innovation systems (Jacobsson and Johnson, 2000; Jacobsson and Bergek, 2011). Embracing different perspectives they have been used to analyse shifts in socio-technical systems. In this context, a *socio-technical system* consists of (networks of) actors (individuals, firms, and other organizations, collective actors) and institutions (societal and technical norms, regulations, standards of good practice), as well as material artifacts and knowledge (Geels, 2004; Weber, 2003). A sustainable transition involves moving from a given socio-technical system to a novel one characterized by production and consumption modes reducing the adverse impact on the natural system. Socio-technical transitions differ from technological transitions in that they include changes in user practices and institutional (e.g., regulatory and cultural) structures, in addition to the technological dimension. In this paper, we loosely focus on the technological dimension but, contrary to the approaches introduced above, we look at the aggregate (i.e. macroeconomic) effect of moving away from fossil-fuels technologies.

In that, we contribute to a recent stream of studies focusing on economies' growth dynamics and the composition of the energy mix. The mainstream economic literature has employed models of directed technical change to explore how policy can move economic development and R&D activities away from fossil fuels (Acemoglu et al., 2012, 2015). As a central result, they report that both subsidies to "green" research and carbon taxes should be used to move the economy towards a sustainable growth trajectory. Despite they call for a marginal and temporary intervention, Lamperti et al. (2015) show that such market based policies might be ineffective as a result of path-dependence and put forward regulation as a valid alternative policy to induce transitions.[2] Moving the attention from R&D to resource availability, other contributions have analysed the optimal trajectory from non-renewable to renewable resources and highlighted the role of renewables' production costs in inducing the transition (Hoel and Kverndokk, 1996; Ploeg and Withagen, 2014; Van Der Ploeg and Withagen, 2012).[3] This feature will be crucial also in our model. Interestingly, while the majority of studies underlines the importance of shifting to renewable energy sources, Smulders and Zemel (2011) highlight possible drawback effects on economic growth linked to crowding-out effects in capacity building. However, they do not account for climate change/environmental damages. Another main shortcoming of such a research body is that it fails to account for the complex relationships tying agents in an economic system, and too heavily relies on the capacity of markets in efficiently allocating both resources and knowledge. In such a context, inducing a transition loosely boils down at finding the correct set of incentives.

Starting from different theoretical constructs and a more realistic representation of the economy, the literature on macro agent based and system dynamics modelling has recently moved towards the analysis of energy transitions, macroeconomic dynamics and policy choices (Balint et al., 2017; Lamperti et al., 2018a). Such a stream builds on the perception of the economy as a complex evolving system (Arthur et al., 1997; Tesfatsion, 2006; Dosi and Virgillito, 2017) and, departing from this basis, looks at the evolutionary mechanisms behind technological development, technological diffusion, and technological transitions with a particular emphasis on energy and environmental issues (Van Den Bergh and Gowdy, 2000; Safarzyńska et al., 2012).[4] This is particularly relevant as sustainability challenges are robustly coupled with and aggravated by the strong path-dependencies, and ensuing lock-ins, we observe in the existing sectors (Åhman and Nilsson, 2008; Unruh, 2000; Safarzyńska and van den Bergh, 2010). Under such conditions, endogenous sustainable transitions can be viewed as positive tipping points, whose determinants needs investigation (Tbara et al., 2018). Both demand and supply sides matter in shaping the final technological landscape. Bleda and Valente (2009) investigate the role of demand induced innovations and eco-labelling in fostering the transition to greener production modes. Safarzynska and van den Bergh (2011) study the role of boundedly-rational investors in driving technological development within the energy indus-

[2] See also Smulders et al. (2011) on the role of regulation in triggering transitions, and Eriksson (2018) for the social desirability of a long run perpetual public support of green technologies.

[3] The interested reader might want to look at Gillingham et al. (2008) for a survey on technical change modelling in mainstream environment-climate-economy models.

[4] We refer the interested reader to Nelson and Winter (1982) and Dosi (1988) for the evolutionary background on technological change, to Tesfatsion and Judd (2006), Farmer and Foley (2009) and Bonabeau (2002) for background material, and to Fagiolo and Roventini (2012) and Fagiolo and Roventini (2017) for excellent surveys on recent developments in macro agent based modelling.

try, highlighting that the emergent energy mix might strongly depend on the investing heuristics. Gualdi and Mandel (2016) and Ponta et al. (2018) focus instead on technological diffusion, and study the effects of stylized feed-in tariffs. The first contribution finds that feed-in tariffs are relatively more effective than preferential market access in supporting the diffusion of radical (green) innovation, with positive consequences on the dynamics of growth. The second study, instead, reports a trade-off: for moderate policy strength the economy benefits from the transition, while for high policy intensity investments crowd-out consumption and increase interest rates. Our paper contributes to the debate, as it study the effects of public subsidies to green energy technologies and, symmetrically, taxes on fossil-fuel ones.

However, the key ingredient we add to the picture is the representation of climate damages. Transitions involve a broad range of actors and typically unfold over considerable time-spans (e.g., 50 years and more, Markard et al., 2012). This is further confirmed by the length of the simulations conducted in the battery of studies reported above and, more specifically, by that the length of the transition itself. Over such long horizons, it is crucial to consider how climate change could affect the economic system and, therefore, the dynamics of the transition. Both in the mainstream economic and complex system literatures, climate damages are either overlooked or vaguely represented as utility losses (Greiner et al., 2014), thereby failing to consider the wide array of impact channels identified by the nascent literature on climate econometrics (Hsiang, 2016; Carleton and Hsiang, 2016). In this respect, we take advantage of the DSK model (Lamperti et al., 2018b), where different micro-level shocks can be modelled and, therefore, we also link to the Integrated Assessment literature Weyant (2017) which, usually, takes into consideration endogenous technical change but oversee the macroeconomic impacts of transitions.

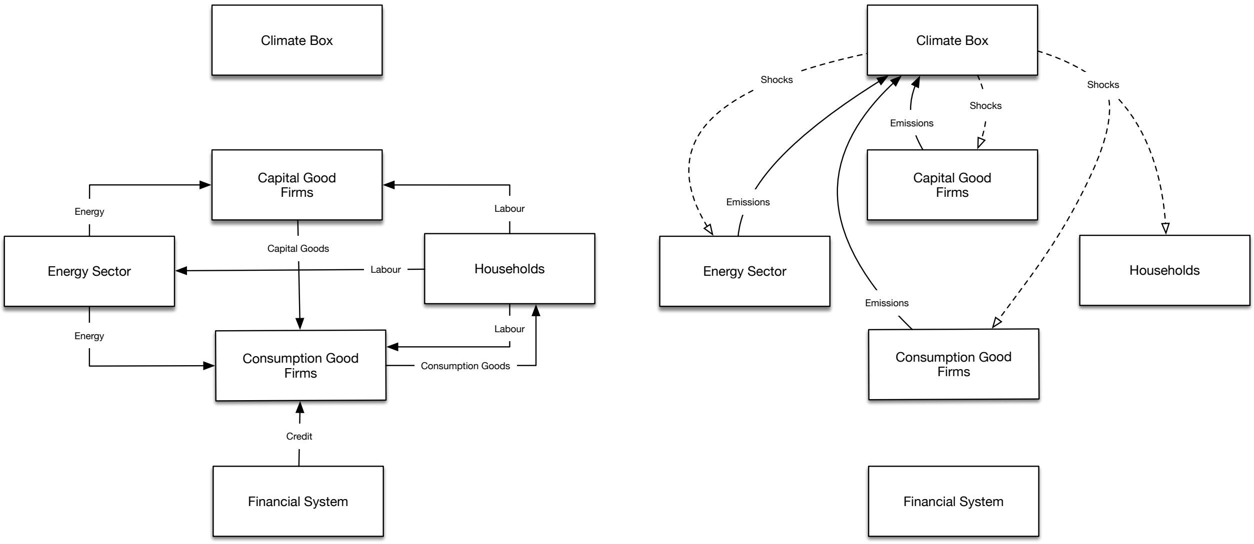
3 The model

The DSK model (Lamperti et al., 2018b) represents a complex economy endowed with a climate box. Economic and climatic variables co-evolve interacting non-linearly, with multiple feedbacks, and emerging tipping points. A graphical representation of the model is provided in Figure 1.

The economic dynamics is grounded on Dosi et al. (2010, 2013) and is composed by two industrial sectors, whose firms are fueled by an energy industry. In the capital-good sector, firms invest in R&D and innovate to improve the performances of the machines in terms of productivity, energy-efficiency and environmental friendliness. In the manufacturing industry, firms invest in machine-tools in order to produce an homogeneous product consumed by workers and they can rely on credit to finance their production and investment plans.[5]

Energy and industrial production emit greenhouse gasses (e.g. CO2), which in turn affect the evolution of the temperature. More precisely, we model a stylized global carbon cycle which drives the projections of Earth's radiative forcing and, finally, the global mean surface temperature. The impact of an increase in the temperature of the Earth on economic dynamics is modeled through a stochastic, time-evolving, disaster generating function (as in Lamperti et al., 2018b). In particular, the probability of large climate shocks hitting firms raises in tandem with the mean size of damages. In that, climate change does not automatically lead to higher aggregate damages as in most IAMs, but rather it modifies the very structure of the economy and the ensuing economic growth (or lack

[5]See Dosi et al. (2016) for a survey of the K+S model family, to which DSK belongs, and Dosi et al. (2017c) for a recent development.



(a) economic flows (b) climate flows

Figure 1: A graphical representation of the DSK model; source Lamperti et al. (2018b).

of). As a benchmark, we also use a standard damage function cutting aggregate output in a linear way as in Nordhaus and Sztorc (2013). The details of the DSK model are spelled out in Appendix A.

3.1 Industrial sectors

The economy features a capital-good industry and a consumption-good sectors. Firms in the capital-good industry produce machines employing labour and energy. Different vintages of machines are characterized by different *productivity of labour*, *energy efficiency* and *environmental friendliness*. The unit cost of production of both capital- and consumption-good firms depends on labor productivity, workers' wage (w), energy efficiency, as well as energy price (p^e). Machines and production technologies induce CO2 emissions via both their electricity consumption (indirect effect) and their environmental friendliness, i.e. the amount of polluting substances they emit in each period for each unit of energy employed throughout the production process.

Technical change and innovation occur in the capital-good sector. Firms invest in R&D a fraction of their past sales in order to discover new machines or copy the ones of their competitors. New machines can be more productive, cheaper, or "greener". Innovation and imitation are modeled as two step stochastic processes. In the first step, the amount invested in R&D affects the likelihood of success. In the second one, technological opportunities determines the size of innovation. In the case of imitation, firms are more likely to copy the competitions with the closest technologies.

The capital-good market is characterized by imperfect information and competition. Capital-good firms strive to get new customers by sending *brochures* to a subset of consumption-good firms, which in turn choose the machines with the lowest price and unit cost of production. Machine-tool firms fix price a constant mark-up on the unit cost of production. Time-to-build constraints characterized the production of machines: consumption-good firms receive their new capital-goods at the end of the period.

Consumer good-firms produce a homogeneous good using their stock of machines, energy and labour under constant returns to scale. Firms plan their production according to adaptive demand expectations. If the current capital is not sufficient to satisfy the desired level of production, they buy new machines. As machine embed state-of-the-art technologies, innovations diffuse from the capital- to the consumption good sector. Relatedly, technical change can also induce firms to replace their current stock of machines with more productive (and environmental friendly) ones. Firms' gross investment is simply the sum of expansion and replacement investments.

Consumption-good firms finance their investments as well as their production relying on imperfect capital markets (Stiglitz and Weiss, 1981; Greenwald and Stiglitz, 1993). Firms first rely on their stock of liquid assets and then on bank credit. The borrowing capacity of firms is limited by their ratio between debt and sales. The bank provides loans to consumption-good firms on a pecking order basis, considering their net worth-to-sales ratio. If credit supply is lower then demand, some firms end up being credit rationed.

Consumption-good firms first produce and they try to sell their product in the market. Hence, production do not necessarily coincide. Consumption-good market is characterized by imperfect competition: firms fix price according to a variable mark-up which evolve reflecting the dynamics of market shares. In presence of imperfect information, demand is allocated through a quasi replicator dynamics, wherein firms competitiveness depends on their price and they successfully satisfied their past demand. Details and equations are collected in Appendix A.

3.2 The energy sector

3.2.1 Electricity production, costs and and revenues

Energy production is performed by a set of heterogeneous power plants featuring green (renewable) or brown (carbon-intensive) technologies. The energy industry produces and sells electricity to firms in the capital-good and consumption-good industries on demand. Demand for electricity, D_e, is then matched by the aggregate energy production, Q_e, obtained from the portfolio of plant. Energy cannot be stored.

Plants are different in terms of their technical coefficients reflecting cost structures, thermal efficiencies and environmental impacts. Brown plants burn fossil fuels (e.g. coal, oil) with heterogeneous, vintage-specific thermal efficiency A^{τ}_{de}, which expresses the amount of energy produced for each unit of employed non-renewable resource (fossil-fuel).[6] For simplicity, we assume that power plants have a unitary capacity and, in the case of brown energy, they consume one unit of fuel. Hence, the average production cost for a brown plant of vintage τ is:

$$c_{de}(\tau, t) = \frac{p_f}{A^{\tau}_{de}}, \tag{1}$$

where p_f is the price of fossil fuels, exogenously determined on a international market.[7] Burning fossil fuels yields em^{τ}_{de} emissions per energy unit, thus increasing the carbon concentration in the atmosphere.

To the contrary, the carbon footprint of green plants is zero. They transform freely available, renewable sources of energy (such as wind and sunlight) into energy units at a null production

[6]The subscript de stands for "dirty electricity", while τ denotes the technology vintage.

[7]Notice that electricity production is a highly capital-intensive process, which mainly requires power generation assets and resources (be them fossil fuels or renewable sources), while the labour input is minimal. We thus assume away labour from electricity production.

cost, i.e. $c_{ge}(t) = 0$ (ge, "green energy").[8]

The total production costs depends on the mix of green and dirty plants. We assume that plants with the lowest unitary generation costs are the first to be activated, in line with the actual functioning of the electricity industry (Sensfuß et al., 2008; Clò et al., 2015). Indeed, even before liberalization, the traditional goal of energy systems management was the minimization of system-wide electricity production, transmission, and distribution costs. In turn, this imply that green plants are the first to be turned on. More precisely, if $D_e(t) \leq K_{ge}(t)$, the set of infra-marginal power plants IM includes only green plants and the total production cost is zero. If $D_e(t) > K_{ge}(t)$, the total production cost corresponds to the cheapest dirty power plants. Assuming the absolute frequency of vintage τ plants is $g_{de}(\tau, t)$, if dirty plants are operative the total production cost is:

$$PC_e(t) = \sum_{\tau \in IM} g_{de}(\tau, t) c_{de}(\tau, t) A_{de}^{\tau}. \tag{2}$$

The energy price is computed adding a fixed markup $\mu_e \geq 0$ to the average cost of the more expensive infra-marginal plant:

$$p_e(t) = \mu_e, \tag{3}$$

if $D_e(t) \leq K_{ge}(t)$, and

$$p_e(t) = \bar{c}_{de}(\tau, t) + \mu_e \tag{4}$$

if $D_e(t) > K_{ge}(t)$, where $\bar{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. By setting a markup on this unit cost level, there is a positive net revenue on all infra-marginal plants.[9]

3.2.2 Expansion and replacement investments

In order to fulfil energy demand, new power plants might be necessary. Moreover, old and obsolete plants should be replaced as well. In particular, we assume that all (brown and green) plants have a constant life-time corresponding to η_e periods. All new plants are built in house (i.e. within the energy sector), but their production cost is technology specific. Specifically, the construction costs for new dirty plants are normalized to zero, whereas in order to install a new green plant of vintage τ, a fixed cost IC_{ge}^{τ} needs to be sustained.

The capacity stock $K_e(t)$ is obtained summing up the capacities of all power plants across technologies (green vs. dirty) and vintages. Recalling that the capacity of plants is normalized to one and denoting with $g_{de}(\tau, t)$ and $g_{ge}(\tau, t)$ the absolute frequency of dirty and green plant respectively, one gets:

$$K_e(t) = \sum_{\tau} g_{de}(\tau, t) + \sum_{\tau} g_{ge}(\tau, t). \tag{5}$$

For a given capacity stock, the maximum production level that can be obtained depends on the thermal efficiencies A_{de}^{τ} of dirty plants (green plants produce at full capacity):

$$\overline{Q}_e(t) = \sum_{\tau} g_{de}(\tau, t) A_{de}^{\tau} + \sum_{\tau} g_{ge}(\tau, t). \tag{6}$$

[8] Some renewable sources, such as wind and photovoltaics, are intermittent and non-dispatchable: their output is highly volatile at high temporal frequencies as it depends on weather conditions that cannot be controlled by the power plant operator. However, our model runs on temporal frequencies that are relevant for macroeconomics, such as annual or quarterly. Over those time horizons, the average output from intermittent renewable is fairly predictable.

[9] In the aggregate perspective of our model, market power exercise through markups can be seen as equivalent in its effects to alternative strategies, such as capacity withholding.

An expansion investment in the energy industry is undertaken whenever the maximum electricity production level $\overline{Q}_e(t)$ is lower than electricity demand $D_e(t)$. The amount of new expansion investments EI_e^d thus equals

$$EI_e(t) = K_e^d(t) - K_e(t), \tag{7}$$

if $\overline{Q}_e(t) < D_e(t)$, whereas $EI_e(t) = 0$ if $\overline{Q}_e(t) \geq D_e(t)$. A choice is available between green or brown new plants. We assume that new green capacity is constructed if green plants are cheaper than brown counterparts in terms of accounting lifetime costs. This means that green energy technologies are chosen up whenever fixed cost of building the cheapest green vintage is below the discounted (variable) production cost of the most efficient dirty plant. Hence, the following payback rule is satisfied:

$$\underline{IC}_{ge} \leq b \cdot \underline{c}_{de}, \tag{8}$$

where b is a payback period parameter (e.g. Dosi et al., 2010, 2013), $\underline{IC}_{ge} = \min_\tau IC_{ge}^\tau$, and $\underline{c}_{de} = \min_\tau c_{de}^\tau$. Accordingly, in case of new green capacity, the expansion investment cost amounts to

$$EC_e(t) = \underline{IC}_{ge} EI_e(t); \tag{9}$$

whereas it is zero if the payback rule is not met and the firm builds new dirty plants.

3.2.3 Technological innovation

The technology of green and dirty plants change over time as result of innovations. The energy firm invests a fraction $v_e \in (0,1)$ of total past sales in R&D. Total revenues $S_e(t)$ are generated from both green and brown energy sales, i.e. $S_e(t) = S_{ge}(t) + S_{de}(t)$. R&D investment in each technological trajectory is proportional to the revenues obtained from the sale of energy generated therein:

$$RD_{ge}(t) = v_e S_{ge}(t-1) \tag{10}$$

and

$$RD_{de}(t) = v_e S_{de}(t-1). \tag{11}$$

Such an assumption is coherent with the evolutionary literature on selection processes and technical change (Nelson and Winter, 1982; Dosi et al., 2010) and, further, reflects the idea that market size plays a role in shaping the direction of technical change and that investments tend to cumulate on the prevailing areas (Acemoglu, 2002; Acemoglu et al., 2012).

We model innovation as a two stage stochastic process as in the capital- and consumption good sectors. More precisely, the innovative search in the two paths is successful with probabilities $\theta_{ge}(t)$ and $\theta_{de}(t)$, conditioned on the R&D investment:

$$\theta_{ge}(t) = 1 - e^{-\eta_{ge} IN_{ge}(t)} \tag{12}$$

$$\theta_{de}(t) = 1 - e^{-\eta_{de} IN_{de}(t)} \tag{13}$$

with $\eta_{ge} \in (0,1)$, $\eta_{de} \in (0,1)$. Successful innovators can then access to the second stage where they project a new green or dirty plant. Innovation along the green technological trajectory reduce the installation fixed costs. Formally, the installation cost of a new vintage of green plants, IC_{ge}^τ, is lowered by a factor $x_{ge} \in (0,1)$ (a random draw from a Beta distribution) with respect to the previous vintage:

$$IC_{ge}^{\tau} = IC_{ge}^{\tau-1} x_{ge}. \tag{14}$$

Innovation in dirty technology can improve plants' thermal efficiency and reduce greenhouse gas emissions. The thermal efficiency and emissions intensity coefficients $(A_{de}^{\tau}, em_{de}^{\tau})$ of the new vintage τ of dirty technology are given by:

$$A_{de}^{\tau} = A_{de}^{\tau-1}(1 + x_{de}^{A}) \qquad em_{de}^{\tau} = em_{de}^{\tau-1}(1 - x_{de}^{em}) \tag{15}$$

where x_{de}^{A} and x_{de}^{em} are independent random draws from a Beta distribution.[10]

3.2.4 Profits and liquid assets

Energy sold to the capital- and consumption-good industry is paid in advance. Hence, the total profits realized in the energy industry reads:

$$\Pi_e(t) = S_e(t) - PC_e(t) - IC_e(t) - RD_e(t) \tag{16}$$

where $S_e(t)$ indicate energy sales, $PC_e(t)$ are production costs, $IC_e(t)$ denotes expansion and replacement investment, and $RD_e(t)$ are R&D expenditures. At the end of the period, the stock of liquid assets in the energy sector is accordingly updated:

$$NW_e(t) = NW_e(t-1) + \Pi_e(t). \tag{17}$$

3.3 Climate change and climate damages

A climate model is added to our economic system to fully endogenize the relationship between climate change and the growth pattern of the economy. In particular, we rely on a discrete-time version of the C-ROADS model described in Sterman et al. (2012, 2013). Such model accounts in a parsimonious away for the complex physical and chemical relations governing climate's evolution, especially including the multiple feedbacks responsible for non-linear dynamics. Note that while the economy reacts quarterly, the climate module updates annually.

A core carbon cycle, whose details are included in Appendix A, takes the annual emissions from the industry and the energy sector as input and models carbon exchanges between the atmosphere, the biomass and the oceans. The latter two elements constitute the main in-take channels, whose dynamics are affected by the temperature through two main feedback loops. Then, the equilibrium concentration of carbon in the atmosphere impacts the size of the Earth's radiative forcing and finally, the evolution of the temperature.

In particular, building on Schneider and Thompson (1981) and Nordhaus (1992), the heat content of the two layers (upper layer: atmosphere and surface of oceans; lower layer: deep oceans) is modulated by their reciprocal exchanges and, with respect to the upper compartment, by the CO_2

[10] A more realistic depiction of green energy technologies would set their thermal efficiencies far below 100% (i.e. they can only convert a relatively small fraction of the energy they receive from renewable sources) and allow for efficiency-improving innovations. Higher thermal efficiency allows a faster amortization of the fixed construction cost. The way we model innovation in green technologies, however, yields the same effects, because a lower fixed construction cost allows to anticipate the break-even point, too.

radiative forcing (F_{CO_2}):[11]

$$T_m(t) = T_m(t-1) + c_1 \{F_{CO_2}(t) - \lambda T_m(t-1) - c_3[T_m(t-1) - T_d(t-1)]\} \tag{18}$$

$$T_d(t) = T_d(t-1) + c_4 \{\sigma_{md}[T_m(t-1) - T_d(t-1)]\}, \tag{19}$$

where T_i is the temperature in the different layers relative to pre-industrial levels, R_i is the thermal inertia in the two boxes, λ is a climate feedback parameter, F_{CO_2} represents the radiative forcing in the atmosphere from greenhouse gasses (relative to pre-industrial levels), and σ_{md} is the transfer rate of water from the upper to lower ocean layers accounting also for the heat capacity of water. The main climate variable we are interested in is the temperature of the surface-upper oceans compartment, T_m.

How does climate change affect economic dynamics? In most IAMs, the negative impact of rising temperatures on the economy is simply captured via an aggregate damage function expressing fractional losses of GDP.[12] Apart from the difficult (and often arbitrary) choice of parameters, one issue with the use of such aggregate damage function is that it does not distinguish among different microeconomic impact channels. Is climate change reducing labour productivity? Is it increasing capital depreciation? Or, is it augmenting, caeteris paribus, energy demand? And are firms and households hit in the same way?[13]

A recent econometric strand of literature is increasingly focusing on the analysis of climate damages, thus providing empirical estimates to answer such questions. Carleton and Hsiang (2016) propose a survey of recently investigated climate impacts on labour productivity, labour supply, mortality, electricity consumption and a series of other variables. There is little doubt that such micro impacts will manifest, in aggregate terms, through a variation of final income. However, disentangling the various channels, the possible heterogenous impacts on agents, and their effects on the behaviour of the economy remains under-investigated.

The DSK model relys on stochastic *agent-based damage generating function*, which endogenously evolve according to the dynamics of the climate. Such a function simply takes the form of a density and, at the end of each period, multiple draws establish the size of the shocks hitting firms and workers. Notably, shocks are heterogeneous across agents and across economic variables, with only a subset of firms facing climate disasters. Given its flexibility, we take advantage of a Beta distribution over the support $[0, 1]$, whose density satisfies:

$$f(s; a, b) = \frac{1}{B(a, b)} s^{a-1}(1-s)^{b-1}, \tag{20}$$

where $B(\cdot)$ is the Beta function and a, b are respectively the location and scale parameters. Both

[11]Radiative forcing is a measure of the influence a factor has in altering the balance of incoming and outgoing energy in the Earth-atmosphere system. It is then an index of the importance of the factor as a potential climate change mechanism (IPCC, 2007b). To simplify we use CO_2 as a proxy for all green house gases and we consider only its radiative forcing.

[12]For example, Nordhaus (2008) uses an inverse quadratic loss function, Weitzman (2009) proposes a negative exponential specification emphasizing the catastrophic role of large climate changes, while Tol (2002) uses sector and area specific loss function.

[13]For more extensive and circumstanced critiques to the existing damage functions see Ackerman et al. (2010) and Pindyck (2013).

Table 1: Summary statistics on selected variables under business-as-usual scenario and no climate shocks, and comparison with historical empirical counterparts.

	MC average	MC st. dev.	Empirical counterpart	Data source
Yearly GDP growth	0.032	0.004	0.044	WDI
Unemployment rate	0.088	0.021	0.061	WDI
Energy demand growth	0.028	0.003	0.023	WDI
Emissions growth	0.013	0.001	0.018	CDIAC
Relative volatility of consumption	0.64	0.03	0.79	FRED
Relative volatility of investments	1.95	0.05	2.77	FRED
Volatility of output	0.258	0.013	0.0157	FRED
Likelihood of crises	0.10	0.065	-	-
Share of green energy at 2100	0.50	0.22	-	-
Emissions at 2100	26.81	9.510	-	-
Temperature at 2100	4.45	0.543	-	-

Note: All values refer to a Monte Carlo of size 200. Emissions are expressed in GtC, which can be converted in $GtCO_2$ using the following conversion factor: 1 GtC = 3.67 $GtCO_2$. Temperature is expressed in Celsius degrees above the preindustrial level, which is assumed to be 14 Celsius degrees. WDI stands for World Development Indicators, provided by the World Bank. Empirical counterparts are computed over large time spans, but are subject to data availability: World real GDP, unemployment and CO_2 emissions data refer to the period from 1980 to 2010; employed energy consumption data go from 1991 to 2013; quarterly data for volatility analysis are from 1970 to 2002 and refer to the US economy, but the reported features are quite robust across countries, see also Stock and Watson (1999); Napoletano et al. (2006). Volatilities are expressed as standard deviations of bandpass filtered series; relative volatilities use output volatility as comparison term. A crisis is defined as an event where the yearly loss of output is higher than a 5% threshold. Growth rates computed as $(y_{\text{final}} - y_{\text{initial}})/(y_{\text{initial}} * T)$.

parameters are assumed to evolve across time reflecting changes in climate variables:

$$a(t) = a_0[\log(1 + T_m(t))] \tag{21}$$

$$b(t) = b_0 \frac{\sigma_{10y}(0)}{\sigma_{10y}(t)}, \tag{22}$$

where $\sigma_{10y}(t)$ is a measure of the variability of surface temperatures across the previous decade and a_0, b_0 are positive integers.[14] Equations (21) and (22) shape the disaster generating function as a right-skewed, unimodal distribution, whose mass moves along the positive axis as temperature increases, thereby raising the likelihood of larger shocks. Equation (22) determines the size of the right tail of the distribution and allows to account for the importance of climate variability on natural disasters (Katz and Brown, 1992; Renton et al., 2014).

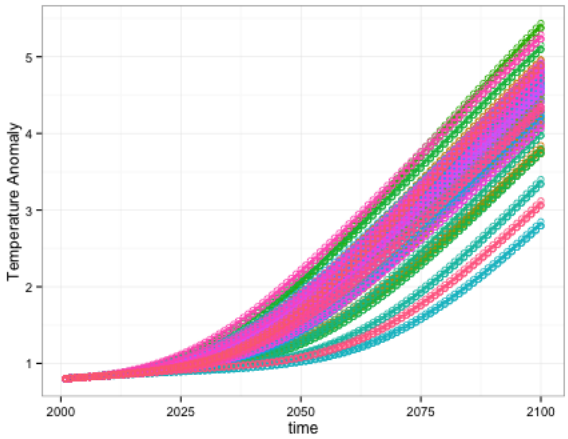
Formally, climate shocks hit the economy at the end of each period according to the following specification:

$$X_{i,\tau}(t) = X_i'(t)[1 - \hat{s}_i^x(t)], \tag{23}$$

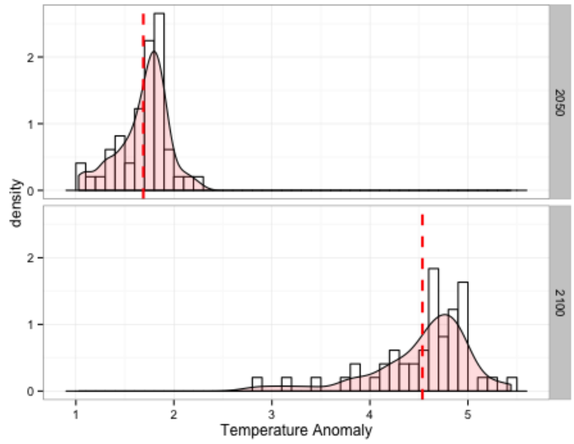
where i indexes firms in the economy, $\hat{s}^x(t)$ is the draw from the disaster generating function, while $X(t)$ captures the target impact variable one wants to study. In the simulation experiments below, we will focus on labor productivity and energy efficiency characterizing machines and production techniques.

[14]For modelling purposes we estimate the standard deviation of previous ten recorded temperatures; however, a widely used measure of climate variability corresponds to the count of extreme temperatures.

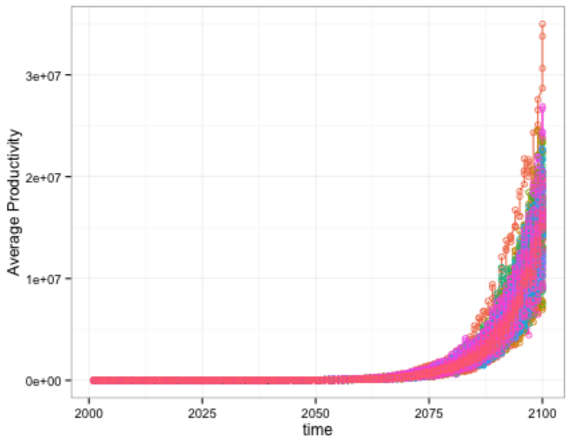
Figure 2: Temperature projections and their density estimates.



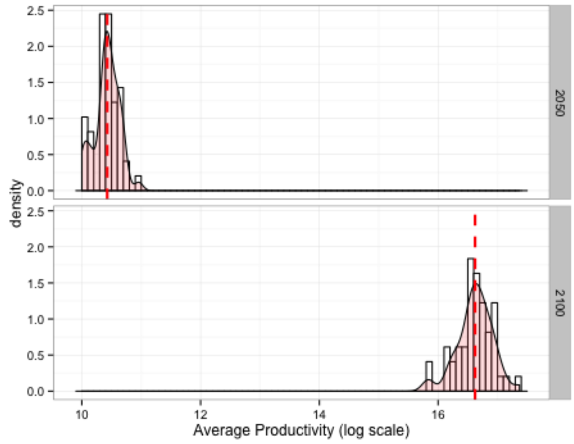
(a) Temperature projections.



(b) Distribution of temperature.



(c) Average firm productivity projections.



(d) Distribution of average firm productivity.

Note: All panels show 50 model runs under different seeds of the pseudo-random number generator. Red dashed lines in panel 2b indicate mean values. In panel 2d the x-axis is in logarithmic scale.

4 Empirical validation

We start exploring whether the DSK model can account for micro and macro empirical regularities concerning economic and climate dynamics. The DSK model should be considered as a global model. In its baseline (benchmark) configuration, the model runs in absence of climate damages and the parametrization reported in Appendix B.

In line with the indirect calibration approach discussed in Windrum et al. (2007) and Fagiolo et al. (2007) and following the prevailing practice in the agent based macro modelling literature (see the survey in Fagiolo and Roventini, 2012, 2017), the parameters of the DSK models have been selected to reproduce six empirical features of the real world system.[15] More precisely, simulated data should account for: (i) presence of self-sustained growth and business cycles punctuated by

[15]In a nutshell, the indirect calibration approach first identifies a set of empirical features that the model wants to match, then employs a search strategy to select points into the parameter space and finally test weather the identified empirical properties are robustly present in the simulated series. For a survey of validation approaches in the macro ABM literature we refer the interested reader to Fagiolo et al. (2017) and to the literature review sections in Lamperti (2017a,b) and Guerini and Moneta (2017).

Table 2: Main empirical stylized facts replicated by the DSK model. Source: Lamperti et al. (2018b).

Stylized facts	Empirical studies (among others)
Macroeconomic stylized facts	
SF1 Endogenous self-sustained growth	Burns and Mitchell (1946); Kuznets and Murphy (1966)
with persistent fluctuations	Zarnowitz (1985); Stock and Watson (1999)
SF2 Fat-tailed GDP growth-rate distribution	Fagiolo et al. (2008); Castaldi and Dosi (2009)
	Lamperti and Mattei (2016)
SF3 Recession duration exponentially distributed	Ausloos et al. (2004); Wright (2005)
SF4 Relative volatility of GDP, consumption, investments and debt	Stock and Watson (1999); Napoletano et al. (2006)
SF5 Cross-correlations of macro variables	Stock and Watson (1999); Napoletano et al. (2006)
SF6 Pro-cyclical aggregate R&D investment	Wälde and Woitek (2004)
SF7 Cross-correlations of credit-related variables	Lown and Morgan (2006); Leary (2009)
SF8 Cross-correlation between firm debt and loan losses	Foos et al. (2010); Mendoza and Terrones (2012)
SF9 Pro-cyclical energy demand	Moosa (2000)
SF10 Syncronization of emissions dynamics and business cycles	Peters et al. (2012); Doda (2014)
SF11 Co-integration of output, energy demand and emissions	Triacca (2001); Ozturk (2010); Attanasio et al. (2012)
Microeconomic stylized facts	
SF12 Firm (log) size distribution is right-skewed	Dosi (2007)
SF13 Fat-tailed firm growth-rate distribution	Bottazzi and Secchi (2003, 2006)
SF14 Productivity heterogeneity across firms	Bartelsman and Doms (2000); Dosi (2007)
SF15 Persistent productivity differential across firms	Bartelsman and Doms (2000); Dosi (2007)
SF16 Lumpy investment rates at firm-level	Doms and Dunne (1998)
SF17 Persistent energy and carbon efficiency heterogeneity across firms	DeCanio and Watkins (1998); Petrick et al. (2013)

endogenous crises; (ii) average growth rate of output between 2.5% and 3.5%; (iii) average unemployment rate between 5% and 15% percent; (iv) investment more volatile than output, consumption less volatile than GDP; (v) growth rate of energy consumption lower than growth rate of output, but higher than the growth rate of emissions, (vi) growth rate of emissions lower than the growth rate of output, but consistent with RCP 8.5, (vii) projected temperature anomaly at 2100 in line with the ranges relative to RCP 8.5.[16]

The simulation protocol adopted to inspect the baseline configuration employs 400 simulation steps, which should be interpreted as quarters. Accordingly, the model can simulate and project GDP and temperature dynamics till the year 2100 as commonly done by integrated-assessment models. To wash away the effects due to stochastic terms, we performs Monte Carlo exercises of size 200 on the seed of pseudo random number generator. The same protocol will be maintained throughout the paper.

Simulation results show that the baseline DSK model is consistent with the seven requested conditions introduced earlier and, further, it reasonably matches the long run empirical counterparts of many key variables (e.g. growth paces of output and energy demand; see Table 1). The economy exhibits endogenous fluctuations and self-sustained growth (3.2% on average; see also Figure 2) punctuated by crises, emissions grow at an average pace that is close to those observed in the last 30 years and energy intensity to GDP is decreasing over time as suggested by the empirical evidence. In addition, final projections of total emissions (average of 26.81 GtC at 2100) are in line with those produced in the business-as-usual scenario by many other integrated assessment models used by the IPCC (Clarke et al., 2009; Nordhaus, 2014). Moreover, the projections of temperature anomaly over pre-industrial levels are consistent with RCP 8.5 and show an average of 4.45 Celsius degrees (see Figure 2).

Beyond these general features, the DSK model jointly reproduces a large ensemble of micro and macro stylized facts characterizing short- and long-run behavior of modern economies. Table

[16] RCP stands for Representative Concentration Pathways; they describe four possible climate futures, all of which are considered possible depending on how much greenhouse gases are emitted in the years to come. RCP 8.5 is the most pessimistic scenario and reflects a world without policy intervention, uncontrolled emissions and high energy demand. See Riahi et al. (2011) for details.

Table 3: Percentages of non-rejection of statistical equilibrium and ergodicity tests.

	baseline		carbon lock-in		transition to green	
Variable	Equilibrium	Ergodicity	Equilibrium	Ergodicity	Equilibrium	Ergodicity
Output	0.85	0.83	0.95	0.91	0.90	0.89
Average productivity	0.91	0.89	0.96	0.92	0.89	0.86
Emissions	0.46	0.41	0.95	0.91	0.89	0.88
Temperature	0.74	0.72	0.92	0.90	0.85	0.83

Note: The results come from $T(T-1)/2$ and $T \cdot M$ pairwise comparisons for equilibrium and ergodicity respectively.

2 reports the main empirical regularities replicated by the model together with the corresponding econometric evidence. Relevantly, from a long run perspective, the model matches co-integration relationships between output, energy demand and emissions. Moreover, growth rates and duration of recessions display fat-tailed distributions, pointing to the fact that crises are more frequent that what expected in a Gaussian world. As a consequence, macroeconomic volatilities are relevant and should be also taken into account in climate change economic analysis as advocated by e.g., Rogoff (2016). Indeed, from a short run perspective, we find that DSK exhibits business cycles properties akin to those observed in developed economies: investments are lumpy and more volatile than output and consumption, R&D expenditures are pro-cyclical and tend to anticipate the economy's fundamentals. This, in particular, supports the idea that technical change is a relevant element in directing the pattern of growth. Finally, we notice that emissions and GDP are strongly synchronized, which suggest a careful interpretation of emission slow-downs.[17]

5 Green transitions and climate change dynamics

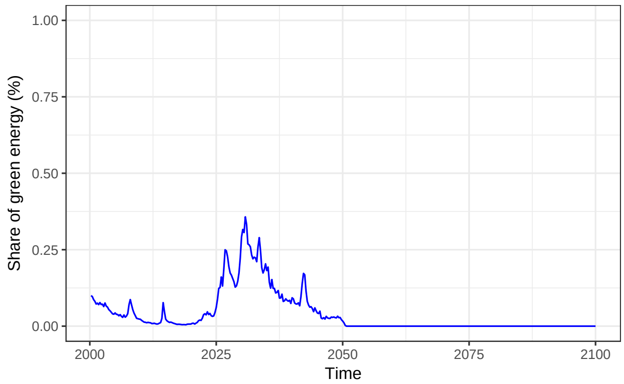
Let us now consider under which conditions a green transition to a sustainable growth path can emerge and if such a process is characterized by path-dependency and possible carbon lock-ins. More specifically, we adopt the following strategy. First, we study green transitions switching off climate-change shocks (cf. Section 5.1). In this way, by isolating the economy from the possible negative impacts of climate change, we can focus on the economic processes and constrains affecting the energy choices of firms. We then introduce feedbacks from climate change to economics dynamics, thus studying the co-evolution of the economy and the climate (see Section 5.2). Finally, we analyze the possible policy interventions to support the transition to a sustainable growth path grounded on renewable energies (Section 5.3).

5.1 Green transition in an economy with zero climate-change impacts

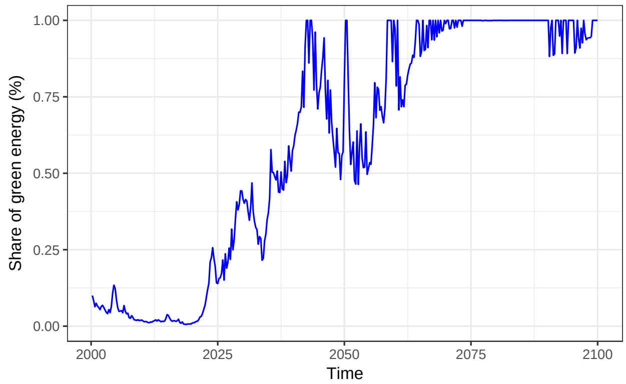
We begin considering the adoption of green vis-à-vis dirty energy technologies and we study the ensuing economic dynamics assuming that higher level of temperatures never trigger climate shocks. This is a strong assumption as a closer scrutiny of Figure 2 suggests that the model projects temperature anomaly at the end of the century well above 4 degrees in the vast majority of cases. However, in some simulation runs, temperature growth is much less pronounced and it does not

[17] For a more detailed analysis of the empirical regularities that the model reproduces, together with their formal investigation, we refer the reader to Lamperti et al. (2018b).

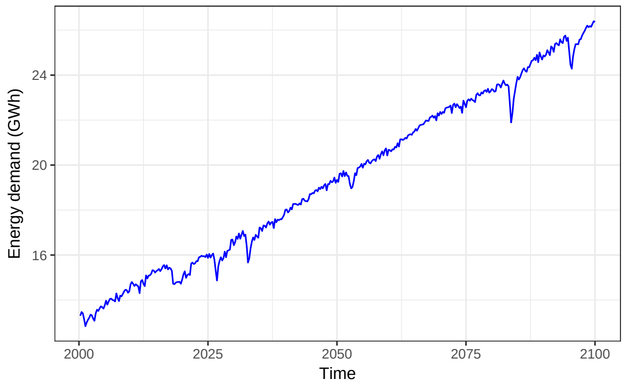
Figure 3: Example of runs where a carbon lock in or a green transion occurs.



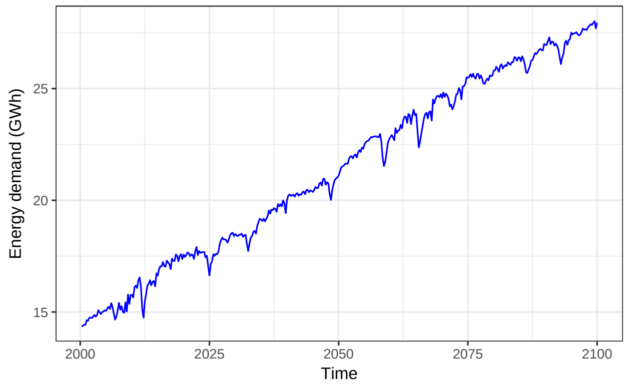
(a) Share of green energy production - Lock in.



(b) Share of green energy production - Transition.



(c) Energy demand - Lock in.



(d) Energy demand - Transition.

Table 4: Kolmogorov-Smirnov tests for difference between equilibria.

Variable	Kolmogorov-Smirnov test statistic	p-value	Test-type	N
Output growth	0.2125	0.1017	two-sided	200
Emissions growth	0.4438	0.0000	two-sided	200
Emissions at 2100	0.8250	0.0000	two-sided	200
Temperature at 2100	0.5688	0.0000	two-sided	200

Note: output and emission growth are averages over the whole time span.

exceed the 3 degrees threshold at 2100. Since the model is run in a business-as-usual (BAU) scenario, i.e. without mitigation and adaptation policies, two reasons could explain the observed patterns. First, the economy growth's engine could loose momentum, thereby reducing aggregate production, emissions and, finally, climate change. Second, the economy endogenously changes its energy mix and, in some cases, moves away from fossil-fuels to renewables, thus reducing the increase in temperature.

To disentangle the two possible effects, we rely on a series of formal tests for stationarity and ergodicity of stochastic simulation models (Grazzini, 2012; Guerini and Moneta, 2017; Dosi et al., 2017b). Such tools allow checking whether a model exhibits one or more statistical equilibria. In a nutshell, the model runs in an ergodic statistical equilibrium state if the properties of the series it generates are constant. In particular, we will first study whether the series (or a transformation of them) have distributional properties that are time-independent. Then, we will test whether the series are ergodic, meaning that the unknown stochastic process selecting the observed time series can be treated as a random sample. Following Guerini and Moneta (2017), we simulate the model in its baseline configuration, transform the data removing trends (if necessary), and collect them in a $M \times T$ matrix, where $M = 200$ represents the size of the Monte Carlo experiment and $T = 400$ the simulation length. Then, we use a series of Kolmogorov-Smirnov tests on pairs of series to detect the presence of a statistical equilibrium and its ergodicity. In particular, the model can be considered in a statistical equilibrium if a good proportion (e.g., 90%, as suggested in Guerini and Moneta, 2017) of tests do not reject the null hypothesis of equality of distributions, where each of these distributions is obtained polling data relative to the same simulation period but to different MC runs. Further, the statistical equilibrium is said to be ergodic if a good proportion (90%) of Kolmogorov-Smirnov tests confirm that distributions across time and seeds do not differ. In particular, ergodicity is determined by checking the equality of pairs of distributions, where the first is obtained pooling observations across time (within the same MC run) and the second pooling observations across runs (at the same time). Additional details on tests for statistical equilibria and their ergodicity are included in Appendix C. In what follows, we focus on 4 variables: (i) GDP, (ii) average productivity, (iii) emissions and (iv) temperature, where trends are removed through logarithmic differences.

Table 3 presents the percentage of non-rejections of the Kolmogorov-Smirnov tests carried out for each pairwise comparison of series. It clearly shows that the time series delivered by DSK model do not appear to exhibit one statistical equilibrium and ergodicity. Emissions and temperature anomaly appear to drive such a result. In particular, the very low non-rejection rate for emissions suggests that different dynamics of climate change may be closely linked to the energy mix adopted in the economy.

In turn, we find that the model produces a *non-ergodic* behaviour characterized by *two statistical equilibria*, each encompassing model runs characterized by specific dynamics of the share of green energy production (cf. Figure 3 and the last columns of Table 3). A *carbon intensive lock in* occurs whenever in a given run, the share of green energy drops below 15% and never rises again. Conversely, in the *transition to green* outcome, the share of green energy reaches the 85% threshold and never fall back afterward. As the energy market employ the cheapest power plant first (see Section 3), the transition toward sustainable growth occurs under comparable energy demand patterns observed in the carbon lock in cases. This suggests that the emergent energy mix depends on the relative competitiveness of different technologies, rather than on market design elements. A battery of Kolgomorov-Smirnov tests applied to average output and emission growth rates, and to the final observation (at 2100) of emissions and temperature anomaly confirm that the two statistical equilibria are statistically different in terms of model behaviour they produce, especially for climate-related variables (cf. Table 4).

Let us now investigate the behaviour of the model under carbon lock ins and green transitions. Table 5 reports the Monte Carlo average values of output growth, unemployment, emission growth, emissions and temperature at 2100, as well as their standard deviations. In addition, it further clusters runs on the basis of the timing they employ to reach their equilibrium state. As one could reasonably expect, carbon-intensive lock-ins are much more frequent (82%) than carbon decoupling outcomes (18%).[18] Moreover, we find that the most of (90%) of carbon lock-ins take place fast, i.e.

[18]In no Monte Carlo runs the share of renewable energy continues to fluctuate in way that does not allow categorization in one of the two types of equilibrium patterns.

Table 5: Likelihood of transition in the baseline configuration and main features of the different endogenous scenarios.

	Stat. Eq. I: Carbon intensive lock-in		Stat. Eq. II:Transition-to green	
Likelihood	82%		18%	
	before 2025 90%	after 2025 10%	before 2075 91%	after 2075 9%
Output growth	3.16% (0.001)	3.14% (0.002)	3.20% (0.001)	3.18% (0.004)
Unemployment	11.4% (0.016)	12.1% (0.020)	9.12% (0.019)	10.0% (0.012)
Emission growth	1.22% (0.001)	1.25% (0.002)	0.77% (0.001)	0.96% (0.002)
Emissions at 2100	28.64 (1.761)	30.12 (2.237)	18.22 (1.52)	23.13 (2.172)
Temperature at 2100	4.59 (0.103)	4.91 (0.178)	1.75 (0.123)	2.68 (0.153)

Note: all values refer to the average computed on the sub-sample of runs from a Monte Carlo of size 200 that are classified in each scenario. Standard errors are reported below each coefficient in parenthesis.

before 2025. A similar feature characterizes the transition to the sustainable scenario: when green technologies start to diffuse and reach some critical mass, their relative share with respect to dirty ones suddenly increases and they saturate the market, showing a typical S-shaped diffusion curve. Such results stems from the large investment outlays required to build renewable energy plants (in line with empirical evidence, see e.g. EIA, 2013). Moreover, a growing penetration of renewables causes a merit order effect whereby fossil-fuel plants are crowded out and the average electricity price falls (see various contributions from de Miera et al., 2008). In turn, unit production costs of capital- and consumption-good firms decline (see also Appendix A), leaving larger cash flows for investments in R%D and new green production capacity.

Our findings suggest that transition to green energy production ought to be *timely* in order to achieve sustainable growth with temperature projections below the +2 degree threshold at the end of the century. More specifically, simulation results show that transition should take place before 2030 to meet the +2 degree target and that temperature will likely rise above +3 degrees if the switch to green energy production occurs after 2075 (cf. Table 5). At the same time, economic growth is higher and unemployment rate is lower in carbon decoupling outcomes vis-à-vis fossil fuel lock-ins. Such results find in line with recent empirical evidence showing that investments in renewable energies creates substantially more jobs than in fossil fuels (Garrett-Peltier, 2017). Transitions toward sustainable growth trajectories could thus lead to *win-win* outcomes characterized by lower temperature and higher economic growth. However, the foregoing results do not account for the possible feedback effects from climate change to the economy. Let us study whether they are robust in presence of climate-change shocks hitting the economy.

5.2 Climate impacts and green transition

In the previous sections we have voluntarily excluded climate change shocks from the picture. This allowed to explore the properties of the model in absence of damages, while keeping consistency

Table 6: Likelihood of transition, economic performances and emissions under the different climate shock scenarios. Aggregate shocks use the damage function in Nordhaus and Sztorc (2013) and target aggregate output. Labour productivity and energy efficiency shocks hit individual firms.

Shock scenario:	Transition likelihood	Output growth	Energy growth	Emissions at 2100
Aggregate output	18%	3.18%	3.09%	28.33
	(of which 83% before 2025)	(0.001)	(0.003)	(6.431)
Labour productivity	20%*	1.51%*	1.16%*	25.70*
	(of which 69% before 2025)	(0.002)	(0.003)	(4.921)
Energy efficiency	7%*	3.02%	3.37%*	40.64*
	(of which 43% before 2025)	(0.003)	(0.003)	(3.872)

Note: all values refer to the average computed from a Monte Carlo of size 200. Standard errors are reported below each coefficient in parenthesis. * indicates a statistically significant (0.05 level) difference with respect to the *Aggregate output* scenario; tests for transition likelihoods are carried out via bootstrapping.

with the macro agent based and system dynamics literature on transitions (e.g. Safarzynska and van den Bergh, 2011; Ponta et al., 2016; see section 2 for details). However, as moving away from fossil fuels and developing low carbon energy capacity can take time (in our simulation the average time is around 40 years, consistent with the discussion in Markard et al., 2012), climate change is likely to exert significant effects on the transition (IPCC, 2014; Schleussner et al., 2016; Springmann et al., 2017), especially in absence of corrective policies. Here we present results from a series of computational exercises that investigate the impact of micro-level climate damages (see section 3.3) on the likelihood and feature of transitions to low carbon energy sources.

We model climate damages across three scenarios:

- *Aggregate shocks on GDP* as in traditional IAMs (Nordhaus and Sztorc, 2013; Nordhaus, 2014).
- *Micro labour productivity (LP) shocks.* Labor productivity ($A^L_{i,\tau}$ and $B^L_{i,\tau}$, see Appendix A) falls by a factor that varies across firms, as climate change negatively impacts on workers' operational and cognitive tasks (see Seppanen et al., 2003, 2006; Somanathan et al., 2014; Adhvaryu et al., 2014.
- *Micro energy efficiency (EF) shocks.* Firm-level energy efficiency ($A^{EE}_{i,\tau}$ and $B^{EE}_{i,\tau}$, see Appendix A) is reduced as climate shocks increase energy requirements in production activities (e.g. more stringent needs of cooling in response to higher temperatures and of heating in response to weather extremes, or partially ruined machines in response to natural disasters; see Auffhammer and Aroonruengsawat, 2011; Auffhammer and Mansur, 2014; Jaglom et al., 2014).

. While in the *aggregate shocks* case we adopt the damage function proposed in Nordhaus and Sztorc (2013), in the two remaining scenarios we employ the bottom-up approach described in section 3.3. In that, heterogeneous climate shocks hitting firms are drawn from a Beta distribution whose first and second moments closely follows the quadratic behaviour assumed in DICE and in a large part of the literature. Indeed, we account both for damages triggered by increases in temperature levels and variability. To provide an insight, equations 21 and 22 imply that the average individual climate shock would size about 1.46% for a temperature anomaly of 2 degrees, which becomes 3.69% at 3 degrees and 6.7% at 4. Table 6 collects the results of our comparison across the three impact scenarios.

Simulation results show that the likelihood of transitions towards green growth depends on how climate damages are modelled. In the standard aggregate perspective commonly adopted by the majority of IAMs (Table 6, upper row), the likelihood of transition is *invariant* to climate damages as shocks affect only aggregate potential output. However, when one assumes that the occurrence and magnitude of micro climate damages affects agents heterogeneously, the probability of achieving a sustainable, low emission growth pattern depends on the dynamics of climate change (cf. Table 6, middle and lower row). More specifically, shocks to labour productivity might increase the likelihood of transitions (20% vs. 18% in the case of aggregate damages), while the opposite happens for energy-efficiency shocks (only a 7% likelihood).

Such results stem from the size of the final demand for energy and the role path dependence. Indeed, if energy efficiency is reduced by climate shocks, the energetic needs to produce a given aggregate output will increase, thereby inducing the energy industry to adapt its generation capacity. Since fossil-fuel technologies start with a lower lifetime production cost, expansionary investment will favour such a technological trajectory.[19] Dynamically, this leads to a much larger spending in R&D activities aimed at improving the efficiency of brown plants, which creates a vicious cycles impeding the shift to low carbon technologies. This phenomenon turns out to dominate the dynamics, notwithstanding the penalizing effect the merit order market mechanisms exerts on brown plants.

By a similar token, shocks to labour productivity induce an increasingly sharp contraction in industrial production, wages and final demand (notice the low growth rate of output in Table 6, see also Lamperti et al., 2018b for additional details). In presence of merit order activation protocol, the lower energy demand will induce an increase in the share of green plants' production in the energy mix, which will further stimulates green R&D and improves the competitiveness of low carbon technologies. When such technologies catch-up their initial backwardness, the transition start to take place and, further self-sustains, as the marginal cost of green plants remains below the one of the brown counterparts, making them operating at increasing under-capacity.[20] At the end of their lifetime, un-activated brown plants will be replaced by green energy generation units, thus sustaining the transition.

5.3 Climate policy and green transition

Given the presence of substantial and heterogenous climate impacts, what is the role of climate policies in triggering and sustaining the transition to renewable energy sources? The last battery of simulations exercises will reply to this question. In particular, we will focus on price-related instruments, which modify the cost of fossil fuels and, in turns, the relative cost-competitiveness of green vs. brown technologies. In that, we study the imposition of an implicit carbon tax (Martin et al., 2014).[21]

In the following experiments, we assign different values to the parameter, θ, which modifies the price of fossil fuels and, in turns, the relative lifetime and production costs of brown energy plants. In particular, the unitary production cost of a fossil-fuel plant of vintage τ can be written as

$$c_{de}(\tau, t) = \frac{p_f + \theta}{A^{\tau}_{de}}. \tag{24}$$

Then, the lifetime total cost of a brown plant, $LC_{de}(t)$, is obtained, under the assumption that

[19] See also Acemoglu et al. (2012) and Aghion et al. (2015) on this point.

[20] This findings are in line with the results in Van Der Ploeg and Withagen (2012) and Ploeg and Withagen (2014).

[21] Note that a good portion of climate policies is ultimately representable through the policy effect on energy prices, which reflect the cost-structure of energy generation (Marin et al., 2017).

the plant is employed at full capacity for its entire life, by simply multiplying $c_{de}(\tau, t)$ by b_e, which represents the accountable life of the plant. On the green side (cf. section 3), unitary production costs of renwable energy plants are virtually set to zero, while installation fixed costs are represented by IC^{τ}_{ge}, which is dynamically affected by innovations in the green technological trajectory. This implies that the lifetime total cost of a green plant, $LC_{ge}(t)$, is exactly equal to IC^{τ}_{ge}. Our policy experiments focus on the ratio LC_{de}/LC_{ge}, which expresses the cost-advantage of dirty technologies. By varying the parameter θ, we modify the relative cost-competitiveness of low carbon technologies: $\theta > 0$ mimics a tax on fossil fuels or a subsidy toward investments in green energy technologies (e.g. a sort of feed-in tariff increasing the expected profitability of a green investment), whereas $\theta < 0$ captures fossil fuel subsidies, which are diffused policy instruments (Coady et al., 2017).[22]

We adopt the following simulation protocol: starting from the baseline configuration described in section 4, where brown energy technologies have a 20% cost-advantage at the beginning of the simulation[23], and we modify θ through the whole simulation time (in line with policy exercises in macro ABMs, c.f. e.g. Dosi et al., 2015; Popoyan et al., 2017; Ponta et al., 2016). Such experiments are combined with the three climate-change impact scenario described in the previous sub-section and, namely, *aggregate shocks* to GDP, *micreconomic shocks to labour productivity* and *microeconomic shocks to energy efficiency*. Figures 4 - 6 summarize our main findings.

Simulation results show that price of fossil fuels influences the likelihood of transition in a non-linear way (panels 4a, 5a and 6a). A policy-engineered increase in the cost-competitiveness of green energy technologies can increase the likelihood of a transition, regardless of the type of climate damage we assume. However, given the initially larger installed capacity of brown vis-á-vis green plants (see Appendix B) and the cumulative nature of the technical change process, small variations of the $\frac{LC_{de}}{LC_{ge}}$ ratio have a remarkable low impact on inducing the transition. In presence of sufficiently carbon tax and/or subsidies to green energy, the likelihood of achieving growth decoupled from carbon emission improves substantially. Naturally, the transition to sustainable growth is almost impossible in presence of subsidies to fossil-fuel energy plants. These results suggest that energy policy interventions needs to be *substantial* in order to significantly affect the environmental sustainability of the economy's growth process. Moreover, policies ought to be *timely* as path-dependence in the process of technological change (David, 1985; Arthur, 1994) deeply affect the policy outcome.[24]

Further, we find that the effectiveness of policy interventions also depends on the type of climate damage. As already documented in section 5.1 with respect to the likelihood of transition, policy impact differs shifting from aggregate to individual climate damage scenarios. When shocks are aggregate, consumers suffer the damage and reduce consumption, thereby cutting output levels but leaving unaltered the production schedule for the next period. In that, aggregate shocks have no memory and policy intervention is not affected by the shock. Things change when climate directly reduce productive abilities of firms. In particular, when climate change shocks affects labour productivity, policies supporting green energy technologies are substantially more effective than in the case of shocks targeting energy efficiency. Similarly to what discussed above, the size of final demand matters. When aggregate demand is lower (see panels 4b, 5b and 6b), the economy is more

[22] Note that such policy experiments are akin to a variation of the price of fossil fuels in international markets.

[23] Such an initial setting is broadly consistent with the existing estimates and modeling assumptions for energy technologies. We refer the interested reader to the series of annual reports of the IEA (`https://www.eia.gov/outlooks/aeo/`) and to Tidball et al. (2010) for information about costs of energy plants.

[24] For further readings on the role of path dependence in shaping the technological landscape, see e.g. Liebowitz and Margolis (1995); Frenken and Nuvolari (2004); Castaldi and Dosi (2006) and, more recently, Dosi et al. (2017a).

responsive to energy policies aimed at increasing the competitiveness of green technologies. On the contrary, when climate change exerts its negative effects on plants' efficiency, the final demand of energy increases, and green plants face a comparative disadvantage in terms of R&D spending, which cuts the chances of observing a surge in green energy production. As a consequence, stronger policies are required to support the transition, whose likelihood remains, however, remarkably low (17%) even when cost-advantage of brown plants is initially reduced to 1% by the policy intervention. Climate damages increasing energy demand exacerbate the role of path-dependence in the energy industry, pointing to the need for additional complementary policy instruments (e.g. command-and-control; see Lamperti et al., 2015) to market-based incentives.[25]

6 Discussion and conclusions

Climate change can impact both the process of transition towards low-carbon energy systems and the effectiveness of related policy interventions. In the paper, we have employed the DSK agent-based integrated assessment model (Lamperti et al., 2018b) to study the shift from brown (fossi-fuel based) to green (low-carbon) energy technologies and its macroeconomic implications in presence of climate change.

We find that the model exhibits two statistical equilibria (a carbon intensive lock-in and a transition to green energy) characterized by different energy mix. Transitions from brown to a green energy system might endogenously happen, but the likelihood of such events is exceptionally small and it depends on exceptional technological breakthrough.[26] Further, we found that climate change can influence the likelihood of carbon decoupling according to the way climate damages are modelled. When an aggregate and linear damage function is considered, as in the majority of general-equilibrium IAMs, the likelihood of transition is invariant to climate shocks, which simply reduce aggregate GDP. However, in presence of microeconomic climate damages, the probability of transition depends on the channels climate damages affect agents and firms. When climate shocks hit labor productivity, economic growth is reduced, but the likelihood of transition to green energy is higher. This result supports the idea that the economic environment is more responsive to climate policy in times of crisis (Jaeger et al., 2011; Ekins et al., 2014), also in line with recent systematic evaluations of the green stimulus programs implemented in the aftermath of the 2008 financial crisis in the U.S. (Mundaca and Richter, 2015). On the other side, climate damages reducing energy efficiency exacerbates the role of path-dependence in the energy industry, thereby increasing the difficulty of the catch-up process of clean energy technology.

Of course, the climate damages emerging in the present paper are somewhat downwardly biased by the fact our impact scenarios constraint shocks to a single variable (e.g. labour productivity or energy efficiency). This is - however - a necessary condition to study how different impact channels affect the macro-economy. Table 7 provides insights on the overall damage of climate change, assuming that all impacts other than those studied in the scenarios can be represented by a variable, labelled "environmental quality", which deteriorates over time by a factor corresponding to the average shock suffered by agents in that particular period (this is consistent with the similar

[25] As reported in Figure 6, in presence of energy efficiency shocks, GDP and emissions growth remains relatively high with respect to the other two scenarios, as individual damages just decrease energy efficiency, whose aggregate, macroeconomic effects are found to be limited (see the extensive discussion on macroeconomic impacts of climate change in Lamperti et al., 2018b).

[26] See also Unruh (2002) for thoughtful discussion on escaping carbon lock-ins with and without supporting policy.

Table 7: A simplified approach to welfare evaluation of climate damages in case of labour productivity and energy efficiency shocks. All values are relative to the case of no damages (a value of 100 would indicate identity with respect to the scenario where climate damages are not considered). Welfare is proxied as a simple average of normalized GDP, employment rate and environmental quality. Environmental quality degradation represents all dimensions of climate impacts other than labour productivity and energy efficiency. Environmental quality is assumed to start at 100 and decrease by a factor equal to the average climate shock suffered by agents in that period.

	GDP	Employment rate	Environmental quality	Well being index
		Labour Productivity Shocks		
2000-25	0.90	0.96	0.98	0.95
25-50	0.76	0.88	0.94	0.86
50-75	0.47	0.71	0.90	0.69
75-2100	0.21	0.48	0.84	0.51
		Energy Efficiency Shocks		
2000-25	0.96	0.99	0.98	0.98
25-50	0.88	0.99	0.94	0.94
50-75	0.87	0.93	0.90	0.90
75-2100	0.84	0.92	0.84	0.87

Note: all values refer to the average computed from a Monte Carlo of size 200.

shape damage functions show in different sectors, see Hsiang et al., 2017). Results show that in both our scenarios climate damages are substantial. For example, using a simplistic "welfare" measure averaging GDP level, employment share and environmental quality (all conveniently normalized), climate change would reduce well-being by 49% in the labour productivity shock scenario and 13% in the energy efficiency shock scenario, pointing to the need of an early green transition whatever the impact channel might actually be.

Our findings have both theoretical and policy implications. From a modelling perspective, the traditional way of representing damages in the climate economics literature in terms of GDP losses oversimplifies the effects of climate change in a complex economic system, hiding the role of climate impacts in fostering a carbon lock-in or in favoring a transition to sustainable energy. As a consequence, policies supporting the transition to sustainable growth fueled by green energy should careful consider the possible different channels through which climate damages affect the economy. Indeed, we find that the effectiveness of policies measures depends on the impact channel of climate change and that, in general terms, policies constructed around monetary incentive often produce limited results in fostering a transition whose likelihood reduces over time due to path dependence in technological change. Such results point to the necessity of rapidly taking into consideration complementary policy instruments to market-based incentives and carbon taxes of a deemed optimal size (see also Unruh, 2002; Aznar-Mrquez and Ruiz-Tamarit, 2016): regulation and adequate monitoring are often much more effective than other tools (Lamperti et al., 2015; Shapiro and Walker, 2015). Finally, one of the future developments of our model envisions the inclusion of financial actors shaping the investment-incentive landscape for different energy technologies, and points to the analysis of credit policies in addition to fiscal and regulatory initiatives as a necessary step forward in the study of green transitions.[27]

[27] The interested reader might want to look at Linnenluecke et al. (2016) for a research agenda on environmental finance.

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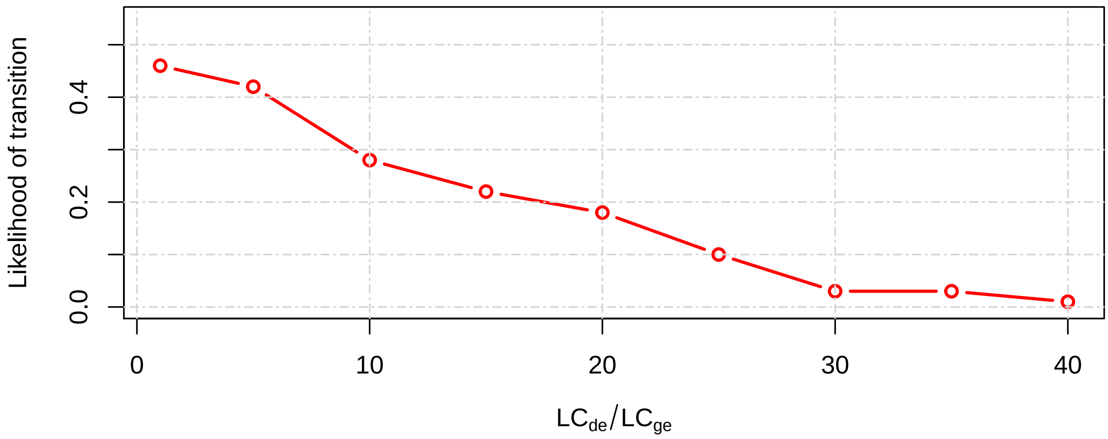
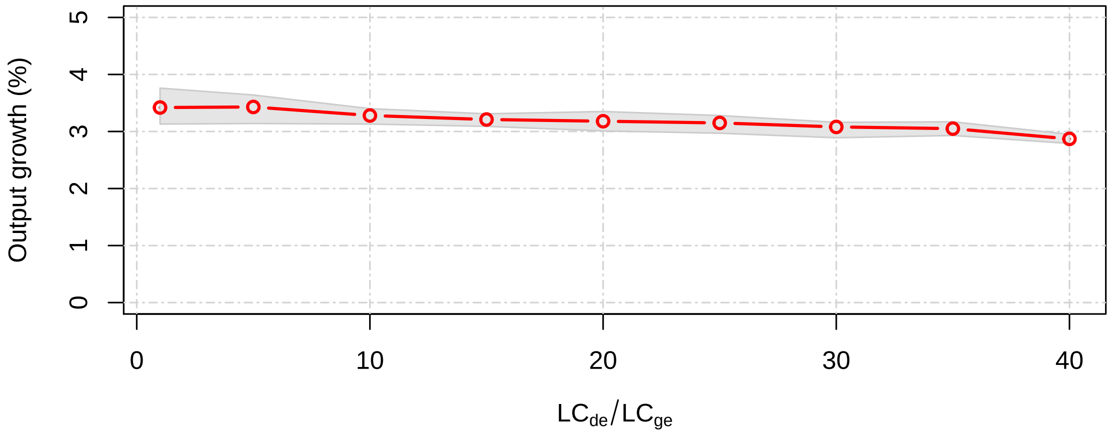
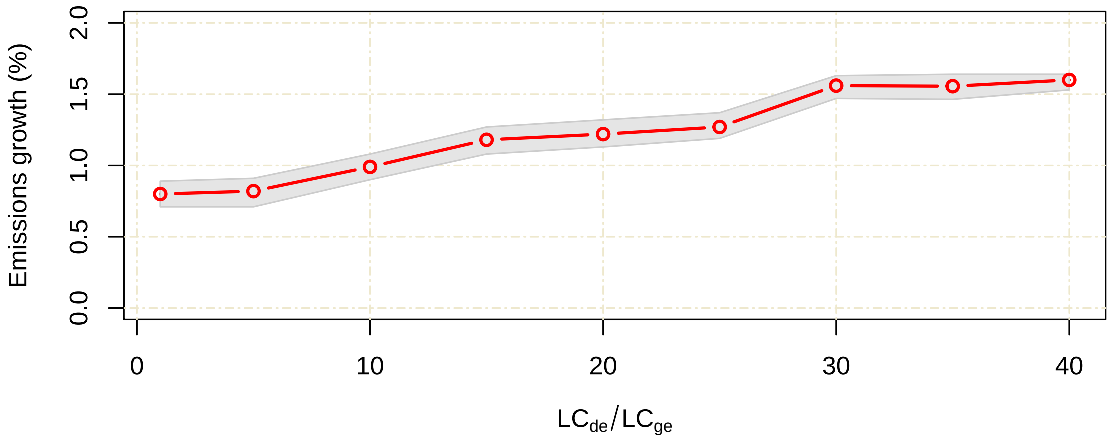
Figure 4: Likelihood of transition, average output and emissions growth under different policy strengths and aggregate climate damages as in (Nordhaus and Sztorc, 2013). LC_{de}/LC_{ge} represents the relative cost-advantage of brown energy technologies at the beginning of the simulation; 20% is the baseline. MC of size 200 is used, shaded area represents 90% percentile interval.



(a) Likelihood of transition - Aggregate shocks.

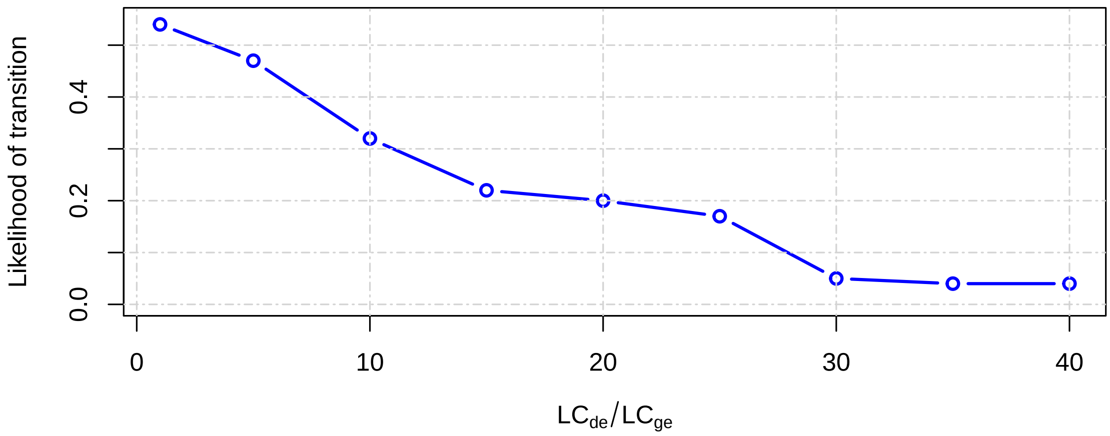


(b) Output growth - Aggregate shocks.

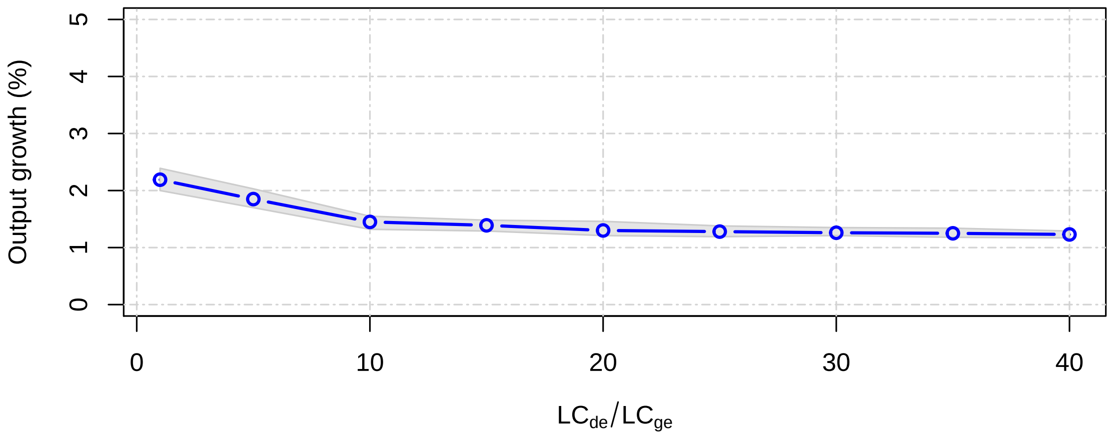


(c) Emissions growth - Aggregate shocks.

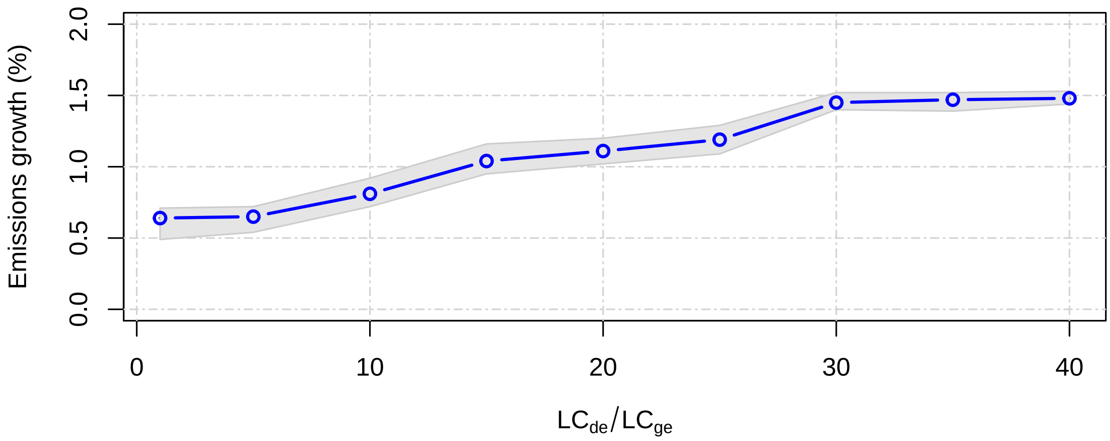
Figure 5: Likelihood of transition, average output and emissions growth under different policy strengths and individual climate damages targeting labour productivity. LC_{de}/LC_{ge} represents the relative cost-advantage of brown energy technologies at the beginning of the simulation; 20% is the baseline. MC of size 200 is used, shaded area represents 90% percentile interval.



(a) Likelihood of transition - Individual shocks to labour productivity.

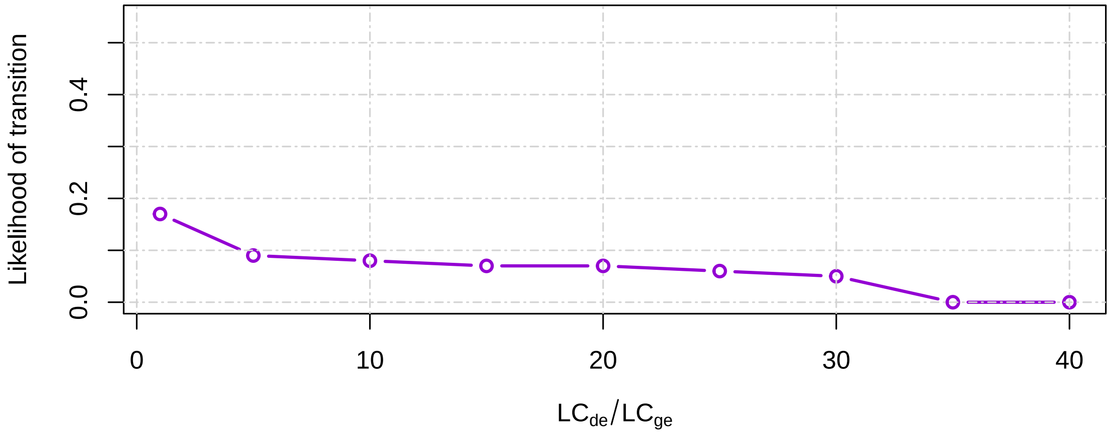


(b) Output growth - Individual shocks to labour productivity.

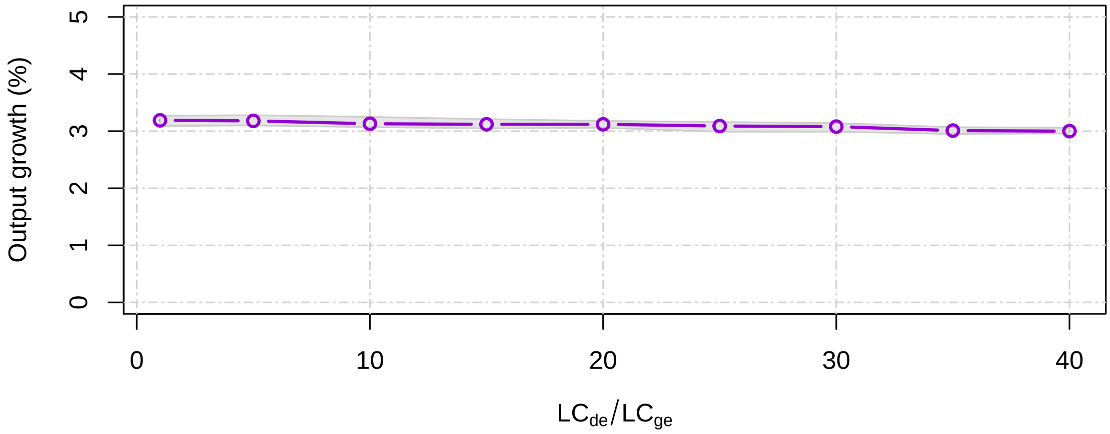


(c) Emissions growth - Individual shocks to labour productivity.

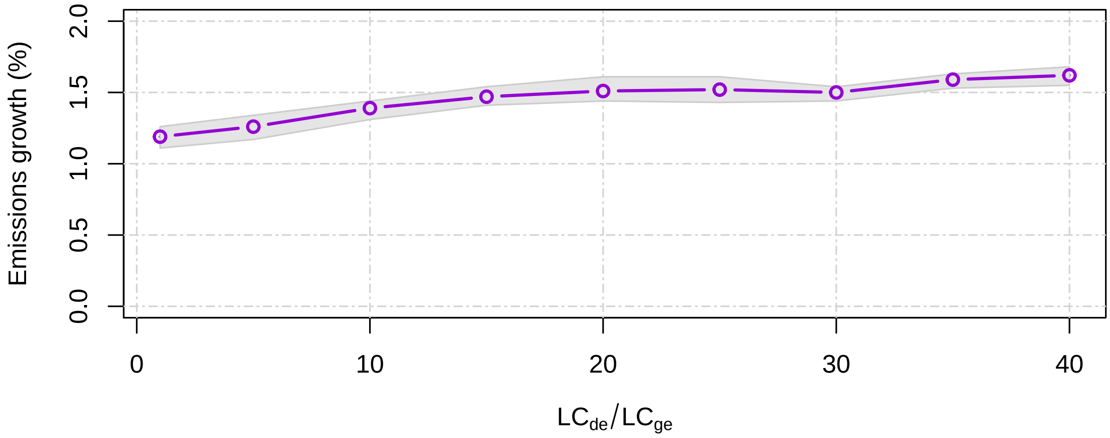
Figure 6: Likelihood of transition, average output and emissions growth under different policy strengths and individual climate damages targeting energy efficiency. LC_{de}/LC_{ge} represents the relative cost-advantage of brown energy technologies at the beginning of the simulation; 20% is the baseline. MC of size 200 is used, shaded area represents 90% percentile interval.



(a) Likelihood of transition - Individual shocks to energy efficiency.



(b) Output growth - Individual shocks to energy efficiency.



(c) Emissions growth - Individual shocks to energy efficiency.

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A Appendix - Model details

The capital good industry

Capital-good firms' technology is defined by a set of six firm-specific coefficients composed by $A^k_{i,\tau}$ with $k = \{L, EE, EF\}$, which represent the technical features of the machine produced, and $B^k_{i,\tau}$, which represent the features of the production technique employed by firm i, with τ being the technology vintage. Firms define their price by applying a fixed mark-up ($\mu_1 > 0$) on their unit cost of production defined by the nominal wage, nominal cost of energy, labour productivity, energy efficiency and, eventually, a carbon tax. Capital-good firms can increase both their process and product technology levels via (costly) innovation and imitation. Indeed, R&D expenditures, defined in each period as a fraction of past sales are split between both activities according to the parameter $\xi \in [0,1]$.

The innovation process has two steps: first a random draw from a Bernoulli distribution with parameter $\vartheta_i^{in}(t) = 1 - \exp^{-\varsigma_1 INNOV_i(t)}$ determines whether firm i innovates or not, with $0 \leq \varsigma_1 \leq 1$. Note that higher amounts of R&D expenditures allocated to innovation, $INNOV_i(t)$, increase the probability to innovate. If an innovation occurs, the firm draws the new technology whose main features are described by equations (**??**), (**??**) and (**??**) in section **??**. The imitation process is similarly performed in two steps. A Bernoulli draw ($\vartheta_i^{im}(t) = 1 - \exp^{-\varsigma_2 IMIT_i(t)}$) defines access to imitation given the imitation expenditures, $IMIT_i(t)$, with $0 \leq \varsigma_2 \leq 1$. In the second stage, a competitor technology is imitated, based on an imitation probability which decreases in the technological distance (computed adopting Euclidean metrics) between every pair of firms. Note that the innovative and imitation processes are not always successful as the newly discovered technology might not outperform firm i's current vintage. The comparison between the new and incumbent generations of machines is made taking into account both price and efficiency, as specified by equation (**??**). Next, capital-good firms advertise their machine's price and productivity by sending a "brochure" to potential customers (both to historical clients, $HC_i(t)$, and to a random sample of potential new customers, $NC_i(t)$[28] consumption-good firms thus have access to imperfect information about the available machines.

The consumption good industry

Consumption-good firms produce a homogeneous good using two types of inputs (labor and capital) with constant returns to scale. The desired level of production Q_j^d depends upon adaptive expectations $D_j^e = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)]$, desired inventories ($N_j^d$), and the actual stock of inventories (N_j):

$$Q_j(t)^d = D_j^e(t) + N_j^d(t) - N_j(t), \tag{25}$$

where $N_j(t) = \iota D_j^e(t),\ \iota \in [0,1]$.

Consumption-good firms' production is limited by their capital stock ($K_j(t)$). Given the desired level of production firms evaluate their desired capital stock (K^d), which, in case it is higher than their current one, calls for desired expansionary investment (EI^d):[29]

$$EI_j^d(t) = K_j^d(t) - K_j(t). \tag{26}$$

Each firms' stock of capital is made of a set of different vintages of machines with heterogeneous productivity. As time passes by, machines are scrapped according to (**??**) . Total replacement investment is then computed at firm level as the number of scrapped machines satisfying the previous condition, and those with age above η periods, $\eta > 0$. Firms compute the average productivity of their capital stock, the unit cost of production, and set prices by applying a variable mark-up on unit costs of production as expressed by equation (**??**). Consumers have imperfect information regarding the final product (see Rotemberg, 2008 , for a survey on consumers' imperfect price knowledge) which prevents them from instantaneously switching to the most competitive producer. Still, a firm's competitiveness ($E_j(t)$) is directly determined by its price, but also by the amount of past unfilled demand $l_j(t)$:

$$E_j(t) = -\omega_1 p_j(t) - \omega_2 l_j(t), \tag{27}$$

where $w_{1,2} \geq 0$.[30] At the aggregate level, the average competitiveness of the consumption-good sector is computed averaging the competitiveness of each consumption-good firm weighted by its past market share, f_j. Market shares are finally linked to their competitiveness through a "quasi" replicator dynamics:

$$f_j(t) = f_{j,t-1}\left(1 + \chi \frac{E_j(t) - \bar{E}_t}{\bar{E}_t}\right), \tag{28}$$

[28]The random sample of new customers is proportional to the size of $HC_i(t)$. In particular, $NC_i(t) = \Upsilon HC_i(t)$, with $0 \leq \Upsilon \leq 1$.

[29]In line with the empirical literature on firm investment behaviour (Doms and Dunne, 1998), firms' expansion in production capacity is limited by a fixed maximum threshold. Moreover, as described below, credit-constrained firms' effective investment does not reach the desired level.

[30]Such unfilled demand is due to the difference between expected and actual demand. Firms set their production according to the expected demand. If a firms is not able to satisfy the actual demand, its competitiveness is accordingly reduced. On the contrary, if expected demand is higher than actual one, inventories accumulate.

where $\chi > 0$ and $\bar{E}_t$ is the average competitiveness of the consumption good sector.

The banking industry, complements.

Our financial system is relatively stylized. We assume a banking sector composed by a unique commercial bank (or multiple identical ones) that gathers deposits and provides credit to firms. In what follows, we first describe how credit demand is calculated by each firm. Next, we discuss how total credit is determined by the bank, and how credit is allocated to each firm.

The financial structure of firms matters (external funds are more expensive than internal ones) and firms may be credit rationed. Consumption-good firms have to finance their investments as well as their production and start by using their net worth. If the latter does not fully cover total production and investment costs, firms borrow external funds from the bank. Total production and investment expenditures of firms must therefore satisfy the following constraint

$$c_j(t)Q_j(t) + EI_j(t)^d + RI_j(t)^d \leq NW_j(t)^d + Deb_j(t)^d \tag{29}$$

where $c_j(t)Q_j(t)$ indicates total production costs, $EI_j(t)^d$ expansion investment, $RI_j(t)^d$ replacement investment, $NW_j(t)$ the net worth and $Deb_j(t)$ is the credit demand by the firm. Firms have limited borrowing capacity: the ratio between debt and sales cannot exceed a maximum threshold: the maximum credit demand of each firm is limited by its past sales according to a loan-to-value ratio $0 \leq \lambda \leq +\infty$. The maximum credit available in the economy is set through a credit multiplier rule. More precisely, in each period the bank is allowed by the Central Bank to grant credit above the funds obtained through deposits from firms in the two industries (and equal to firms' past stock of liquid assets) according to a multiplier $k > 0$:

$$MTC_t = k \sum_{j=1}^{N} NW_{j,t-1}. \tag{30}$$

Since deposits are the only form of debt for the bank, k determines also the debt to asset ratio that should be satisfied by the bank while providing credit. Such a total credit, which generates endogenous money, is allocated to each firm in the consumption-good sector on a pecking order basis, according to the ratio between net worth and sales. If the total credit available is insufficient to fulfill the demand of all the firms in the pecking order list, some firms that are lower in the pecking order are credit rationed. Conversely, the total demand for credit can also be lower than the total notional supply. In this case all credit demand of firms is fulfilled and there are no credit-rationed firms. It follows that in any period the stock of loans of the bank satisfies the following constraint:

$$\sum_{j=1}^{N} Deb_j(t) = Loan(t) \leq MTC_t. \tag{31}$$

The profits of the bank are equal to interest rate receipts from redeemable loans and from interests on reserves held at the Central Bank minus interests paid on deposits. Furthermore, the bank fixes its deposit and loan rates applying respectively a mark-down and a mark-up on the Central Bank rate.

Consumption, wages, taxes and public expenditures

The consumption of workers is linked to their wage. We assume that the wage rate, $w(t)$ is determined by institutional and market factors, with indexation mechanisms upon the inflation, average productivity, and the unemployment rate:

$$w(t) = w(t-1)\left[1 + \psi_1 \frac{\Delta \bar{AB}(t)}{\bar{AB}(t-1)} + \psi_2 \frac{\Delta cpi(t)}{cpi(t-1)} + \psi_3 \frac{\Delta U(t)}{U(t-1)}\right], \tag{32}$$

where $\bar{AB}$ indicates the average productivity in the economy, cpi is the consumer price index and, intuitively, U stands for unemployment rate.

The public sector levies taxes on firm profits and worker wages (or on profits only) and pays to unemployed workers a subsidy, which corresponds to a fraction of the current market wage. In fact, taxes and subsidies are the fiscal instruments that contribute to the aggregate demand management. All wages and subsidies are consumed: the aggregate consumption (C_t) is the sum of income of both employed and unemployed workers. We notice that consumption, in this model, does not directly entail production of emissions. The model satisfies the standard national account identities: the sum of value added of capital- and consumption-goods firms (Y_t) equals their aggregate production since in our simplified economy there are no intermediate goods, and that in turn coincides with the sum of aggregate consumption, investment ($I_t = EI_t + RI_t$) and change in inventories (ΔN):

$$\sum_{i=1} Q_i(t) + \sum_j Q_j(t) = Y_t \equiv C_t + I_t + \Delta N. \tag{33}$$

Climate module: carbon cycle and time-line of events

As in Goudriaan and Ketner (1984) and Oeschger et al. (1975), our carbon cycle is modeled as a one-dimensional compartment box. Atmospheric CO_2 evolve according to anthropogenic emissions and oceans and biomass intakes.

Terrestrial net primary production (NPP), grows with CO_2 stocks (Wullschleger et al., 1995) and is negatively affected by rising temperatures:

$$NPP(t) = NPP(0)\left(1 + \beta_C \log\frac{C_a(t)}{C_a(0)}\right)(1 - \beta_{T_1} T_m(t-1)) \tag{34}$$

where $C_a(t)$ represent the stock of carbon in the atmosphere, T_m is the increase in mean surface temperature from the pre-industrial level (corresponding to $t = 0$), β_C is the strength of the CO_2 fertilization feedback (Allen, 1990; Allen and Amthor, 1995; Matthews, 2007), and β_{T_1} captures the magnitude of the temperature effect on NPP. In line with the recent findings of Zhao and Running (2010), we model a negative effect of global warming on NPP as in Sterman et al. (2012). This constitutes the first positive climate-carbon feedback in our model.[31]

The concentration of carbon in the atmosphere depends also on the structure of exchanges with the oceans. The latter are represented by a two-layer eddy diffusion box which simplifies Oeschger et al. (1975).[32] The equilibrium concentration of carbon in the mixed layer, C_m, depends on the atmospheric concentration and the buffering effect in the oceans created by carbonate chemistry:

$$C_m(t) = C_m^*(t)\left[\frac{C_a(t)}{C_a(0)}\right]^{\frac{1}{\xi(t)}} \tag{35}$$

where C_m^* is the reference carbon concentration in the mixed layer, $C_a(t)$ and $C_a(0)$ are the concentrations of atmospheric carbon at time t and at the initial point of the simulation, and $\xi(t)$ is the buffer (or Revelle) factor.[33] The Revelle rises with atmospheric CO_2 (Goudriaan and Ketner, 1984; Rotmans, 1990) implying that the oceans' marginal capacity to uptake carbon fall as its concentration in the atmosphere increases. Moreover, rising temperatures also reduces seawater solubility of CO_2 (Fung, 1993; Sarmiento et al., 1998), introducing another climate-carbon cycle positive feedback which accelerate climate change by reducing C_m^* (Cox et al., 2000). Finally, CO_2 is gradually transferred from the mixed to the deep layer of the oceans according to a speed that varies with the relative concentration of carbon in the two layers.

The flux of carbon though atmosphere, biosphere and oceans affects the heat transfer across the system and, hence, the dynamics of Earth surface mean temperature. Such a relationship is modelled through equations (18) and (19) in the main text, and mediated by the accumulation of carbon leads to global warming through increasing radiative forcing according to a logarithmic relationship:

$$F_{CO_2}(t) = \gamma \log\left(\frac{C_a(t)}{C_a(0)}\right). \tag{36}$$

Equation (36) represents the main link between anthropogenic emissions, which contribute to increase the concentration of carbon in the atmosphere at any period, and climate change, which is induced by the radiative forcing of atmospheric GHGs. On the other side, global warming exerts two important feedbacks on the dynamics of carbon, affecting its exchanges with the biosphere and the oceans.

[31]Even if the role of climate change on biosphere's carbon uptake of is still object of debate (Shaver et al., 2000; Chiang et al., 2008; IPCC, 2001, ch. 3), the recent IPCC (2007a) provides evidences of stronger positive climate-carbon cycle feedbacks.

[32]In particular, it is composed by a 100 meters mixed layer (which constitutes upper oceans) and a deep layer of 3700 meters for an average total depth of 3800 meters. Our representation of the oceans resembles that in Nordhaus (1992).

[33]The Revelle factor (Revelle and Suess, 1957) expresses the absorption resistance of atmospheric carbon dioxide by the ocean surface layer. The capacity of the ocean waters to take up surplus CO_2 is inversely proportional to its value.

B Appendix - Parameters' value

Table 8: Main parameters and initial conditions in the economic system. For previous parametrization of some sub-portions of the model and for model sensitivity to key parameters see Dosi et al. (2006, 2010, 2013).

Description	Symbol	Value
Monte Carlo replications	MC	200
Time sample in economic system	T	400
Time sample in climate system	T	400
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	200
Capital-good firms' mark-up	μ_1	0.04
Consumption-good firm initial mark-up	$\bar{\mu}_0$	0.28
Energy monopolist' mark-up	μ_e	0.01
Uniform distribution supports	$[\varphi_1, \varphi_2]$	$[0.10, 0.90]$
Wage setting $\Delta \bar{AB}$ weight	ψ_1	1
Wage setting Δcpi weight	ψ_2	0
Wage setting ΔU weight	ψ_3	0
R&D investment propensity (industrial)	ν	0.04
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
R&D investment propensity (energy)	ξ_e	0.01
Share of energy sales spent in R&D	v_e	0.01
Beta distribution parameters (innovation)	(α_1, β_1)	$(3, 3)$
Beta distribution support (innovation)	$[\chi_1, \bar{\chi}_1]$	$[-0.15, 0.15]$
New customer sample parameter	$\bar{\omega}$	0.5
Desired inventories	l	0.1
Physical scrapping age (industrial)	η	20
Physical scrapping age (energy)	η_e	80
Payback period (industrial)	b	3
Payback period (energy)	b_e	10
Initial (2000) share of green energy		0.1

Table 9: Climate box main parameters and initial conditions.

Parameter	Symbol	Value	Unit of Measurement	Source
Preindustrial Global Mean Surface Temp.	T_{pre}	14	degree Celsius	Sterman et al. (2013)
Preindustrial carbon in the ocean (per meter)		10.237	GtonC	Sterman et al. (2013)
Preindustrial reference CO_2 in atmosphere	Ca_0	590	GtonC	Sterman et al. (2013)
Preindustrial Net Primary Production	NPP_{pre}	85.177	GtonC/year	Goudriaan and Ketner (1984)
Initial carbon in the atmosphere		830.000	GtonC	Nordhaus and Sztorc (2013)
Initial carbon in deep oceans		10,010.000	GtonC	Nordhaus and Sztorc (2013)
Initial temperature in atmosphere	T_0	14.800	degree Celsius	Nordhaus and Sztorc (2013)
Response of primary production to carbon conc.	β_C	1	Dmnl	Goudriaan and Ketner (1984)
Reference buffer factor	revelle	9.7	Dmnl	Goudriaan and Ketner (1984)
Index for response of buffer factor to carbon conc.	deltaC	3.92	Dmnl	Goudriaan and Ketner (1984)
Eddy diffusion coefficient for circulation in oceans	d_{eddy}	1	Dmnl	Oeschger et al. (1975)
Mixed oceans depth	d_{mixed}	100	m	Oeschger et al. (1975)
Deep oceans depth	d_{deep}	3500	m	Sterman et al. (2013)
Sensitivity of carbon uptake to temperature by land	β_{TC}	-0.01	1/degree Celsius	Friedlingstein et al. (2006)
Sensitivity of carbon uptake to temperature	β_T	0.003	1/degree Celsius	Friedlingstein et al. (2006)
Diffusion for atmospheric temperature equation	c_1	0.098		Nordhaus and Sztorc (2013)
Equilibrium climate sensitivity	λ	2.9	degree Celsius	Nordhaus and Sztorc (2013)
Diffusion in deep oceans temp. equation	c_3	0.088		Nordhaus and Sztorc (2013)
Sensitivity of atmospheric temp. to deep ocean temp.	c_4	0.025		Nordhaus and Sztorc (2013)
Radiative forcing coefficient	γ	5.35	W/m2	Sterman et al. (2013)
GtC to $GtCO_2$ conversion factor		3.67		IPCC (2001)
		Climate Shocks		
Sensitivity to location	a_0	4		authors
Sensitivity to scale	b_0	100		authors

C Appendix - Tests for statistical equilibrium and ergodicity

This section largely draws on Guerini and Moneta (2017). Assume that a simulation model is used to produce synthetic series X_k for a set of variables $k = 1, ..., K$. In particular M Monte Carlo realizations, each of length T simulation periods are collected. Then, one can test that the series, or a transformation of them, have distributional properties that are time-independent; and that they are, ergodic, meaning that the stochastic process underlying the observed time series can be treated as a random sample. These two assumptions can be tested through a simple procedure. Indeed if we consider all the M time series realization of a variable k of interest we will collect a matrix with dimensions $M \times T$ containing all the observations $X^m_{k,t}$, where m indicates the number of the MC run and t the simulation time. We here define *ensembles* all the possible column vectors of such a matrix; therefore, each of these vectors contains the M observations $X^m_{k,\cdot}$ with $m = 1, ..., M$, in which the time dimension is fixed; we instead define *samples* all the possible row vectors of such a matrix, each of which contains the T observations $Y^{\cdot}_{k,t}$ with $t = 1, ..., T$ in which the Monte Carlo dimension is fixed. Hence, denoting by $F_t(X_k)$ the empirical cumulative distribution function of an ensemble and by $F_m(X_k)$ the empirical cumulative distribution function of a sample, testing for statistical equilibrium and for ergodicity reduces to test respectively for the following conditions using the Kolmogorov-Smirnov statistic:

$$F_i(X_k) = F_j(X_k) \quad \forall i, j \in \{1, ..., T\} \tag{37}$$

$$F_h(X_k) = F_g(X_k) \quad \forall h \in \{1, ..., T\},\ g \in \{1, ..., M\}. \tag{38}$$

Therefore, we performed two kind of tests as represented in Figure 7: we recursively run tests of pairwise equality of distributions and we presented the percentage of non-rejection of such tests. Rejecting the test would imply that the distributions under investigation are different one from the other. For the model to be in an ergodic statistical equilibrium, we need to have high percentages of non-rejection, meaning that we cannot distinguish between distributions. In case this is not verified, MC runs can be clustered and, then, the same procedure will be applied to any cluster. If we register high percentages of non-rejection within each cluster we can claim these clusters represent multiple statistical equilibria. Finally, if some summary statistics of model behaviour exhibit distributions that are statistically different across clusters, we claim that statistical equilibria are truly different one from the other.

Figure 7: Diagram showing the elements of comparison when testing for statistical equilibrium (left) and for ergodicity (right). Source: Guerini and Moneta (2017).

$$X^k = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,T} \\ x_{2,1} & \cdots & \cdots & x_{2,T} \\ \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,T} \end{pmatrix} \qquad X^k = \begin{pmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,T} \\ x_{2,1} & \cdots & \cdots & x_{2,T} \\ \vdots & \vdots & \vdots & \vdots \\ x_{M,1} & x_{M,2} & \cdots & x_{M,T} \end{pmatrix}$$

Distributed Energy Storage Systems: Effects on Load Volatility*

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Abstract

The diffusion of distributed energy producing systems relying on renewable sources poses a challenge to policy-makers, grid operators, and power generating companies in the electricity industry. One such case may be the diffusion of distributed storage systems integrated with photovoltaic units owned by households. On the one hand, they may act as a buffer and smooth the intra-daily variation in electricity flows through the network. On the other hand, they may increase volatility, if a large number of distributed generators simultaneously use the network once their batteries are fully discharged, by amplifying energy demand shocks. Under the latter hypothesis, the system costs would grow due to a need for larger back-up and transmission capacity, questioning the aggregate advantages of distributed storage systems. This work presents a stylised agent-based model to assess the likelihood of the two alternative effects of distributed storage systems of aggregate energy demand volatility, under different parametrisations of the power generation storage systems. The results suggest that distributed storage systems reduce fluctuations, and are thus beneficial at a systemic level, rejecting the volatility increase hypothesis. Further explorations through richer simulation models of the electricity system are welcome.

Keywords: Photovoltaic energy; energy storage; volatility.
JEL: Q4; Q42

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1 Introduction

Tesla's Powerwall has been hailed as a promising technological breakthrough in energy storage. By providing storage opportunities through a small-sized rechargeable lithium-ion battery that can be integrated with rooftop photovoltaic (PV) panels, the Powerwall meets the increasing willingness of consumers to save on the electricity bill and to set themselves free from the electricity grid, as highlighted by recent consumer surveys, e.g. in Galassi and Madlener (2016) or Agnew and Dargusch (2016).

One key motivation for energy storage lies in the quest for load stabilization (Fairley, 2015; Fumagalli, 2016). Power load is subject to wide changes during an average day, following the daily cycle in economic activities. The shortage of economically viable storage technologies has for long time prevented the achievement of a smooth profile in electricity network flows. The increasing penetration of renewable energy (RE) sources with supply varying according to weather conditions, has further complicated matters. Because of ramping costs and response time, most electricity generation technologies cannot promptly respond to the unpredictable variation in RE supply. The possibility of maintaining a reserve capacity may insure against surges of demand – which would disrupt the balance on the grid and cause blackouts – and, less predictable drop in RE supply. The stabilizing effect of storage is all the more needed in transmission grids that are frequently subject to congestion, which can be induced by RE as shown by Sapio (2015) and Ardian *et al.* (2015). Mitigating volatility would allow grid operators and utilities to delay the installation of extra generation and transmission capacity. Besides the sheer costs of a larger back-up capacity, volatile energy sources also reduce the utilization rate of conventional power plants, which therefore operate below their maximal efficiency and require more frequent maintenance. Energy-intensive manufacturing firms would also benefit from load-levelling and constant frequency in their power supplies (Whittingham, 2012).

While distributed storage systems (DSS), such as Tesla's Powerwall, may be appealing for households – once their installation costs and duration will improve (Johann and Madlener, 2014), their system-wide stabilising effects depend on the contemporaneous decisions of multiple interacting actors, and are therefore not easily predictable. The emergence of *prosumers*, enabled by distributed generation facilities, is seen as a destabilizing force for the incumbent technological paradigm (Sioshansi, 2014), which is based on centralised power generation, established in the early decades of the 20th century (Granovetter and McGuire, 1998).[1] Agnew and Dargusch (2015) illustrate some potentially disruptive effects of PV-integrated DSS on the overall performance of the energy system. Adding to these concerns, it is worth noting that because PV energy is not produced in off-peak hours, when electricity prices are low, storage integrated with PV does not provide access to the same arbitrage opportunities as storage technologies explicitly dedicated to smooth peak loads.

The present paper contributes to this debate by comparing two possible effects on load volatility of an hypothetical large scale diffusion of distributed storage facilities integrated with renewable sources such as PV . First, in line with the existing literature on energy storage, distributed storage systems may *reduce* the volatility of electricity demand because batteries act as buffers. Supporting such expectation, DSSs decrease the users' necessity to access the network, whether on the supply or demand side. Thus, the aggregate intra-day load profile would be smoother if all users had access to energy storage.

Second, and opposite, DSSs may *increase* demand volatility by increasing the coor-

[1] See Künneke (2008) for a comparison of the centralized and distributed generation paradigms from the perspective of evolutionary economics.

dination of users. If the capacity of the storage systems is limited (comparable to the consumption level), and the production from RE in different sites is positively correlated, then a large number of distributed generators endowed with storage would simultaneously use the network, causing large jumps in the intra-day load profile. According to this hypothesis, we would observe that although small-scale volatility may be reduced by a large presence of DSS's, fewer but far larger un-balances would be faced by grid operators when a large share of producers suddenly flood the network with energy after having fully charged their batteries, or spike their energy request when all the stored energy is used up (at similar times in the day, by most consumers).

With a view to enhancing forecasts and improving the design of technical infrastructures and policy initiatives, it is crucial to understand which of the two effects is most likely to prevail (if any), and to assess the extent to which the likelihood of the two effects varies with respect to specific features of the system. If the second effect prevails – distributed storage facilities magnify volatility – then policy makers should carefully consider any policy intended to promote the diffusion of storage systems, for example subsidising the installation of PV and wind generators, ensuring priority dispatch to renewables in wholesale electricity markets, and fostering the adoption of distributed generation technologies (see e.g. the policies reviewed in Anaya and Pollitt (2015). The reason is that, in the second scenario the diffusion of storage systems integrated with PV would entail an increment of volatility and, consequently, the need to maintain a large amount of electricity production – possibly from polluting and costly power plants on the grid – to face volatile load peaks.

To investigate the effect of storage systems on volatility, in the presence of RE, we present an agent-based model featuring a large number of users equipped with electricity production systems from renewable sources, such as PV panels, installed in private homes. We assume that a share of the users have also a storage system coupled with their PV facilities. Under a number of reasonable assumptions concerning the mechanics of energy production and consumption, we analyse the effects of storage systems diffusion on the electricity system-wide volatility, the research question of this paper. We assess the size of the 'safety margin' for energy producers, that is, the share of electricity to be produced solely for the purpose of ensuring that a sudden load peak does not disrupt the demand-supply balance. The model provides a representation of a generic power grid comprising consumers, small-scale energy producers from renewable sources, and storage systems so as to assess the levels of volatility under a number of different scenarios.

The preliminary results suggest that the first effect dominates: as the adoption of batteries increase, the system fluctuations, measured as the sum of squares of one-minute variations in the network demand, reduces linearly. As the size of the batteries increases, the fluctuation reduce at an increasing rate, for all adoption rates. That is, storage system can contribute to reducing volatility of demand, therefore the 'safety margin' that energy suppliers need to guarantee, and the overall amount of energy produced and wasted.

The paper is structured as follows. After reviewing the existing literature on the economics of energy storage in Section 2, Section 3 presents the agent-based model of the electricity system. The simulation results are described and discussed in Section 4 and Section 5 concludes.

2 Previous literature

Energy storage has long been felt as a needed technological innovation in the energy industry. Some of the main stylised facts about the liberalised electricity industry, such as volatility clustering and spikes, are seen as coming straight from the shortage of economically viable storage facilities (Graves *et al.*, 1999). While liberalisation has itself been a source of volatility in an industry previously organised as a regulated monopoly, further factors have contributed to spur volatility, such as tensions in fossil fuel producing countries (Sioshansi *et al.*, 2009), supply disruptions due to climate change induced catastrophes, and the increasing penetration of RE sources (Beaudin *et al.*, 2010; Nyamdash and Denny, 2013), thereby further motivating research on energy storage technologies.

As observed in the introductory section, smoothing the short-term fluctuations of exchanged volumes in the electricity industry allows to save on costly reserve generation capacity, cycling-induced maintenance, network congestion, and network upgrades. Alongside such benefits, energy storage is seen as a powerful tool to facilitate the integration of RE technologies in the energy system, relieving issues that slow down their diffusion, such as high overhead costs, low predictability, or supply curtailments. Denholm and Margolis (2007) provided one of the earliest results showing that energy storage can enable the diffusion of solar power generation, followed by Sioshansi *et al.* (2009) on concentrating solar power. Sioshansi (2010) finds that storage enhances the value of wind power plants, using US data. Relatedly, Connolly *et al.* (2012) show that storage allows to improve the penetration of wind power in the electricity market, once investment costs are sufficiently reduced, using data on the Irish electricity system. Kaldellis and Kavadias (2009) underline the potential of energy storage for minimising the energy waste related to wind curtailments, occurring when the stability of the grid is threatened by excessive wind power production and grid operators force curtailments. Madlener and Latz (2013) explore the potential of compressed air storage integrated with wind turbines to balance the fluctuations of wind power production. Storage, moreover, can help improve the planning of new interconnections or substitute for them, whenever the correlations between load and the RE source is negative (Bell et al. 2015). This is particularly valuable as congestion sets is due to either load growth or to surges in RE supply. The strategic placement of energy storage systems may be more viable than the construction of new transmission and generation capacity.

The way storage technologies achieve a smoother intra-day load profile impinges upon arbitrage, induced by within-day electricity price excursions. Assuming price-taking behaviour and perfect foresight, Graves *et al.* (1999), Figueiredo *et al.* (2006) and Walawalkar *et al.* (2007), among others, have shown that the optimal arbitrage strategy by an agent, running an ESS integrated with a conventional power source, involves an all-or-nothing operation of the device. Specifically, according to the optimal strategy, the battery should charge until full capacity when market prices are low, typically in off-peak hours; should fully discharge at prices above the charge threshold, usually on-peak; and should remain idle at all other times. In other words, the deployment of storage should increase the generation of conventional power plants at night and decrease it during the day. According to the estimates reported in Bradbury *et al.* (2014), 4 hours of energy storage would be optimal for most storage technologies, given the round-trip efficiency parameters. Such an optimal size is anyway conditioned by the technology mix in the electricity market, by the growth in energy demand, and by congestion patterns, which affect the gap between on- and off-peak prices.

Along with smoother intra-day patterns in the use of the network, yielding less volatile wholesale electricity prices (shaving peaks and filling throughs), ESS can cause a redistribution of surplus from electricity producers not equipped with ESS to users who have installed a storage facility. As noted by Sioshansi *et al.* (2009), the lower energy demand off-peak implies that the decrease in consumer surplus from the higher price paid off-peak is more than offset by an increase in consumer surplus on-peak due to a drop in the on-peak price. Conversely for the generators who are not equipped with ESS. These welfare-enhancing effects depend on the governance structures linking storage operators, consumers, and power generators (Sioshansi, 2010), and have however been questioned by Hittinger (2017), noting that while the intra-day load profile flattens out, the overall level of energy consumption increases, possibly with growing climate-altering emissions.

Whether the above mentioned benefits materialise, and to what extent, depends on the specificities of the storage technology in use and the associated technical parameters. In a review of the literature, Beaudin *et al.* (2010) provided a thorough comparison of several energy storage technologies (pumped hydro, compressed air, batteries, superconducting magnetic, hydrogen, flywheels, capacitors and super-capacitors) in terms of their contribution to managing time variation in RE outputs (see Table 1 in their article). Batteries were found to be most suitable for maintaining power quality and grid stability, and to possess favourable properties, such as scalability, modularity, duration, and low maintenance costs.

The recently introduced Tesla storage device, a lithium-ion battery which exploits solar power, is expected to share the same advantages of other batteries and, what is more, is characterised by a longer duration than alternative batteries. Indeed, the life of e.g. lead-acid batteries is shorter than that of PV modules, which has been noted by Johann and Madlener (2014) as deteriorating the net present value of investments in storage and slowing down diffusion. The implicit tenet in the reviewed works on arbitrage, though, was that batteries could be charged by means of controllable energy sources, such as dispatchable power plants or pumped hydro (Nyamdash and Denny, 2013). This is not true with Tesla Powerwall, which can be charged only when the sunlight is available. The advantages of Tesla Powerwall in managing intermittent RE sources and mitigating volatility may not hold if the "optimal" arbitrage strategy cannot be implemented. The time pattern of battery charging and discharge, constrained by the availability of sunlight, is at the heart of our conjecture that DSS integrated with PV might make the network flows more volatile on an infra-day time scale.

From a methodological viewpoint, previous works assessing the value of energy storage have analyzed dynamic stochastic programming models, both for computing the optimal arbitrage profile from the perspective of an individual investor and in order to find the optimal dispatch in an electricity system. The only agent-based model on distributed PV that we are aware of has been published by Palmer *et al.* (2015), who have studied the diffusion of PV generation systems under different support schemes, through a simulation model calibrated on Italian data, but does not address the fluctuation properties.

3 The model

In order to test our hypotheses we need to evaluate the volatility of the load balance on different hypothetical electricity distribution grids with different shares of PV and local storage systems. For this goal we develop a simulation model replicating reliably the behaviour of the elements affecting the variables of interests.

The model makes a number of simplifying assumptions, focussing on a fairly detailed representation of the daily energy demand from each consumer, the amount of energy produced from PV systems and the collective impact of distributed storage systems. This model can be considered as a first block of a more complete model of the energy system that, once extended as, may be used as a policy tool to be deployed to examine additional research questions and, in particular, evaluate the effects of different policy measures.

In the simulation time scale, a time step represents a real-time minute. Agents consume energy according to a pattern partly common to all consumers (depending on the time of the day), partly idiosyncratic to each agent, including both systematic and random variations. Consumers equipped with a PV system generate electricity which is used primarily for own consumption. Non consumed PV energy is sold to the network, unless the consumer/producer owns a dedicated, not fully charged, battery. When production is not sufficient to fulfil energy consumption, consumers endowed with a local storage system drain energy from their batteries, if available, before accessing the grid.

3.1 Consumers

The proposed representation is meant to simulate observed consumption patterns. The model represents N of consumers, each following the same consumption pattern with idiosyncratic variations, randomly distributed, variations. The consumption pattern follows a cyclical (daily) pattern defined for each minute of a 24 hours (1440 minutes) day.

Each consumer start their consumption pattern between 6:00 AM and 7:00 AM, randomly distributed. Energy consumption for each consumer is also randomly distributed around and average value μ.

3.2 Producers

A share of consumers, randomly extracted from the population, is assumed to be endowed with PV systems. These agents have the same energy demand as consumers and, in addition, produce electricity that is primarily used to satisfy the user's demand. In cases in which the user produces more energy than requested by current demand, the excess energy is fed into the grid reducing the overall load.

Energy production is modelled following a simulated daily solar cycle. Each consumer receives the same amount of light, though each PV system has a different maximum production. The distribution of production capacity is determined randomly at the start of the simulation (following a rule initialised by the modeller). The sunlight available for solar energy production to all producers is also subject to random modifications simulating varying weather conditions.

3.3 Storage systems

A share of producers, randomly chosen, is assumed to also own a local storage system, whose size is assigned randomly at the start of the simulation run. These producers use the energy in excess of consumption to charge their batteries, releasing electricity to the grid only when the batteries are filled up. In case of insufficient production, consumption is primarily served by the energy in the storage system, resorting to the grid when the batteries are emptied.

3.4 Formal description

The energy consumption of user i, $C_{i,t}$, is determined as a variation from the previous minute energy consumption towards a theoretical value $C^T_{i,t}$:

$$C_{i,t} = \alpha C_{i,t-1} + C^T_{i,t} \tag{1}$$

where α is the measure of the inertia of consumption; and $C^T_{i,t}$ is a random value drawn from a normally distributed function centred on a cyclical variable:

$$C^T_{i,t} \sim norm(C^C_{i,t}, Var_C) \tag{2}$$

The cyclical variable is computed as:

$$C^C_{i,t} = C_{min} + \frac{(sin(\pi + 2\pi\frac{(t+s_i)}{1440}) + 1) \times (C_{max} - C_{min})}{2} \tag{3}$$

where π is trigonometric constant 3.1416; C_{min} is the minimum consumption level; C_{max} the maximum consumption level; s_i is the user specific time shift representing the individual consumer consumption habits, expressed as a temporal differences in starting a daily cycle. This value is defined at the start of a simulation run drawing a random value from a uniform distribution between s^{min} and s^{max}:

$$s_i \sim U(s^{min}, s^{max}) \tag{4}$$

Energy demand net demand from the grid of each user depends on the amount of energy produced, if any, and of the discharge/recharge of the battery, if available. Such demand is positive when production and the flow from the sun and from the battery is not sufficient meet consumption. While batteries are charging (meaning production matches and surpasses consumption, and batteries not yet fully charged) net demand is null. Finally, net demand is negative when the energy produced surpasses consumption and batteries are fully charged. In this latter case the user is selling energy to the grid, increasing global supply. Formally:

$$E_{i,t} = C_{i,t} - S_{i,t} + \Delta_{i,t} \tag{5}$$

where $S_{i,t}$ indicates production from the PV plants and $\Delta_{i,t}$ the flow of energy from or to the batteries.

Energy production is computed as the product of the plant capacity (PV_i) times available sunlight (L_t), equal for all users:

$$S_{i,t} = PV_i \times L_t \tag{6}$$

where production capacity is determined at the start of a simulation run with a random value drawn from a uniform distribution:

$$PV_i = PV^{max} \times U(PV^u, 1) \tag{7}$$

Sunlight is computed as a cyclical variable representing the time of the day measured in minutes (T_t, computed as the remainder of the ratio $\frac{t}{1440}$) times one minus the clouds intensity (Z_t). The sunlight is zero during night and follows the upper section of a sinus function during the day from 6:00AM to 18:00PM:

$$L_t = \begin{cases} sin\left(\frac{2\pi(T_t-360)}{1440}\right) \times (1 - Z_t), & \text{if } 360 < T_t < 1080 \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

The clouds intensity is computed as an inertial random walk:

$$Z_t = \alpha_z Z_{t-1} + (1 - \alpha_z) \times U(0; 1) \times Z_{max} \tag{9}$$

where $U(0;1)$ returns a uniformly distributed random value between 0 and 1; α_z is the inertia of weather conditions; and Z_{max} is the maximal reduction of sunlight. The variable is constrained to take only values in the range $[0;\ Z_{max}]$.

The battery charge variation depends on: current energy consumption $C_{i,t}$, the current production from PV $S_{i,t}$, the past level of the battery charge $B_{i,t-1}$, and the maximum capacity of the battery, B_i^{max}.

$$\Delta_{i,t} = \begin{cases} 0 & \text{, if } B_i^{max} = 0 \\ min\,(S_{i,t} - C_{i,t}; B_i^{max} - B_{i,t-1}) & \text{, if } C_{i,t} < S_{i,t} \\ -min\,(B_{i,t-1}; C_{i,t} - S_{i,t}) & \text{, if } C_{i,t} > S_{i,t} \end{cases} \tag{10}$$

The level of the battery charge is computed as:

$$B_{i,t} = B_{i,t-1} + \Delta_{i,t} \tag{11}$$

The excess energy produced and not used for consumption nor to charge batteries, is fed into the grid, and computed as:

$$G_{i,t} = max(0; S_{i,t} - C_{i,t} - \Delta_{i,t}) \tag{12}$$

As results of the model, we collect all the values for every variable from individual users and the aggregate variables (computed as the sums over every user). Moreover, we compute an index of demand volatility as a 1-minute volatility of net load variation of energy from the grid:

$$V_t = (\sum_{i=1}^{N} E_{i,t} - \sum_{i}^{N} E_{i,t-1})^2 \tag{13}$$

3.5 Main parameters

The model is meant to simulate a complex electricity grid and compute the aggregate properties concerning the load pattern in relation to different assumptions on the number agents (share of producers and share of storage systems) and their characteristics (e.g. capacity of PV plants and size of storage systems). To simplify the implementation we control many of the properties of the simulated system by means of statistical distributions defined with few parameters. All the features of the model may, however, be easily calibrated using data from real-world systems, possibly modified to include the outcome of specific policies, for example in terms of share of observed consumers purchasing PV production systems.

Table 1 reports the main parameters used in the simulation runs presented in the next section (4).

Notice that the configuration tested assumes a system where all consumers are also producers. This assumption is adopted to test the hypothesis under extreme conditions, since any configuration with a smaller percentage of producers will necessarily reduce the volatility, and hence the probability that local storage system increase the volatility of the system.

4 Results

To illustrate the model properties and main result we use an arbitrary setting made of plausible values for the parameters (Table 1). We begin with the presentation of results

Par.	Description	Value(s)
N	Total number of consumers	10,000
C_{min}	Minimum regular consumption	0.05 Kw
C_{max}	Maximum regular consumption	2 Kw
Var_c	Variance of individual random variation per minute	1 Kw
–	Share of users owning a PV energy production system	100%
PV^{max}	Maximum PV capacity (0 means user has no PV)	2 Kw
–	Share of producers owning a storage system*	10% - 90%
B^{max}	Maximum capacity storage systems (0 means user has no storage)*	30 - 90 Kw
s^{min}	Max. anticipation time shift	-120
s^{max}	Max postponement time shift	120
α	Autocorrelation random individual energy consumption	0.7
α_z	Autocorrelation random common weather	0.7
Z_{max}	Maximum PV production reduction due to weather	0.5
PV^u	Maximum rate of underutilization of the PV production	0.5

Table 1: Parameter values tested in the results. Parameters marked with * are explored with multiple values.

for individual members of a grid, consumers and producers, then we show the aggregate properties of the whole system and, finally, we assess the effects of storage systems on the load volatility.

4.1 Individual users

We start by showing the shape of the consumption pattern assumed for individual consumers. Figure 1 presents the energy consumption $C_{i,t}$ for two sample consumers over two days (2880 minutes), and the population average consumption (black line). Every consumer follows the same overall pattern, shifted by a random time gap, and is affected by random noise.[2]

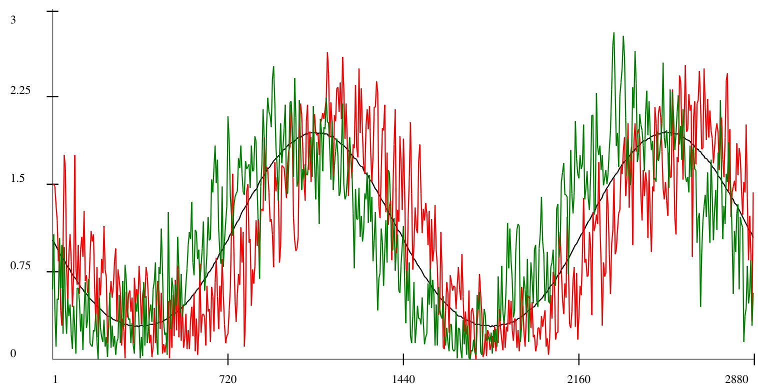

Figure 1: Energy consumption: population averate and sample of two users.

Consumers are also producers, endowed with PV plants with heterogeneous productivity levels (in the current initialisation we assume that all consumers have a PV plant, to

[2]The model may be extended to adapt the consumption pattern may to reflect different typologies of consumers.

study a case of extremely high volatility). Productivity is also influenced by the weather conditions (common to all consumers), which also affects total production. Figure 2 reports the amount of energy produced by two sample producers $S_{i,t}$, in two days.

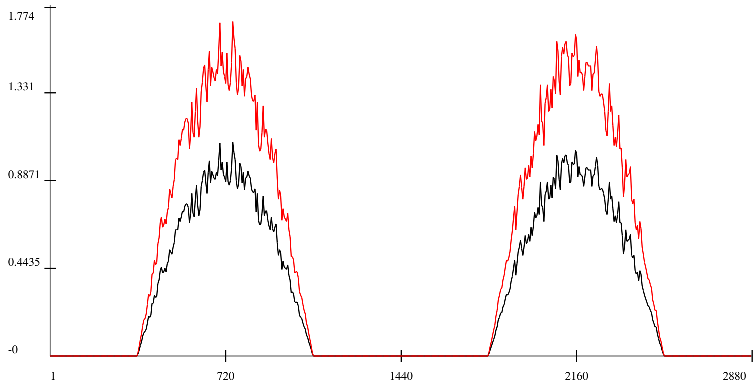

Figure 2: Energy produced by two sample producers.

A consumer owning a PV power plant may reduce the energy demand from the grid, and show a negative load when the production is higher than the consumption. Under those conditions some of the electricity produced by the consumers is returned to the grid. Figure 3 reports the series of energy consumption $C_{i,t}$ and the net demand from the grid for a consumer/producer $E_{i,t}$.

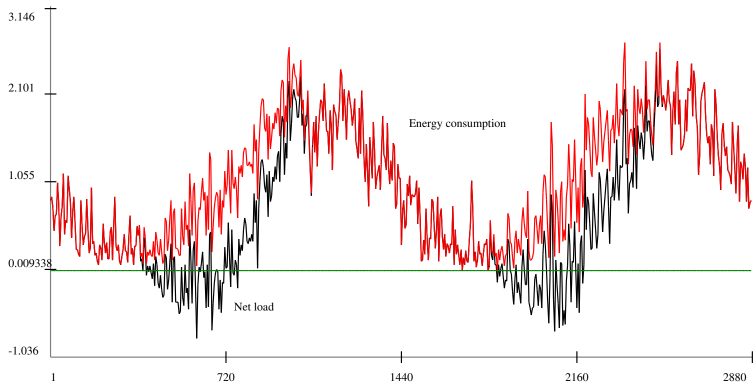

Figure 3: Consumer/producer. Energy consumption and net load on the grid.

The horizontal line reports the null load. When the load touches this line the consumer neither draws energy from the grid nor feed in any electricity, that is the user has zero consumption or consumes exactly the same amount of electricity produced by the PV panels. When the load is above this level the consumer is using some energy from the grid, while when it is below the consumer is selling electricity back into the grid.

For those users endowed with a storage system, the energy produced but not used charges the batteries (if they are not fully charged). When, instead, the consumer demand is higher than supply, and they own a storage system, they use energy from the batteries. Figure 4 reports the charge level of the batteries $B_{i,t}$ for two sample producers endowed with a local storage system. Batteries are charged at a rate proportional to the efficiency of the PV system. When they reach the maximum level the excess energy is fed into the grid. When production terminates because of lack of sunlight the energy stored in the batteries is used and, finally, the user resorts to consume energy from the grid when the batteries are flat.

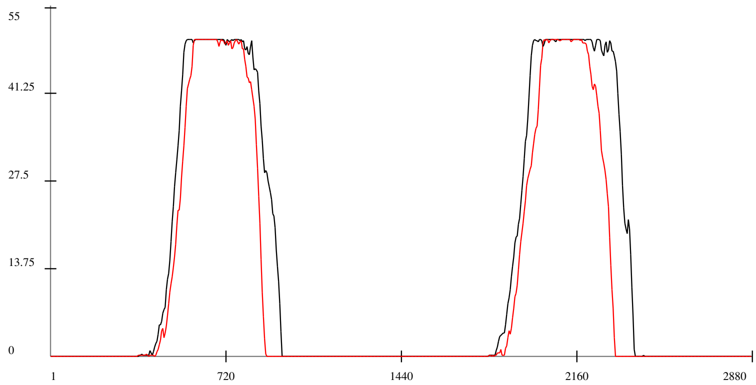

Figure 4: Battery level for two sample storage systems.

For producers owning a storage system the energy is not directly sold, but it is used, firstly, to fill up the battery. When the production falls below consumption needs, the energy is drawn from the batteries, and only when they are exhausted the consumer resort to the grid. Figure 5 reports the two series of consumption and net load for one user, as in the previous figure, together with charge level of the battery.

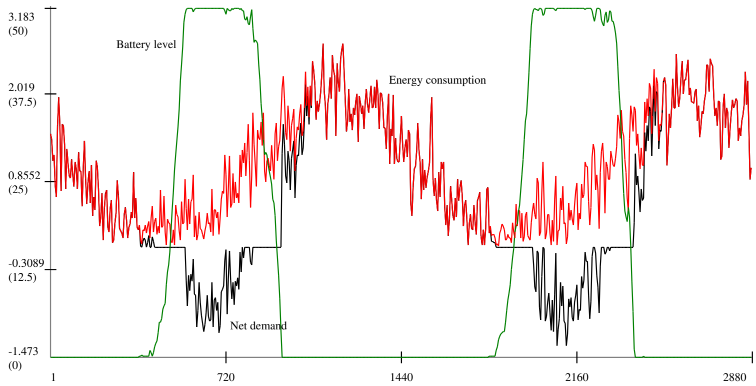

Figure 5: Consumer/producer. Energy consumption, net load on the grid and charge level of the batteries (last series measured on a different scale).

4.2 An empirical case study

The simulation results shown above, generated with arbitrary technical values, offer a qualitatively realistic representation of energy systems. Figure 6 reports, for comparison, the actual graph concerning the outcome of PV system coupled with a local storage[3].

The data are obtained for a system located in Rome during early April over two mostly sunny days. The production system has the maximum potential of 3 Kw/hour and the storage can contain up to 4 Kw. The data concern a two-day period beginning just before dawn with batteries completely flat. Consumption is initially relying on the grid but, at about 8:00 AM, the sun starts producing sufficient energy to meet consumption and charging the battery.

At about noon the batteries are filled up and the production begins to be sold to the grid. When the sun stops to power the PV panels the battery replace direct production.

[3]The figure reports the snapshot of the online control panel of a system by Sonnen, a German company providing storage systems integrated with PV plants.

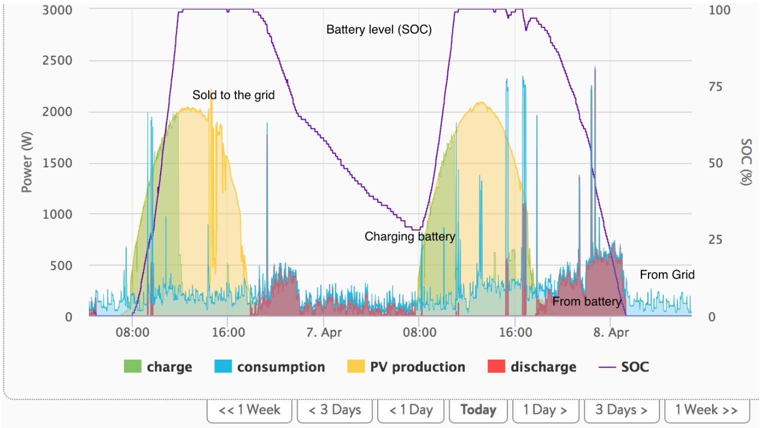

Figure 6: Real-world data for a two-day period of a 3Kw/hour PV system coupled with a 4 Kw storage. Snapshot of the online control panel by Sonnen.

The high consumption level reduces rapidly the battery charge in early afternoon. During the night the low consumption is not sufficient to exhaust completely the stored energy.

The second day begins with some energy in the batteries, so that the sunny day manages to complete the recharge well before noon. However, higher energy consumption (around 4:00 PM and during the evening) depletes the battery just after midnight.

The qualitative comparison between the simulated data and the empirical case study suggests that our model replicates qualitatively the overall pattern of the energy consumption, PV production and effects of a storage system. While more precise data may be obtained, using them would require a far heavier computational effort to manage large datasets instead of simple functional representations as in the present version of the simulation model. For our purposes, assessing an overall property of the system, we consider the similarity between virtual and empirical data sufficient to consider the model a valid representation of real world systems.

4.3 Aggregate results: The impact of batteries on load volatility

Before testing the main hypotheses of our paper, we discuss the aggregate properties generated at system level by the interaction among the heterogeneous users in the model. Figure 7 reports all the relevant aggregate series for a single day, made of 1440 minutes.

The series labelled as *Tot. Consumption* indicates the total consumption by energy users ($\sum_i C_{i,t}$), represented conventionally according to a sinus dynamics, starting at 3:00am. The series *Network Demand* reports the electricity demanded from the network ($\sum_i E_{i,t}$), i.e. the net load. In the early hours of the simulations, during the night, there is no PV production, and thus all consumption must be satisfied by network electricity.

At 6:00am the simulated dawn allows for PV energy production to start (series *Distributed Production* ($\sum_i S_{i,t}$))), so that demand from the grid falls below total energy consumption. The PV production in excess of demand starts filling households' batteries, whose level begins to grow (series *Batteries* ($\sum_i B_{i,t}$)).

As more users fill up their batteries, the excess of energy is sold on the network (series *Energy sold* ($\sum_i G_{i,t}$)), generating consequently a negative network demand. As consumption grows, although sunlight peaks, PV energy production fails to meet demand, and the energy stored in batteries is used up, thereby decreasing their levels. Eventually, batteries are depleted, PV production falls, and network demand quickly catches up with total

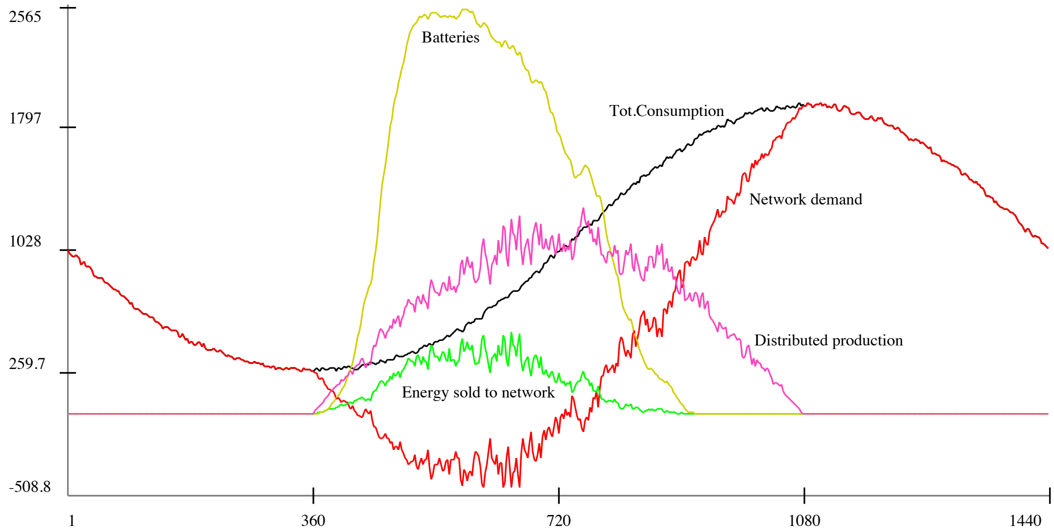

Figure 7: Time series for aggregate variables during a simulated day.

consumption.

The main goal of this preliminary simulation exercise consists in evaluating the impact of distributed storage systems on electricity demand volatility, to assess whether the diffusion of batteries would increase or decrease the size of the safety margin necessary for centralised producers to guarantee the overall network energy balance. For this purpose, we replicated the results varying the two parameters describing the extent of storage systems through their adoption and capacity: the share of consumers that own batteries, and the size of the average battery. With respect to the share of PV producers that also own batteries to store electricity we considered five values: from 10% to 90%, with intervals of 20%. With respect to battery capacity, we also considered 5 values: from 10KW to 90KW. Figure 8 reports for each combination of the two parameters the level of volatility, measured as the sums of squares of 1-minute variations in network demand, cumulated over two full days.

The results show that the volatility falls with increased diffusion levels of storage systems among PV energy producers and for increasing size of such storage systems. Thus, the model suggests that the volatility mitigation hypothesis is correct, rejecting the alternative hypothesis that storage systems may increase volatility in the presence of coordinated behaviour.

5 Discussion and conclusion

This work has presented preliminary results of an agent-based model developed to study the effects of energy storage systems integrated with distributed power generation. The results show that increasing the size of storage systems and their share in the population of energy users, reduces the aggregate electricity volatility of the network load, measured

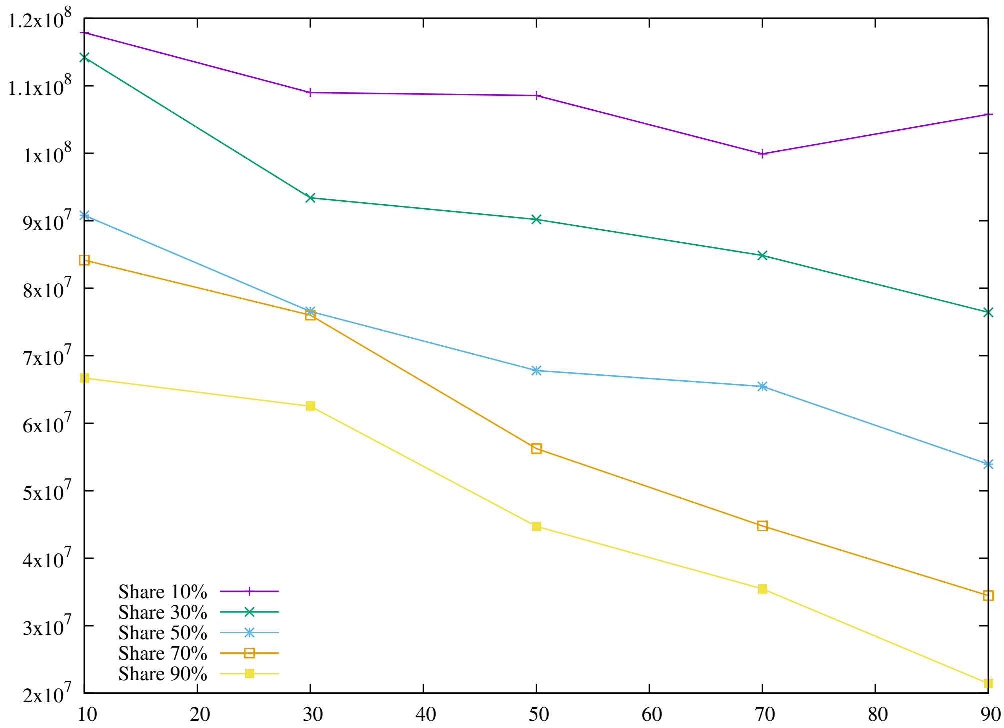

Figure 8: Total network energy demand variation over 1 minute, cumulated over all users and all time steps for a two-day simulation run.

by the cumulated 1-minute variations in demand of energy from the grid.

Policy implications are therefore quite straightforward in this case, suggesting that there are only gains, at the systemic level, from improving battery technology, and promoting their diffusion among users.

The model presented in this paper is designed to be used for more ambitious goals and in a broader set of experiments. Concerning the issue of volatility of demand, it would be interesting to study specific forms of volatility of particular interest to default energy suppliers. For example, it may be possible that a low overall volatility may still include particular conditions with large jumps that may potentially concern central producers.

The model can be extended to include a more detailed representation of real-world energy systems. For example, the model may encompass heterogeneous producers, with differentiated costs and reaction times to changes in demand, in order to assess the best organisation of supply with respect to the rapidly changing needs of a demand sector in which the share of self-consumption is rapidly expanding. Moreover, the model may be extended to include *virtual* energy suppliers, who trade electricity obtained by coordinating actions of large consumers and fringe producers (reference). Within the shifting landscape of the markets for energy, constantly affected by technological innovations and policy initiatives aiming to mitigate the environmental impact of energy production, our model can be used as the foundation of a comprehensive tool assisting decision makers, such as policy-makers, regulatory authorities, network designers, and individual actors of the energy industry.

Besides the specific application discussed in this work, the model can also be calibrated with data from a specific system, and used to test alternative policy measures such as the effect of incentives, expected costs, load imbalances, and any other measure relevant to determine a regulatory framework able to best exploit the technological opportunities in the field of energy production and distribution.

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Diffusion of Shared Goods in Consumer Coalitions. An Agent-Based Model.*

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Abstract

In this paper we study the process of coalition formation conditioning the common decision to adopt a shared good, which is too expensive for one average consumer, who would also not be able to exhaust its use. We develop an agent based model to study the interplay between coalition formation and the diffusion of shared goods. We model coalition formation in an evolutionary game theoretic setting, and adoption drawing from the Bass and the threshold models. Coalitions formation sets the conditions for adoption, while diffusion influences the consequent formation of coalitions. Results show that both coalitions and diffusion are subject to network effects, which also have an impact on the information flow though the population of consumers. Consumers prefer to form large coalitions in order to buy expensive goods and share ownership and use, rather than establishing smaller coalitions. In larger groups the individual cost is lower, although it increases if higher quantities are purchased collectively. The paper concludes by connecting the model conceptualisation to the on-going discussion of diffusion of sustainable goods, discussing related policy implications.

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1 Introduction

Diffusion is usually studied as an individual decision to adopt a good for own consumption, overlooking cases when the decision is taken collectively (Rogers, 1962), such as when sharing a property. While collective action (e.g. Olson, 1971; Hardin, 1982; Oliver, 1993), such as group consumption (Borcherding and Filson, 2002), is usually studied independently from the formation of the group (e.g. Komorita and Chertkoff, 1973; Komorita, 1974).

This paper aims at combining the process of coalition formation leading to the diffusion of a shared good, where consumers agree to act cooperatively in order to share costs and use of a common property. Coalition formation and diffusion are studied as two co-evolving processes. Coalitions are necessary for the diffusion of shared goods, being adoption a collective decision; and diffusion influences the consequent formation of coalitions since it changes the structure of the social network.

We model the diffusion of goods that are characterised by high investment cost – above the budget constraint of an average consumer – but affordable by a coalition of people acting cooperatively. This is, for example, the case of common pool resources (CPR) (Bowles, 2004), such as large irrigation systems adopted by groups of farmers (Bardhan, 1993b,a, 2000). Sustainable goods, such as large-sized decentralised energy systems (DES), can be also considered as CPR (Wolsink, 2012). These are too costly for individual households, but can be purchased by a group of neighbouring households to access energy off the grid.

We model coalition formation in an evolutionary game theoretic setting (Axtell, 1999, 2002), and diffusion using elements from both the Bass and the threshold models in which the role of innovators is central. In the model, agents sequentially interact in order to form a coalition: they form links, communicate, evaluate options, establish stable groups, and eventually adopt a shared good that produces a services available from a centralised provider at a higher cost, if convenient. Adoption is feasible only when a coalition is stable.

The network structure is not fixed, but evolves throughout time allowing for the formation of new spatially bounded links. The model differs in two main aspects with respect to the literature on diffusion over networks. First, instead of studying which network structure facilitates or prevents diffusion, it studies diffusion that co-evolves with the process of group formation, as the network of linked individuals grows. Second, the diffusion process is not considered to be dependent on an individual adoption decision, but, conversely, it is studied as a collective decision, conditioned by prior steps of coalition formation (Schlager, 1995).

The model fits in the category of sequential games of coalition formation as those formulated by Bloch (1995, 1996) and Mutuswami and Winter (2002), but is closer to the evolutionary model by Axtell (1999, 2002) on firms formation as the result of coalition. We differ from the these models in a number of ways.

In the bargaining process to form the coalition, social interactions (Oliver and Myers, 2003) and individual characteristics play an important role. Negotiations aimed at the common investment depend on how much each individual is willing to contribute to the fixed costs of capital, and how much they expect to consume of the service produced with the good (demand). Agents communicates their demand for the service and the monetary contribution that they are willing to commit into the common investment. This contribution is a portion of agent's income and it is the amount that maximises individual utility. Agent's decision is not only based on individual income and demand, but it also considers their consumption preference. Agent's utility in coalition is also related to the monetary contribution that other members have committed, and to the cumulative coalition demand for the service. Therefore, since agents adapt their behaviour and choices in relation to the evolving interactions with others, their attitude towards the common investment in coalition also changes over time. Once adopted, we assume that the shared good guarantees a more efficient service at a lower price, compared to the existing supply.

Results show that the formation of coalitions and the diffusion of shared goods co-evolve. Both are subject to network effects: agents' behaviour is affected by others' decision and by societal trends, and the social network evolves because of the changing links between consumers. Although the formation of coalitions is essential to the adoption of shared goods, they also reduce future adoption, by isolating consumers that do not find a suitable coalition on time. Network clustering and geography (the size of neighbourhoods) and the speed at which information flows among consumers determine higher adoption in consumers' coalitions. We also find that consumers prefer to form larger coalitions which allow them to buy expensive goods with higher capacity, rather than smaller coalitions that can adopt smaller goods. This is because, although larger coalitions require longer negotiations, the individual consumer monetary contribution to the common investment is lower than in smaller coalitions, and the unit price of the service is lower. However, smaller coalitions are more cohesive, and agents' connectivity and centrality is higher. Larger coalitions also tend to induce free riding, up to a size ($N = 8$) after which free riding falls because the large cost of the investment would not be sustainable. Results crucially depend on the speed at which networks form and information circulates, and on the composition of individual preferences.

We connect these results to implication for the diffusion of sustainable energy technologies that can be adopted by groups of consumers, and provide a local service, such as decentralised energy systems (Ackermann et al., 2001).

The paper has the following structure: the next section 2 reviews the literature regarding diffusion and coalition formation. Based on these two, the model conceptualisation is also explained. Section 3 presents the mathematical formulation of the model and its sequential process of coalition formation. Then, section 4 presents and discusses the results. Section 5 explains the potential of this model in the context of diffusion of sustainable goods and its policy implications. Section 6 concludes.

2 The Literature: Diffusion and Coalition Formation

Our modelling strategy builds on two rich literatures: diffusion of innovation (especially in networks), and coalition formation. We briefly discuss each in turn.

The literature has discussed extensively how diffusion is related to the influence of the social network on potential adopters (Burt, 1987). Innovation diffusion theory often deals with an individual decision-making process to adopt a new good or process, where the choice may change through time, as the awareness of adopting changes. The role of *initiators* or *early knower* is pivotal (Rogers, 1962) in starting the diffusion process, since they create the initial *critical mass* of adopters (Gersho and Mitra, 1975). Over time, social interactions is important for diffusion, facilitating *imitation effects* (Bass, 1969) and *fashion effects* (Smallwood and Conlisk, 1979; Arthur, 1989). *Late adopters* may imitate the innovation behaviour of *early adopters* in order to reach the same *social status* (Tarde, 1962). Therefore, interactions among individuals determine the *bandwagon effect* which influences the behaviour of *later adopters* (Abrahamson and Rosenkopf, 1993, 1997).

To examine the role of social networks, diffusion has been studied as part of network theory, where adopters are modelled as nodes of a social network and links represent the interactions necessary to spread information among nodes (Rogers, 1976; Cowan and Jonard, 2004). In this context, diffusion has been shown to depend on the network structure (Delre et al., 2010; Peres, 2014). The regular network is locally very dense and has a long average path since every node has the same number of nearest neighbours. With this structure, diffusion is slow since information must travel around the whole network before reaching nodes located at the opposite side. The small world structure (Watts and Strogatz, 1998) is a regular network in which few randomly chosen links are reconnected to distant nodes. This structure maintains the same level of clustering of the regular network, but reduces dramatically the average path, resulting in a faster process. In random networks (Erdos and Renyi,

1960) nodes are connected randomly to each other. This structure has low average path and low clustering, resulting in fast diffusion, although nodes are not locally connected.

Beyond the structure, the position of potential adopters in the network also matters for diffusion (Granovetter, 1973).

Social networks also evolve over time, as new links are formed and existing links are severed, influencing information flows and individuals' decisions, which are, consequently, dynamic and spatial-dependent (Jackson and Wolinsky, 1996; Dutta and Mutuswami, 1997; Bala and Goyal, 1998; Johnson and Gilles, 2000; Jackson and Watts, 2002). In the evolving process of network formation, highly connected nodes are *hubs* in the social structure, and they accelerate the contagion between individuals, thereby facilitating diffusion over the network (Barabasi, 2002).

Coalition formation has been mainly studied in the context of game theory. Studies on coalitions in triads (Caplow, 1956; Gamson, 1961) and the n-person coalition formation games, with n>3 (Komorita and Chertkoff, 1973; Komorita, 1974), have analysed the bargaining process among agents in relation to individual resources share. Negotiations is influenced by the initial distribution of resources and coalition members aim at forming coalitions that guarantee stability. Smaller and homogeneous coalitions are most likely to be formed compared to larger and heterogeneous coalitions, since the probability to reach stability and reciprocity is higher.

The *hedonic coalitions* literature (Dreze and Greenberg, 1980) has studied the process of coalition formation in relation to individuals' effort, where the objective is to carry out joint activities, such as production. In these models the individual payoff depends on her own and other members' characteristics and effort. As a result, members tend to form coalitions that maximise the common utility. They have been used, for example, to investigate strategic alliances among firms (Axelrod et al., 1995) and task allocations within an organisation (Shehory and Kraus, 1998). More recently, players' motivation and trust have been introduced (Griffiths and Luck, 2003; Griffiths, 2005), which were shown to lead to the formation of small *clans*.

Bloch (1995, 1996) models the process of pairwise coalition formation with infinite horizon and with finite number of players. In these models the aim is to find a stable equilibrium with all the players belong to a coalition. Mutuswami and Winter (2002) extends those models, allowing agents to remain out of coalitions and have a payoff equal to zero, and introducing in the offer to form a coalition a "conditional cost contribution" (Mutuswami and Winter, 2002, p. 244) which represents the cost an agent is willing to pay to form the coalition. Both Bloch (1995, 1996) and Mutuswami and Winter (2002) study the payoff division rule that guarantees stability, efficiency and equity among agents.

In conclusion, the model in this paper fits in the category of sequential models of coalition formation with the "best reply" type of adjustment dynamic, that are common in the evolutionary game theory. It makes it possible to overcome two common difficulties relative to the one-stage models of coalition formation, as explained by Bloch and Dutta (2011). First, agents in sequential models of coalition formation are not anymore "myopic", meaning that they are aware of what might be the subsequent outcomes. Second, sequential models are more likely to result in efficient coalitions since agents are "forward-looking" and there is an endogenous resolution of the problem of coordination among agents.

3 The Model

We model self-interested agents that have two options to satisfy their demand for a given service: purchase it from the market from a central provider, or invest in an expensive capital good, whose cost is larger than anyone's income, and which can provide the same service.[1] The cost and the utility related to the first option are given and depend on the individuals' utility function. The second option requires to form a coalition of consumers. The cost and utility of this option also depend on characteristics of the other coalition members and on characteristics of the coalition, such as its size. Driven by their interest in improving their utility, each agent interacts, attempts to form coalitions, and compare the different options. At the offset, all agents satisfy their demand from the general provider, and no coalition exists (all agents are singletons).

In the sequential process of coalition formation, an agent announces the investment they intend to make, and proposes to form a coalition to a different agents. These agents, in turn, after negotiation, may accept or reject the proposal. Agents decide to become coalition members if their utility is higher, and cost of service is lower, compared to the case of acting as singleton. If no subset of the contacted members reaches an agreement to form a coalition, the coalition formation process evolves by including more agents, or allowing for the exit of some the members contacted earlier (some members may manage to free-ride). After each interaction, agents adjust decisions, which are also influenced by what happens in the whole population, such as changes in the potential members, their monetary contribution to the investment, and demand of the service.

[1]One may think, for example, at transportation or energy. Consumes may purchase transport from a local service, or purchase a car; or they can buy energy from the grid, or invest in a smart grid.

More formally, agents (i) have the following characteristics: demand for the service (d_i), income (e_i) and preferences for income, equal share of the common good consumption, and equal contribution (respectively θ_i, α_i and β_i). Agents have two options to consume the same service: purchase it form a central provider at a given price (singleton), or purchase a capital good in coalition and use its services shared with other members (investment in coalition). The latter implies an investment cost, I, which is shared among the agents belonging to the coalition. To decide among the two options, consumers compare their cost and utility.

Singletons ($i1$) pay a given unitary price p_1 to purchase the service. Agents in coalition ($i2$) pay the unitary price of the services produced by the shared capital good (p_2) and a share of the fixed cost of the investment. We express the two cost functions (c_i) as:

$$c_{i1} = d_i p_1 \tag{1}$$

$$c_{i2} = d_i p_2 + x_i \tag{2}$$

where x_i<I In the second option (Eq. 2) is the monetary contribution that an agent is willing to commit in the joint investment. x_i is computed as to maximises agent i utility in coalition, such that U_{i2}: dU_{i2}/dx=0.

The utility functions for the two options are computed using a Cobb-Douglas function combining the indirect utility of saving, the direct utility of consuming, and in the case of coalitions the utility derived from other members' contribution and the disutilty of their consumption. Formally, the two utility functions are written as follows:

$$U_{i1}(e_i; c_{i1}; d_i; \theta_{i1}) = (e_i - c_{i1})^{\theta_{i1}}(d_i)^{1-\theta_{i1}} = [e_i - d_i p_1]^{\theta_{i1}}(d_i)^{1-\theta_{i1}} \tag{3}$$

$$\begin{aligned} &U_{i2}(e_i; c_{i2}; d_i; D_{-i}; x_i; X_{-i}; N; \theta_{i2}; \alpha_i; \beta_i) = \\ &= (e_i - c_{i2})^{\theta_{i2}}\{(d_i + D_{-i})[\frac{\alpha_i d_i}{d_i + D_{-i}} + (1-\alpha_i)(\frac{\beta_i x_i}{x_i + X_{-i}} + \frac{1-\beta_i}{N})]\}^{1-\theta_{i2}} = \\ &= [e_i - (d_i p_2 + x_i)]^{\theta_{i2}}\{(d_i + D_{-i})[\frac{\alpha_i d_i}{d_i + D_{-i}} + (1-\alpha_i)(\frac{\beta_i x_i}{x_i + X_{-i}} + \frac{1-\beta_i}{N})]\}^{1-\theta_{i2}} \end{aligned} \tag{4}$$

where Eq. 3 refers to consumers purchasing from the central provider (singletons), and Eq. 4 to consumers that enter a coalition; $\theta_i \in [0;1]$ is the preference for income; 1-θ_i is the preference for consumption; $\alpha_i \in [0;1]$ the importance given by agent to the proportional division rule based on consumption; $\beta_i \in [0;1]$ measures the preference for the proportional rule to divide the consumption from the shared investment based on the agent's contribution, with respect to the equal rule, when all agents receive the same amount of service, irrespective from the contribution; e_i is the given agent's income; X_{-i}=(X-x_i) is the total monetary contribution of the $N-i$ coalition members belonging to the coalition; D_{-i}=(D-d_i) is the total demand of the other $N-i$ coalition members belonging to the coalition; and N is the coalition size.

The function of the members purchasing from the central provider (Eq. 3) is straightforward. The utility reduces with the cost of purchasing, relative to income, and increases with consumption. The relative importance of each factor depends on θ_i. This is the reference utility whenever an agent evaluates the opportunity of joining a coalition.

In this second case (Eq. 4) we use a function similar to Axtell (1999, 2002), and take into account the agents' characteristics and their willingness to commit part of their income into the common investment[2]. Higher θ_{i2} indicates a higher preference for saving rather than consuming, reducing the propensity to invest, and vice versa. More importantly, the utility in coalition is function of other members' contribution. α_i measures a member preferences for sharing consumption based on each relative demand, rather than sharing on the basis of the contribution. β_i measures the preference for a proportional division of consumption based on each member relative contribution, with respect to an equal division with all coalition members. The individual utility in coalition also depends on the sum of the contributions and of the demand of the other $N-i$ members.

To compute the individual's utility in each time period we model an iterative process with feedbacks between negotiating members, which stops only when a stable coalition is either formed or or not. During this process X_{-i} and D_{-i} vary as a result of members' decisions, affecting the remaining members' utility.

At the outset of the simulation, agents are nodes of a regular network with l neighbours with whom they can tie and form a link. Agents have limited number of interpersonal connections which, additionally, require efforts to be created and maintained (Amaral et al., 2000; Watts and Strogatz, 1998). We also assume that neighbours must be within one step from the originating node, because the shared good provides a localised service.[3]

We distinguish between regular, *active*, and *initiator* agents. The sequential game of coalition formation starts with m randomly chosen agents that are *initiators*, the innovators needed to start the diffusion process according to Rogers (1962).

An *initiator* is always *active*, meaning that they are always aware of the technol-

[2]Please see Annex I for a complete discussion regarding the properties of equation 4 and its parameters.

[3]Therefore the model does not consider the role of social media.

ogy, and willing to consider joining a coalition.[4] An agent becomes *active* as soon as an *initiator* proposes to form a link with them. *Active* agents become aware of the opportunity to make the common investment, and replace the centralised service provider. When *active* agents become *initiators*, they can tie new links, thereby continuing the processes of knowledge diffusion following the percolation diffusion model in networks (Mort, 1991; David and Foray, 1994; Solomon et al., 2000). An *active* agent becomes *initiator* when the interest for the investment in coalition is higher compared to a minimum level, computed endogenously each time step. This threshold is defined *visibility*, as in Faber et al. (2010), and represents the minimum level of agent's awareness towards the new good. Every time step a random value, $RND \in [0;1]$, is generated and associated to *active* agents. An *active* agent becomes *initiator* when this number is lower than the *visibility* (W_t):

$$W_t = MAX[V_{t-1}; min[1; Adv + (ShareInCoalition_{t-1})^{\xi}]] \tag{5}$$

where Adv is the level of advertising, exogenously defined, as in the Bass model; $ShareInCoalition_{t-1}$ is the share of agents that have entered a coalition; and ξ is an exogenous parameter reflecting the bandwagon effect (Smallwood and Conlisk, 1979). Once an *active* agent becomes *initiator*, this characteristic is maintained for the remaining time steps.

Only *initiators* can contact other agents, tie new links, and start the process of coalition formation. As more capital goods in coalition are diffused, *visibility* increases, and more agents become *initiators*, increasing the likelihood that agents are involved in coalition formation and adoption. However, agents who already belong to coalitions cannot participate in further coalition formation processes, reducing the number of *initiators* and the likelihood that new agents are contacted. For this reason, coalition formation and diffusion co-evolve.

In each time period the process of coalition formation begins with *initiators* (not yet in coalition) that randomly tie a new bidirectional link with one of their neighbours not yet linked (Action 1). *Initiators* then choose the product they want to purchase and propose the investment to their linked neighbours (Action 2). The choice is done considering the set of products available in the market, each of them with different investment cost (I), amount of service supplied (S) and price (p_2). A product q is chosen randomly with probability proportional to its share, $Diff_q$, over of the total number of products already adopted, $\sum_{q=1}^{Q} Diff_q$. Therefore, the

[4] But not all *active* agents are *initiators*.

probability that a product is chosen by an *initiator* is:

$$\Omega_q = \frac{Diff_q + 1}{(\sum_{q=1}^{Q} Diff_q) + Q} \tag{6}$$

where the terms (+1) and (+Q) are needed in order to guarantee equal probabilities at the beginning of the simulation, when diffusion is zero. *Initiators*, therefore, are subject to the indirect network influence. This feature integrates in the model the concepts of *imitation* and *fashion effects* that are common in diffusion theory.

Next, *initiators* explore the investment in coalition options (Action 3), taking into account investment, demand, utility and cost constraints (Eqs. 7, 8, 9 and 10). First, they evaluate all coalitions of size two. Then, one of the two coalition members chooses randomly one of his or her linked neighbours and invites him or her to join the coalition and evaluate the investment proposed by the *initiator*. After evaluation, one more linked neighbour is invited. Actions 2 and 3 are repeated a number of time in each time step, allowing *initiators* to evaluate different coalitions, with different members and products.

Since agents are constrained with respect to time and computational power, they cannot evaluate all the possible combinations of products and coalitions. After evaluating each coalition, agents make a conditional decision between invest in it or remaining singleton, and stores as optimal the option with highest utility and lowest cost. If a subsequent coalition yields higher utility and lower cost in comparison to the optimal condition stored previously, the decision is updated. At the and of the evaluation process, a final decision is taken. All agents announce separately their optimal decision. If all members of a coalition announce that this option is their optimal decision, the coalition is established. Consequently the common good is adopted.[5] *Adopters* may not take part in future coalition formation processes.

The evaluation of coalitions is a multi-step bargaining process occurring in each time step of the simulation. Negotiation is necessary because agents try to maximise individual utility in coalition, which depends also on what other agents have announced in previous bargaining steps (which determine continuous variations in the value of X_{-i}). In other words, agents adjust behaviour continuously in relation to other agents' announcement and to new opportunities, aiming at improving individual utility and at experiencing cost reduction. Coalition formation, therefore, is modelled as a dynamic and as a long process of continuous interactions among agents because many features evolve over time and agents adapt behaviour accordingly.

[5]Annex II describes in detail how the coalition formation works, by means of an illustrative and numerical example.

The iterative process of coalition formation stops when stability among a group of members is reached. A coalition is stable when Pareto efficiency is reached – each member is better off without making at least one other worse off: (i) all members maximise their utility; (ii) no member has an incentive to move to another coalition; and (iii) no other agent would prefer to enter the coalition. Two more conditions that must be satisfied to reach stability among the group of agents. First, the sum of all members monetary contributions has to be at least equal to the investment cost (I) and not exceeding 110% of its value (equation 7). Second, the common investment capacity (S) must satisfy the total coalition demand (equation 8). Formally:

$$I \leq x_i + X_{-i} \leq I * 1.1 \tag{7}$$

$$d_i + D_{-i} \leq S \tag{8}$$

Pareto efficiency and conditions in equations 7 and 8 guarantee coalition stability, and a secure investment. This is also granted by two further conditions: that a member's utility (cost) in coalition is higher (lower) than utility (cost) as singleton: Eq. 9 (Eq. 10). Formally:

$$U_{i2} > U_{i1} \tag{9}$$

$$c_{i2} < c_{i1} \tag{10}$$

To summarise, at the outset every agent acts as singleton and purchases the service from a central provider. A few *innovators*, interested in purchasing jointly a shared good that could provide locally the same price at a lower cost, but which is too expensive to buy individually, contacts neighbours to inform about the opportunity. Increasing the size of the network by forming new links, agents interact and explore several coalition options of different size. Once a group of agents cannot improve their utility by changing coalition, and no other linked agent would want to join, or would be accepted by all existing members, they reach a stable coalition. Once they and commit to the joint investment, no agent would move to another coalition because this would incur a high sunk costs.[6] We thus assume the good is purchased and the coalition stable forever.

[6]This is in line with the fifth stages of the Innovation-Decision Process in Rogers' theory where confirmation of adoption implementation is a decisional step which comes later in time, once the product reaches its maturity phase (Rogers, 1962).

4 Results and Discussion

4.1 Model Initialisation

The model simulates the co-evolution of coalition formation and diffusion of shared goods in a population of $P = 200$ agents. Tables 1 and 2 report the initial values of the parameters.

Total population of agents	P	200
Number of *initiators* at t=0	m*	4
Spatially bounded links in the neighbourhood	l*	8
Income	e_i	μ=1000, σ=250
Demand	d_i	μ=45, σ=10
Preference	θ_{i1}=θ_{i2}	μ=0.5, σ=0.1
Preference for proportional division rule (consumption)	α_i	0.5
Preference for proportional division rule (contribution) and equal share division rule (size)	β_i	0.5
Advertising	Adv	0.01
Bandwagon effect	ξ	0.85
Price singleton	p_1	10
* Parameter analysed		

Table 1: Model initialisation

Agents are distributed on a regular network, which represents a relatively large neighbourhood (figure 1). Only 2% are *initiators* (m=4), randomly chosen at the beginning of every simulation (t=0). Each agent has eight potential neighbours ($l = 8$) with whom they can tie links (dotted edges in figure 1) and form a coalition.[7] At the end of this section, two different analyses evaluate whether the diffusion outcome changes in relation to the variation of these two parameters: number of initial informed agent (m) and size of neighbourhood, or network clustering (l).

Agents are heterogeneous in terms of income (e_i), demand (d_i) and preference (θ_i) and all values are proportional and compatible. Individual values are assigned randomly from a normal distribution. Agents have the same preference for the service regardless from whether it is bought centrally or produced by the joint investment

[7] Although the degrees of separation between agents in a coalition may be larger then one, as members may invite their own neighbours and so on.

(θ_{i1}=θ_{i2}). They are homogeneous in respect to the two remaining preferences: proportional division rule based on consumption (α=0.5) and proportional division rule based on contribution and equal share division rule based on coalition size (β=0.5).

Agent's awareness towards the common investment increases at each time step (Adv=1%), meaning that chances for more agents to become *initiators* increase over time. Further, the bandwagon effect related to the share of adopters is almost linear (ξ=0.85). The unit price of the service paid by singletons to a general provider (p_1) is higher than the unit price of the service produced by the shared good (p_2) (table 2).

Product	Investment (I)	Supply (S)	Price (p_2)
q_1	500	200	5.00
q_2	600	250	4.75
q_3	700	300	4.50
q_4	800	350	4.25
q_5	900	400	4.00
q_6	1000	450	3.75
q_7	1100	500	3.50
q_8	1200	550	3.25
q_9	1300	600	3.00
q_{10}	1400	650	2.25

Table 2: Model initialisation: available products

There are 10 capital goods in the market. Each of them has a different cost, maximum capacity, and price: the larger the capacity (the higher the investment cost), the larger the economies of scale, the lower the unit price.

The model has a time horizon of 200 time steps, where each step defines the time needed to initiate a face-to-face contact and to evaluate investment in coalition. To control for the random effects we show results as averages over 40 simulations with different random seeds.

4.2 Diffusion in Coalition: Emergent Properties

We first discuss the emerging aggregate properties of the model. The model simulates agents' interactions aiming at forming coalition needed to buy jointly a common good to replace service provision from a centralised provider. At the outset, only 2% of the population is aware of the good. The information is spread throughout the network by means of contacts among agents.

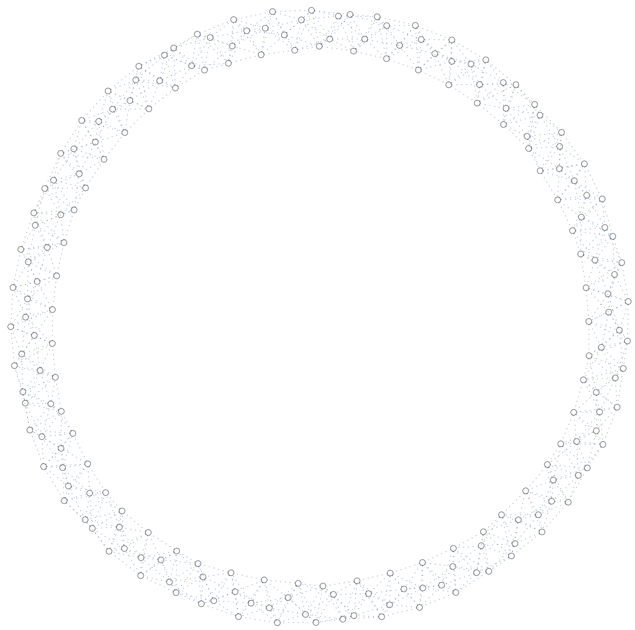

Figure 1: Initial regular network, 200 agents

Diffusion

After 200 periods, still only about 75% of the population is informed (Fig. 2), meaning that on a regular network 'contagion' is relatively slow (as discussed earlier). Two more factors are relevant. First, potential direct links are geographically bounded, due to the need to adopt a good that provide a service locally, and an agent can communicate only to the nearest neighbours (l=8). Second, the low number of *initiators* (m=4) slows down the initial 'contagion', since the formation of new links and dissemination of information start from these agents.[8]

Awareness, does not imply adoption: only 50% of the population establishes a coalition and adopts the shared good. The cumulative adoption follows the characteristic S-shaped curve, although adoption is higher in the initial time steps compared to traditional diffusion curves. This is due to the fact that in our model, when adoption in coalition reaches a higher utility than buying from the central provider for several

[8]Interpersonal communications are necessary to spread information in social networks (Lin, 1999; Woolcock and Narayan, 2000): these are particularly important for the diffusion of environmental motivations (Ek and Patrik, 2010) and energy-efficiency innovations (McMicheal and Shipworth, 2013).

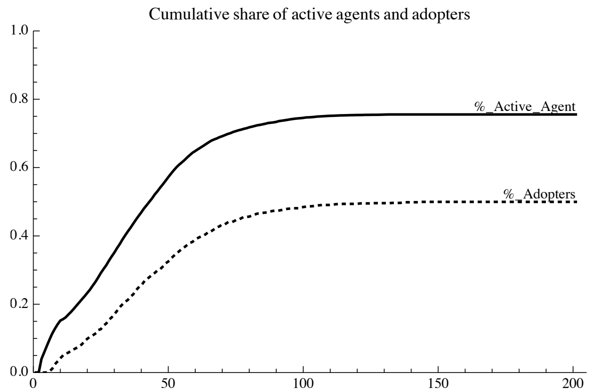

Figure 2: Cumulative share of active agents and agent in coalition

agents, this is for certain, reducing the risk of early adopters.[9] 50% adoption rate is not new in the literature on diffusion of capital goods, such as for micro-CHP (Faber et al., 2010) and electric vehicles (Higgins et al., 2012; Shafiei et al., 2012). We will test this outcome against different initial configurations of the network structure (m and l).

Size of coalitions and shared investment

Initiators may choose among ten different products ($q_1 - q_{10}$), where q_1 is the smallest, cheapest, but which provides the service with the highest unit cost; and q_{10} is the largest, most expensive, providing the service at the lowest unit cost. The more a product is adopted, the higher is the probability to be chosen (Ω_q) in new coalitions. Figure 3 shows the value of Ω_q for each of the ten products over time. At the very beginning of the simulation all products have the same probability to be chosen. After a transition period in which probabilities vary rapidly, we observe a long term pattern.

Overall, the most-chosen products are those with a lower investment cost (I), lower capacity (S) and higher unit cost (p_2). Among these, products q_1 and q_2 are those that have the highest rate of adoption during the initial time steps. This is due to both the network structure and to coalition size. At t=0 there are few *initiators* that can tie links with neighbours, the network of connected agents is far from dense,

[9] In order to test whether the model is able to reproduce the traditional S-shaped diffusion curve, Annex III presents diffusion outcome when uncertainties are added at the beginning of the process. We show that uncertainty does reduce initial levels of adoption.

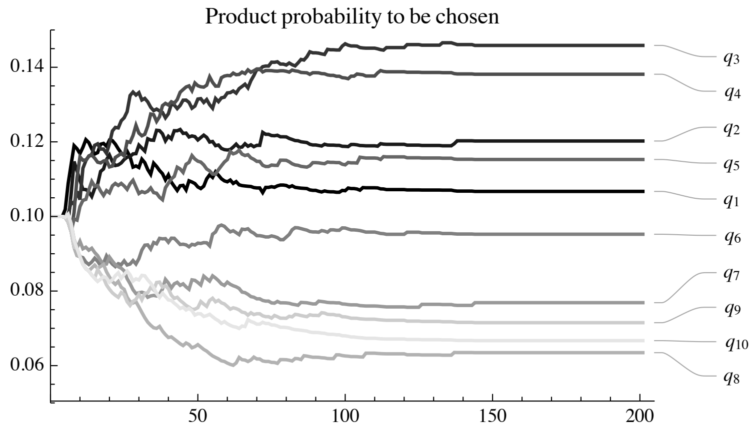

Figure 3: Product probability to be chosen, Ω_q

and there are few *active* agents that can enter in coalitions. Therefore, only small coalitions can be evaluated and established, which have a small budget and can afford less expensive goods (Figure 4 shows).[10]

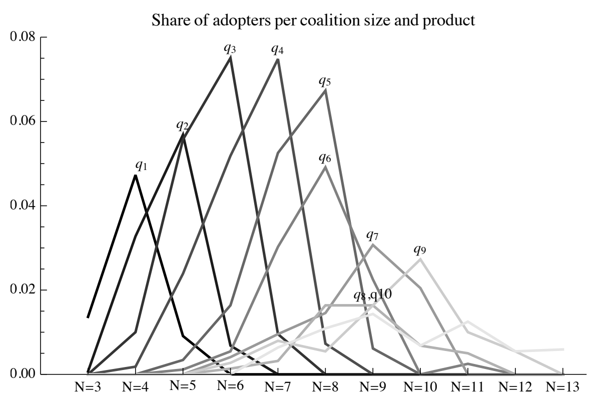

Figure 4: Share of agents in coalition, for each product adopted

Figure 4 plots the share of adopters for different coalition sizes (between 3-13) and

[10]These results resonate with notions of group size developed in the collective action literature (Olson, 1971) and in the coalition formation literature (Komorita, 1974). Accordingly, small groups are formed faster than bigger groups and these are more stable than the others. Further, coordination among agents in large-sized groups requires more time and in these formations agents have higher bargaining power and higher opportunity to defect.

type of capital good purchased. The figure shows that agents organise themselves in different coalitions to buy specific products. Larger coalitions are established to adopt goods with higher investment cost and higher capacity, whereas smaller coalition are formed to purchase smaller goods. However, depending on the product purchased, some coalitions are more likely to be formed compared to others. For small investments, one type of coalition (small) is markedly more frequent than others. The variability of coalition size increases with I and S, meaning that larger goods are purchased by more heterogeneous types of coalitions (in terms of size).

We then put forward the following propositions.

Proposition 1: *The investment costs (I) and capacity (S) of the shared goods adopted in coalition increase with the coalition size.*

Proposition 2: *Coalitions tend to be of homogeneous size (small) when purchasing common goods with low I and S. The heterogeneity of coalition size increases with I and S.*

Figure 5 plots the average number of options evaluated before establishing a coalition and the coalition size: we find a positive significant correlation (r=+0.939, p<0.001). Beside the timing (smaller coalitions are evaluated early in time, when few individuals are *active*), this result suggests that, when agents have the opportunity to choose between smaller and larger coalitions, they opt for the latter; and for larger shared goods with higher I and S (proposition 1).[11]

Proposition 3: *Agents prefer larger coalitions, with larger investments and lowers unit cost, despite they take longer to form.*

Average contribution to coalition

In the model, agents commit to the common investment a monetary contribution (x_i) that maximises their utility (U_{i2}), and may vary with respect to preferred size of coalition and shared good. Figure 6 plots the individual average contribution by coalition's size and, within each coalition, by good's size. We shows that, the larger the coalition, the lower the average agent monetary contribution, regardless the level of the investment cost: N and x_i are negatively correlated (r =-0.985, p=0.011).[12].

[11] This result may support criticisms of Olson's theories of small groups, suggesting that, in the case of shared goods, large groups may favour collective action (Hardin, 1982; Oliver and Marwell, 1988).

[12] r is the Pearson correlation coefficient and p is the p-value

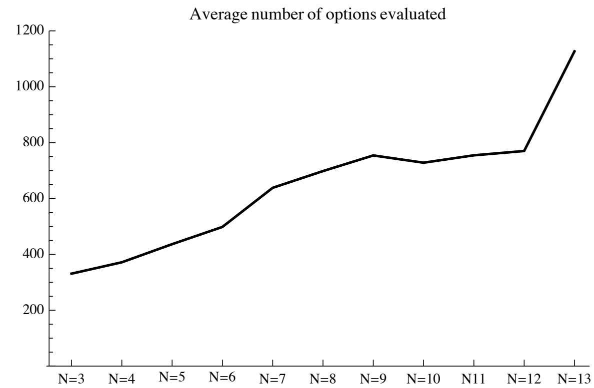

Figure 5: Average number of options evaluated by agents before establishing a coalition

Whereas, for a specific coalition size, the larger the investment cost (and the lower the cost of the service supplied) the higher the average agent individual contribution: I (or S) and x_i are positively correlated (r=0.997, p=0.001). This result conforms with the theory of sharing groups showing that: the more the people in coalition, the less the individual costs; the larger the quantity purchased in group, the higher the individual cost (Lindenberg, 1982).

Proposition 4: *Average agent contribution to the shared investment (x_i) decreases with coalition size (N) and increases with the size of the investment (I and S).*

Free riding

One possible interpretation is that In large coalitions individual behaviour is non-influential for the whole group: as group size grows, the individual contribution becomes less relevant. This may give raise to free-riding, and explain the tensions in large groups between cooperation and free-riding (Canning, 1995; Glance et al., 1997; Huberman and Glance, 1996; Shehory and Kraus, 1998; Axtell, 2000). In our model we find that this relation is confirmed only partially. Figure 7 plots the share of free riders by coalition size.[13] The aveage share of free-riders in coalitions increases

[13] Free-riders are coalition members that do not contribute to the common investment (x_i=0), but pay the unit consumption costs (c_{i2}>0).

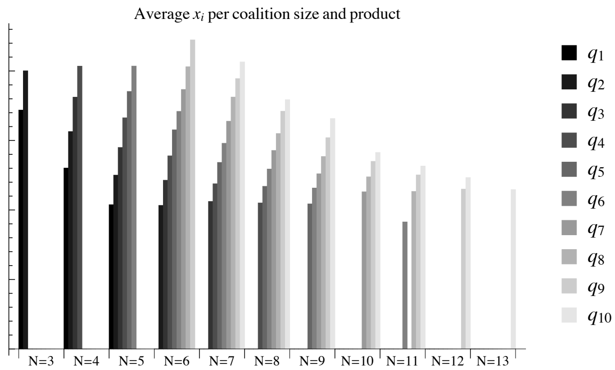

Figure 6: Average agents' contribution in coalition per size and product

with coalition size up to a point ($N = 8$), to decrease again. This is explained by the fact that large coalitions purchase, on avearge, large and expensive common goods which require commitment of all memebrs.

Proposition 5: *The relation between free-riding and coalition size follows an inverted V shape.*

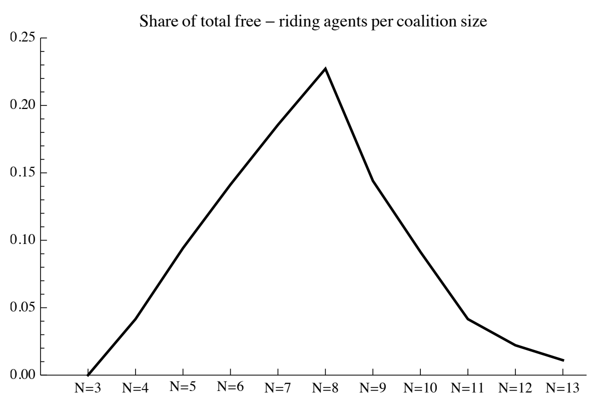

Figure 7: Free-riding agents

4.3 Network analysis

Coalition formation and collective adoption occur in a network of agents whose structure evolves over time, as part of coalition formation. In this section we study how adoption and network structure co-evolve, as part of the coalition formation process.

The co-evolution between coalition formation and diffusion

In each time step t, an agents i neighbours can take one of the following alternative status: linked (f_{it}) – can be part of the coalition, not linked (g_{it}) – cannot be part of the coalition, or in coalition (h_{it}). With the current initialisation (see table 1): $l_{it}=\sum f_{it}+\sum g_{it}+\sum h_{it}=8$. If w_t is the total number of *active* agents at time t, it is possible to calculate the share of linked neighbours by *active* agent (L_t, eq. 11) and the share of linked and not linked neighbours in the total population (V_t, eq. 12) as following:

$$L_t = \frac{\sum_{i=1}^{w_t} \frac{\sum f_{it}}{l_{it}}}{w_t} \tag{11}$$

$$V_t = \frac{\sum_{i=1}^{w_t} \frac{\sum f_{it}+\sum g_{it}}{l_{it}}}{P} \tag{12}$$

L_t can be interpreted as the share of potential members (among those already aware) and V_t as the share of agents that could be potentially involved in the process of coalition formation (in the whole population). Figure 8 plots both series over time.

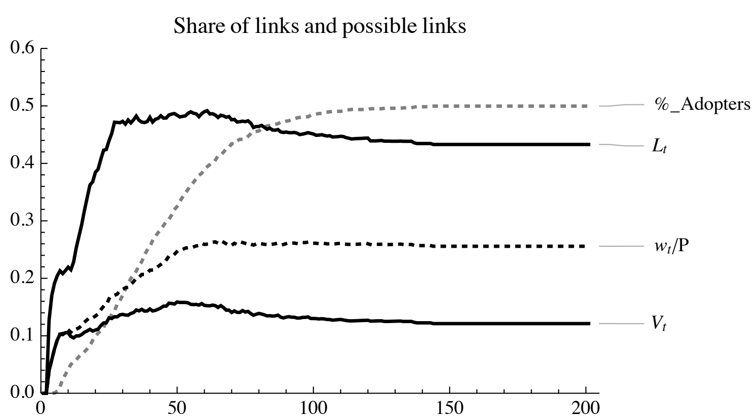

Figure 8: Co-evolution: links, network, coalition and adoption

At the very beginning of the simulation, the share of linked agents (series L_t) and the share of agents that potentially can enter in coalition (series V_t) increase rapidly. When the first coalitions are established, both series stop to grow because the number of *active* agents stabilises (series w_t/P). This is because adopters are no more available for further coalitions, they break links with neighbours, reducing communication between remaining agents. As soon as information starts to flow again (when the share of *active* agents increases again), the two series start to rise again but with a different slope.

L_t grows faster than V_t because while the number of new links f_{it} increases (equation 11), the increasing share of agents in coalition (series %_Adopters) reduces the number of neighbours that could be part of new coalitions ($\sum f_{it}$+$\sum g_{it}$=l_{it}-$\sum h_{it}$ in equation 12). Both curves reach their maximum when the share of remaining *active* agents (w_t/P) becomes stable, and eventually decrease until a stable state. We can explain this better looking at the actual networks.

Figure 9 plots the network configuration of agents (left) and the network structure of all established coalitions (right) at the end of one simulation run.[14]

Black nodes and edges represent connected agents belonging to a coalition that has adopted a shared good (h_{it}). Grey nodes and edges are agents that have been informed and that have participated to the coalition formation process but remained singletons (f_{it}). White nodes connected with dotted edges are neither *initiators* nor *active* (g_{it}), and could not participated in any process of coalition formation. The top-left part of the final network configuration in Fig 9 shows a substantial number of agents that have not been informed during the simulation rub, clustered in the same area. A part of a relative low rate of adoption is then explained by a slow information flow.

However, there is also a substantial number of singletons, active, between established coalitions, with no connections to other individuals. As adopters break their links with neighbours, once they coalesce and adopt, some singletons who did not agree to enter any coalition, are left behind. Figure 10 shows a section of the network in which three agents (69, 71 and 73) are not involved in any of the closest coalitions (64-65-67-68, 59-60-61-62-63-66-70 and the one including agents 73, 74, 75 and others). Since adopters are out of the game, these three isolated agents cannot enlarge further their social contacts and a coalition of size does not improve the utility of all of them. This reduces diffusion.

[14] Because it is not possible to plot an average network configuration over the 40 simulation runs, for illustrative purposes we plot results from a single simulation, representative in terms of average numbers of adopters.

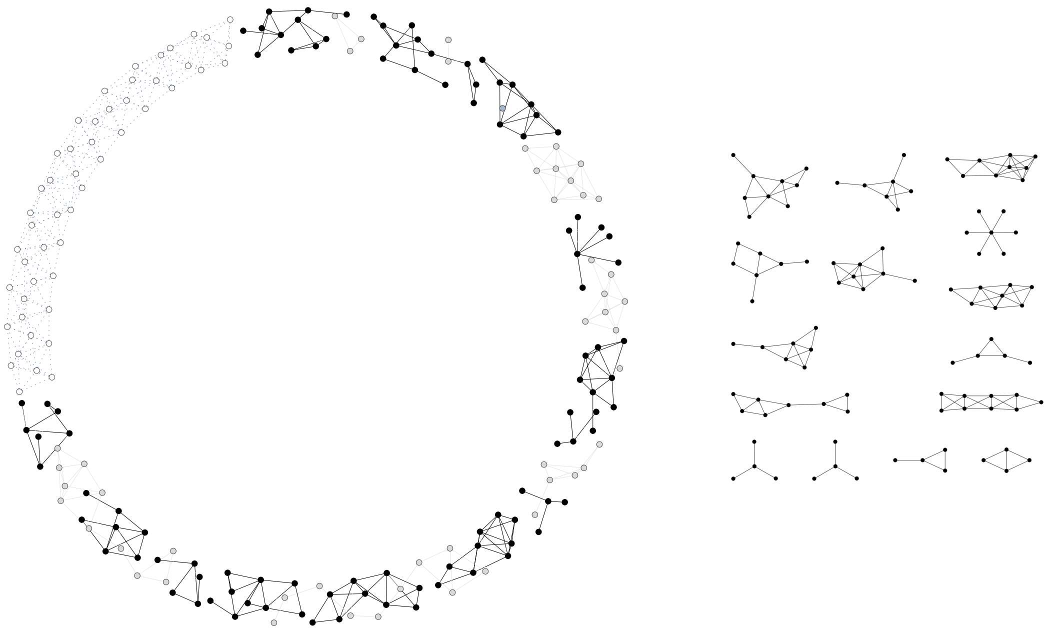

Figure 9: Final configuration: network (left) and coalitions (right)

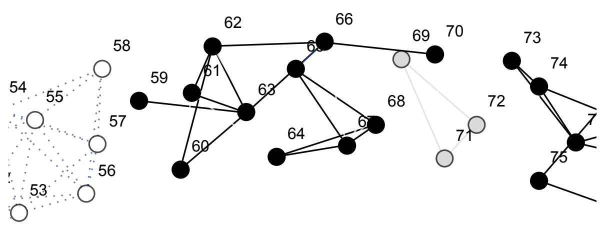

Figure 10: Isolated agents and established coalitions

Proposition 6: *Although coalition formation is necessary for the adoption of shared goods, it may also reduce future coalitions and therefore adoption by reducing the number of available links among remaining agents. Coalition formation and diffusion are co-evolving processes.*

Network properties of coalitions

Figure 11 plots the relation between network metrics (density, radius and diameter, and centrality) and coalition size.

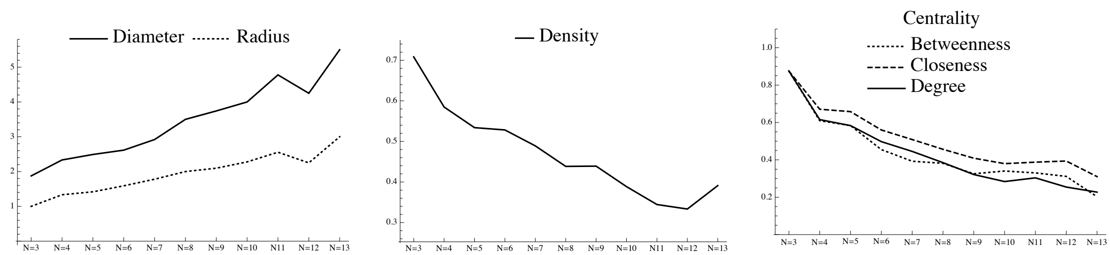

Figure 11: Network metrics

Network radius and diameter (first panel) define the size of networks (the distance between the two most distant nodes). Both measures are not surprisingly positively correlated to N (diameter: r=+0.972, p<0.001; radius: r=+0.968, p=0.009), suggesting that the minimum and maximum absolute shortest paths (or eccentricity) in coalitions increases with size.

Network density (second panel) is the ratio between the number of links over the total possible number of links among agents in a coalition.[15] The negative correlation (r=-0.933, p<0.001) suggests that smaller coalitions are more cohesive than large ones, leaving out a lower number of isolated potential users.

The connectivity within coalitions can be measured with network centrality (third panel). The level of connections between agents is inversely proportional to N. This indicates that in larger coalitions the number of links that agents have with others (Degree: r=-0.935, p<0.001), the extent to which agents serve as bridge between other coalition members (Betweenness: r=-0.901, p<0.001), and agents' degree of being connected to all other agents (Closeness: r=-0.934, p<0.001) decrease.

Proposition 7: *Smaller coalitions to buy shared goods are more cohesive than bigger ones, and agents' connectivity and centrality is higher.*

Taken together, as time goes by, the number of aware and linked agents increases, allowing for larger coalitions. These are preferred with respect to smaller ones (see Proposition 3), thus contributing to the decrease in adoption rates.

[15] A proxy of structural cohesion (Friedkin, 1981).

4.4 The Role of Geography

The relation between the network structure and coalition formation, suggest that the size of the neighbourhood is likely to influence the processes of coalition formation and the diffusion of shared goods. To examine its role, we run the model with different initialisations of parameter l (between 4-14), the number of closest neighbours that an agent can form links with. Figure 12 shows the relation between adoption rates, the % of active agents, and different values of l.

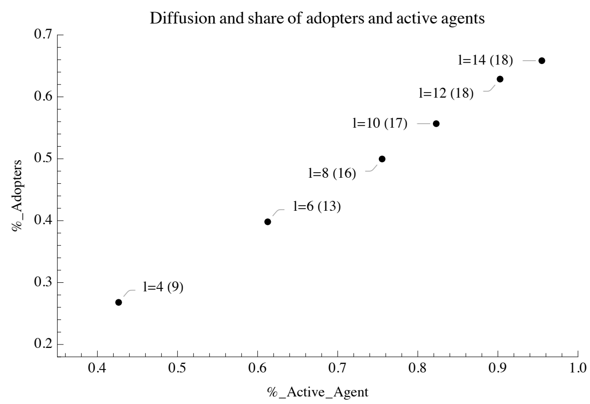

Figure 12: Diffusion, in brackets, and share of adopters and active agents per different values of l

We find a positive and linear relation between the share of adopters and of *active* agents (r=+0.998, p<0.001), and between these two shares, l, and the diffusion of common goods (in brackets) (*active* agents: r=+0.971, p=0.001; adopters: r=+0.977, p<0.001; diffusion: r=+0.950, p=0.003). That is, when the good can be shared between users located at a larger distance, agents have more opportunities to build contacts, form larger coalitions (figure 13), and increase adoption, than when they can form coalitions with the immediate neighbours.

Figure 13 plots the distribution of coalition size for varying values of l. We find that increasing the number of closest neighbours leads to larger coalitions. The higher the value of l the higher the average number of adopters, and the higher the number of larger coalitions.

Coalition size is also related to the size of the investment. Figure 14 plots the distribution of shares of adopters per product (where q1 is a good with low investment cost and high service unit cost; and q10 is a good with high investment cost and low service unit cost). For low values of l, on average, coalitions decide to buy common

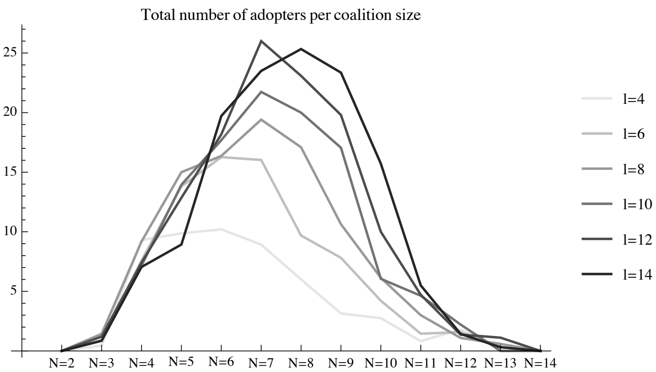

Figure 13: Total number of adopters per coalition size and different values of l

goods that have low investment costs and service supplied. Along with the increase of agents neighbourhood, the share of goods with higher level of I and S increases.

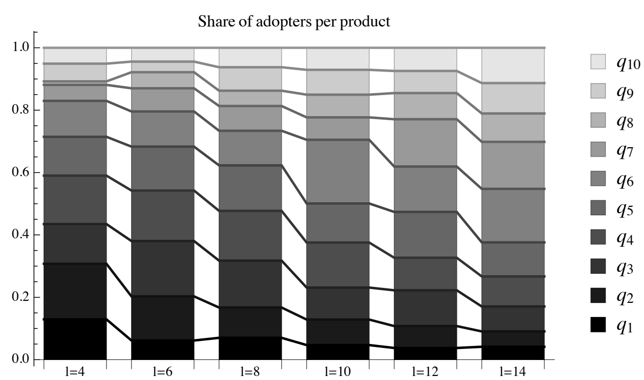

Figure 14: Share of adopters per product and different values of l

Proposition 8: *As the size of the neighbourhood that can share a good increases (the service provided is less tied to the location), information about the shared good flows more rapidly, adoption increases, coalitions are, on average, larger, and buy goods with higher I and S.*

4.5 The Role of Initiators

So far we have investigated a system with few *initiator* agents (m=4, as suggested by the literature). What happens if all agents in the economy are aware of the shared good? In this section, we compare results with the case of all agents being *initiators* (m=200): all agents are connected to their closest neighbours (l=8). This initialisation allows to study diffusion in a complete network. At t=0, agents already know what their utility in all possible groups.

Figure 15 compare the share of adopters resulting from the baseline ($m = 4$) and the complete network scenario ($m = 200$). In complete networks, adoption occurs very rapidly and rate of adoption is higher: after few time steps, the share of adopters reaches its steady state, which is higher than the baseline scenario. This indicates that the absence of communication, which instead occurs simultaneously with the network formation process in the baseline scenario, speeds up the diffusion of shared goods (and is necessary to obtain the S shaped diffusion curve). However, although all agents are informed and connected, differently from many earlier studies, diffusion does not reach 100%. In the case of the complete network, this is because some agents prefer to purchase the service from the central provider, i.e., it depends to structure of individual heterogeneous preferences.

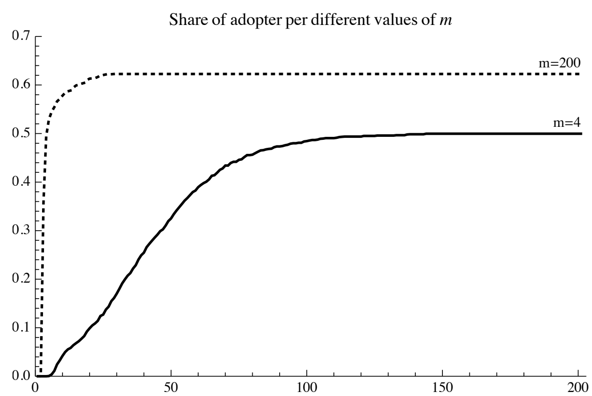

Figure 15: Share of adopter for different values of m

Figure 16 plots the distribution of adopted goods by size. In the complete network, the majority of the coalitions buy the largest product, with the highest value of both I and S (q_{10}). As above, this is related also to coalition size. Figure 17 plots the share of adopters per coalition size. Moving from incomplete ($m = 4$) to complete network ($m = 200$) the average size increases. When possible, agents decide to establish larger coalitions (proposition 3) despite the high level of negotiation and alternative options. Large groups purchase shared goods with higher investment cost, and providing higher quantity of the demanded service (proposition 1) at a lower cost. In these large groups, in agreement with proposition 4, agents minimise their individual contribution x_i.

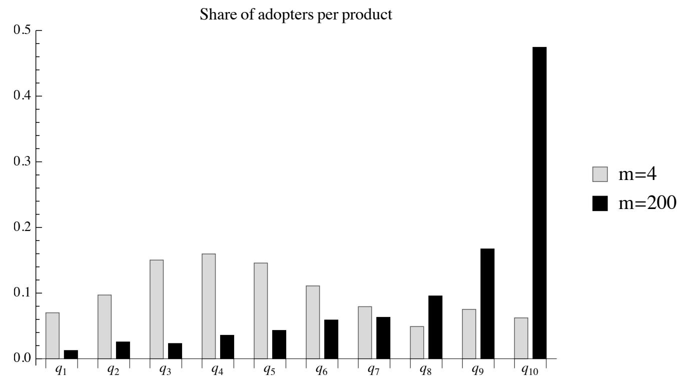

Figure 16: Share of adopters per product and different values of m

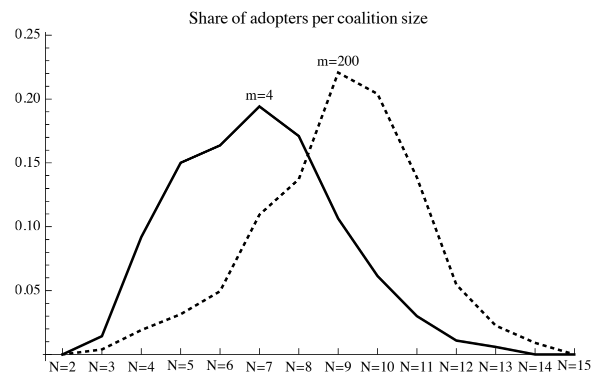

Figure 17: Share of adopters per coalition size and different values of m

Proposition 9: *In a population of fully informed and linked agents, the share of adopters is higher than in a population where information and connections build as an outcome of diffusion.*

5 Implications for the Diffusion of Sustainable Goods

The literature on the diffusion of sustainable energy has focused on adoption as an individual decision. Hence, it studies mainly small-sized goods which are affordable to the average consumer, such as water-saving technologies (Schwarz and Ernst, 2009), micro-cogeneration (Faber et al., 2010), or solar PV panels (Murakami, 2014). Some of these studies examine the role of social interactions and diffusion through networks (Tran, 2012; Bale et al., 2014) and find that networks directly and indirectly influence the individual choices and preferences regarding sustainable goods (Choi et al., 2010; Bollinger and Gillingham, 2012) and might accelerate the diffusion of sustainable energy innovations.

However, to study the diffusion of large-sized sustainable goods, such as smart micro grids, it is necessary to consider adoption as a collective decision. The analysis presented in this paper is suitable to study different cases where a group of individuals may choose to buy a good which is too expensive for a single, such as large-sized decentralised energy systems (DES). DES are too expensive for individual households, but can be purchased by group of neighbours. DES are considered to be indivisible, capital-intensive good with high fixed costs; DES may be beneficial only to users that are connected to it and that share its use; consequently, diffusion of DES is as a case of technology adoption that takes place through collective action; adoption and diffusion of DES requires to first study how such coalitions are formed.

There is still an open discussion about which technologies should be considered as DES. Ackermann et al. (2001) propose four categories, distinguishing distributed generation based on the power installed: these are micro, small, medium and large. The model presented in this paper, accordingly, studies agents who can choose among a set of goods availableof different size. Overall, DES are considered to be small-scaled electric power sources and, since these are non-movable common goods, they have to be physically installed close to the end users directly connected to them (Hatziargyriou and Meliopoulos, 2002; IEA, 2002). Coherently, a more direct involvement of final users can widely boost diffusion of DES (Sauter and Watson, 2007). They can buy and use these systems independently, and experiencing economic benefits (Watson, 2004).[16] Therefore, as simulated in the present model, the adoption of DES can be seen as an emerging bottom-up process requiring a careful understanding of consumers' behaviour, features and preferences (Groh et al., 2014; Pasimeni, 2017).

Results discussed in section 4 can then provide useful policy advice regarding the diffusion of DES, where an adequate regulation is required (Lopes et al., 2007; Driesen and Katiraei, 2008; Marnay et al., 2008; Agrell et al., 2013). A large diffusion of DES might bring environmental benefits (Hadley and Van Dyke, 2005; Tsikalakis and Hatziargyriou, 2007; Akorede et al., 2010), reduction of transmission losses (Chi-

[16] Adoption of DES can also be improved by private and public investments. However, since the focus of this paper in on consumers' coalitions aiming at purchasing (independently) and sharing a common property, these aspects are not considered in the model.

radeja and Ramakumar, 2004; Pepermans et al., 2005) and enhancing energy security (Asmus, 2001; Battaglini et al., 2009). As suggested by our model, to facilitate the transition towards a more decentralised energy system, the first requirement is to increase awareness. DES might diffuse more if consumers were sufficiently connected, and DES were able to provide services at higher distance (higher clustering in the neighbourhoods). Under these conditions, large-sized DES (for example those between 50MW and 300MW, as defined in Ackermann et al., 2001) may have a larger probability to be adopted than smaller systems, and, at the same time, consumers might spend less for their energy consumption.

In conclusion the study on diffusion of common goods in consumers coalitions applied to the case of DES permits to analyse what are the factors that can facilitate the direct involvement of final users into the necessary shift towards a less centralised energy system. The importance of consumers' empowering in this transition process has been recognised by both the scientific community (Hyysalo et al., 2016; Schot et al., 2016) and public organisations (European Commission, 2015a,b). The European Commission clearly endorses this necessity, as communicated in the Energy Union Strategy:

> "To reach our goal, we have to move away from an economy driven by fossil fuels, an economy where energy is based on a centralised, supply-side approach and which relies on old technologies and outdated business models. We have to empower consumers through providing them with information, choice and through creating flexibility to manage demand as well as supply" (European Commission, 2015c, p. 2).

6 Conclusion

This paper has presented ad discussed a model to study the co-evolution of diffusion of expensive shared goods and the formation of the coalitions required to adopt them. Differently from earlier studies on diffusion, our model considers the adoption decision as a collective action, taken by a group of consumers. These groups are endogenous: consumers organise themselves following a bargaining process, as studied in coalition formation game theory. Similarly, links between agents are evolve over time endogenously by means of interpersonal contacts occurring in the social network. By combining different contributions from diffusion and game theory in one agent-based model, this paper aims at contributing to the discussion on the diffusion of shared goods, for which a collective adoption is required.

Results show that larger coalitions are preferred with respect to small ones, to adopt more expensive goods that satisfy a larger demand at a lower unit cost for the service provided. Adopters in large coalitions experience a greater cost reduction than in smaller coalitions. However, small coalitions form at the beginning of the process, when the network is too sparse to involve many consumers.

Coalition formation and diffusion both depend on spreading information abut the good in a given population, which depends on the connectivity among individuals. In larger networks, information flows rapidly and more people decide to join a coalition and to adopt a shared good. However, diffusion also reduces future coalition formation and adoption: because coalitions include only some of the neighbours, those who do not enter (because they do not benefit from those coalitions) remain isolated in the network, and are not able to join further coalitions which may be more suitable to them. For this reason, and contrarily to common outcomes in the literature, adoption in coalition does not guarantee full diffusion, also in cases when information the is available to the whole population.

As discussed in section 5, the modelling exercise presented in this paper can be applied to sustainable energy technologies where the role of consumers' ownership is crucial, as for example in relation to investments regarding local energy infrastructures. For instance, the directive 2010/31/EU of the European Parliament provides guidelines towards the *nearly zero-energy building*. These are "building [with] very high energy performance" where the "energy required should be covered to a very significant extent by energy from renewable sources, including energy from renewable sources produced on-site or nearby" (European Parliament, 2010, p.18). The implementation of this directive, together with other propositions supporting direct energy production and consumption, may substantially benefit from our analysis. For instance, as emerges from our analysis, when not all users are involved in the transition towards a more sustainable energy infrastructure, they main remain isolated, with a negative impact on social inclusion and on the energy transition (due to lower formation of groups of adopters).

The model may also be extended to study related dynamics, such as network and coalition formation in the international climate agreements (Barrett, 1994; Benchekroun and Claude, 2007; Tavoni et al., 2011; Balint et al., 2017). The model can be extended in different ways, such allowing the reintegration of agents in the game after a certain period after the adoption. Shared goods may be considered as mobile, allowing to study the fifth stages of the Innovation-Decision Process in Rogers' theory where confirmation of adoption implementation occurs once the product reaches its maturity phase. Another relevant modification concerns the possibility to have agents in different network structures, such as random networks or small word.

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Annex I

In the utility function of option 2 (equation 4), the two parameters α_i and β_i allow for the linear combination of three elements. The first, $\frac{d_i}{d_i+D_{-i}}$, is, approximately, the percentage of the total service, S, provided by the common good consumed by agent i, once the coalition is formed (see equation 8). Second, in the same way, $\frac{x_i}{x_i+X_{-i}}$, is, approximately, the percentage of the value I of the shared good, purchased by agent i through their monetary contribution x_i, once the coalition is formed (see equation 7). Third, $\frac{1}{N}$ represents the equally shared percentage of the service based on the number of coalition members. Eq. 4 can be rewritten as follow:

$$U_{i2}(e_i; c_{i2}; d_i; D_{-i}; x_i; X_{-i}; N; \theta_{i2}; \alpha_i; \beta_i) = \\ (e_i - c_{i2})^{\theta_{i2}} \{\alpha_i d_i + x_i \frac{d_i + D_{-i}}{x_i + X_{-i}}(1-\alpha_i)\beta_i + \frac{d_i + D_{-i}}{N}(1-\alpha_i)(1-\beta_i)\}^{1-\theta_{i2}} \quad \text{(A1)}$$

Equation A1 means that, neglecting the effect of α and β, the agent's utility function concerning the second option, along with the money saved from individual income (first part of the equation) depends on the linear combination of (i) the individual demand of the service, (ii) the return of the common investment (total service produced, $d_i + D_{-i}$, divided by the total cost spent to purchase the common good producing that service, $x_i + X_{-i}$) multiplied the individual monetary contribution in that investment, and (iii) the total service produced by the common good equally divided to each of the coalition members.

Figure A1 shows how the utility function terms, *cœeteris paribus*, influence the agent's utility in coalition, their relative monetary contribution, and, most importantly, their relation.

High level of θ_i indicates that an agent has a higher preference to save money, while low level of θ_i indicates a higher preference to satisfy the demand for the service. When $\theta_i = 1$, the utility depends only on the income saved. In the opposite case, when $\theta_i = 0$, agent's utility depends only on consumption. When preference for income is high (high θ_{i2}) (and preference for consumption low), *cœteris paribus*, an agent in coalition maximises utility (U_{i2}) by reducing individual monetary contribution (x_i). When θ_{i2} has a lower value (hence, higher consumption preference), agents in coalition are willing to contribute more in order to maximise utility.

The relation is similar for d_i on x_i and U_{i2}. A higher demand raises also the cost (c_{i2}=d_i p_2), reducing the contribution thatt maximises utility. Instead, agents in coalition with higher income (e_i) are willing to contribute more, in comparison to those with lower income. This is because savings are higher when the income is higher, and utility increases even if contribution is higher, *cœteris paribus.*

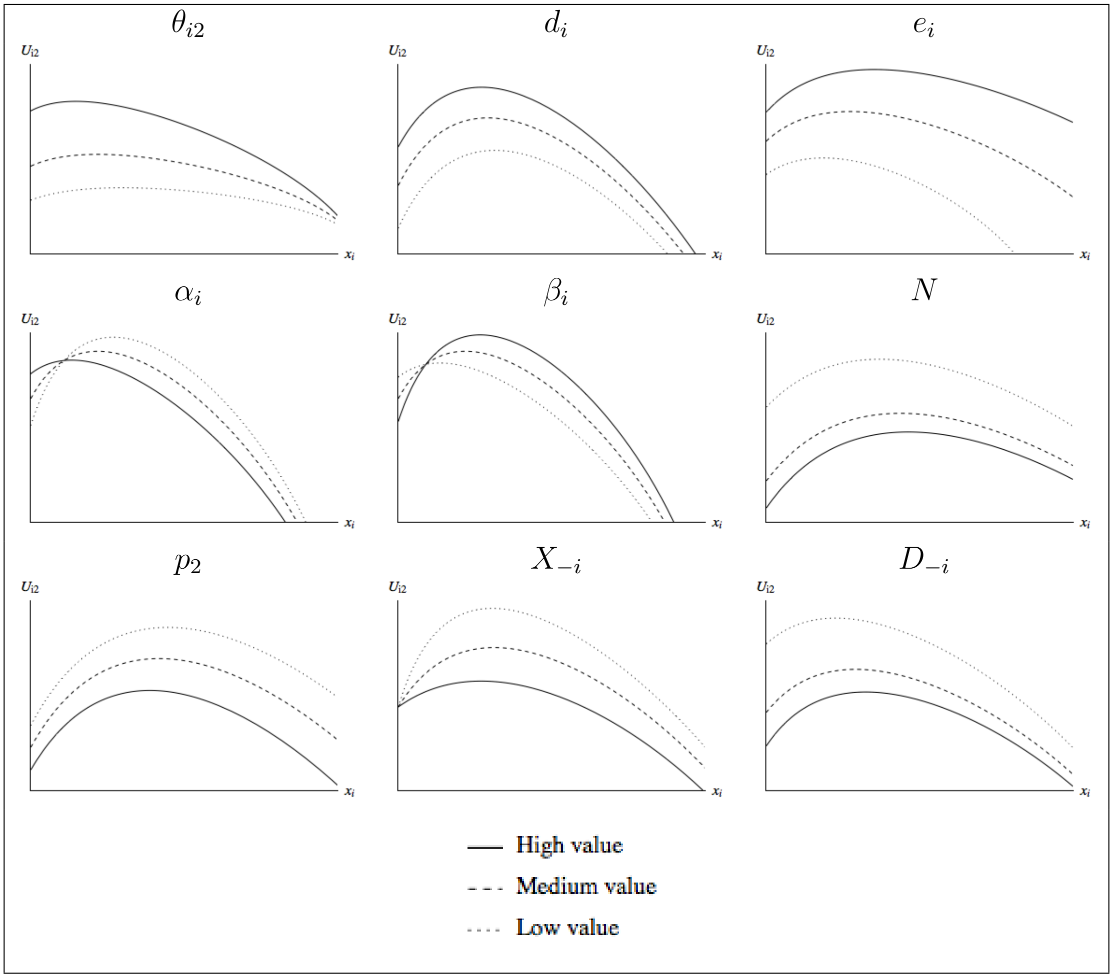

Figure A1: impact of model variables on x_i and U_{i2}

α_i and β_i influence individual utility and contribution in opposite ways. With higher (lower) value of α_i (β_i), utility reaches its maximum at a low levels of monetary contribution. This is because α_i measures the importance given by an individual to the proportional division rule based on consumption. The higher is α_i, the higher is the importance that the individual assigns using only part of the service provided by the common good. Therefore, when this share grows, utility decreases. Parameter α_i, therefore, captures the individualistic perception of the sharing attitude; an agent agrees to share the use with others, but, at the same time, is also reluctant to limit her own consumption. β_i instead measures the importance given by an individual to the proportional division rule based on contribution. Higher value indicates a preference for consuming a lower portion one's income while owning and using part of the common good. Higher β_i also signals that agents attach lower relevance to the number of coalition members. As a result, individuals with high β_i are willing to contribute more to the common purchase, having a higher interest in sharing the cost proportionally with others.

With respect to coalition size (N) individuals participating in smaller coalitions increase their utility by contributing more than in larger coalitions. The last three terms are also straightforward. The higher the price (p_2) of consuming the service in coalition, the lower the utility. The higher is the other members total contribution (X_{-i}), the lower is the individual contribution; the higher is the total demand (D_{-i}), the higher the individual contribution. These two latter characteristics, in combination with other factors in the utility function, might induce members to free-ride.

Annex II

In order to simplify the explanation of the coalition formation process and its co-evolving decisional process, an illustrative example is used. The initial parameters are set as in table A1. For simplicity, it is assumed that *initiators* can only choose one product. Agents are heterogenous only in respect to their demand (d_i), while all the other parameters (e_i, θ_{i2}, θ_{i1}, α_i and β_i) are set equal to all agents. Because of this heterogeneity, agents acting as singleton have different costs and utilities for option 1 (table A2).

p_1	10
p_2	5
θ_{i1}=θ_{i2}	0.5
e_i	1000
α_i	0.5
β_i	0.5
S	175
I	200

Table A1: Initial parameters

For graphic purposes, the example represents eight agents only, that are located in a regular lattice. Each of them has four spatially limited potential links in his or

Agent	1	2	3	4
d_i	30	55	35	45
c_{i1}	300	550	350	450
U_{i1}	145	157	151	157

Table A2: Agents' parameters

her own neighbourhood. Figure A2 below shows an *initiator* agent in the population and his or her neighbours.

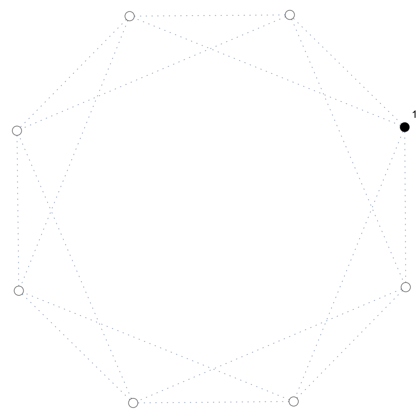

Figure A2: *Initiator* (in black) and the regular network structure

Every time step, the *initiator* ties a link with one of his or her neighbours, which is not linked yet. Therefore, (s)he chooses randomly another agent among spatially limited links. Links formed are bidirectional. The contacted agent becomes *active*, and (s)he is also informed of the opportunity to make the common investment. In this example, as shown in Figure A3, agent-1 contact agent-2 and they establish a link.

In this moment, agent-1 is the *initiator* while agent-2 is not. Both agents, as well as all the other agents in the population, satisfy their demand via external provider that supplies the requested services. This status is defined as singleton and equations 1 and 3 are needed to calculate cost and utility of this option for each agent. Only the *initiator* (agent-1 in the example) can start the process of coalition formation.

Before doing so, (s)he first has to choose which product (s)he wants to purchase and for which (s)he will try to form a coalition (in this example only one product is available). Once the product has been chosen, the process of coalition formation

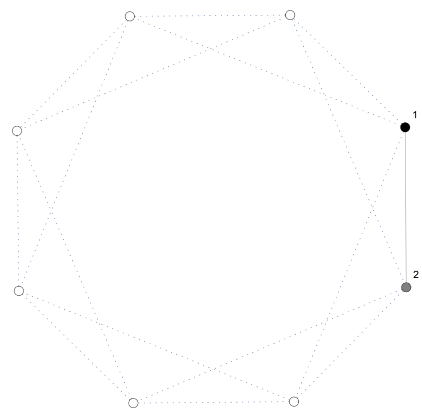

Figure A3: Step 1: *initiator* ties link with agent-2

can start. The *initiator* contacts one of the linked agent. In the example in figure A3, agent-1 contacts agent-2 and they evaluate the joint investment in coalition, needed to buy the product chosen earlier by the *initiator* (equation 2 and 4). Once agent-1 and agent-2 have evaluated the opportunity to invest in coalition, they make a conditional decision among the option to invest in coalition or to remain as singleton. The option that makes an agent better off is stored as optimal. When all coalitions have been evaluated (in the example only coalition (1-2) is currently available to these two agents), all agents announce their optimal conditional decision.

Now, assuming that the coalition (1-2) is not established because it does not satisfy all the stability conditions, the two agents can contact more neighbours and tie more links, thereby improving and enlarging their network. This activity can be performed only by *initiators*. Nevertheless, at the start of the new time step, all *active* agents check, through equation 5, if their level of awareness is enough to become *initiators*. Let's assume that also agent-2 becomes *initiator*. In the current situation, therefore, both agents can, firstly contact one more neighbour each, secondly choose a product, and thirdly start the process of coalition formation. As shown in figure A4, while agent-1 contacts and forms a bidirectional link with agent-3, agent-2 does the same with agent-4. After that the two *initiators* choose the product they want to buy jointly with others, they start the process of coalition formation as explained before.

The coalition formation starts from *initiators*. First agent-1 and later agent-2 begin this process by contacting one linked neighbour. They firstly evaluate coalition size 2 and then, depending on the available links, evaluate bigger coalitions. In

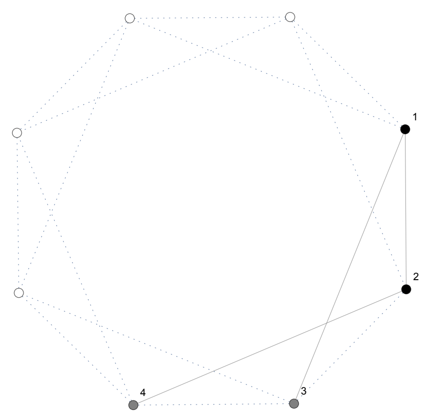

Figure A4: Step 2: *Initiators* tie one link each

this case, the full coalition, size 4, is the largest they can form. Table A3 below summarises all possible coalitions that can be formed and can be evaluated in this network of agents. There are three coalitions size 2 (1-2, 1-3 and 2-4), two coalitions size 3 (1-2-3 and 1-2-4) and one coalition size 4 (1-2-3-4).

		Agent									Agent				
Coalition		1	2	3	4	$\sum x_i \geq I$		$\sum d_i \leq S$			1	2	3	4	
1-2	x_i	101	72			173	x	85	✓	stop					
1-3	x_i	97		89		186	x	65	✓	stop					
2-4	x_i		78		88	166	x	65	✓	stop					
1-2-3	x_i	138	76	127		341	✓	120	✓	continue					decision
	c_{i2}	288	351	302						$c_{i2}<c_{i1}$	✓	✓	✓		
	U_{i2}	163	169	164						$U_{i2}>U_{i1}$	✓	✓	✓		
1-2-4	x_i	142	84		108	334	✓	130	✓	continue					decision
	c_{i2}	292	359		333					$c_{i2}<c_{i1}$	✓	✓		✓	
	U_{i2}	167	173		171					$U_{i2}>U_{i1}$	✓	✓		✓	
1-2-3-4	x_i	161	81	145	113	500	✓	165	✓	continue					stop
	c_{i2}	311	365	320	338					$c_{i2}<c_{i1}$	x	✓	✓	✓	
	U_{i2}	163	169	164	167					$U_{i2}>U_{i1}$	✓	✓	✓	✓	

Table A3: Coalitions evaluated

The three coalitions size 2 do not satisfy condition in equation 7, that is the total monetary contribution added up by the participants is not enough to cover the investment cost. Consequently, these three coalitions are not feasible and they do not provide any optimal conditional decision for the agents involved. Agents stop evaluating these coalitions. Then, agents evaluate the two coalitions size 3. These satisfies both conditions in equation 7 and equation 8, so agents continue the evaluation process and consider their individual cost and utility in coalition (equations 9 and 10). All agents are better off in these two groups, therefore, the two coalitions size 3 are subject to further negotiation in the final decisional step. In the option of the full coalition, size 4, even if it satisfies both initial conditions, agent-1 does not experience improvement compared to the singleton option (cost in coalition is higher). Therefore, (s)he does not agree to form this coalition, which implies that it is not a feasible solution. Consequently, the full coalition is not further considered by agents.

The four agents involved in the final decisional step have their own optimal conditional decision. Agent-1 and agent-2 want to establish coalition (1-2-4) since their utility is higher than in coalition (1-2-3). On the one hand, agent-3 has coalition (1-2-3) as the only available option to improve individual utility. Agent-4, on the other hand, has coalition (1-2-4) as the only available option to improve individual utility. Based on these considerations that agents make explicit, coalition (1-2-4) is established. This implies that these three agents have coordinated their efforts, agreed on the monetary contribution and that they jointly purchase the common good. Coalition is established, and it means that they are out of the game, making agent-3 isolated in the network. Figure A5 shows how network in figure A4 evolves after adoption. The three agents in the established coalition (1-2-4) break the existing links, those already formed (e.g. link 1-3) and those potentially available in their spatial geography (e.g. links 2-3, 3-4, etc.). Agent-3, then, remains isolated. Since (s)he is an *active* agent, in the next time steps (s)he will check whether or not could become *initiator* (equation 5). If so, agent-3 can continue the process with the remaining agents in the population.

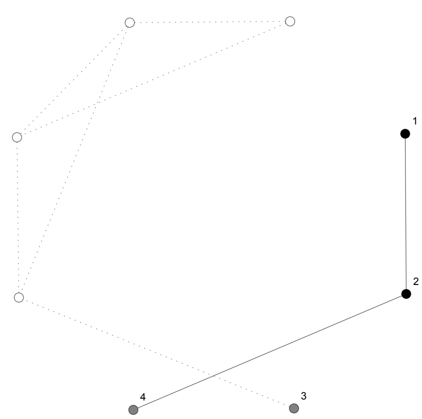

Figure A5: Step 3: coalition established and agent-3 isolated

Annex III

Figure A6 shows a cumulative adoption curve where uncertainties are added at the beginning of the simulation. For the initial times steps, utility in coalition is slightly reduced by means of a coefficient representing a lower utility for early adopters. This produces a lower degree of cumulative adoption in the first stages of the process compared to the case without uncertainties (dotted line, equal to that in figure 2. However, a slower adoption implies that contacts among agents increase, since more agents are in the game. And, as explained in both sections 4.4 and 4.5, more communication implies higher adoption, as indicated by the higher final share in figure below.

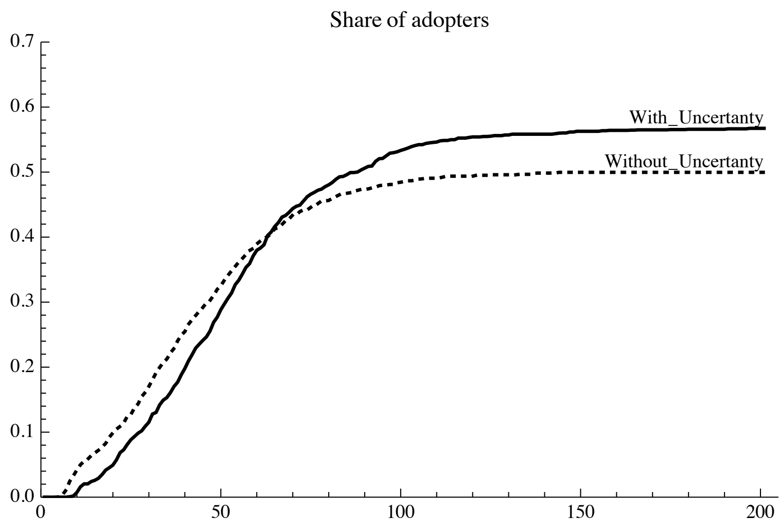

Figure A6: S-shaped diffusion curve