System Dynamics modelling in the Innovation Systems literature

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Abstract: Current developments within the innovation systems field are calling for less static and descriptive approaches and more dynamic and forward looking ones. In this article, we focus on a particular modeling and simulation approach known as system dynamics modeling. This methodology has been widely used for modelling complex socio-economic systems. However, little is known about its use in the innovation studies domain in general and in the innovation systems field in particular. By systematically analyzing a total of 34 studies we present the current state-of-the-art in the use of system dynamics in the innovation systems field. Our main results are that most studies have been used to explore assumptions, hypotheses and policy at the conceptual/ theoretical level, as exploratory modeling tools. Second we have identified six main dynamics that have been modeled using system dynamics: i) R&D, ii) diffusion, iii) absorptive capacity, iv) science and technology, v) learning processes and vi) regional agglomerations, in both qualitatively (through causal loop diagrams) and quantitatively (through stock and flow diagrams). We conclude by reflecting on the current and future challenges for more inclusive system dynamics modeling within the field of innovation systems.

Keywords: innovation systems; systems of innovation; system dynamics; literature review

Word count: 8.581

1. Introduction

The innovation systems approach (IS) suggests innovation is the result of agents' dynamic interactions, shaped by several institutions (Lundvall, Johnson, Andersen, & Dalum, 2002). Since the 1980s it has attracted the attention of scholars and policy makers and has been adopted as a key framework within a broad international audience in both developed and developing country contexts.

Even though there are different streams within the innovation systems community (national, regional, sectoral and technological dimensions), there is a general agreement that an innovation system is a complex and dynamic system – arising from the continuous change and evolution of agents, organizations and institutions (Hekkert, Suurs, Negro, Kuhlmann, & Smits, 2007; Niosi, 2011). There is growing interest in developing an improved understanding of such system dynamics and in doing so, a call has been made for less static/descriptive approaches and more dynamic/forward looking ones.

In this vein, recent analytical frameworks, such as the 'functions' of innovation systems tend to consider the dynamic patterns of the system by looking at how it changes and evolves over time (Hekkert et al., 2007). Also, approaches such as 'innovation system foresight' studies have tried to integrate forward-looking techniques within the innovation system, in order to develop more effective and efficient innovation policy (Andersen & Andersen, 2014). However, such approaches are heavily grounded on a qualitative perspective and suffer from a lack of incorporating a quantitative perspective as well.

In this sense, complex systems modeling might offer an additional perspective by including quantitative assessments of systems under study. Currently, the literature on complex systems modeling is divided into two paradigms: system dynamics (SD) and agent-based modeling (ABM) (Malerba, Nelson, Orsenigo, & Winter, 2008; Rahmandad & Sterman, 2008). Studies reviewing the use of ABM in the innovation studies field have been previously published (Ahrweiler, 2016; Kiesling, Günther, Stummer, & Wakolbinger, 2012) however, no known previous publications exist on systematically reviewing SD models.

In order to address this gap, the aim of this paper is to review how SD has been applied to innovation studies, in general, and in the innovation systems approach, in particular, and in doing so, to highlight insights through the use of SD over more traditional research methods. Based querying several scholarly databases (Web of Science, Scopus and Google Scholar)[1] to locate extant literature, we systematically analyze 34 studies[2] which included journal articles, conference papers, Masters Theses and Doctoral Dissertations in order to present the current state-of-the-art in the use of SD in the innovation systems field.

The structure of the paper is as follows: in Section 2 we explain the fundamentals for system dynamics modeling, in section 3 we explore the theoretical foundations of models of innovation system in the SD domain; in section 4 we reflect on the validation and testing that has been completed on these

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[1] Keywords included: 'innovation systems', 'system dynamics' and several combinations of them.

[2] The list of all 34 documents is available in Appendix A.

models with section 5 presenting our brief conclusions on the state of the field and areas for future research.

2. System Dynamics modelling

System Dynamics originated in the late 1950s as a method to explore interlocking complex problems specifically in the area of supply chain management (Forrester, 1989). The building blocks and core concept of SD therefore rely on using a systems thinking perspective to understand and explain complex systems (Sterman, Oliva, Linderman, & Bendoly, 2015). Complex systems, according to SD literature, are composed by bounded rational agents (Sterman, 2000); by cumulative patterns producing positive reinforcing and negative balancing causation (Niosi, 2010); by nonlinearity and disequilibrium dynamics (Niosi, 2004) and by key temporal delays or phase lags (Sterman, 2000).

Due to the appeal of the systems thinking perspective, the notion of complex systems and a growing computational processing power, SD rapidly gained territory in several domains, ranging from environmental policy and management (Fiddaman, 2002; Meadows, Meadows, Randers, & Behrens, 1972), urban planning (Forrester, 1969) and economic policy (Forrester, Mass, & Ryan, 1976; Radzicki & Sterman, 1994) to health science (Fallah-Fini, Rahmandad, Huang, Bures, & Glass, 2014; Homer, 1987), Operations Research/Management Science (Sterman et al., 2015) and renewable energy policy and technologies (Cardenas, Franco, & Dyner, 2016; Jimenez, Franco, & Dyner, 2016).

SD modeling has been developed as method and tool to i) elicit such feedback loops in order to discover the main growth, balancing and erosion (stagnation) mechanisms driving the dynamic behavior of socio-economic systems, ii) to reproduce – i.e. simulate – the system's dynamic behavior through the use of differential equations and iii) to test and design better policies leading towards improved system performance. In this sense, the modeling process in system dynamics is iterative between all five main steps: problem articulation, dynamic hypothesis, model formulation, model testing (validation) and policy formulation/evaluation.

First, the problem (or problematic behavior) of the system is defined, in order to define the model boundary. Then, a model is built in order to explain problematic behavior in a system. This is done by using two distinct – yet complementary – modeling tools: a qualitative one, known as "causal loop diagrams" (CLDs), which are used to elicit the main feedback loops which lead the system to growth, erosion or equilibrium; and a quantitative one, known as "stock and flow diagrams" (SFDs), which are used to build formal simulation models for policy testing and design (Sterman, 2000). An example of a CLD is shown in Figure 1 and an SFD is shown in Figure 2.

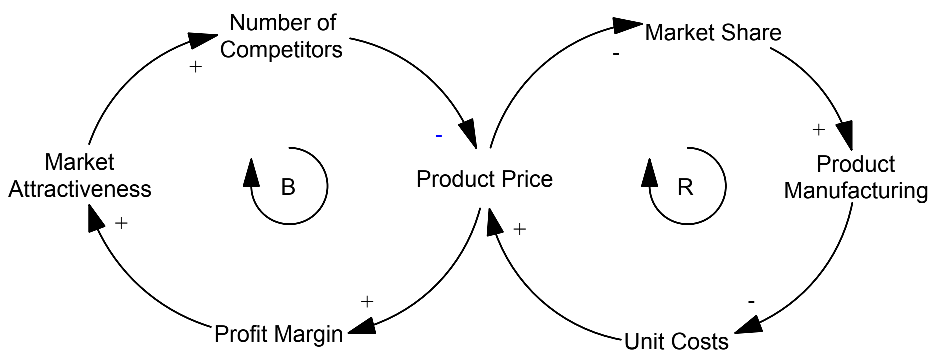

Figure 1. Example of a causal loop diagram (CLD) with two feedback loops. [3]

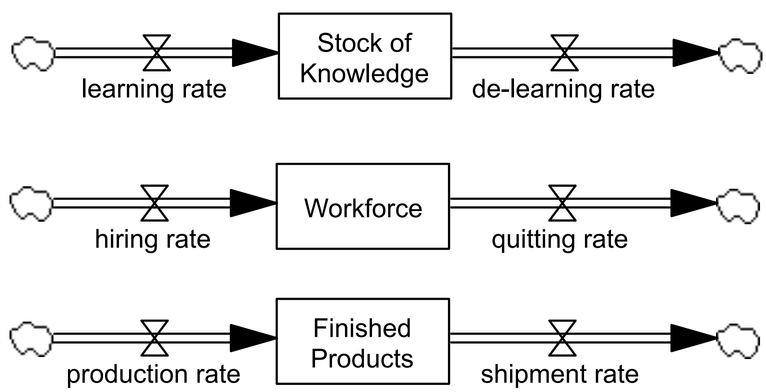

Figure 2. Three examples of stocks and flows.[4]

Following the formulation of the SFD, the simulation model passes through a series of testing procedures, in order to develop confidence in the model structure accuracy of the model's recreated of observed behavior of the real word system. In this sense, model validation in system dynamics differs from traditional model validation in statistics, economics or other sciences. For SD scholars, the main purpose of model validation is to 'gain confidence' in the model structure and behavior rather than on simply assessing how well the model adjusts to real data (Barlas, 1996; Forrester & Senge, 1980; Sterman, 2000). There are tests that assess the structure of the model, against the structure of the real system, and tests that asses how well the simulated behavior fits the real system behavior (Barlas, 1996) (See **Appendix B** for the test categories and descriptions). Finally, the last step refers to policy formulation and evaluation, through what-if scenarios, in order to test the response of the system to different policies (Sterman, 2000).

3. Models of innovation system dynamics

[3] B indicates a balancing feedback loop and R indicates a reinforcing feedback loop.

[4] Rectangles represent stocks that accumulate at the inflows rate minus the outflows rates.

In ***Figure 3*** we present the chronological distribution of the 34 papers that have been included in our study for the period 1995 to 2015. The paper reviewed have been applied in developed and developing countries' contexts. This is of particular interest as it has been acknowledged in the theoretical literature of IS that developed and developing countries' innovation systems are fundamentally different and exhibit different developmental dynamics and policy priorities.

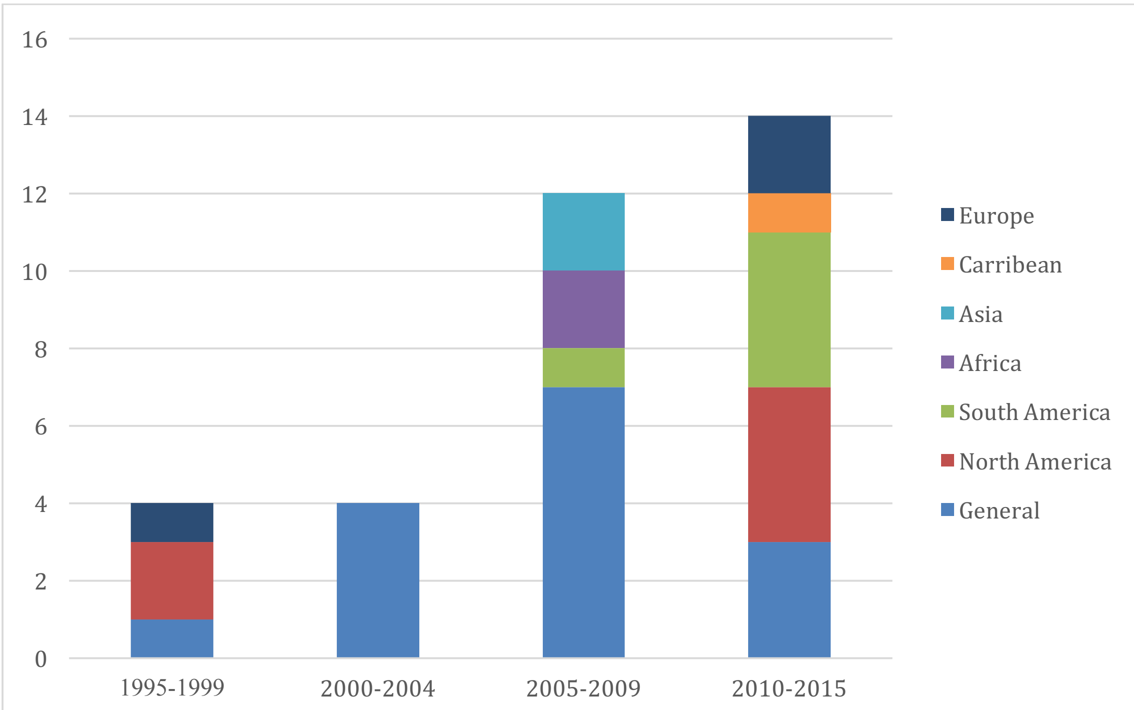

Figure 3: Chronology of SD model research outputs

As previously discussed, system dynamics has been used to model several dynamics within the innovation systems literature. A more in-depth look, however, highlights more studies (65% of them) are of conceptual nature, i.e. studies with no specific real-world problem (aiming at theory-building)[5]. In this sense, it could be stated, system dynamics models have been used as ***explorative models*** (Bankes, 1993), serving to explore the implications of varying assumptions and hypotheses about innovation system dynamics and policymaking. Next, some of the key dynamics modeled with system dynamics are described.

As far as theoretical foundations are concerned, many of the IS models tend to draw on evolutionary economics; capabilities theory and the theory of interactive learning. This is in line with the fundamentals of IS literature to acknowledge the dynamics of innovation and complex feedback loops that exist in the process of innovation and on the systems level, many of the papers acknowledged complexity and refers to the inclusion of complexity theory and systems in the models.

[5] Studies with an empirical purpose, on the other hand, refer to studies where system dynamics has been applied to real – specific - problems with real data.

From a regional perspective the papers included not only traditional RIS foundations, but also some of the regional science frameworks such as innovation districts and clusters. We have uncovered some innovations in these models which included some non-traditional aspects such as fuzzy logic, fuzzy-front-end and game theory principles in NSI models. The potential of these approaches needs further study and exploration to support the development of an improved understanding of IS models (See *Figure 4*).

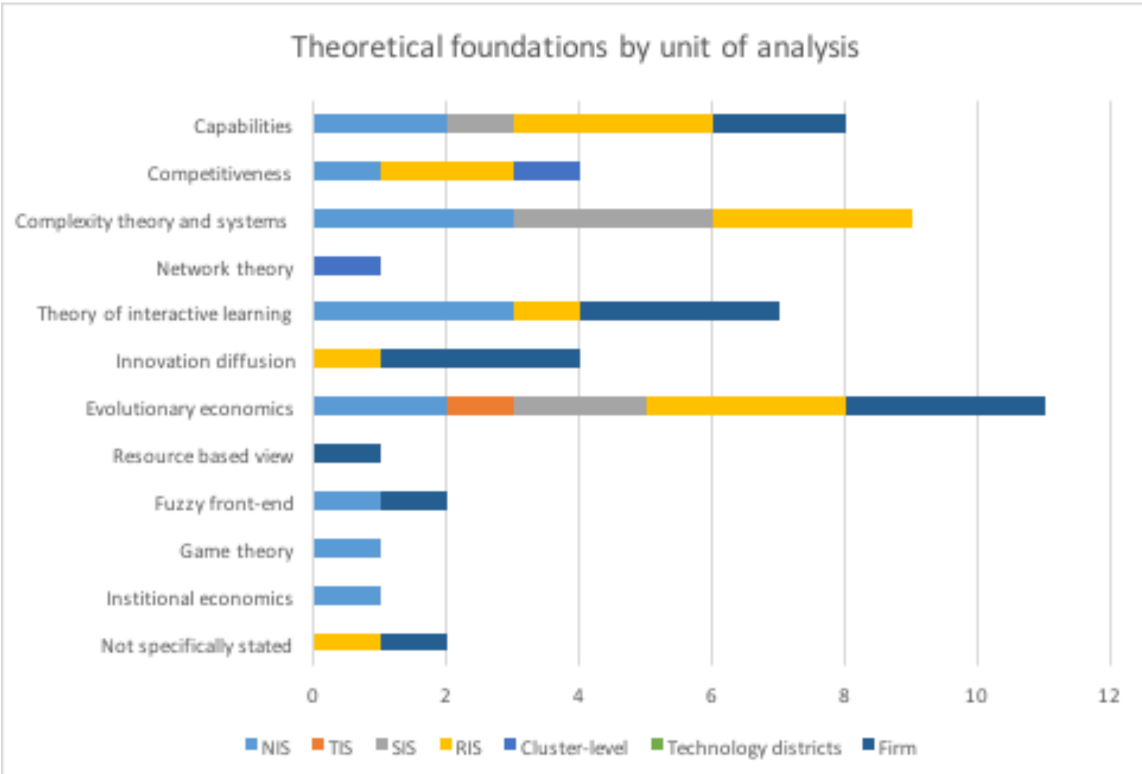

Figure 4: Theoretical underpinning of the SD paper by unit of analysis

We from here on explore six groups of models that have been identified in order to consider the dynamics of innovation system models in the SD domain: This includes the dynamics of 1) R&D expenditure; innovation diffusion/technology adoption; knowledge creation and absorption; science and technology; learning and innovation and regional agglomeration.

3.1 The dynamics of R&D expenditures

The first dynamic process relates to two reinforcing loops linking product and process innovations with R&D expenditures. Literature on innovation studies acknowledges R&D processes as highly relevant for the well-functioning of the innovation system (Edquist, 2011; Hekkert et al., 2007; Jensen, Johnson, Lorenz, & Lundvall, 2007).

In a nutshell, these two feedback loops hypothesize product and process innovations increase the sales rate and revenues of firms, therefore increasing R&D expenditures, which in turn lead to even more product and process innovation in the future, through R&D (Galanakis, 2006; Kim & Choi, 2009; Lee, 2006; Lee & von Tunzelmann, 2005; Samara, Georgiadis, & Bakouros, 2012; Uriona-Maldonado, 2012; Uriona-Maldonado, Pietrobon, Bittencourt, & Varvakis, 2015). Even though there are slight differences between these studies, in terms of which variables compose the feedback loops, there is a general agreement on their structure. Figure 5 shows a simplified CLD representing R&D expenditure dynamics, composed of the two reinforcing feedback loops, explained above.

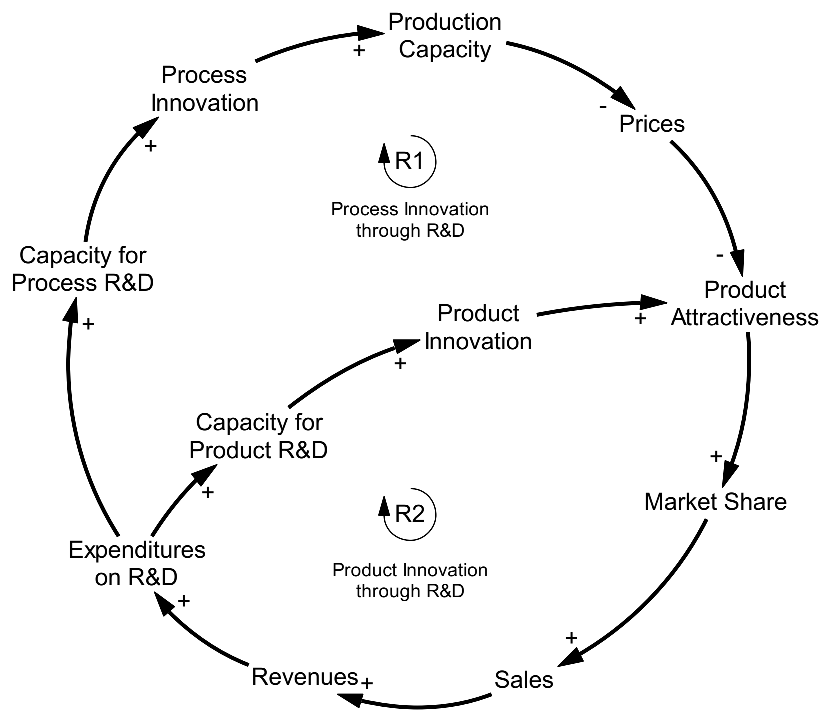

Figure 5. Key reinforcing feedback loops in the dynamics of R&D expenditures.

R&D dynamics – according to these group of models – determine the rate at which innovations occur, depending on the intensity of quantitative parameters such as the ***R&D expenditures*** and ***sales***; and of less quantifiable parameters, such as ***product attractiveness***. In this sense, these models serve to aid decision making – and policy making – by helping decide, for instance, on the share of R&D expenditures for a given case and the possible outcomes – in terms of product and process innovations.

Ultimately, CLDs tend to show a simplified cause-effect relationship by means of focusing on key dynamic processes. Stock and flow diagrams, on the other hand, tend to be more detailed in nature as they will serve to perform quantitative analysis in the forthcoming stages. Therefore, stock and flow diagrams need to categorize which variables are stocks, flows and parameters, and more importantly, how these are connected. Figure 6 shows an adapted version of one of the stock and flow diagrams, within our sample. Following the stock and flow notation, Kim and Choi (2009) represent ***product innovation*** and ***process innovation*** as stocks, which accumulate at different rates depending on factors such as ***product differentiation*** or ***labor/capital productivity***. Also, two additional stocks influence the product and process innovation levels: the stock of knowledge in product and processes, which accumulate as the rate of R&D intensity increases.

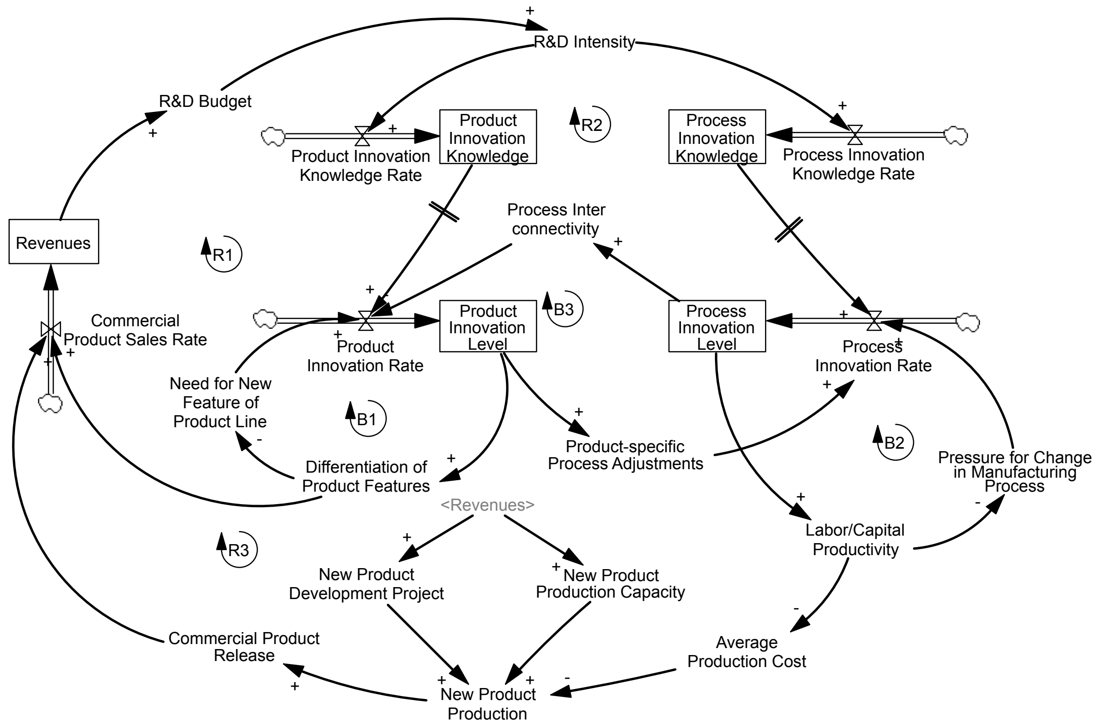

Figure 6. Stock and flow diagram for the dynamics of R&D expenditures. Source: Adapted from Kim and Choi (2009)

3.2 The dynamics of innovation diffusion/technology adoption

Dynamics of innovation diffusion and technology adoption have also been modelled using system dynamics. According to these model, diffusion processes are uneven and evolve as innovations are communicated through certain channels over time. The first group adopting the product (or technology) are called innovators in the sense of Rogers (1962) and they are followed by imitators in different levels of the product life cycle.

In this sense, the main dynamic hypothesis is drawn from three feedback loops: adoption by innovation, adoption by imitation and adoption by market potential (Bass, 1969; Mahajan, Muller, & Bass, 1990). In a nutshell, the adoption probability of a product (or technology) follows a contagion process, similar to what is observed in epidemics (Sterman, 2000): demand by innovators, which increases sales and reduces the potential market (or potential adopters) because they have become "infected"; as the share of "adopters" increases, demand by imitators increases as well, boosting total demand and sales and reducing, even more, the potential market (Ahmadian, 2008). Figure 7 shows a causal loop diagram including the key feedback loops of innovation diffusion and technology adoption.

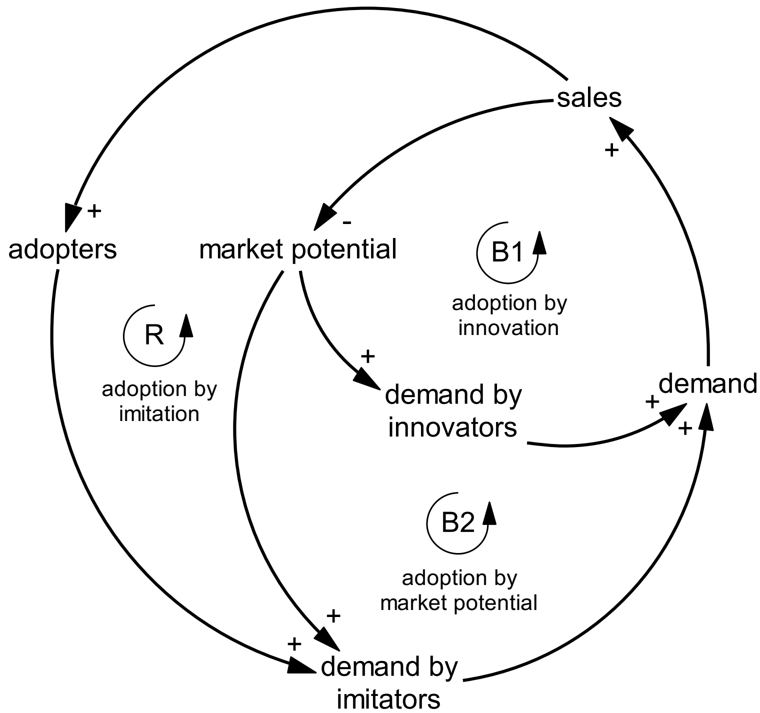

Figure 7. Key feedback loops in the dynamics of innovation diffusion

In addition to modeling innovation diffusion as a "contagion process", following the Bass Diffusion Model (Bass, 1969; Mahajan et al., 1990), literature on innovation diffusion acknowledges the adoption process depends on several factors, beyond "social imitation", including the supply side, the demand side and the institutional side (Ahmadian, 2008; Maier, 1997; Milling, 1996). In this sense, system dynamics models have also been used to highlight the feedback mechanisms between total demand – as a sum of innovator and imitator demand – and operations/manufacturing variables, such as production capacity, production volume (and order processing, manufacturing and delivery delays) and quality control (Milling, 2002); market structure (monopolistic, oligopolistic or dynamic), advertising and timing entry (Maier, 1997); technology legitimacy (Ahmadian, 2008) and regulations (Janszen & Degenaars, 1998). Figure 8 shows a more detailed model in the stock and flow notation, developed by Milling and Maier (2001), demonstrating the linkages between total demand and some of the previously mentioned variables.

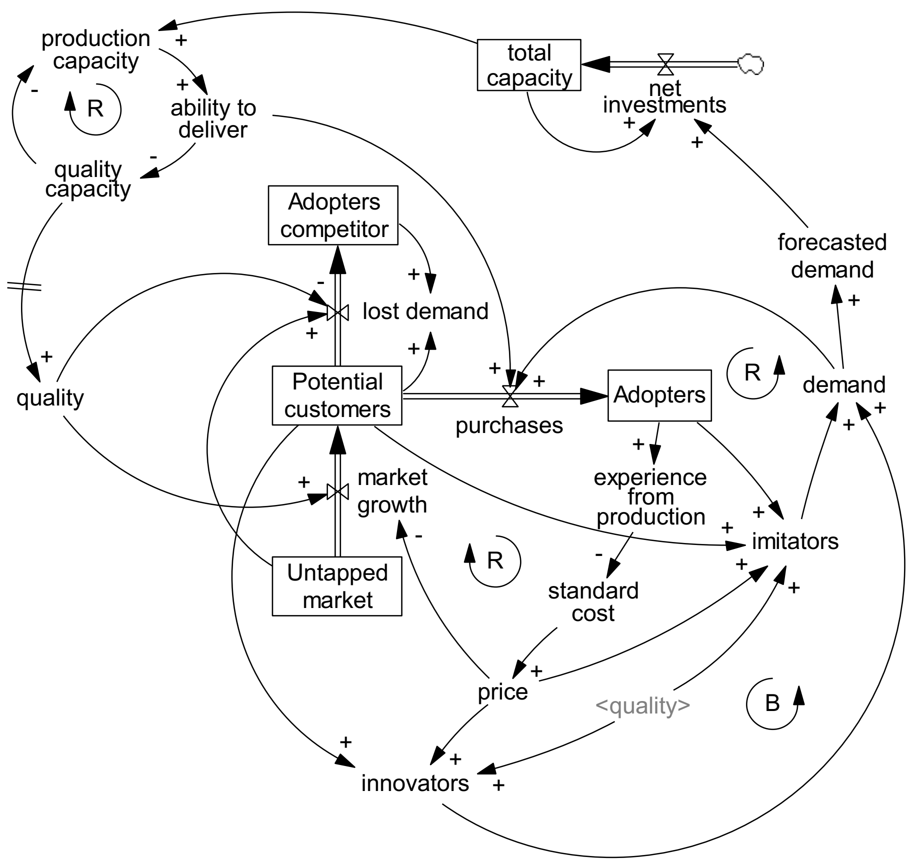

Figure 8. Stock and Flow diagram for the dynamics of innovation diffusion. Source: Adapted from Milling and Maier (2001)

3.3 The dynamics of knowledge creation and absorption

As mentioned above, the investment in R&D and knowledge creation are core functions of the innovation system framework. A range of System Dynamics models have been developed in order to model and explain the effect of investment in research and knowledge creation also as a form of organizational learning.

Mora-Luna & Davidsen (2006) explored learning dynamics in the context of the Columbian innovation system based on Robledo's theory of causal relationships that virtuous cycles can be created through learning processes with the interplay between the development of infrastructure components and innovation processes. Innovative capabilities of firms is the cumulative effect of learning, infrastructure- and skills development.

A second model of interest is that of Grobbelaar which is based on the theory of Cohen and Levinthal's two faces to R&D (See Figure 9). A reinforcing loop (R1) shows how learning takes place through the process of production of knowledge that contributes to the overall knowledge in the system. A second reinforcing loop (R2) shows the process of absorption of external knowledge through engaging in the research process take place through learning by doing, learning by using and learning by interacting. These processes contribute to the tacit knowledge and absorptive capacities of an innovation system.

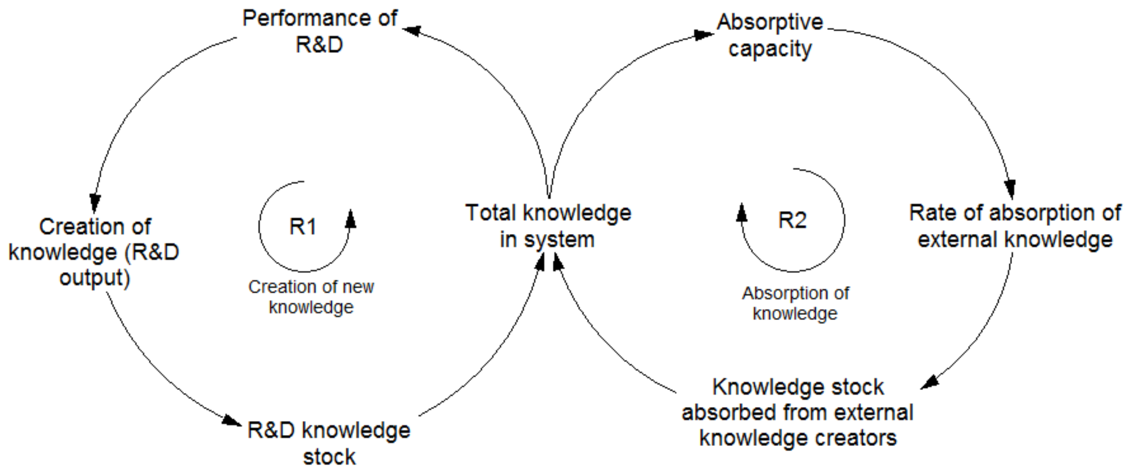

Figure 9. Casual loop diagram of the process of the accumulation of knowledge – the two faces of R&D. Adapted from (Grobbelaar 2006; Grobbelaar & Buys 2005)

Of particular interest for both these models is that they acknowledge the importance of the investment in capability development and the development of absorptive capacities. These need to be viewed as long term investments in codified knowledge but also tacit knowledge that resides in human resources. Such capacities are developed over time and at considerable cost. Grobbelaar (2006) and Grobbelaar & Buys (2005) developed a stock and flow diagram of the process of the accumulation of knowledge (See Figure 10 for a simplified version of this). A key finding is that if various knowledge stock are allowed to deteriorate over time through a lack of investment it is very difficult and costly to rebuild and redevelop a science system. This provides a strong rationale for continued investment in R&D on the systems and firm level.

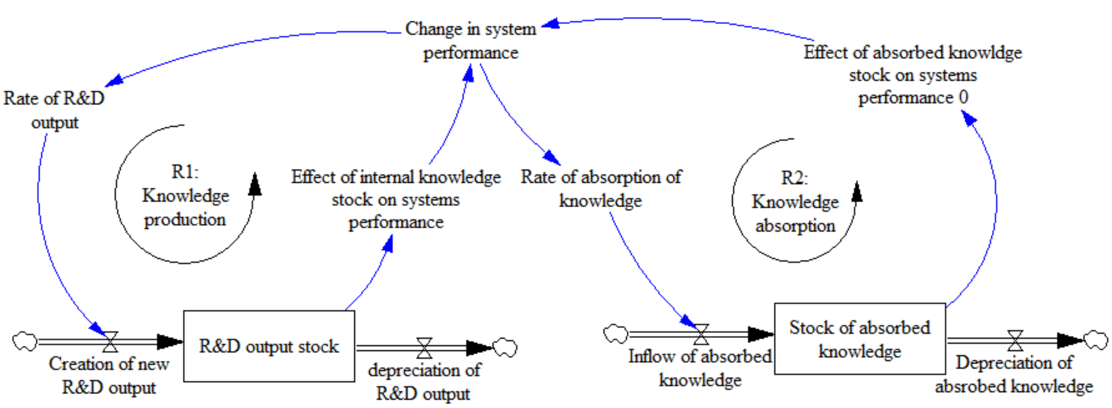

Figure 10. Stock and flow diagram of the process of the accumulation of knowledge – the two faces of R&D. Adapted from (Grobbelaar 2006; Grobbelaar & Buys 2005)

3.4 The dynamics of science and technology

Of particular interest of the models considered in this group is that some effort was made by the authors to link investment in S&T to the development of economies or to regional innovation systems (Castellacci & Hamza, 2015; Rodríguez & Navarro-Chávez, 2015; Rodríguez & Navarro‐Chávez, 2011; Rodríguez, Navarro‐Chávez, Gómez, & Mier, 2014).

For instance, Castellacci & Hamza (2015) developed a macro model to link GDP growth to four major modules that include (1) production; (2) science and technology (S&T); (3) education and human capital and (4) population and health. We however look in more depth at the work of Rodrigues and colleagues developed three different models with similar underlying structures each with a unique application - one on the role of anchor tenants on an RIS (Rodríguez & Gómez 2012), agricultural biotechnology in emerging economies (Carlos Rodriguez et al. 2015) and on policy to sustain regional innovation systems (Rodríguez & Navarro–Chávez 2015).

The main model has 20 reinforcing feedback loops and 2 balancing loops. Due to a lack of space we capture the most prominent behaviors modeled where positive reinforcing behaviors are postulated (See ***Figure 11***). Firstly, through R&D investment the system is able to develop research outputs, drive human resource development, and the delivery of Masters and PhDs. The link is made back to how the production of these S&T outputs link back to the availability of resources for R&D investment. Of particular importance is also that the model includes a distinction and link between basic and applied science and its implications for the development of innovations. Although such a linear relationship may be criticized – the model's main contribution is to close the loop in terms of the dynamics of S&T investment to stimulate innovation and the subsequent increase in availability of funding for further investment in R&D.

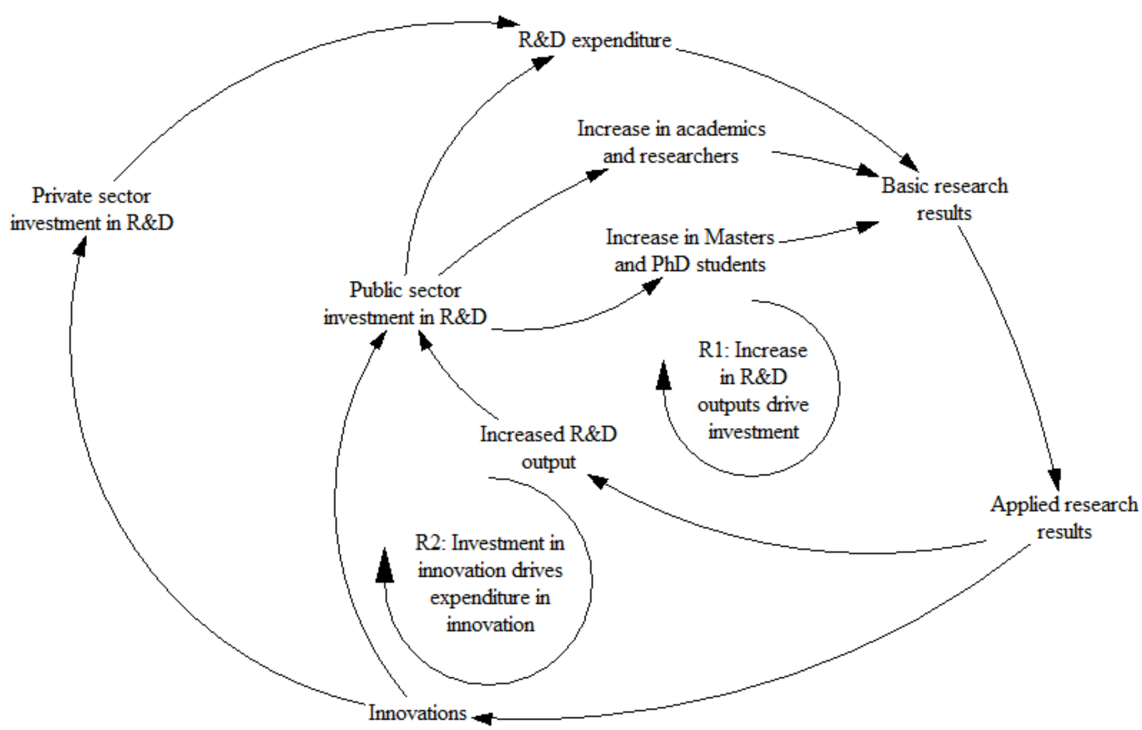

Figure 11. Simplified casual loop diagram of S&T dynamics in a regional innovation system. Adapted from (Castellacci & Hamza, 2015; Rodríguez & Navarro-Chávez, 2015; Rodríguez & Navarro–Chávez, 2011; Rodríguez et al., 2014).

3.5 The dynamics of learning for innovation

Closely related to the models described above, learning processes have been accounted as essential for innovation to occur (Lundvall & Johnson, 1994) and it has been acknowledged there are several types of learning processes in firms, which can be grouped into two categories: STI-mode and DUI-mode (Jensen et al., 2007).

STI-mode (science, technology and innovation mode) refers to learning stemming out of formal and science-based activities, such as R&D activities (both in-house and outsourced) (Jensen et al., 2007). On the other hand, DUI-mode (doing, using and interacting mode) refers to knowledge created and acquired from learning activities other than STI (Jensen et al., 2007). As Jensen et al. (2007) explains, DUI-mode is acquired "on the job", as employees face problems and on-going changes and that results in a higher level of tacit knowledge. Such interactions constitute additional technological opportunities for firms in the innovation system which can be exploited by collaborating and interacting with other actors outside the traditional STI context (Castellacci, 2007).

In particular, system dynamics has been used to represent learning dynamics of both, the STI-mode and the DUI-mode. Figure 12 shows a simplified CLD, including usual variables in the key feedback loops of the dynamics of learning.

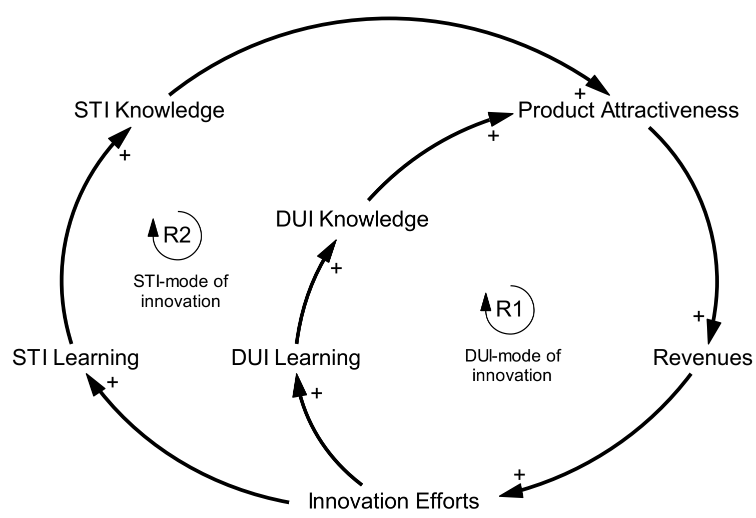

Figure 12. Key feedback loops in the dynamics of learning for innovation

Figure 12 shows two main reinforcing feedback loops: R1 represents the DUI-mode, in which DUI learning flows add knowledge to the current stock of DUI knowledge, increasing product attractiveness, revenues and innovation efforts, increasing DUI learning even more; R2 represents a similar feedback mechanism, in which STI learning and the stock of STI knowledge increase product attractiveness, revenues and innovation efforts.

Even though there is a close relationship between the aforementioned STI-mode and the R&D dynamics presented in Section 3.1, the view of "learning" offers an intangible assessment of what actually goes on inside the R&D process. In this sense, system dynamics is useful to represent both views due to its ease of representing both tangible and intangible phenomena.

It is worth noting there are several types of STI and DUI learning processes in the literature. The most frequent learning process in our sample was learning by doing (Ahmadian, 2008; Stamboulis, Adamides, & Malakis, 2002) while other – at least equally important – learning types found in our sample were: ***learning by internal search*** and ***learning from external advanced S&T*** (both related with STI) (Tayaran, 2011); and ***learning by interacting, learning to learn*** and ***learning by imitating*** (all three related with DUI) (Uriona-Maldonado, 2012; Uriona-Maldonado et al., 2015).

As one can imagine, each learning process will behave differently, depending on the specificities of the innovation system in study. In terms of stock and flow notation, learning processes have been modelled as ***flows*** and knowledge as ***stocks***, following the innovation system literature (Edquist, 2011). As in other feedback loops, both, learning and knowledge depend of other factors as well. Figure 13 shows a simplified SFD accounting for some of the interdependencies of learning and knowledge with other factors, such as sales, R&D funding, absorptive capacity and innovative capability, as mentioned before.

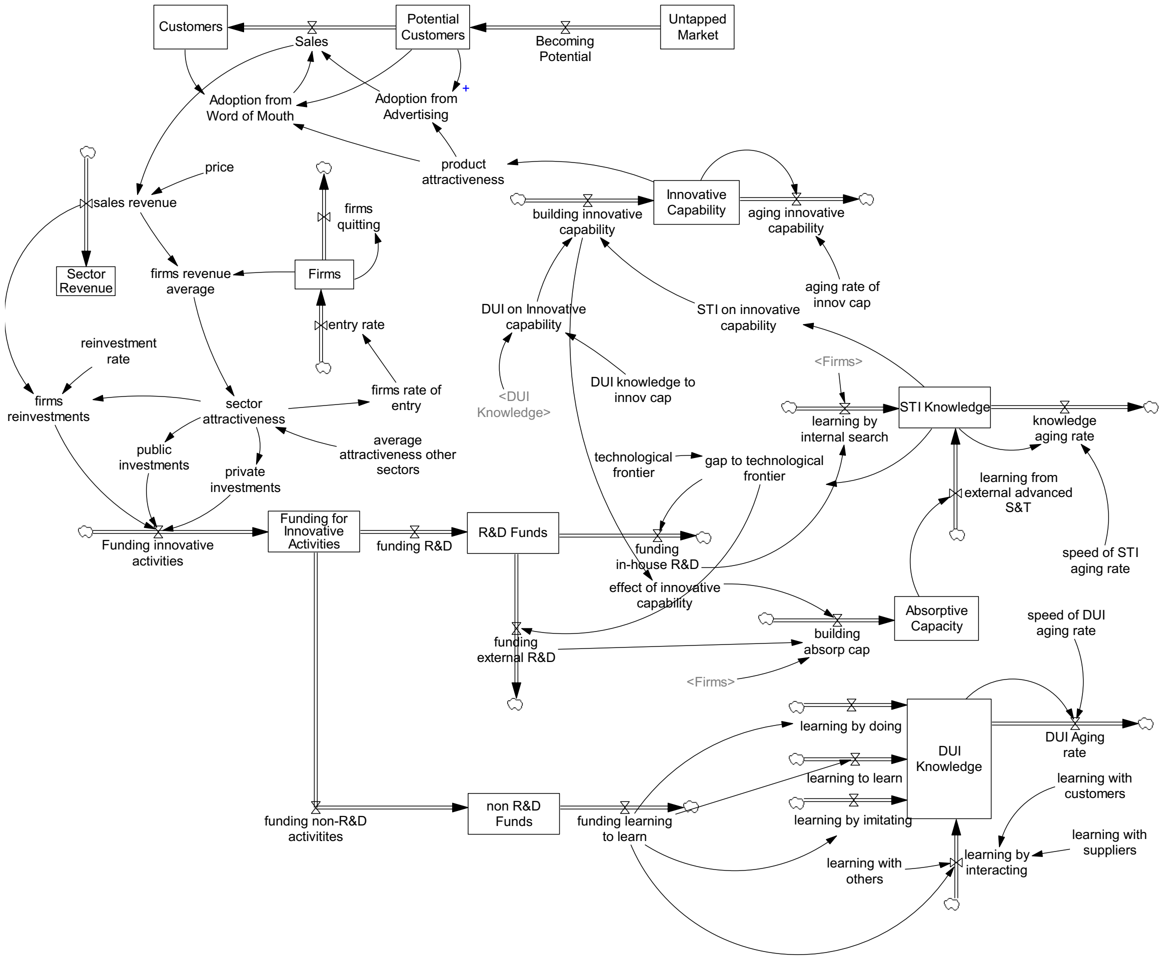

Figure 13. Stock and Flow diagram for the dynamics of learning. Source: Adapted from Uriona-Maldonado et al. (2015)

3.6 The dynamics of regional agglomeration

Agglomeration effects – the clustering of firms, suppliers, service providers and institutions in a geographical area (Dangelico, Garavelli, & Petruzzelli, 2010) – have also been modelled with system dynamics. The theory on regional agglomerations introduce different traditions: the industrial district, Perroux poles, regional systems of innovation, clusters and anchor firms (Niosi & Zhegu, 2005) which, despite their differences, account for important benefits for the actors within the agglomeration, such as knowledge spillovers and the common sharing of resources (Dangelico et al., 2010).

Specifically, Figure 14 shows three main feedback loops, retrieved from our sample, explaining agglomeration dynamics. R1 is a reinforcing loop showing the growth of knowledge spillovers through the increase of actors (firms, suppliers, service providers, etc.) in the agglomeration (Dangelico, Garavelli, & Messeni Petruzzelli, 2008a, 2008b). R2 is the second feedback loop in the model, which reinforces the effect of R1, by reducing the repulsiveness of the agglomeration and thus reducing the number of actors leaving the agglomeration, therefore, increasing even more, the attractiveness of the agglomeration. B is the balancing loop which refers to a ***crowding effect***, this is the effect of an ever increasing number of actors in the agglomeration, leading towards a decrease in the attractiveness of the agglomeration, due to its carrying capacity.

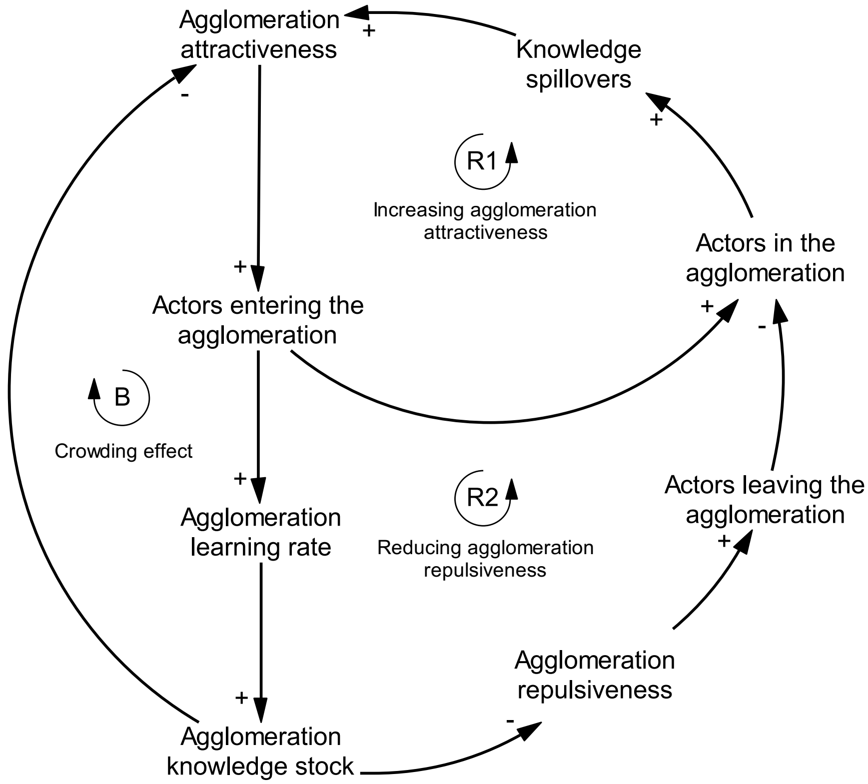

Figure 14. Key feedback loops in the dynamics of agglomeration

In addition, other specific factors have also been modelled within our sample, such as the concept of regional proximity, which encompasses organizational, institutional and cognitive proximity (Dangelico et al., 2010). Also, the influence of anchor tenants to the success of the agglomeration through positive externalities, have been modelled (Rodríguez & Gómez, 2012). Lastly, within the resource-based view, resources such as human, technological, monetary, natural and infrastructure, besides the "entrepreneurial spirit", have also been included in the most complex models within this dynamic hypothesis (Lin, Tung, & Huang, 2006) as influencers of the agglomeration effect or level. Figure 15 shows a stock and flow model developed by Dangelico et al. (2010), representing both, the ***knowledge inside the district*** and the ***shared knowledge*** as stocks, which accumulate at different flow rates depending on factors such as proximity (organizational, cognitive and geographical), district attractiveness/repulsiveness, and the number of actors within and without the district.

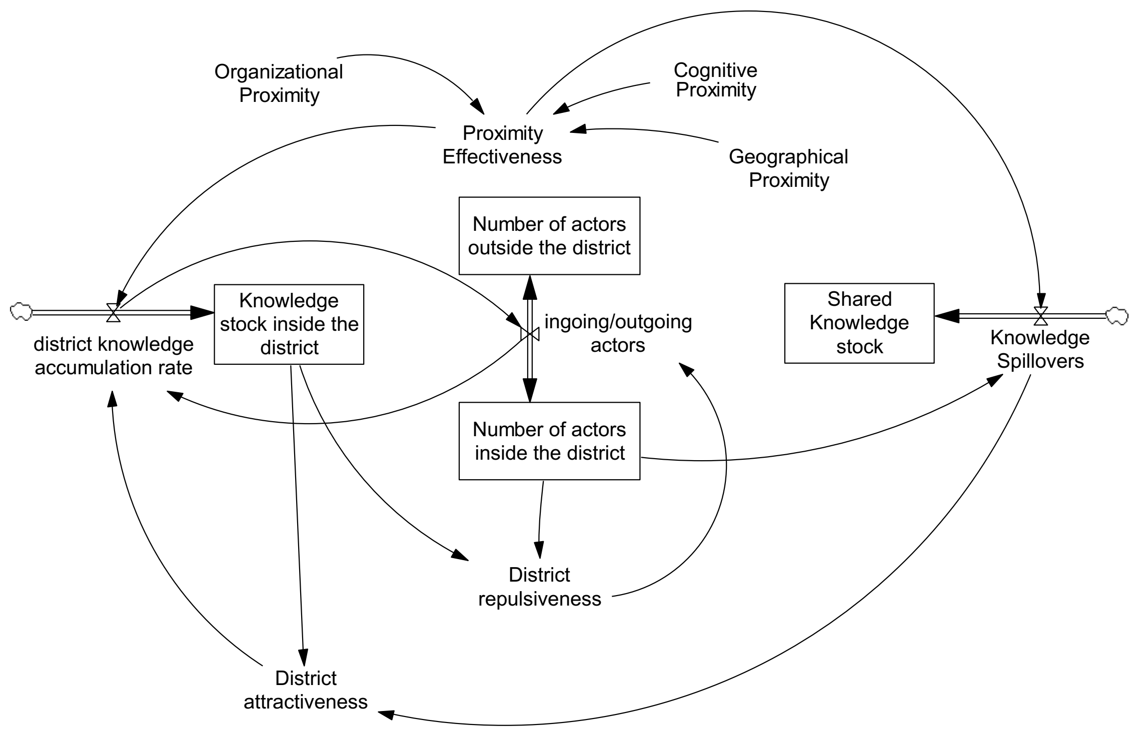

Figure 15. Stock and flow diagram for agglomeration dynamics. Source: Adapted from Dangelico et al. (2010)

4. Data and model validation

In this section, we focus our attention on the types of data that have been used, within the models surveyed, in order to calibrate and validate the models' inputs and outputs against historical data (i.e. how accurate the simulation models have reproduced real systems behavior).

In general terms, the largest share of data used was 'real data' stemming from varied sources such as innovation surveys, experts, government and firms (73%). The second category was 'dummy data', which serves to show generic behavior or system response to policies but lacks in showing how the model would behave or respond in a real problem (17%). Finally, 10% of the studies in our sample used no data (Figure 16). Also, it is worth noting most studies used more than one data source, such as data from firms, innovation surveys or expert-based data.

On the other hand, data commonly used in other modeling approaches such as econometrics (Castellacci & Natera, 2013) and structural equation modeling (SEM) (Verworn, 2009) were found to be of less use in our sample (we specifically refer to patent data, survey data and some other data sources, such as World Bank data). In a sense, it reinforces the difference in the purpose of building models in system dynamics with other approaches, which is to describe system behavior over time, rather than to forecast specific data points in time (Forrester & Senge, 1980; Sterman, 2000).

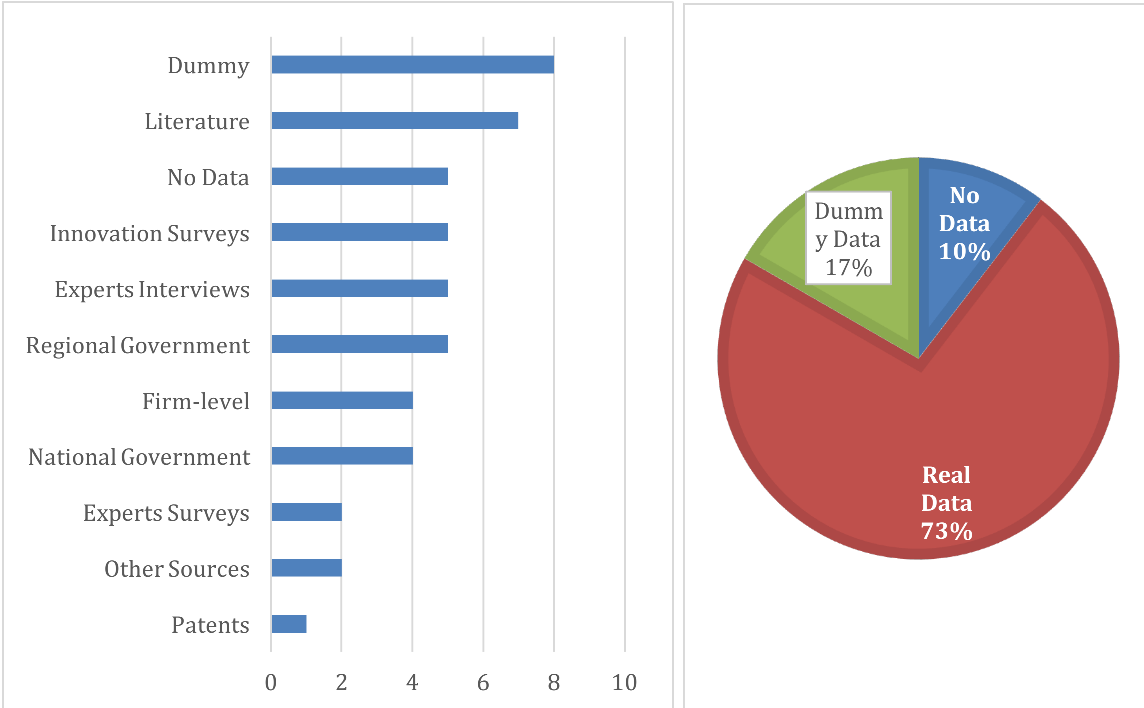

Figure 16. Frequency of data types (left). Relative share of data types (right).

Figure 17 shows the share of usage of model testing and validation procedures (See **Appendix B** for the test categories and descriptions): 26% of the studies in our sample performed both structural and behavior validity tests; 39% performed either structural or behavior testing and 35% of the studies in our sample did not perform either one. The fact 35% of studies do not present any formal validation procedures may be linked with i) there is an important share of studies that were conceptual in nature and developed CLDs only (see sections above) and ii) there are some studies that used no data, therefore did not developed validity tests.

Alternatively, the most frequent validity tests in our sample were 'dimensional consistency', 'behavior reproduction' and 'sensitivity analysis'. The second group includes less frequently utilized tests, such as 'extreme conditions', 'parameter assessment' and 'structure assessment' tests. Finally, the last group includes tests performed little or not at all: 'behavior anomaly', 'integration error', 'boundary adequacy', 'surprise behavior', 'family member' and, with no applications, 'system improvement'. Furthermore, almost all studies with formal validity tests were carried out in the two most recent time periods (2005-2009) and (2010-2015). These results are consistent with recent pressures within the SD community in terms of model verification and accuracy (Lane, 2015; Martinez - Moyano & Richardson, 2013).

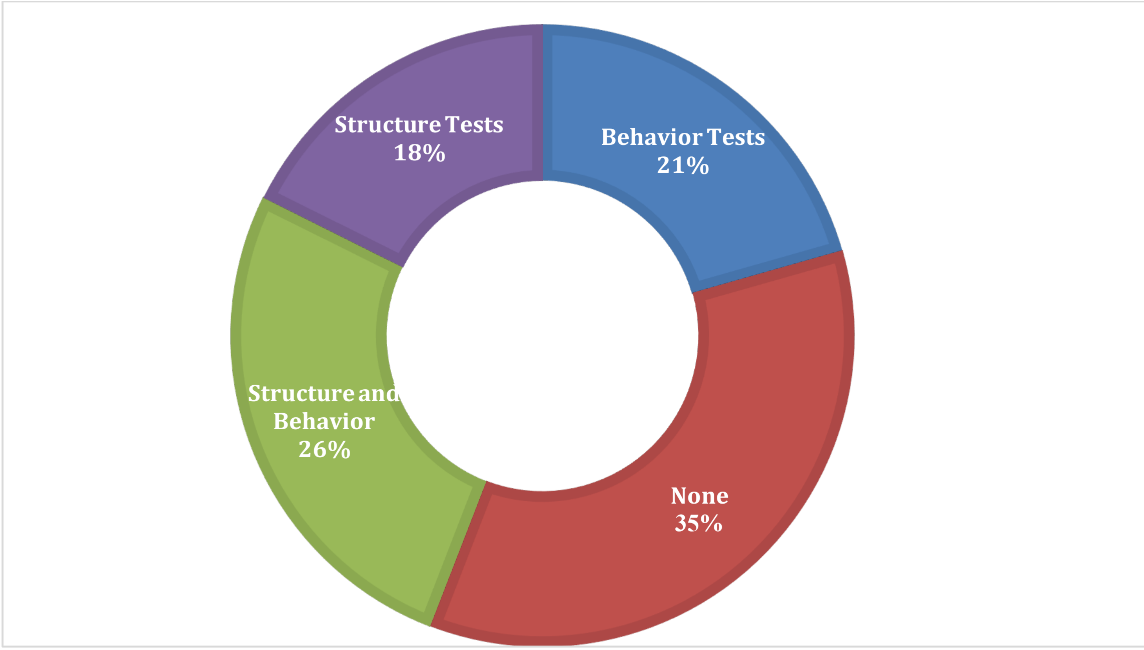

Figure 17. Total share of model validity test use in the reviewed literature

In summary, most studies in our sample have used testing and validation procedures to assess the 'confidence level' of the stock and flow models. In doing so, however, the standard battery of tests – as recommended by the system dynamics literature – has not been applied evenly as some – the most intuitive ones – have had larger usage share, such as dimensional consistency, behavior reproduction and sensitivity analysis. It is also worth mentioning that tests aimed to develop deeper insights about the structure and behavior of the system have been used less, such as extreme conditions, behavior anomaly and integration error tests.

5. Conclusions: The state of the field and future issues

Through reviewing 34 research outputs of where SD has been used to model innovation systems, we have developed a systematic analysis of the literature in this topic area. The theoretical framework against which we conclude the contribution of SD to innovation systems framework research builds on the work of (Bergek, Jacobsson, Carlsson, Lindmark, & Rickne, 2008), (Iizuka, 2013) and (Lundvall, 2007). Here the outcome of SD models of IS has been concluded against the goals of the IS framework as well as continued challenges that are being experienced.

The SD models reviewed remain to be poorly cited indicating a limited scientific impact to the innovation system domain. Given the limited models that have been validated the main use of this methodology remains as a learning device and simulator.

It can be concluded that evolutionary processes that are inherent to innovation system thinking is well represented in the models reviewed. 11 of the models draw on evolutionary economics and 9 also have been developed from a complexity theory and system approach. There are also continued innovation in including other theoretical approaches such as fuzzy-logic, fuzzy front-end and game theory in these models that may have interesting future implications for the methodology especially in addressing requirements for new forms of innovation (innovation for inclusive development).

The models reviewed are often intended for conceptual use only and it was quite common that the modelling process was part of a learning process to understand dynamics and feedback loops inherent to systems. It is then also why dummy data was often used in order to populate models and develop quantitative outputs.

System Dynamics has a number of modelling tools through which these models are developed which is Causal Loop Diagramming and Stock and Flow diagramming. Most of the models did include CLD and SFD diagrams which also supports the assertion that the methodology is useful in conceptualizing complex behaviors and developing causal assumptions. However, if it comes to the validation of these models much remains to be done in order to improve the validation aspects of SD models in innovation systems. A possible reason for this is the availability of appropriate data sources as to fully base innovation systems models on hard data is highly data intensive and depends on time series data sources that in many cases are very difficult to compile or does not even exist. Especially if one considers aspects around institutions, environment and context that is hard to quantify.

The SD models have a strong process focus and are often focused on a specific part of the innovation system also tend to be focused on the unit of analysis and tend have weak linkages to other big picture factors such as economic performance and forces of globalization. Also, within the perspective of new regimes of innovation the SD models only focus on the most traditional approaches to innovating systems and the issue of inclusive innovation systems is still completely neglected. In order to ensure effective models of inclusive innovation systems the expansion of modelling to new and non-traditional actors need to be supported with the integration of bottom up processes of activity and how that links to society's greatest challenges. Here challenges arise such as the ability of Stock and Flow diagrams to model issues such as power asymmetries, conflict, and context.

In relation to data collection procedures, there is evidence of a relatively significant number of studies using 'dummy data' or not data at all (27% of total studies). At first, this fact may look troublesome, since it refers to studies with no real data to support neither conclusions nor policy implications. On the other hand, it was possible to identify most studies with 'dummy data' and 'no data' as conceptual ones, in terms of model purpose. Recalling system dynamics theory, one of its fundamental benefits and advantages, in relation to other methodologies, is its suitability to work as a learning laboratory, where assumptions and hypotheses in the model can be tested against the mental models of policy makers or managers (Forrester, 1980).

We conclude that SD implemented in the traditional way may be criticized for perpetuating approaches to reductionist thinking. Here we also consider future areas for exploration for SD and the development of innovation policy tools e.g. the promise of (and ongoing) integration with other methods such as agent based modelling (ABM) or complex adaptive systems related (bottom-up approaches). We propose that the potential for policy-tools i.e. evaluation frameworks and what-if analysis of policies may be improved.

The review concludes a range of strengths and weaknesses of the SD approach specifically pertaining to the successful achievement of key objectives of such studies. Here we consider the range of issues considered as outlined above and draw conclusions and create insights into cases and problems for which SD is an appropriate methodology (See Table 1).

Table 1: Conclusion regarding SD models and the Innovation System framework

	Description (Iizuka, 2013; Lundvall, 2007)	The state of SD models and contribution to IS literature
Goals of IS framework	The co-evolution and importance of evolutionary processes in the IS	Evolutionary processes and dynamic feedback loops are core to many of the models that have been developed; a number of models have specifically included complexity theory and also evolutionary economic as a foundational basis of the models
	A requirement to understand causal relationship and the need for new analytical methods to do so	This is core to the development of CLDs. This is a key strength of the SD methodology and a way through which these assertions may be tested and developed further; With the little impact the SD modelling has had i.t.o. citation analysis – one may ask the question if SD modelling has been applied to its full potential in this area
	To better understand the institutional setting and its impact on diffusion of innovations	Although often hard to quantify – many of the models have aimed to include some institutional aspects; however -this remains more of a focus of CLDs and not necessary the actual development of empirically supported models
	Role of Actors and their capabilities	The choice of model boundary and also the unit of analysis proved to be central to this element of IS models in SD literature. However, the 'operational perspective' of SD models to represent decision rules of actors were not fully addressed by the studies in our sample.
	To better understand the process of knowledge development and learning	Learning theories and the process of learning was core to a range of models – and the theoretical analysis has shown that this is one of the key dynamics often modelled in the SD domain. However, we have evidenced most studies have focused on STI-based modes innovation to model knowledge development and learning processes.
	The centrality of the firm as sites of learning and activity – also emphasizing that there is often weak correlations between science base and innovative performance	A range of the models has the firm as the unit of analysis with its role in the system - these also seem to be the most widely cited models.
Continued and new	An explanation of the often weak link between the science	The link between innovation performance and economic growth not readily made in most of the models – more

challenges for the IS framework	base and economic performance	focus on understanding the process of innovation – has a great focus on process.
	To acknowledge forces such as globalization – e.g. global value chain approaches to be integrated here	Hitherto neglected area to include value chain analysis in the SD models – this is flagged as an issue for future focus and development. Especially recent trends in terms of the digitization of supply chains may help in this regard.
	Acknowledge power aspect and conflicts in power for development – in particular the role of inequality in capability-based development – has implications for how we develop these models	This requires a bottom-up possibly ABM approaches to be included in the standard SD modelling programmes; Will have implications for SD modelling to explain rather than predict; Traditional stock and flow diagrams may need to be adapted.
	The importance of context and the rise of Sustainability based approaches	Only one of the studies showed the use of SD models to provide insight in the diffusion of clean technologies, through the theoretical lens of TIS but using dummy data. Thus, sustainability based approaches may be hard to model and to quantify – but certainly systems thinking will have a role to play in better understanding these new drivers of innovation and innovative performance. This will also have implications for scenario testing and also how these models need to be interpreted as context remains hard to define and quantify.
	The shifting aim of innovation from 'improving the productivity of the firm' to 'solving a problem for better quality of life for the community' – often challenge based approaches and focus on the demand side	SD modelling has not kept up with new paradigms of innovation such as innovation for inclusive development and also distributed manufacturing; SD approach will be very well placed and is well equipped to model any kind of behaviours and target setting processes – but will need adoption in terms of defining demand-side and bottom-up processes.
	Engagement and support of a new constellation of actors where a wider range of diversity – with dynamic of self-organizing users or community as new driving force for innovation; also the inclusion of non-conventional actors in knowledge networks	This remains a challenge for the SD approach – as data availability and also understanding of these bottom-up processes need to be developed. Again a motivation for SD modelers to adapt the SD approach towards also including bottom-up processes and ways to integrate that in models.
	Requirements for new capabilities and new processes of knowledge creation and learning; new capabilities in traditional and new actors engaged in the process which	Only a small number of studies take an in-depth view on less formal learning processes, such as learning-by-doing, learning-by-using and learning-by-interacting. Thus, SD offers a great potential as a focusing device for such processes and also opportunities for further research.

	has implications for the type and form of learning that needs to take place	
	New bottom-up process - reconsider the way we implement traditional mechanisms for regions – e.g. clustering, "collective experimentation", "collaborative learning"	Such processes offer a challenge for traditional SD modeling. None of the studies in our sample developed a bottom-up approach. Opportunities arise for both: i) integrating SD with ABM into hybrid-modeling approaches, as mentioned above and ii) disaggregating key dynamic structures within SD models per se, aiming at emulating bottom-up emerging behavior.

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Appendix A.

Number	AUTHOR	YEAR	TITLE	JOURNAL/CONFERENCE/UNIVERSITY PHD
1	Milling, P. M.	1996	Modeling innovation processes for decision support and management simulation	System Dynamics Review
2	Lopez-Ortega, E.	1997	A Dynamic Model for Regional Competitiveness Based on the Regional Innovation	15th ISDC
3	Maier, F. H.	1997	New Product Diffusion Models in Innovation Management - A System Dynamics Pe	System Dynamics Review
4	Janszen, F. H. A. and Degenaars, G. H.	1998	A dynamic analysis of the relations between the structure and the process of Natio	Research Policy
5	Milling, P. M.	2002	Understanding and Managing Innovation Processes	System Dynamics Review
6	Milling, P. M. and Maier, F. H.	2002	Research and Development, Technological Innovations and Diffusion	Encyclopedia of life Support Systems
7	Stamboulis, Y. A., Adamides, E. D. and Malakis, T. E.	2002	Modeling the Product-Process R&D Dynamics	20th ISDC
8	Niosi, J.	2004	National systems of innovation are evolving complex systems	13th IAMOT
9	Grobbelaar, S. S. and Buys, A. J.	2005	A conceptual systems dynamics model of research and development activities in So	South African Journal of Industrial Engineering
10	Lee, T. L. and von Tunzelmann, N.	2005	A dynamic analytic approach to national innovation systems: The IC industry in Tai	Research Policy
11	Galanakis, K.	2006	Innovation process. Make sense using systems thinking	Technovation
12	Lee, T. L.	2006	An alternative approach to technology policy assessment: Dynamic simulation ana	International Journal of Technology, Policy and Management
13	Lin, C.-H., Tung, C.-M. and Huang, C.-T.	2006	Elucidating the industrial cluster effect from a system dynamics perspective	Technovation
14	Mora-Luna, A. M. and Davidsen, P. I.	2006	An investigation of the innovation performance in the capital goods sector in Color	Revista Dinamica de Sistemas
15	Grobbelaar, S. S.	2007	R&D in the National system of innovation: A system dynamics model	University of Pretoria
16	Ahmadian, A.	2008	System dynamics and technological innovation system	Chalmers University of Technology
17	Dangelico, R. M., Garavelli, A. C. and Messeni Petruzzelli, A.	2008	Knowledge gatekeepers and technology districts development: a system dynamics	International Journal of Innovation and Regional Development
18	Dangelico, R. M., Garavelli, A. C. and Messeni Petruzzelli, A.	2008	Knowledge creation and transfer in local and global technology networks: a system	International Journal of Globalisation and Small Business
19	Stamboulis, Y. A.	2008	Exploring the System Dynamics of Innovation Systems	26th ISDC
20	Kim, S. W. and Ro, G.	2009	A Dynamic Analysis of Technological Innovation Using System Dynamics	20th POMS
21	Dangelico, R. M., Garavelli, A. C. and Petruzzelli, A. M.	2010	A system dynamics model to analyze technology districts' evolution in a knowledge	Technovation
22	Ulli-Beer, S. and Wokaun, A.	2010	Substantiating endogenous models on induced technology change	28th ISDC
23	Uriona-Maldonado, M.	2010	A preliminary framework for modeling innovation systems in Latin America	7th System Dynamics Latin America Conference
24	Rodriguez, J. C. and Navarro-Chavez, C. L.	2011	A Science and Technology Policy Model to Support Regional Innovation Systems	Revista Nicolaita de Estudios Economicos
25	Tayaran, E.	2011	Investigation of the Critical Factors in the Early Stage of the Innovation Process in B	Concordia University
26	Youssefi, H., Nahaei, V. S. and Nematian, J.	2011	A New Method for Modeling System Dynamics by Fuzzy Logic: Modeling of Researc	The Journal of Mathematics and Computer Science
27	Rodriguez, J. C. and Gomez, M.	2012	Anchor tenants, technology transfer and regional innovation systems in emerging	International Journal of Transitions and Innovation Systems
28	Samara, E., Georgiadis, P. and Bakouros, I.	2012	The impact of innovation policies on the performance of national innovation syster	Technovation
29	Uriona-Maldonado, M.	2012	Sectoral Innovation System Dynamics: A simulation model of the software sector in	Federal University of Santa Catarina
30	Uriona-Maldonado, M., Pietrobon, R. and Varvakis, G.	2012	A Preliminary Model of Innovation Systems Innovation Systems and System Dynam	30th ISDC
31	Rodriguez, J. C., Navarro-Chavez, C. L., Gomez, M. and Mier, M.	2014	Science, technology and innovation policy to sustain agricultural biotechnology in	International Journal of Biotechnology
32	Castellacci, F. and Hamza, K.	2015	Policy Strategies for Economic Development in Cuba: A Simulation Model Analysis	13th Globelics International Conference
33	Rodriguez, J. C. and Navarro-Chavez, C. L.	2015	A system dynamics model of science, technology and innovation policy to sustain r	International Journal of Innovation and Regional Development
34	Uriona-Maldonado, M., Pietrobon, R., Bittencourt, P. F. and Varvakis, G.	2015	Simulating Sectoral Innovation Dynamics with Differential Equation Models	13th Globelics International Conference

Appendix B

Table 2. Main SD model validity tests

Testing Category	Validity Test	Brief description
Structure-based	**Dimensional consistency testing**	The models' equations should be dimensionally consistent without the use of parameters with no real world meaning.
	Boundary adequacy testing	The boundary of the model should be adequate and include all the important variables and parameters needed to explain the problem or system structure.
	Structure assessment testing	The overall structure of the model should be consistent with the actual knowledge about the system, as well as with the level of aggregation.
	Parameter assessment test	All the parameters in the model should have real world counterparts and be consistent with the actual knowledge of the real system.
Behavior-based	**Extreme conditions test**	The model should behave adequately when inputs take on extreme values and thus, it should respond as the real system should, if subjected to extreme policies (values).
	Integration error test	The model should not be sensitive to different time steps or to different numerical integration methods.
	Behavior reproduction test	The model should reproduce adequately the real system behavior, generating similar modes of behavior and reproducing the behavior of interest in the system. In this category, statistical fitness techniques could be used.
	Behavior anomaly test	The model should not reproduce anomalous behavior when different parameters (assumptions) are changed.
	Family member test	The model should be able to generate the behavior observed in other instances of the same system, such as innovation systems of different countries.
	Surprise behavior test	The model – when adequately built – should serve to generate previously unobserved or unrecognized behavior.
	Sensitivity analysis test	The model should be consistent and robust enough to support numerical, and policy-based sensitivity tests.
	System improvement test	The model should serve to improve the real system for the better

Source: Adapted from Sterman (2000), Barlas (1996) and Forrester and Senge (1980).