UNIVERSIDADE FEDERAL DO PARANÁ

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**THE MICROFOUNDATIONS OF EVOLUTIONARY ECONOMICS' DEMAND SIDE: AN ADAPTIVE MODEL OF CONSUMER CHOICE**

CURITIBA

2017

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# THE MICROFOUNDATIONS OF EVOLUTIONARY ECONOMICS' DEMAND SIDE: AN ADAPTIVE MODEL OF CONSUMER CHOICE

Dissertação apresentada como requisito parcial à obtenção do grau de Mestre em Desenvolvimento Econômico, no Programa de Pós-Graduação em Desenvolvimento Econômico, Setor de Ciências Sociais Aplicadas, da Universidade Federal do Paraná.

Orientadora: Prof[a]. Dra. Adriana Sbicca Fernandes

CURITIBA

2017

UNIVERSIDADE FEDERAL DO PARANÁ. SISTEMA DE BIBLIOTECAS.
CATALOGAÇÃO NA FONTE

Souza, Daniel Fernando de
The microfoundations of evolucionary economic's demand side: an adaptative model of consumer choice / Daniel Fernando de Souza. - 2017.
98 f.
Orientadora: Adriana Sbicca Fernandes.

Dissertação (mestrado) - Universidade Federal do Paraná, Setor de Ciências Sociais Aplicadas, Programa de Pós-Graduação em Desenvolvimento Econômico.
Defesa: Curitiba, 2017.

1. Economia evolucionária. 2. Consumo (Economia). 3. Demanda (Teoria econômica). 4. Heurística. I. Fernandes, Adriana Sbicca, 1969-. II. Universidade Federal do Paraná. Setor de Ciências Sociais Aplicadas. Programa de Pós-Graduação em Desenvolvimento Econômico. III. Título.
CDD 330.1

MINISTÉRIO DA EDUCAÇÃO
UNIVERSIDADE FEDERAL DO PARANÁ
PRÓ-REITORIA DE PESQUISA E PÓS-GRADUAÇÃO
Setor CIÊNCIAS SOCIAIS APLICADAS
Programa de Pós-Graduação DESENVOLVIMENTO ECONÔMICO

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Os membros da Banca Examinadora designada pelo Colegiado do Programa de Pós-Graduação em DESENVOLVIMENTO ECONÔMICO da Universidade Federal do Paraná foram convocados para realizar a arguição da Dissertação de Mestrado de **DANIEL FERNANDO SOUZA** intitulada: **The Microfoundations of Evolutionary Economics Demand Side: An Adaptive Model of Consumer Choice.**, após terem inquirido o aluno e realizado a avaliação do trabalho, são de parecer pela sua APROVAÇÃO.

Curitiba, 27 de Março de 2017.

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# AGRADECIMENTOS

A realização dessa dissertação de mestrado contou com o apoio e incentivo de diversas pessoas e instituições sem os quais não seria possível a conclusão do trabalho. Minha trajetória acadêmica até este momento jamais teria sido a mesma sem as contribuições de tantos amigos e familiares.

Primeiro, gostaria de agradecer à minha orientadora Adriana, ao professor Felipe, ao Programa de Pós-graduação em Desenvolvimento Econômico (PPGDE-UFPR) e à Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES) pelo apoio acadêmico, profissional e institucional à realização dessa dissertação.

Agradeço também à minha mãe Cássia por sempre primar pela minha educação e ao meu irmão Lucas, pelas dicas e pelo carinho de sempre. Irmão, obrigado por acreditar em mim em todos os momentos, você me inspira a alcançar voos mais altos. Você sempre será o primeiro pra mim.

Gostaria também de agradecer às pessoas que fizeram minha experiência em Curitiba mais leve. Obrigado Levy, Léo e Hector pelos momentos engraçados e as grandes discussões acadêmicas que me intrigaram e incentivaram. A rotina e as aulas foram muito mais agradáveis com a presença de vocês.

Devo agradecer também aos amigos que estiveram longe durante minha estadia em Curitiba, mas sempre se fizeram presentes através de redes sociais, pelo telefone e pelo whatsapp. Obrigado Fúlvio, Lívia, Gabriela, Malu, Gustavo e Bertha por se manterem próximos apesar da distância. Em especial, gostaria de agradecer a Gustavo por me guiar no mundo da programação com paciência e dedicação e a Berthinha por rever meus textos, me ajudar no inglês e compartilhar comigo o fardo de ser um estudante de mestrado. Vocês são demais!

Agradeço também à minha amiga, parceira de trabalho e eterna professora Lízia. Desde os tempos de graduação você me guiou, incentivou e me demonstrou as belezas e dificuldades do mundo acadêmico. Sua postura questionadora e sua curiosidade pela natureza humana me deram a coragem necessária para navegar em águas desconhecidas para muitos economistas. Muito obrigado pela confiança no meu trabalho e pelo apoio incondicional.

Por último, gostaria de agradecer aqueles que fizeram minha estadia em Curitiba tão especial. Angelo e Thiago, nunca poderei agradecer o bastante por tudo que vocês me ensinaram e por todos os momentos que passamos juntos. Obrigado por aguentarem minha falação incessante e meus dramas pessoais. Seja nas nossas jantas, nas nossas viagens, assintindo o futebol de domingo ou reclamando do frio curitibano, vocês foram os melhores amigos que alguém poderia desejar. Não importa onde estivermos, nossa amizade vai sempre se manter forte e verdadeira.

## ABSTRACT

Evolutionary economics is as well established approach in economics that has presented various theories to explain the most diverse economic phenomena. Nevertheless, we argue in this dissertation that the demand side of the theory is underdeveloped. In order to provide insights into demand side theorizing in evolutionary economics, this research investigates the consumption behavior in an evolutionary economics perspective. I identify typical assumptions in evolutionary economics in which a consumer theory may be built. In order to overcome some difficulties in modeling evolutionary consumption models, I introduce an approach in the psychological literature that could contribute to advance the evolutionary economics theories in consumption: the fast-and-frugal heuristics program (Gigerenzer and Selten, 2001). In this approach, which was inspired by Herbert Simon's bounded rationality, the cognitive mechanisms called heuristics play a major role in explaining human decision-making. After reviewing the evolutionary economics investigations into consumer behavior and the fast-and-frugal heuristics approach, I develop an agent based model featuring the main assumptions identified in each of these approaches. I propose a model framework – based on Valente (2012) – to analyze a semi-durable market evolution with agents using different decision strategies (i.e., heuristics) that can change depending on the structure of the environment in each stage of the market development. Having developed an appropriate model, I investigate the implications of the inclusion of three heuristics (Take-the-best, Tallying and Imitate-the-majority) in the market structure and dynamics through a series of computer simulations. Based on these simulations, I confirm that the different heuristics decision process affect the dynamics of the market evolution, the firms' performance measured by sales and consequently the market concentration. This dissertation contributes to the understanding of the microfoundations of the demand side of evolutionary economics. I conclude that simple heuristics strategies used by the consumers to decide which product they will purchase may enhance the comprehension of evolutionary economists of the demand-side drives that underlie phenomena like innovation, path dependency, consumer learning, and routine formation.

**Key-words:** Evolutionary economics. Consumer theory. Bounded rationality. Fast-and-frugal heuristics research program. Agent-based models. Market structure.

## RESUMO

A economia evolucionária é uma abordagem bem estabelecida nas Ciências Econômicas que apresentou várias teorias para explicar os mais diversos fenômenos econômicos. No entanto, o lado da demanda em suas teorias é relativamente pouco desenvolvido. Com o objetivo avançar teoricamente as discussões sobre o lado da demanda na economia evolucionária, esta pesquisa investiga o comportamento do consumo a partir de uma perspectiva econômica evolucionária. Hipóteses típicas da economia evolucionária que podem embasar uma teoria do consumidor evolucionária são identificadas. Com o intuito de superar algumas dificuldades na modelagem de modelos de consumo evolucionário, é introduzida uma abordagem na literatura da psicologia que poderia contribuir para o avanço das teorias da economia evolutiva no consumo: o programa de pesquisa em heurísticas rápidas e frugais (Gigerenzer e Selten, 2001). Nessa abordagem, inspirada pelo conceito racionalidade limitada de Herbert Simon, mecanismos cognitivos chamados "heurísticas" desempenham um papel importante na explicação da tomada de decisão humana. Depois de analisar as investigações da economia evolucionária sobre o comportamento do consumidor e a abordagem de heurísticas rápidas e frugais, desenvolvemos um modelo baseado em agentes que apresenta os principais pressupostos identificados nessas abordagens. Propomos uma estrutura de modelo baseada em Valente (2012) para analisar uma evolução de um mercado de bens semiduráveis com agentes que utilizam diferentes estratégias de decisão (i.e., heurísticas) que podem mudar dependendo da estrutura do ambiente em cada fase do desenvolvimento desse mercado. Tendo desenvolvido o modelo adequado, as implicações da inclusão de três heurísticas (Take-the-best, Tallying e Imitate-the-majority) na estrutura de mercado e dinâmica são investigadas através de uma série de simulações computacionais. Com base nessas simulações, é possível dizer que os diferentes processos de decisão heurística afetam: a dinâmica da evolução do mercado, o desempenho das empresas medido pelas vendas e conseqüentemente a concentração do mercado. Esta dissertação contribui para a compreensão das microfundações do lado da demanda da economia evolucionária. Conclui-se que as heurísticas simples usadas pelos consumidores para decidir qual produto eles vão comprar pode melhorar a compreensão dos economistas evolucionários em relação aos microfundamentos que determinam a demanda e subjazem fenômenos como inovação, dependência do caminho, aprendizagem do consumidor e formação de rotinas.

**Palavras-chave**: Economia evolucionária. Teoria do consumidor. Racionalidade limitada. Programa de pesquisa em heurísticas rápidas e frugais. Modelos baseados em agentes. Estruturas de mercado.

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# 1 INTRODUCTION

## 1.1 RESEARCH BACKGROUND

Evolutionary economics is often characterized as being a hybrid, interdisciplinary and fairly fragmented stream of research in heterodox economics, comprised of different approaches and methods held loosely together by the reference of the concept of evolution (HODGSON; STOELHORST, 2014; WITT, 2008). Its long history can be traced back to Veblen (1898, 1899) and the American Institutionalists from the beginning of the 20th century, though its main research topics have changed dramatically over the years, passing by long-run development perspective of Schumpeter (2011 [1934], 2008 [1942]), the societal evolution theory of Hayek (2011 [1988]) and economic sustainability questions of Georgescu-Roegen (2014 [1976]). This fragmentation and diversity is confirmed by recent bibliometric analysis, which identify a recent expansion of the evolutionary perspectives without the establishment of a strong and well-defined theoretical core (HODGSON ; LAMBERG, 2016; DOLFSMA; LEYDESDORFF, 2010; SILVA; TEIXEIRA, 2009).

Even with this diversity of views in evolutionary economics, it is safe to say that one of the common goals of many evolutionary economists is to present a theoretical alternative to neoclassical theory. In spite of the significant success of evolutionary economics in this endeavor, some research topics have been often neglected, especially subjects from the demand side of economic phenomena (WINTER, 2014, p.620). This may be explained by the huge influence of the seminal work of Nelson and Winter (1982) on the recent expansion of evolutionary economics. Hodgson and Stoelhorst (2014) notice that the three main themes of Nelson and Winter's Evolutionary Theory of Economic Change - the biological metaphor, administrative behavior and innovation - are still central in most discussions in evolutionary economics. The dominance of supply side topics may be due to the fact that the book by Nelson and Winter (1982) is still the reference point of evolutionary economics but does not cover extensively themes from the demand side.[1]

Hodgson and Stoelhorst also notice that, although Evolutionary Theory of Economic Change is mainly regarded as a Schumpeterian analysis of economics, there is a great

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[1] Hodgson and Lamberg (2016) shows empirical evidence that Nelson and Winter (1982) is indeed a reference point for the period. In analyzing the role of *Evolutionary Theory of Economic Change*, Hodgson and Lamberg state "Rather than creating an immediate cluster of closely related and spin-off research, the seminal role of Nelson and Winter (1982) has been to serve as a point of reference for other clusters." (HODGSON AND LAMBERG, 2016, P.7)

similarity between Nelson and Winter (1982) and Veblen's approach. Yet, one of the most important themes for Veblen was consumption behavior (VEBLEN, 1899) – which was exactly one of the gaps in Nelson and Winter early works and the following inquiries. This gap has been recently identified by evolutionary economists, leading Nelson and Consoli (2010, p.667) to highlight the void on this aspect of the evolutionary demand side theorizing: "Evolutionary economics badly needs a behavioral theory of household consumption behavior, but to date only limited progress has been made on that front".

Even when evolutionary economists disagree that demand side studies have been completely disregarded, they appoint that evolutionary economics have emphasized the supply side. Malerba (2005) argues that, in spite of the existence of some theoretical and empirical work that has studied the relationship of demand and innovation, the evolutionary economists related to the Schumpeterian perspective have treated demand in a marginal manner, focusing on supply studies. Furthermore, Malerba (2006, p.9) adds that "[…] Schumpeter himself might have been responsible for that, given his emphasis on the passivity of the consumer in the innovation process".

Some efforts have been made in the direction of building a theory to explain consumer behavior. Some of these theoretical works studies consumption in an appreciative and conceptual level (ALMEIDA; PESSALI, 2011; WITT, 2001); others sketches a formal model of consumption (KAPPELER ET AL. 2013; NELSON; CONSOLI, 2010); and some use new methodologies like computer simulations and evolutionary game theory (BERNARDINO; ARAÚJO, 2013; VALENTE, 2012; REINSTALLER; SANDITOV, 2005). However, only modest advances have been made so far in modeling the microfundaments of an evolutionary demand behavior. For example, Kappeler et al. (2013) presents various behavioral decision strategies that are cognitively plausible, but do not integrate any of them in their sketch model and Bernardino and Araújo (2013) have a detailed a sophisticated decision criterion although using a conventional and not empirically supported utility maximization process of choice.

Thus, the purpose of this dissertation is to contribute to fill this gap and propose a model of consumption which integrates a detailed and cognitively plausible decision process within an evolutionary demand dynamic from a neo-Schumpeterian perspective, without losing sight of an over-arching evolutionary theoretical framework. Hodgson and Lamberg (2016, p.14) stresses the importance of the formation of a core theoretical framework to avoid further fragmentation of the field, which could hinder the development of an alternative consumer theory. Hence, the methods and theories used in the construction of this model are going to be selected keeping in mind a broader evolutionary perspective.

As stated above in the citation of Nelson and Consoli (2010, p.667), the scope of this theoretical effort demands a behavioral analysis of consumption, which indicates the need to go beyond economic theory and points to other areas of knowledge that can contribute to the understanding of consumption behavior in evolutionary terms. Following the interdisciplinary tradition of evolutionary economics, I will look into the recent literature of psychology for some concepts and theories that can be used as building blocks and open a fruitful path for the expansion of an evolutionary consumption theory. In particular, I will base myself on the fast-and-frugal heuristics program of Gerd Gigerenzer and the ABC Research Group.

## 1.2 RESERCH AIM

This dissertation seeks to provide further insights to the psychological underpinnings of evolutionary economics and to advance a step forward in addressing demand issues in evolutionary theoretical framework. Thus, based on the considerations made so far, I propose the following research question: What are the effects of the consumer's decision making process on the structure of a market within an evolutionary economic perspective? The main goal of this dissertation is to propose a model of consumption compatible with the evolutionary perspective and to highlight the relevance of psychological processes affecting demand behavior. Relating to this main goal, the following sub-goals are defined:

- To identify typical assumptions of evolutionary economics used in the field to explain economic phenomena
- To examine the compatibility of the fast-and-frugal heuristics research program with evolutionary economics
- To develop a model framework based on fast-and-frugal heuristics appropriate to describe evolutionary consumption behavior
- To analyze the effects of different fast-and-frugal heuristics in the dynamics and structure of a market through simulations

The purpose of the model is to illustrate for evolutionary economists the fruitfulness of the more recent psychology theories to contribute to the advancement of evolutionary comprehension of economic behavior and its market outcomes. It will also stress the importance of incorporating psychology concepts as completely as possible in order to harvest the full potential of this interdisciplinary effort, thereby nurturing a close link with the psychology theories and the empirical evidence that supports these concepts and assumptions.

## 1.3 DISSERTATION OUTLINE

This dissertation is structured in four chapters besides this introduction. The Chapter 2 is divided in three sections. In the first section, I review the relevant literature in the field on consumer choice and identify some basic premises of evolutionary economics which are necessary for the elaboration of a consumer behavior model. The second section’s goal is to present a brief revision of the fast-and-frugal research program and to argue that evolutionary economics may greatly benefit from recent works in psychology. Finally, in the last section of this chapter, I advance the model of evolutionary consumption behavior proposed in this dissertation. In Chapter 3, I introduce agent-based models methodology and then I present the model’s parameters specifications and the experiments simulated. In Chapter 4, I discuss the results of the simulations and relate then to the literature in evolutionary economics. I conclude the work in Chapter 5, where I draw some implications from this study and discuss a research agenda for further scholarly inquiry.

# 2 LITERATURE REVIEW

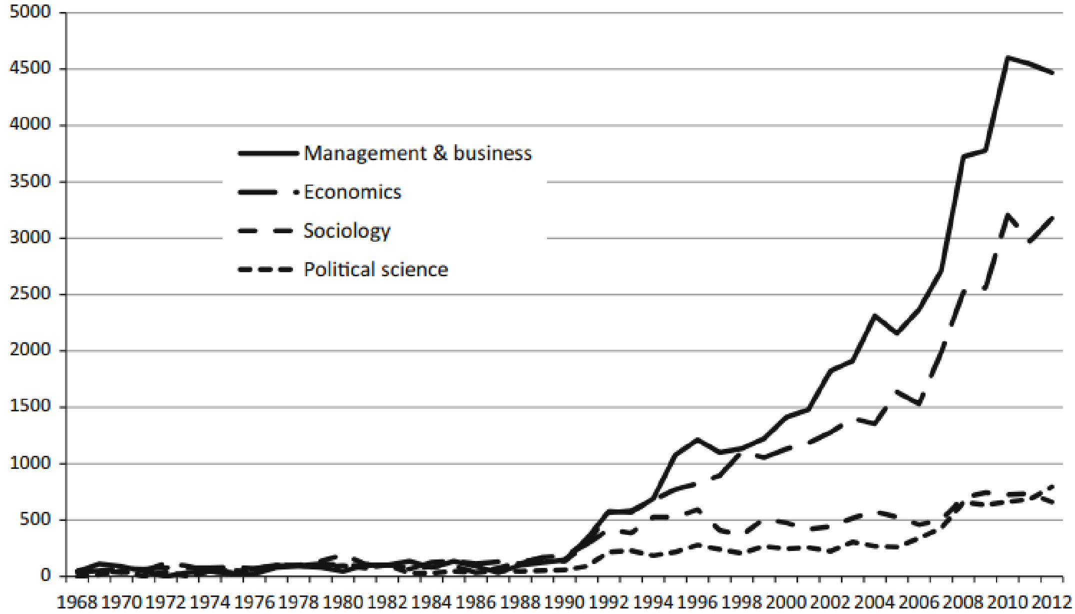
## 2.1 EVOLUTIONARY ECONOMICS' CONSUMPTION THEORY

This section proceeds in three steps. First, I will present the interpretation of the term "evolutionary economics" that will be used in this dissertation. The main difficulty in defining the meaning of evolutionary economics is the fragmentation of the field that require us to choose one among many valid interpretations of the divisions in this field of inquiry. Therefore, I will define evolutionary economics knowing the inherent limitations of this effort. Subsequently, I review some relevant works on evolutionary consumption theory done in the most recent years. Finally, the final step consists in the definition of some basic assumptions for the consumption model put forward in this dissertation, based on the literature revision of consumer models in the evolutionary economics and other works that investigates the most common assumptions made by evolutionary economists.

### 2.1.1 Modern evolutionary economics approaches

Evolutionary economics has dealt with many subjects since its origins in the end of the 19th century and consumption was one of the main research topics of Thorstein Veblen, the "father" of evolutionary economics. However, the theories related to Veblen and followers lost influence throughout the 20th century, while other evolutionary approaches emerged. A new wave of evolutionary economics begun on the 1980s and has continuously gained influence since then. In FIGURE 1, it is presented a graphic showing the recent growth in evolutionary analysis in social sciences, where the lines represent the number of publications in management, economics, sociology and politics from 1968 to 2012 with "evolution" or derivatives in the title, abstract or keywords retrieved from Thomson Reuter's Web of Science. In the beginning of the 1990s, Witt (1992, p.405) identifies four different traditions in evolutionary economics at that time: the Schumpeterian tradition, which focused on technical progress, innovation, industrial development and market structure, business cycles and growth in long waves; the Austrian economists, who emphasized the role of subjective knowledge and market process guided by discovery activities; the Institutionalists, which focused on routinized patterns of behavior and habits of thought which influenced economic change; and the Neo-darwinian works, which relied heavily on biological analogies and models.

FIGURE 1 – NEW WAVE OF EVOLUTIONARY ECONOMICS




SOURCE: Hodgon and Lamberg (2016)

Later on, Witt (2008) depicts a more complex division between evolutionary economist's works. Witt (2008) analyses the differences in each evolutionary research agenda based on three levels: the ontological level, the heuristic level and the methodological level. The ontological level is related to the assumptions about the structure of the reality used to shape the perception of economic phenomena, e.g. economic activities have its own sphere of reality which is disconnected from the natural world. The heuristic level is associated with the way research problems are framed and how concepts are interpreted, e.g. the definition of "evolution" used in a particular approach. The methodological level is related to the methods used to theorize and test theories, e.g. which way should the role of history be incorporated in economic theory (WITT, 2008, p. 548-549).

Although starting his analysis of the different approaches in evolutionary economics based on three levels, Witt (2008) realizes that the multiple methods used in evolutionary economics are not source of controversies that split the field, thus are not relevant to the analysis of the divisions in evolutionary economics. Therefore, he argues that the different traditions in evolutionary economics diverge primarily in the ontological and heuristics levels. Then, the author identifies two ontological stances and two heuristics strategies used by evolutionary economists: the monist and the dualistic ontological stances; and the generalized Darwinian conceptualization and the generic concept of evolution (WITT, 2008, p.555).

Witt describes two ontological stances assumed in evolutionary economics: the monist and the dualistic stances. The monist stance is based on the assumption that the economic and the nature phenomena are connected in a unique sphere of reality. This interpretation implies that there is continuity between nature and human evolutionary processes, e.g. genetic endowment of the human race can influence the socio-economic phenomena. Discordant from this position is the dualistic stance, which is based on the idea that economic and biological processes are not interdependent, each one having its own sphere of reality. In a dualistic stance, socio-economic phenomena are not dependent of any natural selection considerations (WITT, 2008, p.550).

Besides the ontological stances, Witt describes two heuristic strategies used by evolutionary economists to frame their research problems. One of them is the heuristic based on the use of analytical tools and models imported directly from evolutionary biology to economics. This heuristic assumes that the Darwinian theory is universal and can be extended beyond evolutionary biology using analogies based on the key elements of natural selection: blind variation, selection and retention. The other heuristic device described by Witt is the use of a generic concept of evolution to conceptualize economic phenomena. This heuristic considers that the main characteristic of something that evolves is the capacity of endogenous change over time caused by the ability to create novelty that is contingently disseminated to other entities (WITT, 2008, p. 551-552).

Based on these considerations about ontological stances and heuristic strategies used by evolutionary economists, Witt (2008) represents on FIGURE 2 the different traditions in the evolutionary economics field on a 2 x 2 matrix. The idea is to identify the main discrepancies between different approaches and categorize them from their basic assumptions about reality and the way the frame the problems. On the upper left cell and the lower right cells are approaches that have little or no followers on the evolutionary field. Universal Darwinism is the idea of using the principles of variation, selection and retention to all processes in reality, including economics. This approach is advocated by Hodgson (2002) and Hodgson and Knudsen (2006), but Witt does not identify many works applying these assumptions. On the lower right cell there is the seminal work of Schumpeter (1912), Theory of Economic Development. Witt argues that in this work, Schumpeter stressed the importance of novelty emergence and dissemination in his discussion about the role of innovations in economic development but did not resort to the natural word to explain economic phenomena. Witt also identifies that Schumpeter’s students did not follow this approach, which remained a unique evolutionary economic analysis.

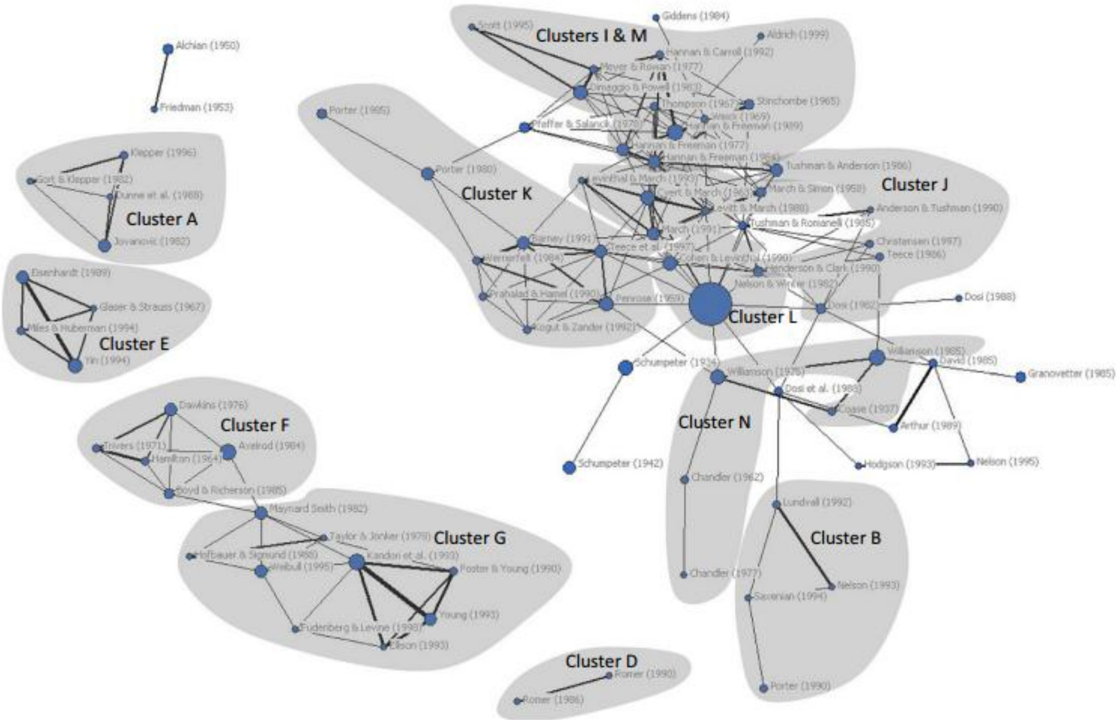
FIGURE 2 – INTERPRETATIONS OF EVOLUTIONARY ECONOMICS

| | | ***ontological stance*** | |
|---|---|---|---|
| | | monistic | dualistic |
| ***heuristic strategy*** | generalized Darwinian concepts (variation, selection, retention) | **Universal Darwinism** | **neo-Schumpeterians** *(Nelson and Winter)* topics: innovation, technology, R&D, firm routines, industrial dynamics, competition, growth, institutional basis of innovations |
| | generic concept of evolution (novelty emergence & dissemination) | **naturalistic approaches** *(Veblen, Georgescu-Roegen, Hayek, North)* topics: long-run development, institutional evolution, production, consumption, growth & sustainability | **Schumpeter** (1912) |

SOURCE: Witt (2008)

On the lower left cell there are the naturalistic approaches pointed by Witt. The author stresses that the different traditions that combine a monistic stance with a generic concept of evolution are not part of a coherent alternative to neo-Schumpeterian thought. In fact, there are multiple works that share the same heuristic and ontological stances and they cover a wide range of subjects, from Veblen institutional economics to Hayek's societal evolution theory. On the upper right cell is the Nelson-Winter approach, whose followers are frequently called neo-Schumpeterians. Nelson and Winter (1982) focused on innovation, technology, institutions and the dynamics of economic change. On this approach, which was born right before the evolutionary economics "boom" in the late 80s and early 90s, the dualistic approach of Schumpeter is maintained, but they relied on the Darwinian metaphor of selection as a main tool to conceptualize economic change on firms and industries – organizational routines are the units subjected to selection in the market process.

FIGURE 3 – EVOLUTIONARY ECONOMICS CLUSTERS




SOURCE: Hodgson and Lamberg (2016)

It is important to notice that most of the topics of research from the Nelson-Winter approach appointed by Witt are related to the supply side of the economy. Moreover, it seems that modern evolutionary economics have been heavily influenced by this Nelson-Winter approach and its topics of interest, which is mostly related to the supply side of the economy. The recent growth in evolutionary economics works followed the publication of the seminal work of Richard Nelson and Sidney Winter in 1982 and there is evidence it is in fact an important reference for the new wave of evolutionary economics. This centrality of Nelson-Winter approach can be seen in FIGURE 3, where there is representation of a cluster analysis and co-citations of publications in evolutionary economics made by Hodgson and Lamberg (2016)[2].

[2] The cluster nomenclature used by Hodgson and Lamberg is the following: cluster A - industrial evolution and product life cycles; cluster B - national innovation systems; cluster C – economic sociology; cluster D – endogenous growth theory; cluster E – qualitative research methods; cluster F – socio-genetic evolution; cluster G – evolutionary game theory; cluster H – genetic algorithms; cluster I – organizational ecology; cluster J – evolution of technology and dominant designs; cluster K – resources and capability-based views; cluster L – organizational learning and behavioral approaches; cluster M – new institutional sociology; and cluster N – transaction cost economics.

The size of each node represents the relative amount of citation of the work and the thickness of the connection lines between the documents represents the strength of the link between them.

Although the evident fragmentation of the field of study, Hodgson and Lamberg (2016) point out the impressive influence of Nelson and Winter (1982) and its role as point of reference for evolutionary economists. It is the most cited work and is surrounded by a constellation of related research programs. However, the fragilities of the work may have been "imported" to the adjacent cluster. One of them is the lack of a consumer theory described by Nelson and Consoli (2010) and Winter (2014).

Thus, as this dissertation deals with the consumer theory demanded by neo-Schumpeterians, it also has the Nelson-Winter approach as a reference point and could be mostly included in the upper right cell in Witt's matrix. However, this work will not be restricted to this quadrant, because it will discuss consumption and use a generic concept of evolution, characteristics of the lower left cell in Witt's scheme. The use of a generic concept of evolution is important for this work because I will analyze the results of the model based on the emergence of market properties and dissemination of information. Furthermore, I aim to present a more general model, which can be regarded by most evolutionary economists as an advance on evolutionary consumption theory. Thus, using a more broad definition of evolutionary phenomena will help with the generality seek for the model. These aspects will be discussed later on our work, but it is important to notice that this dissertation attempts to present an integrative analysis that surpasses the fragmentation of the field presented by Witt, including in the same model a neo-Schumpeterian theory with a generic concept of evolution.

From now on, when I use the term "evolutionary economics" or "modern evolutionary economics", I am specifically considering the neo-Schumpeterian economists in Witt's matrix. However, I am surpassing the definition made by Witt (2008) when it is adopted a less strict definition of evolution and propose an evolutionary analysis based on novelty, emergence and dissemination. I am aware that this definition excludes part of the original institutional economists and other approaches that deem themselves evolutionary, but this definition is necessary to situate the work on the literature and enable a concise but moderately comprehensive literature review of the subject.

In the next section, I review a part of relevant literature and give an overview of the framework guiding my model. I will discuss briefly some specific works that have tried to present an evolutionary consumption theory, showing how diverse and fragmented were these efforts and try to identify some common ground on which my model can be based. It is not the main objective here to make a complete revision of the literature, but to review selected works which represent the various ways in which consumption is being modeled by evolutionary economists.

### 2.1.2 Previous works on evolutionary consumption theory

As discussed in the previous section, it seems that some evolutionary economists – those who support the neo-Schumpeterian approach – believe that there is a need for an evolutionary consumption theory. Some researchers have tried to contribute to this field proposing appreciative, formal and simulation models of evolutionary consumption choice. Some of these models are going to be discussed in this section in a concise literature review. The focus will be on more micro discussions (i.e. models discussing the behavior of individual consumers) than on aggregated analysis of consumption (i.e. studies evaluating the effects of total demand in the market dynamics).

The papers reviewed on this section were chosen searching papers on the last 25 years with keywords like “consumption”, “consumer” and “evolutionary economics” in main journals related to the subject, such as the Journal of Evolutionary Economics, Journal of Institutional Economics, Evolutionary and Institutional Economic Review. The period analyzed broadly falls into the “new wave” of evolutionary economics identified in FIGURE 3 by Hodgson and Lamberg (2016). I am aware of the limitation of this method of reviewing compared to a systematic review of literature and other bibliometric methods, but the objective here is not to exhaustively review the works in evolutionary economics related to consumer behavior. The aim is to identify some trends and common assumptions in which the model will be grounded.

As it will become clear from this revision, the efforts to build an evolutionary consumer theory are fairly fragmented and tend to use different concepts and assumptions, which makes even harder to identify some common assumptions. It is possible to say that the efforts to theorize on the demand side of the modern evolutionary economics emulate the difficulties of the field as a whole. One possible way to organize the literature is by categorizing the works in methodological terms. Silva and Teixeira (2009) identify two types of methodologies used in evolutionary economics following the Nelson-Winter approach, “formal theorizing” and “appreciative theorizing”. Nelson (1995, p.50) defines the former as “what economists do when they are self consciously putting forth a theoretical argument” and the latter is when economists use complex causal arguments to explain a specific phenomena, normally introducing it in the form of stories.

In this dissertation I will go further and make a distinction in formal theorizing efforts, which will be divided between economists using more traditional methods – namely formal mathematical analysis and game theory – and the ones who use computational methods to formulate their theories, like agent based models. This distinction is important to frame this dissertation's model in the literature. Thus, there are three types of methods that will guide our review: appreciative theorizing, formal modeling and computational modeling. The evolutionary works on consumption will be reviewed in the next sections following these three categories.

#### 2.1.2.1 Apreciative theorizing

Some analyses do not rely on the more conventional mathematics tools generally used by economists. These studies use stories to explain the complex relationships between different elements that are the cause of a particular economic phenomenon. Within this kind of theorizing approach we have Earl and Potts (2004), who introduce a consumer theory where boundedly rational agents and learning are essential features. The authors try to theorize about the integration of knowledge and preferences based on a search mechanism and specialization of the agent's preferences. Earl and Potts divide preferences into two types: high-level preferences, which refer to innate wants; and low-level preferences, which include particular preferences acquired through learning and specialization. Agents would obtain knowledge and develop low-level preferences to meet high-level ends. This process of knowledge acquiring could be coordinate by a market-like system, which the authors call market for preferences.

Witt (2001) takes the same methodological approach to explain the sustained growth of per capita consumption. Witt first revives the notion of wants and needs and links them with psychological process and biological needs. Then he considers the possibility of learning and specialization in consumption to discuss acquired wants and the knowledge of consumption technology. Witt divides learning in two categories: cognitive, which is based in the need to satisfying innate wants with new combinations of consumption; and non-cognitive, which is based on associative learning caused by conditioning and creates new wants. Based on the hypotheses made using this wants notion, Witt develop an analysis of the long term evolution of consumption and the growth of demand.

In a following work, Witt (2016) investigates the relationship between consumption and satisfaction of preferences and proposes a theory based on motivational issues drawn from biology, behavioral science and psychology to explain the evolution of consumption growth patterns. The author keeps the idea of innate wants and acquired wants discussed in Witt (2001) to establish his concept of motivation and develop a theory of consumption based on satiation of wants derived from innate needs or learned through conditioning. Using his analytical model, Witt concludes that the need of increased arousal and the continuous learning of new wants may drive the consumption expansion without bringing enduring satisfaction.

Alternatively, Nelson and Consoli (2010) propose to sketch an alternative consumer theory, based on behavioral assumptions already used by other evolutionary economists. They try to build a broader choice model, but not formally, which could be then further developed in subsequent works. The starting point of Nelson and Consoli model are heterogeneous households that do not have a common and general utility function. Instead, they have some instinctive and acquired desires which change dynamically with age and composition of the members of the household. These households respond dynamically to changes in income and new products and services available, changes which are possibly affected by social influences and uncertainty.

With a slightly different subject but in a similar manner, Almeida and Pessali (2011) seek to explain consumer behavior linking the Neo-schumpeterian concept of competition with insights from institutional economics. The authors also use Herbert Simon’s bounded rationality concept, arguing that consumers with bounded cognitive capacities rely on habits of thoughts and institutions to make their decisions. Institutions would influence the preferences formation and decision-making through a reconstitutive downward causation process, in which consumers use their personal history and learning experience to choose between consumption alternatives. The same kind of process can be ascribed to the entrepreneur, who can innovate and exploit consumers learning process to form a new social image for their product and thus change habits.

What these analyses have in common is the concern with the precise definition of concepts and the detailed description of the causal mechanisms involved in the phenomena studied. Furthermore, they are quite interdisciplinary, often recurring to notions in psychology theory to support their definitions and the characterization of consumer behavior. They cite various psychology papers.

#### 2.1.2.2 Formal modeling

There are also consumer models that are advanced using a more conventional approach which rely on formal mathematical methods, including the use of utility functions and optimization analysis. For example, Metcalfe (2001) develops the analysis of some issues on the evolution of consumption. He discusses the formation of preferences and the intrinsic association of individual and social factor influencing it and highlights some aspects related to consumption and demand. The author stresses the importance of constraints of rationality and time to model consumption behavior and uses the concept of reinforcements from behavioral psychology to propose a formal model including routine-based behavioral rules capable of generating conventional response to changes in economic data.

In a different context, Reinstaller and Sanditov (2005) draw inspiration from Veblen's analysis of conspicuous consumption to propose a model of consumption and study diffusion patterns of product innovations. The authors regard consumption as a social activity and try to model social group influences in consumption behavior. They present a formal evolutionary game model where boundedly rational heterogeneous agents use simple consumption routines to acquire positional goods. There are two kinds of agents, a population of high income and social status whose members innovate in consumption and a group with low income and social status whose members imitate the consumption of a higher class. Two kinds of goods are available: positional or status good which signalize high class status and basic goods that do not produce social signals. This analysis is focused on the changes in norms of consumption caused by the introduction of new products and the change of social parameters. The authors find that the diffusion of novelty is more rapid when there is more equality and higher variety in behavioral strategies.

Kapeller et al. (2013) call attention to the problems related to the assumption of a rational consumer and then propose a solution for the paradoxes that emerge when multidimensional goods are considered on a rational choice theory framework. After formally demonstrating the impossibility of rational consumer choice with multidimensional goods due to lack of the transitive property, the authors suggest a solution based on Simon's bounded rationality sketching a formal satisficing model of consumption. They use some of the assumptions of Witt (2001) about basic needs and acquired wants and assume a sequential elimination heuristic to construct a model that do not incur in the paradox of intransitivity.

These works have some similarities from the other presented in the previous sections but they are more heterogeneous in relationship to each other. They still have "story telling" sections that justify the causal relationships they will be modeling and the assumptions made. However, the consumer behavior is less complex and nuanced than in the appreciative models – frequently using some kind of bounded optimization rule. Psychology links are still used, but in a less extensive and detailed manner. Curiously, with the exception of Reinstaller and Sanditov (2005), they are not closed models but unfinished attempts to model an evolutionary consumer. This may indicate a difficulty to create models using these tools.

#### 2.1.2.3 Computational modeling

Computational models are quite common in evolutionary analysis – a famous example is in the seminal work of Nelson and Winter (1982). One of the earliest simulation models on modern evolutionary economics specifically designed to analyze consumption behavior was proposed by Aversi et al. (1999). The authors stress the importance of cognitive psychology, social psychology and sociology as a source for consumer behavior theorizing and establishing a few stylized facts about consumption. Aversi et al. build a model in which agents with lexicographic preference structure are represented by genetic algorithms. Other assumptions of income dynamics and old and new products are made, together with social adaptation algorithms that affect preferences. Some statistical properties of the models are drawn and compared with empirical data, which has a surprising fit with the models previsions.

Other efforts followed this initial work. Babutsidze (2001) presents a computational model of consumption in which heterogeneous agents have learning and socialization capacities. The author includes in his model the need of skills to consume the products and those skills can be acquired along the consumption process and by spillovers from social networks. Thus, in this model agents can learn by consuming and diffuse the knowledge by local social interactions outside the market and use a maximization process to choose between products with different quality and user-friendliness. On the supply side, firms can advertise and change the valuation of the product and diminish the skill necessary to purchase it. Babutsidze analyzes the returns on advertising for the firms in a duopoly, finding that it is not monotonic and have an inverted U shape given the quality of competing product.

Another work using learning and advertising is the one of Valente (2012), which answers to the call of Nelson and Consoli (2010) for a generalized evolutionary model of demand and proposes an agent based model as an alternative. Valente departs from boundedly rational agents that use the Take-the-Best[3] heuristic to build their preferences and choose between products. Hypotheses about the influence of different types of information on the consumer and the agent's product value perception are made. Marketing and social induced preferences are included in this model. Using all these assumptions, Valente derives a micro-founded multidimensional demand function from his agent-based model. This is a work that has a similar goal to this dissertation and will be discussed with more details in the section 2.3.

Bernardino and Araújo (2013) propose another agent-based model, but modeling positional consumption behavior and its interaction with technological innovation. The positional consumption is a kind of consumption choice behavior that depends on other consumer choices, like the consumption of status goods. On their model, there is only one type of good with a technological attribute that can be changed by the firms by introducing new products with more technology. Consumer choice depends on expected utilities provided by the goods, prices and income. In addition, some parameters of the model are changed exogenously: income inequality, proportion of income allocated to positional goods, and size and type of consumer network. A dynamic of cyclical creation of new goods was observed as result of this model, the effects of inequality were negatively correlated with innovations and the influence of social groups on consumers' preferences and creation of goods was complex and highly dependent on initial conditions.

The most prominent feature of computational consumer models is diversity. These models use a variety of assumption, parameters and market dynamics. They often use the bounded rationality argument, but model consumers' decision-process in decidedly different manner. Mentions to psychology are common, but not lengthy discussed. The models are also presented in a more straightforward manner, with less of that storytelling rhetoric presented in the other works.

Still, in the midst of so many approaches, a common ground may be proposed. There is an expressive number of works resorting to boundedly rational agents. Social context and learning is also a recurrent feature on these consumer models. Most of the models also assume heterogeneous agents and endogenous preferences. The theorizing efforts are often trans-disciplinary and appeal to various disciplines, especially psychology. In an effort to avoid reinforce fragmentation in the field, the model framework proposed in this dissertation will be based in encompassing assumptions of evolutionary economics, which embraces the work

[3] The definition of this heuristic is going to be made latter on this work.

that has already been done and proposes an integrated path for the development of this consumer theory. These assumptions are going to be discussed in the next section.

### 2.1.3 Evolutionary consumption theory assumptions

One of the main concerns of the works on consumer theory is to build a theory that is compatible with the current framework of evolutionary economics. The main challenge is to define the basic assumptions that guide the work, given the diversity of evolutionary economic approaches. Recently, some evolutionary economists have raised concerns about the lack of common core in the field, arguing that it this a weakness that hinders the cumulative theoretical advances experimented by other successful research fields (HODGSON; LAMBERG, 2016; STOELHORST, 2014; WITT, 2014; SILVA; TEIXEIRA 2009; WITT, 2008). As stated by Hodgson and Lamberg (2016, p.14): “A core theoretical framework is necessary to show that the approach has improved answers to pressing research questions, to claim its superiority over rival approaches”.[4]

Based on this consideration, the hypotheses made in this work are chosen taking into consideration the less controversial and most used assumptions in the field, which were identified as such by bibliometric evidence (HODGSON; LAMBERG, 2016; SILVA; TEIXEIRA, 2009), surveys and reviews (SAFARZYNSKA; VAN DER BERGH, 2009; WITT, 2008; ANDERSEN, 1994) as well as the works in evolutionary consumption theory reviewed above.

A general aspect of the evolutionary approach is the rejection of pure methodological individualism: “Evolutionary economics is oriented to the system level (or the ‘population’ level) from the start, and is not encumbered by commitments to fiction at lower levels of analysis (organism, individual, organization)” (WINTER, 2014, p.629). This does not necessarily mean that modeling individual choices is not evolutionary, but that an evolutionary account of choice needs to incorporate context and system level thinking, which is different from the atomistic individual of mainstream theory that only interact through the market institution (DAVIS, 2010).

There are some studies that attempt to delineate evolutionary economics based on its assumptions. One of them is Andersen (1994) who lists a series of assumptions and

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[4] Not all evolutionary economists agree with the need of a common core of assumptions. Some believe that the vagueness of definitions is one of the strengths of evolutionary theory and this diversity should be preserved. For more on the subject, see Klaes (2004).

characterizations of evolutionary economics that are typical in the field. Although Andersen admits this endeavor has its difficulties and limitations, he believes that enumerating certain common assumptions can be useful to outline an evolutionary approach. The list goes as following:

> “1.The agents (individuals and organizations) can never be ‘perfectly informed’ and they have (at best) to optimize locally rather than globally.
> 2.The decision-making of the agent is normally bound to rules, norms and institutions.
> 3.Agents are to some extent able to imitate the rules of other agents, to learn for themselves and to create novelty.
> 4.The processes of imitation and innovation are characterized by significant degrees of cumulativeness and path dependency but they may be interrupted by occasional discontinuities.
> 5.The interactions between the agents are typically made in disequilibrium situations and the result is successes and failures of commodity variants and method variants as well as of agents.
> 6.The processes of change occurring in a context described by the above assumptions and characteristics are non-deterministic, open-ended and irreversible” (ANDERSEN, 1994, p.15)

Witt (2008) attempts to go beyond Andersen (1994) and present empirical evidence supporting the claims that some concepts are typically evolutionary. Thus, Witt does a survey with specialists on the field of research to identify some keywords deemed being part of the most significant insights from evolutionary economics literature. The keywords identified were: innovation and technological change, evolution of institutions and norms, learning behavior, knowledge creation and use, variation and selection mechanisms, diversity and population thinking, industry evolution and life cycles, path dependence, non-equilibrium market dynamics, novelty and invention, bounded rationality, co-evolution institutions/technology, general features of evolution, routines, spontaneous order, evolutionary game theory (WITT, 2008, p.566).

With a similar motivation, Silva and Teixeira (2009) identify some evolutionary economics jargons to obtain their database of articles for bibliometric analysis. They used a combination of keywords to use in its search method to define the papers that would be analyzed. The keywords were the following: evolutionary, routines, path dependency, learning, out of equilibrium, heterogeneity, uncertainty, satisficing, selection, cumulative, Shumpeterian, systems of innovation, Darwin, non-optimal, irreversible, diversity, complexity, bounded rationality (SILVA; TEIXEIRA, 2009, p. 636). Moreover, Safarzynska and van der Bergh (2009) follow a similar path but without using the bibliometric analysis to present the literature review. They identify the following building blocks of evolutionary economics: diversity, innovation, selection, bounded rationality, diffusion, path dependence and lock-in, coevolution, multi-level and group selection and mechanisms of evolutionary growth (SAFARZYNSKA; VAN DER BERGH, 2009, p.344).

These works can be use as guides to pinpoint some of the important evolutionary concepts that could be used in a model framework to analyze consumer choices. The keywords and concepts which are present on these works and the ones in the literature review of the section 2.1.2 might give a clue about the shared concepts of evolutionary economics. If we take out of the analysis concepts and keywords related to specific methods and areas of study (e.g. evolutionary game theory, mechanisms of evolutionary growth and Schumpeterian), it is possible to see that some ideas are regularly linked to evolutionary economics: bounded rationality, learning, general features of evolution (selection, variation and diversity), routines, path dependence, innovation and non-equilibrium.

Within this list, some concepts and assumptions are not going to be included in the model framework. First, the model in this dissertation will not be concerned with the generalized Darwinian concepts of selection and variation. As stated on the section 2.1.1, this dissertation will assume a generic concept of evolution, which focuses not on selection mechanisms but on novelty, emergence and dissemination. Moreover, innovation and non-equilibrium are concepts more related to the supply side of the economy and the interaction between supply and demand. Our work is focused in the consumer behavior of the demand side, hence it will hardly benefit from such concepts.

Along this line, the sections 2.1.3.1 to 2.1.3.5 are dedicated to concisely describe the assumptions used in this analysis of consumer choice which I believe to be compatible with an over-arching evolutionary economic theory. The objective here is not to extensively survey all the possible meanings and formulations of each assumption, but to broadly define and justify their use in evolutionary economics. The several hypotheses identified are separated in different categories for a brief discussion: bounded rationality and agent heterogeneity; endogenous and path dependent preferences; fundamental uncertainty, learning, and routines and habits.

#### 2.1.3.1 Bounded rationality and agent heterogeneity

Evolutionary economists regularly resort to Herbert Simon’s concept of bounded rationality to justify departing from assumptions of perfect rationality assumption common to standard economics (NELSON, 2011 p.295; AVERSI et al., 1999). An array of evolutionary economists emphasizes the need to incorporate limits on human cognition on evolutionary models and this hypothesis is frequently used on the works on evolutionary consumption theory (AVERSI et al. 1999, METCALFE, 2001; EARLS; POTTS, 2004; REINSTALLER; SANDITOV, 2005; NELSON; CONSOLI, 2010; VALENTE 2012; KAPELLER et al., 2013). Simon (2008) defined bounded rationality as the “rational choice that takes into account the cognitive limitations of the decision-maker – limitations of both knowledge and computational capacity”. The use of the term “rational choice” in this definition can be misleading. It should be understood as rationality in a procedural way, as a process or mechanism of the human mind, not the substantive rationality of conventional economics (SIMON, 1997).

Although bounded rationality is a general feature of the human species, this does not imply all human individuals and groups behave in an equal manner. Agent heterogeneity is not only desirable but necessary for an evolutionary explanation of consumption. As suggested by Nelson and Consoli:

> [...] the propositions that households at any time possess certain competences and not others, and that their actions are guided by broad strategies that may or may not be appropriate to the situation they are in, in our view are as appropriate for a theory of household behavior, as their analogues are for a theory of the firm (NELSON; CONSOLI 2010, p. 671).

Capabilities on dealing with time and information are limited and differ among individuals, what can have an important impact on consumption behavior. Diversity in strategies, goals and knowledge of the agents is deemed central for an evolutionary thought (SAFARZYNSKA; VAN DER BERGH, 2009). Therefore, bounded rationality and agent heterogeneity are not only desirable but necessary for an evolutionary explanation of consumption.

#### 2.1.3.2 Endogenous and path dependent preferences

Economists are used to making the assumption of stable preferences ordering to study consumption behavior as a simplification of the problem of choice. However, an evolutionary consumer theory cannot be based on such assumption, as the conventional rationality process is not accepted by evolutionary economists and social context and learning matter. As Hodgson (2007, p.14) puts it: “The idea of endogenous and context-dependent preferences ties in with a more open ended and evolutionary approach. If in principle every component in the system can evolve, then so too can individual preferences”. The idea is that preferences are influenced by the economic phenomena at with they refer to, being endogenous to the models and not given and static. For example, consumers’ preference may change as a result of the continuous use of a product that was chosen based on these same preferences, which demonstrates one possible endogenous mechanism.

Chai (2016) points out that the works following Witt (2001) stress the endogenous aspects of the demand, but Safarzynska and van der Bergh (2009, p. 348) claim that there is no consensus on the correct way of modeling formally endogenous preferences on the field. Aside being endogenous, preferences in an evolutionary framework may be correlated with past predilections or even past behavior, thus following path dependent pattern. Witt (2016) highlights the influence of learning process in acquiring and reinforcing a consumption preference pattern: “Yet, the fact that new wants and goals are learned over and again prevents this form of consumption motivation from ever vanishing.” This premise emphasizes the role path dependency in consumption – consumer behaviors that persist even when the circumstance of the initial decision is no longer relevant, which are important behavioral patterns of firms and individuals in evolutionary economics.

Aversi et al. (1999) argue that imperfect social adaptation, learning and search entail path dependency at the individual and even at the collective level of the demand analysis, reinforcing the claim that endogenous and path dependent preferences are an important feature of an evolutionary approach. Other important issue regarding endogenous preferences is the understanding of the way social and cultural context might influence consumers. Aversi et al. (1999) remind us that individuals in evolutionary theories are social embedded and stress the importance of the process of socialization and identity building to the emergence of consumption patterns.

#### 2.1.3.3 Fundamental uncertainty

Uncertainty has been a long discussed topic in evolutionary economics, arguably because of the huge impact it plays in the innovative process. This discussion draws heavily from considerations about uncertainty given by economists such Knight, Schakle, Schumpeter and Keynes. More recently, analogies with complexity science reinforce the relationship between evolutionary economics and uncertainty and uncertainty is one of the jargons of the evolutionary approach identified by Silva and Teixeira (2009). One of the main questions is the type of uncertainty in which economic phenomena is embedded. Dosi and Egidi (1991) classify uncertainty as "procedural" and "substantive", while Lane and Maxfield (2005) differentiate "truth uncertainty", "semantic uncertainty" and "ontological uncertainty".

Dequech (2001) says that these different uncertainty typologies are based on distinct approaches to probability. He separates the different theories of probabilities in epistemic theories and ontological theories. Epistemic theories are the ones in which probabilities are" a property of the way one thinks about the world, a degree of belief" and are related with the lack of knowledge; and ontological theories are the ones "where probability is a property of the real world" and are related to the nature of reality (DEQUECH, 2001, p.914). Dequech argues these approaches do not exclude each other and that uncertainty has both epistemic and ontological aspects.

Along these lines, Dequech presents his own typology in which "strong uncertainty" is a situation where a distribution of probability of the events is absent. A subtype of strong uncertainty is "ambiguity", where the lack of a probability distribution is due to lack of knowledge and all the possible events are already determinate. The other subtype is "fundamental uncertainty", where there is a significant indeterminacy of the future and a list of possible event is not know in advance. In fundamental uncertainty "[…] some relevant information cannot be known, not even in principle, at the time of making many important decisions" (DEQUECH, 2001, p. 915).

The definition of fundamental uncertainty proposed in Dequech (2001) encompasses both procedural and ontological uncertainty and is also related to bounded rationality (HODGSON, 1997) and habits and rule-driven behavior (SAFARZYNSKA; VAN DER BERGH, 2009), thus being suitable for being part of the basis for an evolutionary consumption theory.

#### 2.1.3.4 Learning

If we are to assume endogenous and path dependent preferences, a theoretical treatment of learning is required considering that preference formation is intertwined with learning behavior (WITT 2016, 2001). Evolutionary economists have acknowledged that and have considered biological and psychological theories which are related to the learning process and preference formation. Nelson and Nelson (2002) discuss the learning process and evolution of human know-how based on the debate between classical AI theorists and late cognitive psychologists. Witt (2001, 2016) addresses the relationship between consumption and learning to study the long run growth of consumption, specifying the innate and acquired motivations of consumer behavior[5]. Chai (2016, p. 12) goes as far as stating that "understanding precisely what determines the degree to which consumers learn and accumulate knowledge is a topical issue in Evolutionary Economics".

According to Dosi et al. (2005), there are three possible circumstances in which learning may occur: when information about the subject or the structure of the knowledge is not completely available for the agents; when the agents do not know all the possible set of actions that could be used in a problem situation; and when their wants and goals are not well defined or not fixed. It is safe to say that most evolutionary economists would characterize these contexts as typical in an evolutionary consumption analysis.

Although there is a consensus on the important role learning have in evolutionary economics, there is still the unanswered question of how the learning processes takes place. There is a wide array of learning models, developed mainly in the fields of psychology and artificial intelligence, which have been used in evolutionary economics. Dosi et al. (2005) develop a basic model that express an evolutionary learning mechanism and review a series of learning models. Brenner (2006) reviews learning models that could be used in computational models and present a list as diverse as Dosi et al. (2005). It is possible to say that there is no consensus on the matter and no preferred model of learning in evolutionary economics.

#### 2.1.3.5 Routines and habits

Routines and habits are widely regarded as fundamental to evolutionary economics (AVERSI et al 1999; METCALFE 2001; NELSON; CONSOLI, 2010; WINTER 2014).

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[5] Chai (2016) calls Witt's approach Learning to Consume (LTC) – after Witt's (2001) paper title – and reviews the recent literature that follows Witt's perspective on preference formation.

Hodgson (2010, p. 4) defines habits as “submerged repertoires of potential behaviour; they can be triggered or reinforced by an appropriate stimulus or context”. As an acquired propensity, habits can also be an adaptive mechanism in which past experience is stored in our limited brain storage capacity – thus being compatible with boundedly rational agents. This notion of habit can be complemented with the concept of routines, defined by Felin et al. (2012, p.5) in the organizational context as “repetitive, recognizable patterns of interdependent actions, carried out by multiple actors”. The advantage of this definition of routine is that it focuses on the interactive and collective aspects of behavior and not only on individual characteristics. Thus, routines would be the behavioral manifestation of habits.

Automated and routinized behaviors are also an integrative part of bounded rationality and satisficing behavior. Although being a source of repetitive and automatic behavior, Aversi et al. (1999) suggest that habit and routines coexist with search and innovative behavior. Along these lines, Winter (2014) remembers that routines and habitual behavior are not restricted to simple and rigid repetitive action. Winter argues that routines are broad in scope, flexibility and intentional design – which mean they “enable complex, coordinated responses to information arising from a rapidly changing environment” (WINTER, 2014, p.630). They may be highly adaptive, can be socially learned and accommodate deliberative processes.

## 2.2 BOUNDED RATIONALITY AND FAST-AND-FRUGAL HEURISTICS

I have argued that evolutionary economists have identified the lack of a fully developed consumer theory in their approach. However, there is a question still to be made: has evolutionary economics already developed the necessary concepts to build its consumer theory? The discussion presented so far suggests that the answer is no. According to Felin et al. (2012), even the supply side of evolutionary theory does not provide the microfoundations to explain heterogeneous firms’ behavior and performance. They specifically point out the lack of an individual level explanation of creation, development and reproduction of routines and capabilities, which could lead to improved comprehension of collective phenomena, such as firm performance. Still on the microfoundations front, Dopfer (2004) argues that an evolutionary economic theory needs to have an adequate understanding of human cognition and behavior, for which empirical evidence could come from evolutionary biology, anthropology and related sciences.

On both works, Felin et al. (2012) and Dopfer (2004) acknowledge that there is no intrinsic need for a micro analysis from an evolutionary perspective, though it may enhance the explanation of some specific phenomena – especially when the object of analysis involves human cognitive capacity. As Rizzello (2004, p.5) suggests: “microfoundations of economic behaviour are directly linked to the nature and role of the human mental mechanisms in charge of the production of knowledge and the emergence and use of rules, routines and their evolution”.

The use of psychology assumptions in evolutionary thought is not new. As stated before on this dissertation, evolutionary economics is an interdisciplinary approach since its beginning with the American Institutionalist. Hodgson and Stoelhorst (2014) remember the importance of Thorstein Veblen as the pioneer for both evolutionary and institutional economics and highlight the connection between these economic approaches and psychology in the beginning of the twentieth century. Considering the modern evolutionary economics perspective in which this dissertation subscribes and the literature review presented, interdisciplinary efforts are quite common. Winter (2014, p.638) emphasizes the interdisciplinary aspect of evolutionary economics, stating its “commitment to open borders” with the other domains in social science, especially psychology.

The neo-Schumpeterian approach’s extensive use of the bounded rationality concept as a basic assumption only reinforces the connection between psychology and modern evolutionary economics. Furthermore, various works draw insights from psychological theory. Nelson and Nelson (2002) explain the possible contributions of psychology to the understanding of the learning mechanism in evolutionary economics. Rizzello (2003) compiles a series of works linking cognitive psychology with evolutionary economics. Witt (2016, 2001) analysis that resorts on the psychology literature to explain mechanisms of learning, motivation and endogenous preferences was already mentioned in this dissertation. On the specific consumption models reviewed on chapter 2.1, there are numerous and direct reference to works in psychology (e.g. AVERSI et al. 1999; WITT, 2001; VALENTE, 2012; KAPPELLER et al. 2013). Hence, searching for solutions and inspiration in psychology theory to build evolutionary economics models is not unfamiliar in the literature and it is a path that will be taken in this work.

Following the request for microfoundations in evolutionary theory and the possible interaction of the field with psychology, I present an approach which provides concepts that could help to explain consumption behavior in evolutionary terms. The first one is the fast-and-frugal heuristics program of Gigerenzer and the ABC Research Group, which advance a theory of choice based on bounded rationality and simple step-by-step rules. It will be discussed with more detail in the following subsections.

### 2.2.1 Fast-and-frugal heuristics research program

The fast-and-frugal heuristics research program (F&F) is a new approach in decision-making process investigations put forward by cognitive psychologists to explain how individuals make choices in real world context, identifying various anomalies on conventional decision theories paradigms. Gigerenzer and Selten (2002) propose to build upon the bounded rationality concept of Herbert Simon, providing new psychological basis and empirical evidence to a theory of human behavior.

Gigerenzer and Gaissmaier (2011) claim that their research is motivated by Simon's question: "how do human beings reason when the conditions for rationality postulated by the model of neoclassical economics are not met?". For them, the traditional rationality conditions hold in the context described by Savage's as "small worlds": a situation where there is knowledge of all relevant choice alternatives with their consequences and probabilities, a predictable environment without surprises – in such a manner that an optimal solution can be established. Conversely, when relevant information is not known or has to be estimated from small samples, the rationality assumption cannot be made, there is not a way of determining an optimal solution and we are on a case of "large worlds". In this context, bounded rationality is a necessary hypothesis for properly investigate human choice.

Todd and Gigerenzer (2003, p.147) describe bounds to rationality as "emerging from the joint effect of two interlocking components: the internal limitations of the (human) mind, and the structure of the external environments in which the mind operates". For Gigerenzer and Selten (2002, p.8) bounded rationality "consist of simple step-by-step rules that function well under the constraints of limited search, knowledge, and time — whether or not an optimal procedure is available". The basis of their bounded rationality models are the fast-and-frugal heuristics.

Gigerenzer and Gaissmaier (2011) define heuristics as "strategies that ignore information to make decisions faster, more frugally, and/or more accurately than more complex methods". These fast-and-frugal heuristics process patterns of information available on the environment to produce goal directed behavior (TODD ET AL., 2013). Heuristics are made of search rules, stopping rules and decision rules which are based on evolved capacities. According to Todd et al. (2013, p. 11), evolved capacities are potential abilities coded in the genes of a species that generally needs experience to be fully expressed (e.g. recognition memory, frequency monitoring, object tracking and the ability to imitate).

Heuristics in this approach have three important characteristics (GIGERENZER; SELTEN 2002, p.7): simplicity, efficacy and domain-specificity. Heuristics are simple because they need to be compatible to limited knowledge and human computational capability; they can be effective because their simplicity enables fast, frugal and accurate decisions[6] that exploit the structure of the environment of choice; and they are domain-specific because they work in a class of situations, they are adaptations to certain environmental problems that were evolutionary selected from specific species, differently from the "all-purpose" optimization of man-made calculus. Additionally, following Simon's insights, Gigerenzer and Selten characterize three building blocks of the heuristics on their bounded rationality model: simple search rule, simple stopping rule and simple decision rules. These are algorithms that describe precisely the heuristics' mechanisms. They are all "simple" in the sense that they do not rely on computation of probabilities, optimal weights or Bayesian solutions (GIGERENZER; SELTEN 2002, p.8).

Furthermore, Gigerenzer and Selten (2002, p.9) propose a research program that is guided on four main lines: the search for evidences of the existence of a bundle of heuristics available to humans; the analysis of why and when heuristics work; consider the role of emotions and non-cognitive factors of bounded rationality; and the role of institutions and social norms on bounded rationality. The authors stress the interdisciplinary aspect of the research on bounded rationality and the potential of the concept to disciplines like economics, psychology and animal biology (GIGERENZER; SELTEN 2002, p.11).

#### 2.2.1.1 The adaptive toolbox and ecological rationality

It is already possible to see some compatibility between evolutionary economics and the fast-and-frugal heuristics program. First, both don't agree that optimization is a good description of human behavior. Second, they emphasize the evolutionary aspect of humans – their innate endowments and mental processes – which is very similar to the naturalistic approach described by Witt (2008). Third, they stress the importance of norms and institutions to human conduct. These similarities can be synthesized on Gigerenzer's concepts of "adaptive toolbox", "ecological rationality" and "social rationality".

[6] As examples of the accuracy of the fast-and-frugal heuristics, Gigerenzer and Gaissmaier (2011) cite empirical evidence showing that when the heuristics are ecologically rational, they can have an accuracy in predicting outcomes that goes from 72% of the results of the matches in the Wimbledon tennis tournament to 92% of court decisions in London.

Selten (2002, p.25) uses the metaphor "adaptive toolbox" to describe the various basic modes of choice behavior involved in human decision making. These modes are thought to be like special instruments used alone or in combination with other to achieve distinct ends. According to Gigerenzer and Gaissmaier (2011, p.456), the adaptive toolbox consists in "the cognitive heuristics, their building blocks (e.g., rules for search, stopping, decision) and the core capacities (e.g., recognition memory)". In other words, the adaptive toolbox encompasses all the strategies we use to decide and the cognitive processes that underlie them.

Gigerenzer (2002, p.38) argue that the adaptive toolbox is based on three premises: psychological plausibility, the necessity to build models of bounded rationality that uses the range of cognitive, emotional, social and behavioral aspects that are actually available for each species; domain specificity, already discussed above; and ecological rationality, which is going to be discussed below. The aim with the concept of adaptive toolbox is to go beyond a list of heuristics and present a theoretical framework that explains how the heuristics' building blocks are arranged to form cognitive strategies that can be frugal and accurate. The toolbox framework is a difficult hypothesis to be empirically tested, yet there are recent advances in empirically test this hypothesis (SCHEIBEHENNE et al., 2013)

Although the bounds of cognition are part of the original bounded rationality, the structure of the environment is as essential for Simon as the human cognitive limitations. The "ecological rationality" is the degree of adaptation of certain heuristics to the physical and social environment involved. Thus, the study of ecological rationality investigates in which environments a given strategy is better than other strategies – that is to say that ecological rationality studies the context in which a heuristic is more precise and accurate than other decision-making processes (GIGERENZER; GAISSMAIER, 2011). Ecological rationality diverges from the idea of rationality as coherence with rule of logic or consistency in a set of preferences– "it is not defined by internal criteria but by the match between strategy and environment" (GIGERENZER 2002, p.46). It is important to remember that Gigerenzer and Gaissmaier (2011) suggest that the adaptation of the heuristics to an environment is not necessarily the result of biological evolutionary process. According to the authors, there is a relationship between the study of ecological rationality and the notion from evolutionary psychology that the human cognition is adapted to its past environment (COSMIDES; TOOBY, 2006). However, Gigerenzer and Gaissmaier argue that the match between heuristic and environment does not imply that heuristic evolved because of that environment. Ecological rationality is a kind of correspondence between an environment and a heuristics that enables a goal in the world to be achieved (GIGERENZER; GAISSMAIER, 2011, p. 458).

To understand how ecological rationality emerges, one must study how heuristics are selected. Gigerenzer and Gaissmaier (2011) point out four principles that guide the selection of fast-and-frugal heuristics for a given problem (e.g., consumer behavior). First, some heuristics are partially wired by evolution and are used instinctively; second, individual learning might be the principle by which a strategy is chosen; third, social process like imitation and explicit teaching may guide the selection of heuristics; and finally, individual memory may determine the strategy chosen, then the ecological rationality of the heuristic may be correlated with its applicability.

Knowing how heuristics are selected, an explanation of why heuristics works is still needed. The conventional reason for the use of heuristics is that information search and computation cost time and effort and heuristics would be strategies to trade-off accuracy for faster cognition (SHAH; OPPEHEIMER, 2008). However, the findings of the fast-and-frugal research program show that this accuracy-effort trade-off is not as common as it is promoted – simple heuristics are often as accurate or more than sophisticated prevision tools.[7] Simple heuristics empirically demonstrate the idea that less can be more.

The reason for this less-is-more effect is the fact that simple heuristics exploit the environmental structure of information– they ignore noisy information environments and works with scarcity of information. Likewise, heuristics can exploit humans' evolved mental abilities as our ability to discriminate quantities and for recognition memory. They are also frugal enough to be robust in the sense that they can generalize well to new problems and different structures of environment – there are fewer free parameters like the weights in a regression model and thus there is a smaller chance the heuristic was only accurate with that specific sample (Gigerenzer, 2002, p.47).

With all these concepts explained, it is possible to categorize simple heuristics in groups based on the core capacities they rely on and the structure of environment in which they are ecologically rational. Gigerenzer and Gaissmaier (2011) establish four categories of heuristics using this strategy: recognition-based decision making; one-reason decision making; trade-off heuristics; social intelligence. The TABLE 1 shows these categories and some examples of the heuristics already identified by psychologists of this area of study. I will not describe all heuristics, only those that will be used latter on the work. For a detailed

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[7] See Goldstein and Gigerenzer (2009) for a review of the evidences supporting this claim.

review of all the heuristics mentioned in TABLE 1, see Gigerenzer and Gaissmaier (2011) and Goldstein and Gigerenzer (2009).

TABLE 1 – SIMPLE HEURISTICS CATEGORIES

| **HEURITICS CATEGORIES** |
|---|
| **Recognition-based decision making** |
| Recognition Heuristics |
| Fluency Heuristic |
| Neural Basis of Recognition and Evaluation |
| **One-reason Decision Making** |
| One-Clever-Cue Heuristics |
| Take-the-Best |
| Fast-and-Frugal Trees |
| **Trade-off Heuristics** |
| Tallying |
| Mapping Model |
| 1/N Rule |
| **Social Intelligence** |
| Recognition-Based Decisions |
| One-Reason Decision Making |
| Trade-Off Heuristics |
| Social Heuristics |
| Moral Behavior |

SOURCE: Gigerenzer and Gaissmaisser (2011)

Recognition-based decision making category includes heuristics that exploit the core capacity of memory, sense of recognition and familiarity. These heuristics explore the environment identifying alternatives that are positively correlated with their criterion values (more recognition, more certainty). For example, the recognition heuristics works as follows: *If one of two alternatives is recognized and the other is not, then infer that the recognized alternative has the higher value with respect to the criterion*. The higher the recognition validity $\alpha$ for a given criterion, the more ecologically rational it is to rely on this heuristic and the more likely people will rely on it. For each individual, $\alpha$ can be computed by $\alpha = C/(C + W)$, where C is the number of correct inferences that the recognition heuristic would make, computed across all pairs in which one alternative is recognized and the other is not, and W is the number of wrong inferences (GIGERENZER; GAISSMAIER, 2011, p.460). The higher the recognition validity α for a given criterion, the more ecologically rational it is to rely on this heuristic and the more likely people will rely on it.

One-reason decision making category heuristics use the core capacity of recall the heuristics base judgment on one reason only, ignoring other cues. This kind of heuristics work well on environments with high variability of cues validity (the correlation between the cue and a property in the world, like when the color of a banana predicts if its ripe), moderate to high and redundancy (correlation between cues) and small sample size. As an example, there is the Take the Best heuristic, which is consisted of the following building blocks:

> *Take the best heuristic:*
> *1. Search rule: Search through cues in order of their validity.*
> *2. Stopping rule: Stop on finding the first cue that discriminates between the alternatives (i.e., cue values are 1 and 0).*
> *3. Decision rule: Infer that the alternative with the positive cue value (1) has the higher criterion value* (Gigerenzer and Gaissmaier, 2011, p.464).

In other words, the Take-the-best heuristic "[…] infers which of the two alternatives has a higher value on a criterion on the basis of binary cue values retrieved from memory" (Hertwig et al., 2012, p. 31). It compares cues values of the alternatives until one signalizes that its alternative is the "most correct". One can ask if the Take-the-best heuristic is really simple or can be complex. It is true that complex computations may be required to order cues. But these steps are simpler than calculating linear regression weights and can be inferred from small samples. Also these cues ordering can also be learnt from others or through another social mechanism as we will see in the model proposed in this dissertation.

The trade-off heuristics are a class of heuristics which relies on compensatory strategies using equal cues weights. One of these strategies is tallying:

> *Tallying: it entails simply counting the number of cues favoring one alternative in comparison to others.*
> *1. Search rule: Search through cues in any order.*
> *2. Stopping rule: Stop search after m out of a total of M cues (with 1 < m ≤ M). If the number of positive cues is the same for both alternatives, search for another cue. If no more cues are found, guess.*
> *3. Decision rule: Decide for the alternative that is favored by more cues*

Goldstein and Gigerenzer (2009) and Gigerenzer and Gaissmaier (2011) suggest based on previous works that these heuristics are ecologically rational when the ratio of alternatives to cues is 10 or smaller, there is a low cues validity variation and when cues have a low redundancy. However, they stress that there are few studies investigating the use of tallying. It seems that they prefer one reason heuristics than cue order or weights.

The last category of heuristics is called by Gigerenzer and Gaissmaier (2011) social intelligence. Social intelligence is the name by which the authors designate the category of heuristics that have social components. I will further discuss these social components in the next section.

#### 2.2.1.2 Social rationality

When the environment consists of sensory cues and information coming from individuals that interact with each other, the ecological rationality that emerges in this context has a special name: social rationality. According to Gigerenzer and Gaissmaier (2011, p. 471), social interaction does not require complex mental calculation, it can also work with simple heuristics. This happens because social contexts are less predictable and thus demands that more information is ignored in order to make good predictions. Social rationality exists because there are "goals that are important for creating and maintaining social structure and cooperation", which are dealt with through strategies in the adaptive toolbox (GIGERENZER, 2002, p.48).

Two application domains of social heuristics are defined by Hoffrage and Hertwig (2011): games against nature and social games. Games against nature concern "[…] situations in which one person needs to predict, infer, or outwit nature in order to achieve his or her ends" (HOFFRAGE; HERTWIG, 2011, p.140). In other words, games against nature refer to situations where the outcomes experienced by the agents involved depend on their decision and the state of nature (e.g.. foraging for food, deal with hard to predict hazards like earthquakes and lightning, exploring difficult terrain). These situations are related to our ancestral tasks, but they have equivalents in the modern world, as our ability to forage food could be related to the strategies used nowadays to meet our necessity to feed ourselves. What all games against the nature have in common is that the payoff or efficacy of a person decision, judgment or prevision does not depend on the decisions of other individuals, but an entity with no consciousness – nature itself (HERTWIG et al., 2012).

Social games “refer to situations involving social exchanges, in which other people create the most important aspects of an agent’s “reactive” environment” (HOFFRAGE; HERTWIG, 2001, p. 140). In social games, the payoffs or efficacy of prediction depends on the strategies of other players. A strategy the adaptive strategies for one individual in a particular context (game) rest on the decisions made by another individual that have its own interests. The environment is “reactive”, that is, it consists in conscious human beings that also have predictive abilities and will respond to the player’s strategies (HERTWIG et al. 2012)

Hertwig et al. (2012) suggests each type of game use a different of heuristics of the adaptive toolbox, which also depends on the nature of the cues involved. When the cues used as inputs for the heuristics have originated from behaviors, intentions or properties of a social being or social system, this information is considered social. If the cues consist in information regarding physical entity or system, it is considered nonsocial (Hoffrage and Hertwig 2001, p.141). According to Gigerenzer and Gaissmaier (2011), some heuristics are designed to operate exclusively with social information or in social games situations. These heuristics are called social heuristics and are particularly appropriate to situations where the agents have little knowledge. An example of social heuristic is the Imitate-the-majority heuristic:

> *Imitate-the-majority heuristic: determine the behavior (e.g., action, judgment, choice, decision, preference, or opinion) followed by the majority of those in your peer group and imitate it* (HERTWIG et al., 2012, p. 7).

The same heuristics used in a game against nature can also feed on social information, but the converse is not true – social heuristics use only social information or are specific to social games. For instance, a tallying rule may be applied to group decisions. The *majority rule (choose the alternative that has more than half of the votes)* in which democratic voting systems are based is an example of the tallying heuristic being used in a social game (GIGERENZER; GAISSMAIER, 2011).

Hertwig et al. (2012) argue that the most important source of information of an individual is another person – individual learning is an exception, not the rule. There are various examples of social heuristics[8] that capture this idea and are based on the learning of social information, such as the search for advice and the interpretation of institutional

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[8] See Laland (2004) for a collection of social learning strategies.

arrangements as implicit recommendations – as the default heuristic*: "if there is a default, do nothing about it"* (GIGERENZER; GAISSMAIER, 2011) – or the imitate-the-successful heuristic: "*determine the most successful agent and imitate his or her behavior*" (HERTWIG et al., 2012, p.7). McElrath et al. (2010) reinforce the adaptive value of social learning heuristics and describes the distinctiveness of human psychology in regard to social influence.

### 2.2.2 Not so fast and frugal – heuristics-and-biases and optimization

It is important to notice the effort of the proponents of the F&F heuristics research program to distance their theory from bounded rationality models based on "optimization under constraints" – often used Williamson's New Institutional Economics (NEI) – and the "irrationality" interpretation of bounded rationality – championed by economists and psychologists from Behavioral Economics (BE), like Kahneman, Thaler and Sunstein.

Gigerenzer (2002) believes that economists like Oliver Williamson, Thomas Sargent and Stigler misuse the concept of bounded rationality. For instance, Gigerenzer analyses the decision-process in Stigler's (1961) model of the market for "lemons":

> "Stigler (1961) used the example of a person who wants to buy a used car, and stops searching when the costs of further search would exceed the benefit of further search" (GIGERENZER, 2002, p.5).

According to Gigerenzer (2002), this optimal stopping rules introduced in these economists' models is not a good representation of cognitive processes because they demand large amount of knowledge, incur in an infinite regression argument where cost-benefits computations needs more cost-benefits computations and assume people have massive computational capabilities. All these motives are not compatible with the bounded rationality proposed by the advocates of the F&F research program.[9]

Yet the disagreements of researchers in F&F program go beyond the interpretation of psychological concepts by economists. Gigerenzer (1996) has fiercely criticized the heuristics-and-biases program introduced by Kahneman and Tversky (1996). In their

[9] Sent (2005) makes a similar argument claiming that the interpretation of bounded rationality of several mainstream economists also misrepresents the original Simon contributions. However, it is possible that Simon himself has sometimes endorsed these misrepresentations as he eventually recognized works like the ones from NEI as making the bounded rationality assumption (SENT, 2004).

program, Kahneman and Tversky (K&T) propose that judgments and predictions are possibly mediated by mental operations called “judgmental heuristics”. These operations would be “cognitive shortcuts” that could be useful, but often lead to systematic errors or biases – often called “irrationalities”. These authors conducted several experiments which provided empirical evidence contradicting traditional theories of judgment under uncertainty like the expected utility hypothesis (KAHNEMAN; TVERSKY, 1996, p. 582).

However, Gigerenzer (1996) has contested these results, claiming that these systematic errors were the result of the research strategy used by K&T and not a feature from human reasoning. The author argues that the biases and errors identified are the result of a narrowly defined norms used to evaluate judgment and that the cognitive processes K&T call heuristics are defined too vaguely. Errors and deviations are always related to a specific result deemed “correct” or “adequate”, a normative standard in which the judgments can be compared. Gigerenzer challenges the standards used by K&T – normally based on formal logic and the expected utility theory – arguing they are too narrow to match real-world phenomena, which would explain how many behaviors fail to conform to the norm. Furthermore, Gigerenzer criticize the vagueness of the definition of heuristics that exposes the lack of decision-process models in their research program which hinders the understanding of the specific cognitive processes underlying judgment and choice. For example, Gigerenzer (1996) replicates the definition given by Kanehman and Tversky (1996) of the heuristic called representativeness:

> The two major surrogates for modeling cognitive processes have been (a) one-word-labels such as representativeness that seem to be traded as explanations and (b) explanation by redescription. Redescription, for instance, is extensively used in Kahneman and Tversky's (1996) reply. Recall Moliere's parody of the Aristotelian doctrine of substantial forms: Why does opium make you sleepy? Because of its dormative properties. Why does a frequency representation cause more correct answers? Because "the correct answer is made transparent" (p. 586). Why is that? Because of "a salient cue that makes the correct answer obvious" (p. 586), or because it "sometimes makes available strong extensional cues" (p. 589). Researchers are no closer to understanding which cues are more "salient" than others, much less the underlying process that makes them so. (GIGERENZER, 1996, p.594)

With the notions of heuristics, adaptive toolbox, ecological and social rationality, Gigerenzer extends Simon’s bounded rationality in a direction that may help evolutionary economics to construct a consumer choice theory. The most obvious point of compatibility is the notion of bounded rationality, starting point of Gigerenzer and the ABC group approach and basis of their ecological rationality proposition. Nonetheless, there are other areas to which the heuristics program can contribute significantly, such as questions related to uncertainty, endogenous preferences and routines and habitual behavior.

### 2.2.3 Contributions for an evolutionary consumption theory

Until now I have described the general goals of the fast-and-frugal heuristics research program. This section will discuss the specific contributions of the simple heuristics for an explanation of consumer behavior in evolutionary economics. The first and most direct contribution would be the fast-and-frugal heuristics themselves as a judgment and decision process of boundedly rational agents. Bounded rationality is an important hypothesis for many evolutionary economists, but some have not specified the mechanism on which agents cognitively bounded rely to behave in a “large world” context – e.g., Nelson and Consoli (2010) refer to bounded rationality and openly criticize conventional economic theory for ignoring choice procedure in its theories, yet they do not specify any kinds decision procedure, only relying on vague statements like “households engage in various activities to meet the wants they attend” and “we propose that the concept that particular wants are satisfied through activities aimed at that objective” (NELSON; CONSOLI, 2010, p.671-672). The authors state that these activities may include the purchase of goods and services, without describing the decision mechanisms that underlie the purchase behavior. Simple heuristics may provide this mechanism because they necessarily need to be stated as a clear algorithm, avoiding the ambiguities of vague general statements about choice process.

Some of these heuristics have already been used to analyze consumption behavior. Besides the works in evolutionary economics already cited here that use fast-and-frugal heuristics (e.g. AVERSI et al., 1999, VALENTE 2012, KAPELLER et al., 2013), other investigations in the psychological literature have dealt with these heuristics. Yee et al. (2007) have analyzed the decision process of purchasing smartphones by the evaluation of their features. Smartphones have multiple attributes that varies greatly between options. An optimizing strategy to choice based on this attributes is not feasible due to the extent and complexity of the information related to the product.

They identify four possible (one-reason) heuristics: the lexicographic by feature (LBF), acceptance by aspects (ABA), elimination by aspects (EBA) and a mixed strategy called lexicographic by aspects (LBA). In LBF, consumers evaluate smartphone’s profiles sequentially – first by one feature, then another, until a judgment or choice is made. In ABA the consumer might rank smartphone by aspects, say, by first accepting BlackBerry-based smartphones, then Microsofts, Nokias, and, finally, Samsungs until all smartphones are ranked; EBA is a heuristic in which consumers successively eliminate aspects instead of accepting it – they first eliminate the smartphone alternatives which have (or lack) a specific features, then it proceeds sequentially using different criterions to eliminate all the choices which do not have; finally, consumers may mix acceptance and elimination criteria and they call such a mixed process lexicographic by aspects. After defining the heuristics, Yee et al. (2007) identify through an experiment two heuristic which are ecologically rational for purchasing smartphones with a definite set of features. They show that with the heuristics' algorithm it is possible to predict the choices of respondents better than with other choices processes.

Food consumption is another phenomenon that may be explained by simple lexicographic decision rule. Scheibehenne et al. (2007) identify the most commonly investigated factors in the food literature: taste or sensory appeal, health-related issues, ethical concerns, convenience, price, and weight control considerations. People have also been shown to seek emotional comfort, mood improvement, familiarity, and novelty when choosing food. Despite the various factors involved, the aspects of taste and sensory appeal seem to be the most important factors underlying food choice. After reviewing the factors influencing food consumption, Scheibehenne et al. (2007) investigate the use of lexicographic heuristics (LEX) when choosing different dishes when eating out. LEX predicts that people base their decisions on just one reason by choosing whichever option has the highest value on the attribute that is regarded as most important (e.g., pick the food that is most convenient). The results show that a LEX heuristic that decides based on a single good reason and does not integrate information makes predictions almost as well as a complex process of weighting and adding all available information. This result questions the widely held belief that when choosing food, people take into account many different aspects and weight them according to their importance. It is as likely that people choose food based on a much simpler process, selecting whichever option fulfilled their most important need.

The works of Yee et al. (2007) and Scheibehenne et al. (2007) show how simple heuristics studies may be applied to study real-world consumption problems. Moreover, they demonstrate the potential benefits of using the F&F heuristics framework: the use of precisely formulated cognitive process; the possibility of empirically test various decision strategies; the demonstration of influence of various decision strategies in consumption behavior.

The contributions of heuristics for consumer theory go beyond the decision process and incorporate other aspects of evolutionary theory. The problem of fundamental uncertainty is directly dealt by Mousavi and Gigerenzer (2014). These authors introduce fast-and-frugal heuristics as indispensible tools for a fundamental uncertain world. Similarly to Dequech (2001), they state the difference between risk and fundamental uncertainty in Knightian terms and go further, trying to connect that typology with the concept of simple heuristics. They propose an overview of different kinds of uncertainty and link each one of them to a probability theory category, the kind of decision processes adequate to them, the theorizing method used to model these types of uncertainty and the kind of knowledge that arises from them.

Gigerenzer and Gaissmaier (2011) also notice that ecological rationality does not imply that all people are perfectly adapted to their environment. Referring to Simon (1992), the authors assert that the investigation of heuristics would be obsolete in the case where agents always use the ecologically rational heuristic in any situation - one would only need to study the environment to predict behavior. However this is not the case since some individuals are better in using simple heuristics than others, which implies that agents have different skills and capabilities – they are heterogeneous. According to Gigerenzer and Gaissmaier, there are multiple studies identifying systematic individual differences in the use of heuristics, given different expertise in the subject (e.g. expert groups use efficient heuristics more often than laypeople) and variant core capacities (e.g. older people have poorer recognition memory).

Learning and endogenous preferences are also domains in evolutionary economics that can profit from the heuristics approach. First, heuristics can be learned, as clearly stated by Todd and Gigerenzer (2000, 743): “Humans may learn new heuristics, new principles for selecting heuristics, or develop expertise with their application through problem solving”. Moreover, it has been argued in this dissertation that several heuristics rely on social information and are deemed to be tools of learning from peers (e.g., imitate-the-majority and imitate-the-succesful). Social learning heuristics are important cognitive processes that may be used to model learning in an evolutionary economics considering that it respects the bounded rationality assumption and can be used as an explanation of endogenous preference insofar the social information influences the preferences formation (WITT 2016, NELSON; CONSOLI, 2010)

Habits and routines are also considered on the fast-and-frugal heuristics framework. Selten (2002) states that much of human behavior is not connected to conscious deliberation, using as example the process of walking. For Selten, walking and other human actions are automatic routines which in turn can be a genetic preprogrammed or acquired by learning. The relationship with bounded rationality is stated below:

> One might want to distinguish between bounded rationality and automatic routine; however, it is difficult to do this. Conscious attention is not a good criterion. Even thinking is based on automatized routine. We may decide what to think about, but not what to think. The results of thinking become conscious, but most of the procedure of thinking remains unconscious and not even accessible to introspection. Obviously the structure of these hidden processes is important to a theory of bounded rationality (SELTEN, 2002, p.16)

Moreover, Gigerenzer (2008) analyzes intuition in terms of heuristics. He relies on the adaptive toolbox notion to explain how gut feelings may work and how they can be successful in solving problems. Gigerenzer (2008, 19) affirms “The intelligence of the unconscious is in knowing, without thinking, which rule is likely to work in which situation”. This does not mean that heuristics cannot be used in a reasoned and conscious way, but it shows that much of our adaptive toolbox works in an automatic fashion (MOUSAVI; GIGERENZER 2013, 1673). Therefore, unconscious processes which could be related to habits and routines are considered in the fast-and-frugal heuristics program.

Social learning heuristics can also be understood as the formation process of habits and routines – thus being an answer to evolutionary economics critics who points to the lack of explanation for origin, adoption and transmission of routines and habits in evolutionary theory. There are even neuroscientists like Vlaev and Darzi (2014) who define Gigerenzer’s heuristics as mental automatisms, an extension of psychology mental habits that work as tendencies to behave. Thus it seems reasonable to say that routines and habits are covered by bounded rationality on this interpretation and may provide new insights to evolutionary economics theories.

In sum, there is some evidence that the fast-and-frugal heuristics program have developed concepts that are fairly compatible with the evolutionary economics basic assumptions presented in this work. The next step is to implement these heuristics in an evolutionary economic model and analyze the implications of this concept to the overall theoretical framework. In the next section, I will systematize the F&F heuristics in an evolutionary consumer model.

## 2.3 AN ADAPTIVE AGENT-BASED MODEL OF CONSUMER CHOICE

Let us recall from the previous sections that the literature of evolutionary consumption models is marked by the use of diverse methodologies and behavioral assumptions. In this section I will try to synthesize the findings discussed in the literature review in an agent based model of consumption behavior using the typical assumptions identified in the revision of the literature and the bounded rationality concept from the fast-and-frugal heuristics perspective. I will base this dissertation's model on the framework presented in Valente (2012), which already respect many of the usual assumptions of evolutionary economics and uses fast-and-frugal heuristics.

The goal of this section is to describe the general structure of the model of consumer choice, propose some modifications and reinterpretations and to evaluate the consequences of these alterations in the general framework of the model. I will stress the importance of the decision-making process in the model, its adequacy with the psychological theory that supports it and its relationship with evolutionary economics basic assumptions.

### 2.3.1 General structure

As mentioned above, the underlying model for this dissertation is the synthetic model for the evolution of markets presented by Valente (2012, p. 1062). In his exercise, Valente models the development of a semi-durable product market in which several agents require one unit of the product every few periods. The demand side is represented initially by one buyer, with the growth of the number of consumers following a contagion pattern[10] until it reaches the maximum number of individuals defined. Each consumer purchase one product when it enters the market and waits until it fails to purchase another to replace it. Consumers have the same preference formation mechanism and budget constraints, but may not perceive perfectly the characteristics of the product consumed. The supply side consists in a fixed number of firms each one offering one different product with multiple characteristics that do not change. The supply is exogenously fixed - there is neither the entry of new firms nor modification in any of the products' characteristics values.

Valente's goal is to identify the contribution of demand aspects to the market configuration, thus explaining the restrictive hypothesis made by the author. Valente's intention is to "purposefully build a highly abstract (and, essentially, unrealistic) market in

[10] A detailed description of the contagion pattern is described in the Table 4.

which all possible sources of differentiation other than the economic behavior of consumers are either suppressed or controlled" (VALENTE 2012, p. 1062). The model in this dissertation will follow the same line and focus on economic behavior of the consumers, but it is going to adjust some aspects to expand its adherence to evolutionary economics usual hypothesis and make it more compatible with the bounded rationality framework developed by Gigerenzer and colleagues. In the following section I describe in details the supply side and demand side of my model.

### 2.3.2 The supply side

The supply side in this dissertation's model is modeled in exactly the same way as Valente's model. As stated above, the supply side is modeled in a notably simplified way. Each firm offers one product in the market and they are close substitutes goods. Valente assumes that products can be represented as vectors over a set of characteristics (dimensions) and defines supply as "[…] the set of alternative products that consumers consider as a potential purchase for a specific use, and their "quality" values must be measured in respect of that use" (VALENTE, 2012, p. 1036). In Table 2 there is an outline of the product space representation where the generic value $v_X^i$ is the measure of product X in respect of characteristic i. This value must be interpreted as a measure of the quality for the "service" that the product provides in respect of a specific use.

In this representation, it is only required that there exist a weak ordering on the instances for each characteristic. That is, it is possible to assess one product X as inferior, superior or equivalent to another product Y in respect of a specific characteristic, or dimension.

TABLE 2 – PRODUCT'S QUALITY VALUES

| | Char. 1 | Char. 2 | ... | Char. m |
|---|---|---|---|---|
| Prod. A | $v_A^1$ | $v_A^2$ | ... | $v_A^m$ |
| Prod. B | $v_B^1$ | $v_B^2$ | ... | $v_B^m$ |
| ... | ... | ... | ... | ... |
| Prod. N | $v_N^1$ | $v_N^2$ | ... | $v_N^m$ |

SOURCE: Valente (2012)

Each producer also has a market strategy, which is defined as the relative importance given by each firm to the characteristics of their product, symbolizing the aspects of their goods they want to promote. Thus, “the producer assigns higher values to the characteristics it would like to be in the top positions in consumer preferences, and lower values to those aspects of its product more likely to be dominated by competing products” (Valente 2012, 1049). In Table 3 the marketing strategies are formally represented as a vector of values where a generic element $k_X^i$ represents the relative importance that producer X gives to characteristic i of the product. As of the vector k it is possible to establish the ideal raking of characteristics the firms want to advertise for the consumer arranging each characteristic in descending order based on their *k* value.

TABLE 3 – PRODUCERS’ MARKETING STRATEGIES

| | Char. 1 | Char. 2 | ... | Char. m |
|---|---|---|---|---|
| Prod. A | $k_A^1$ | $k_A^2$ | ... | $k_A^m$ |
| Prod. B | $k_B^1$ | $k_B^2$ | ... | $k_B^m$ |
| ... | ... | ... | ... | ... |
| Prod. N | $k_N^1$ | $k_N^2$ | ... | $k_N^m$ |

SOURCE: Valente (2012)

In Valente’s model, the marketing strategy has an important role in influencing consumer preferences. The mechanism of endogenous preferences is going to be explored in the next section. For now, it is enough to define the concept of marketing strategy and its implementation in the model.

### 2.3.3 The demand side

The demand side is partially based on Valente’s model, with some adaptations in the decision mechanism. Each consumer purchase one product and waits until it fails to purchase another to replace it. The number of consumers (N) increases over time with each consumer triggering a group of new users in successive generations, like a virus spreading in a population, with the size of the group of buyers “contaminated” diminishing over time. For instance, the market starts with one buyer and this buyer influence seven of their friends to purchase the product, which in turn convince other six consumers each one, and so on until the market is saturated. This dynamic has as a result an “S” shaped curve (see FIGURE 5.a) of total consumers over time. Each consumer is defined by information’s perception mechanisms, a level of tolerance to difference of characteristics, some decision algorithms and endogenous preference formation system[11].

The information from the supply side that reaches the consumer is modeled using a product value's perception mechanism. The product characteristic's values considered by the individuals is not the real value $v_X^i$, but:

$$\hat{v}_X^i = Norm\left(v_X^i, \Delta\right)$$

where Norm($v_X^i$, Δ) represents a normal distribution with mean $v_X^i$ and variance Δ. This incorporates perception errors of consumer due to different capacity and skills to evaluate the product. The higher the perception errors represented by Δ are, more different is the observed value by the consumer from the true value of that products' characteristic.

Following Valente (2012), I will assume that a constant perception errors parameter value Δ will be assigned to each consumer at their time of entry in the market. After the entry, the variable changes following the dynamics described below:

$$\Delta_t^i = \Delta_{t-1}^i + 0.05 \times (\hat{\Delta} - \Delta_{t-1}^i)$$

where $\widehat{\Delta}$ is the minimum perceptual error reached by the consumers. If it is set to 0, then the observed value of the agents will eventually be equal to the real value of the products' characteristics. The changing in Δ value over time reflects a learning process that cause a decrease in the chance of making evaluation errors as time passes and the consumer accumulates experience and knowledge about the product.

There is also a mechanism to assess the tolerance for difference in product's qualities in the model. Products that do not differ significantly from one another in that particular characteristic are deemed equivalent. The following equation represents the minimum amount of differences in characteristics which the consumer considers relevant:

$$\hat{v}_X \approx \hat{v}_Y \Longleftrightarrow \frac{|\hat{v}_X - \hat{v}_Y|}{max\left(\hat{v}_X, \hat{v}_Y\right)} < \tau$$

[11] The Valente (2012) model framework also includes a kind of budget constraint in the form of a minimum requirement vector – a consumer may discard a product as a possibility depending o the affordability and because some other products is considered better than other. Therefore, there are some minimal requirements for the consumer to consider a product. This is incorporated embedding each agents j with a minimal requirement m for each characteristic, represented by the vector $\vec{m}_j = \{m_j^1, m_j^2, \ldots, m_j^m\}$. The potential set for a consumer is defined by all products which have $v_X^i > m_X^i$ for all characteristics. Following Valente's model of the evolution of markets, this aspect is not included in the dissertation model. The motivation for this is the fact that it is not the goal of this model to investigate income effects, but only the market effects of consumer's decision process.

where the coefficient $\tau$ is the tolerance level of the consumer and it ranges between [0,1]. This coefficient is a measure of the minimum percentage difference in observed product values considered relevant to establish a strong preference relation between these characteristics. The closer $\tau$ is to 0, more small differences are deemed significant in the evaluation process of the product, while the opposite is true when $\tau$ is close to 1. For instance, if $\tau$ is 0.02 it means that consumer will be indifferent to characteristics' values with differences lower than 2% of the characteristics with a higher value. In this circumstance, consumers will be indifferent between products X and Y in regard to characteristic $i$ in the case where $v_X^i = 100$ and $v_Y^i$= 99, because the percentage difference between $v_X^i$ and $v_Y^i$ is lower than 2%.

These two mechanisms enhance the realism of the model and are an interesting way of modeling cognitive aspects of the human mind. Nevertheless, the most important cognitive aspect of consumer behavior is arguably the decision-making process which is going to be discussed in the following sections.

#### 2.3.3.1 Structure of the environment

Until now, the aspects incorporated in the model are identical to the models presented in Valente (2012). Nevertheless, the core aspect of the demand side – the choice process – is going to be modified in relation to Valente's models. The decision mechanism used in his models is the fast-and-frugal heuristic called Take-the-Best. However, it was implemented as the only choice rule and without any considerations on the structure of the environment of choice. As a result of that, it is not possible to evaluate the ecological rationality of the Take-the-best heuristic and the consumers are not able to adapt their choosing strategy to new information and context in the market. Furthermore, Take-the-best is not a social heuristic, thus the model does not take into account the possibility of social rationality through a social learning process described by Herwtig et al. (2012).

As argued in previous chapters, the proponents of the fast-and-frugal heuristics believe human decision-making involves different basic models of thoughts, described by the "adaptive toolbox". When implementing only one heuristic on his models, Valente (2012) does not endow his consumers with diverse adaptive tools to deal with an uncertain and rapidly changing environment like the onset of a market. On his model, some variables change drastically, like the number of consumers and the average perception errors, but these changes do not influence the decision process of the agents. This undermines the claims of realism and adherence to the principles of bounded rationality (VALENTE, 2012, p.1043).

To overcome these problems, the consumers are going to be modeled with three different simple heuristics discussed in the section 2.2: Imitate-the-majority (ITM), Take-the-best (TTB) and Tallying (TLL). ITM consists in the imitation of others behavior, TTB is a sequence choice based on one reason and TLL is a frugal trade-off mechanism based on counting positive characteristics. The heuristics were chosen for three different reasons. First, each one fits in different categories of heuristics in the literature: ITM is a social heuristic; TTB is a one-reason decision procedure; and TLL is a trade-off heuristic. The diversity of kinds of heuristics in the model mirrors in some extent the various choice strategies available to humans in their adaptive toolbox as described by Gigerenzer and Gaissmaier (2011), making it more realistic. Second, they all fit in the context of a consumer choosing between multi-characteristics products – in other words, they may be adapted to a consumption problem. It is reasonable to make the assumption that the cues these heuristics use as information come from the values of product's characteristics $v_X^i$. Finally, these heuristics ecological rationality may be established by parameters already included in the model. Thus, this addition is parsimonious and does not contribute to the problem of proliferation of parameters common in agent-based models (ROGERS; VON TESSIN, 2004).

As stated before in this work, heuristics are domain-specific. Their use is regulated by their adaptation to specific environments – their ecological rationality. The literature on heuristics presented some evidence of the structure of the environment of decision where the heuristics chosen for the model are ecologically rational. The ITM heuristic, like other social heuristics, is used exclusively in social context where the environment changes slowly or not at all (HERTWIG et al., 2012; GIGERENZER, 2008). In turn, the TTB heuristic has been found to be ecologically rational when cues validities vary highly, there is moderate to high cue redundancy (correlation between cues) and information is scarce (GIGERENZER; GAISSMAIER, 2011; GIGERENZER, 2008). The TLL heuristic is accurate in situation where the cue validities vary little and there is low redundancy (GIGERENZER; GAISSMAIER, 2011; GIGERENZER 2008).

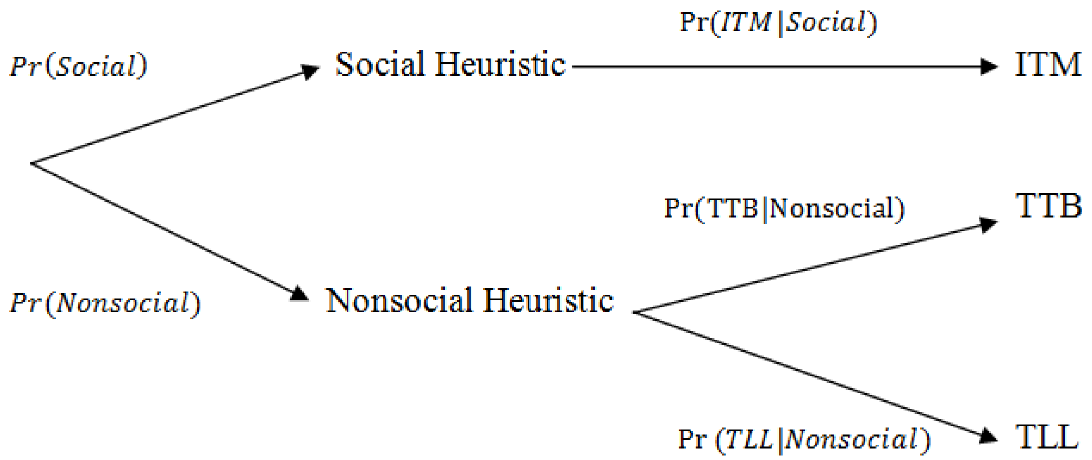
In regard of the structure of information from the environment presented in Valente's models, three parameters stand as candidates for the definition of the ecological rationality of the heuristics – the total number of consumers N, the population average deviation $\Delta$ and the population tolerance level $\tau$. The number of consumers may serve as a proxy of social pressures, where the greater the N, more likely is the consumer to be influenced by their peers and social groups. The average $\Delta$ can be a proxy of the amount of information about the products spread in the population and the social understanding of the products aspects. The lower the deviation, more information is socially available and there is less uncertainty regarding the evaluation of the products. Finally, $\tau$ measures the tolerance of the individuals to quality differences, but may also be related to how redundant are the products characteristics perceived by the individuals. The lower the tolerance level of the consumers, more the differences in the cues are perceived and less redundant they will seem to them.

Based on these considerations about the structure of the environment in the underlying model, it is possible to match the cognitive decision processes (heuristics) with the environmental parameters (N, $\Delta$ and $\tau$), as bounded rationality demands. The ITM heuristic is better suited to environments where N is high and there are little changes in the parameters. The TTB is ecologically rational with little information and high redundancy – in other words, when $\Delta$ and $\tau$ are high. Conversely, TLL is more adapted to situations where there is low redundancy and $\tau$ is low. These are the criteria that define which heuristic the consumers are going to be using in each period of time. Now, it is necessary to describe how these criteria will be implemented on the model.

In the first place, it will be assumed that the variation of the parameters will cause an increase in the probability of the use of a given heuristic. Defining the influence of the environmental parameters in probabilistic terms is based on the idea that not all individuals are the same: they differ in the skills and abilities needed to correctly use the ecologically rational heuristic to that particular context. In other words, we are assuming agents heterogeneity. Likewise, it also incorporates a certain level of uncertainty to the model outcomes which is one of the goals.

There are three possible outcomes in the sample space in question: consumers apply ITM, TTB or TLL. The first partition of the probability space is given by the probabilities of using a Social Heuristic or a Nonsocial Heuristic - these are the more general categories of heuristics and will be taking into account first. If the consumers use a social heuristic, it follows that they will use the only social heuristic in the model, the ITM. If not, they will need to choose between two nonsocial heuristics, which can be either the TTB or the TLL. The probabilities to use each one of the heuristics are going to be described with a tree diagram in FIGURE 4.

FIGURE 4 – STRUCTURE OF THE ENVIRONMENT PROBABILITIES




SOURCE: Own elaboration (2017)

Where Pr(Social) is the probability of the consumer use a social heuristic, Pr(Nonsocial) is the probability of the agents using a nonsocial heuristic and Pr(ITM), Pr(TTB) and Pr(TLL) are the probabilities the agents effectively using the ITM heuristic, the TTB heuristic and the TLL heuristic, respectively. These probabilities are defined by functions depending on the environmental parameters (N, Δ and τ) defined previously.

The probability of using a social or non social heuristic is governed by the total number of agents N. A simple implementation of this characteristic may be the following. Let Y be a continuous random variable uniformly distributed in the interval [0,1]. Then, Pr(Social) can be described as the following:

$$\text{If } Y \sim \text{Unif}(0,1), \text{ then}$$

$$\Pr(Social) = \Pr(Y \leq \eta)$$

$$\Pr(Social) = \Pr(ITM|Social)$$

$$\Pr(Nonsocial) = 1 - \Pr(\text{Social})$$

$$\text{where } \eta = \frac{N_t}{N_{max}}$$

$$\text{with } \eta \epsilon [0,1]$$

$$N_t \epsilon [0, \infty]$$

$$N_{max} \epsilon [\max{(N_t)}, \infty]$$

Where $N_t$ is the number of consumers in the time t and $N_{max}$ is a parameter to control the maximum reach of the social influences in the model. If $N_{max} = N_t$ , then $\eta = 1$ and the $\Pr(X \leq \eta) = 1$. In other words, the agents are always going to use ITM. If $N_{max} \to \infty$, then $\eta = 0$ and $\Pr(X \leq \eta) = 0$. That is to say, none of the consumers will use the ITM. The probability of using ITM gradually increases with η.

In the case where the consumers do not use the social heuristic, they need to chose between TTB and TLL. First, as the dynamics for changes in the perception errors parameter Δ is already defined, we can assume that Δ is correlated to τ. It is reasonable to think that as the market develops and consumers enhance their knowledge of the product, they become more intolerant to difference in qualities – it matches the learning process taking place. Thus, for matters of simplicity, we can define our probability function using only the parameter τ and know that Δ is also being taken into account. The probabilities of using the nonsocial heuristics can be described according to the following equations:

$$\Pr(TTB|Nonsocial) = \Pr(Y \leq T)$$
$$\Pr(TLL|Nonsocial) = 1 - \Pr(TTB)$$

$$\text{where } T = \frac{|\tau_t - \tau_0|}{\Delta\tau_t}$$

$$\text{with } \tau_t, \tau_0, \epsilon[0,1]$$

On this equation, T ($\tau_t$) is a parameter which depends on the level of tolerance of individuals at time $\tau_t$, the initial value of tolerance $\tau_0$ and the difference between maximum level of tolerance and the minimum level of tolerance reached in the overall model is $\Delta\tau_t$. This means that T is a value in the range [0,1] where and $|\tau_t - \tau_0|$ captures the variation of the level of tolerance in the simulation and $\Delta\tau_t$ captures the total variation in the tolerance during the simulation. Therefore, this parameter captures the extent of relative changes in the overall level of tolerance in the model.

### 2.3.3.2 The decision-making mechanisms

These considerations being made, it is necessary to describe how the adaptive toolbox will be implemented in the model. First, let us define each one of the heuristics in our toolbox. The ITM algorithm is defined in the following way:

*Imitate-the-majority: follow the behavior of the majority of those in your peer group*

1. *Determine the choice made by the majority of the consumers.*
2. *Imitate this choice.*

This is indeed a simple and frugal algorithm, cognitively feasible and easily implemented by the consumers. They only need to observe the most popular product, which is not an unrealistic assumption and does not demand complex calculations. The most popular product may be defined using another simple heuristic, like the recognition heuristic or inferred based on the firms marketing strategies.

The TLL decision procedure is describe in the following manner:

*Tallying: it entails simply counting the number of characteristics favoring one product in comparison to others.*

1. *Search through products' characteristic in any order.*
2. *Stop search after m out of a total of M characteristics (with 1 < m ≤ M). If the number of positive products' characteristics is the same for both alternatives, search for another characteristic. If no more cues are found, guess.*
3. *Decision rule: Decide for the alternative that is favored by more cues.*

To the correct application of the counting in this algorithm there is a need to define what a "positive" product characteristic is. For reasons of simplicity, the product characteristic is going to be evaluated as positive when its value is above the average value of that characteristic in the products pool. For instance, if the value of characteristic $i$ of the product X is $v_X^i = 102$ and the average value of the characteristic *i is* $\bar{v}_i = 100$, then this characteristic is considered positive.

It can be argued that this definition of positive product characteristic is too demanding for human cognition. Indeed, it is unfeasible to imagine that consumers are able to calculate the characteristics mean values observing each one of the possibilities. However, as stated before, the characteristics values do not need to be measured in real numbers. It could be said that another fast-and-frugal heuristic could use qualitative cues to infer if the characteristic is above or below average. In fact, it is not unreasonable to say people intuitively recognize products with qualities which are roughly above average. The recognition heuristic or a social heuristic like imitate-the-majority could be a frugal mechanism to that inference. The algorithm proposed is one possible in various simple and feasible ways of modeling the positive cue in this consumer context.

Last, there is the TTB algorithm for choice, which is going to be modeled in the same fashion as Valente's models:

*Take-the-best: frugal way to inferring which of two products have a higher criterion*

1. *Consider initially all options that may potentially be chosen.*
2. *Choose one characteristic among the m available.*
3. *If one single option scores highest in respect of that characteristic, this is the choice.*
4. *Otherwise, if more than one option scores similarly in respect of the adopted characteristic, remove the options with values lower than the maximum, and restart from step 2.*

Based on this algorithm, the order of the characteristics used to filter the set of available products influence the result. As it is the case of the TLL heuristic, the TTB also needs another mechanism to be fully implemented in the model. To solve this problem, there is a need to formalize the formation of the cue orders used in the decision procedure. Based on the structure of the TTB, Valente (2012, p. 1045) defines the cue order used by the consumer as their preference set – "Consumer preferences are the ordered set of a product's characteristics ranked according to their descending relevance in the consumer purchasing decision". Valente then gives an example: there could be two types of preferences, price-first or quality-first. Some agents may prefer quality over price, so they will start the search with the quality characteristic of the product and vice-versa.

Following Valente (2012), the mechanisms for preferences building on the model is going to use the marketing strategies of the firm. As defined in the previous section, the marketing strategy is modeled as the "desired" preferences of the producer, the ranking of characteristics that the producer would like to respect and it is represented by a vector $k_X^i$ as illustrated in Table 3. To incorporate this information on the preference ordering of the individual, Valente assumes that social influence defines the effectiveness of the marketing strategy. First, only the marketing strategies affect consumer preferences. Then, Valente assumes that the more the product is bought, the more the marketing strategy is successful. So, the ranking of the characteristics assumed by the consumer will be the strategies of the firms (vector $k_X^i$) weighted by their respective market shares. The logic used is one of social influence: the higher the numbers of buyers, more the consumers have influence from their peers, more effective is the market strategy.

The idea is to structure the preference generation mechanism in such a manner that “the likelihood that a given characteristic will appear higher in the ranking of a consumer’s preferences (and, therefore, that it will be highly relevant for the purchasing decisions) will be higher the higher is the marketing value for that characteristic in the strategies of the highest selling firms” (VALENTE, 2012, p. 1052). Valente targets to generate consumer preferences defined by an ordered set of integers referred to the m characteristics representing the product space.

$$< c_1, c_2, \ldots, c_m >, c_i \in \{1, 2, \ldots, m\}$$

For example, if m=3, the possible sets of preferences is composed by:

$$< 1, 2, 3 >; < 2, 1, 3 >; < 1, 3, 2 >; < 3, 1, 2 >; < 3, 2, 1 >; < 2, 3, 1 >$$

And the probability of each one of these combinations to appear is a function of the market share of the firm and its marketing strategy, given by the indicator $p_i$ where $k_j^i$ is the marketing strategy, $s_j$ is the market share and δ a parameter to model the difference of this indicator:

$$p_i = \sum_{j=1}^{n} \left(k_j^i s_j\right)^{\delta}$$

The first characteristic in the ranking is defined by drawing randomly one of the m characteristics in the pool of characteristics with the probability $\Pr(i = c_1)$ equals to:

$$\Pr(i = c_1) = \frac{p_i}{\sum_{h=1}^{m} p_h}$$

And then, the second characteristic is defined with the same probability but excluding the possibility of drawing again the same characteristic:

$$\Pr(i = c_2) = \begin{cases} 0 & , i = c_1 \\ \dfrac{p_i}{\sum_{h=1, h \neq c_1}^{m} p_h} & , \text{otherwise} \end{cases}$$

Using this algorithm iteratively, the final result is an ordered set of integers $< c_1, c_2, \ldots, c_m >$ representing the preferences of each agent in the model. Valente stresses that this is not the only way of modeling preference formation: "the proposed generation mechanism is only one possible way to model the generation of preferences depending solely on marketing strategies and no exogenous determinants" (Valente, 2012, p. 1052). Nevertheless, it will be included in my model so I can focus on the effects of the decision process in the market and be able to compare with Valente's simulations outcomes.

### 2.3.4 Compatibility with evolutionary economics assumptions

The underlying model for this dissertation already respects most of the main assumptions of evolutionary economics discussed in this dissertation so far. Valente's model features heterogeneous products defined over a multidimensional characteristic space; contagion-like dynamics of entry of consumers, biased consumer perception; a fast-and-frugal decision-making strategy; and endogenous preferences. Therefore, it could be argued that it uses a boundedly rational choice mechanism, there is some agent heterogeneity, preferences are endogenous, there is uncertainty embedded in the model and a learning mechanism. However, this compatibility can be improved to fully incorporate the psychological literature of fast-and-frugal heuristics program into an evolutionary consumption model with some minor adjustments.

First, it is essential to implement the structure of the environment of choice and different heuristics in the models. The structure of the environment is an essential aspect of the bounded rationality theory developed by Gigerenzer and colleagues – it explains the ecological rationality of a given heuristic and justifies their fitness for the specific decision problem. Furthermore, the model does not incorporate an important aspect of the fast-and-frugal heuristic: the idea of adaptive toolbox, the multiple context-specific heuristics which are available for the individuals in a given moment. The homogeneity of Valente's agents in respect to their choice process is a weakness in his model of consumer behavior.

Furthermore, the agents do not show routines or habitual behavior in Valente's models. As discussed before, routines and habits are processes that may be based on heuristics. However, not all heuristics will have as result routinized behavior or habits of thought. Nothing on Valente's models outcomes, the TTB do not appear to generate habitual routinized behavior in any way. However, social heuristics are embedded in the notion of habit. Imitate-the-majority is a mechanism which not only may be the expression of an acquired propensity – Hodgson (2010) definition of habit – but also may underlie a routine that is focused on "the interactive and collective aspects of behavior and not only on individual characteristics" as Felin et al. (2012) argue how a routine should be defined. Therefore, it is important to add a social heuristic into the pool of possible decision strategies for the consumer, assuming that this is going to put habits and routines in evidence.

Given these considerations the implementations made into Valente's model framework are not only an improvement but also completely compatible with evolutionary economic theory. The description of the structure of the environment incorporates the learning processes demanded by evolutionary economists, adds an agent heterogeneity factor and also represents the uncertain environment in which consumers make their choices. Moreover, the implementation of an adaptive toolbox comprised of ITM, TTB and TLL not only enriches the decision-making process modeled, but also makes it fully compatible with bounded rationality hypothesis, enables the emergence of habits and routines and further stresses the fundamental uncertainty hypothesis – after all, fast-and-frugal heuristics are adaptive tools to deal with a fundamental uncertain world.

It is important to notice that the decisions rules and the pairing of structure of the environment and heuristics were modeled after the available empirical evidence collected by researchers on the fast-and-frugal heuristics research program. Thus, we tried to avoid *ad hoc* modifications on Valente's model – we aimed to use assumptions that have strong empirical and theoretical justifications.

# 3 RESEARCH METHODOLOGY

## 3.1 AGENT-BASED MODELS

The model developed in this dissertation is based on the Agent-based Computational Economics (ACE) modelling approach, defined as "the computational study of economic process modeled as dynamic systems of interacting agents" (TESFATSION, 2006, p. 835). In this context, "agents" are computational objects – the representation of entities like individuals, social groups, institutions or even physical entities as a collection of data and behavioral rules. ACE methodology is based on the notion that economic systems are complex adaptive systems, which can be described in a very broad way as systems of interacting units that display emergent properties and react to environmental changes to fulfill a given goal (TESFATSION, 2006, p.836-837).

The objective of agent-based models (ABMs henceforth) is to describe these complex adaptive systems and analyze their properties in a bottom up perspective (PYKA; FAGIOLO, 2007). They have been used by an increasing number of researchers from different scientific disciplines since the development and diffusion of information processing technologies in the 80s and 90s. In economics, ABMs have been used as alternative to DSGE models, to describe social-economic evolution, to investigate cooperative behavior, to analyze the logic of techonology and innovation diffusion, among others[12] (TESFATSION, 2006, PYKA; FAGIOLO, 2007).

This modeling approach is particularly well-suited for the goals of this work for several resons. First of all, this method has being designed to deal with heterogeneous agents with limited information and computational capabilities from the start. Therefore, bounded rationality agents can be implemented in a natural and straightforward way. This is also true for the implementation of learning processes, routines and different decision-rules. It is especially compatible with the algorithmically defined fast-and-frugal heuristics, which can be coded with little effort in an ABM.

Moreover, it is a technique developed to deal with the complicated feedback loops of endogenous mechanisms in the model and realistic description of historical time, making it perfect to deal with endogenous preferences and path-dependent phenomena. As stated by Pyka and Fagiolo (2007, 472), "the massively parallel and local interactions can give rise to

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[12] To a full review of agent-based models applications in economics, see Tesfatsion (2006).

path dependency, dynamic returns and feedbacks between the two". Consequently, the modeling of highly complex phenomena and lack of oversimplifying hypothesis may enable the inclusion of fundamental uncertainty. For these reasons, Pyka and Fagiolo (2007) think ABMs have proved to be the most appropriate method for evolutionary economics.

However, this method – as any other methods – has its disadvantages. Tesfatsion (2006) argues that ABMs need to be programmed in a dynamically complete model – i.e. all the starting initial conditions and model algorithms must be defined in way that permits the simulation go on without any intervention of the modeler, mostly because small differences in initial specifications may greatly influence the results. In addition, it is hard to validate empirically these models as "real world is a single time-series realization arising from a poorly understood data generation process" (TESFATSION, 2006, 845), which implicates in a difficulty to verify accurately if the processes incorporated in ABM is a good representation of real process with standard statistical tools. Scaling-up models to represent large-scale systems and methods to empirically validate ABMs are challenges to this approach still to be solved.

Even though these challenges do exist, I do not believe they hinder the use of ABM method to achieving the goals of this dissertation. My aims are strictly theoretical and do not suffer from the empirical validation problems of this approach. Moreover, I consider the consumption simulations envisaged is simple enough to be completely specified in an ABM. To provide further support for this argument, I will describe the settings of the simulation which are going to be run for further analysis in this work.

## 3.2 SIMULATION SETTINGS

In this work, I aim to analyze the effect that the addition of different heuristics and changes in the structure of the environment in the market of a semi-durable product with the characteristics described in the previous chapter – a demand side composed of consumers endowed with different choice strategies and perception mechanisms and a static supply side with 100 firms, each one producing one product with 10 characteristics. To achieve this goal, I will run a series of simulations[13] with different initial parameters settings and then compare the different patterns of the evolution of the market that emerge from each setting. The TABLE 4 summarizes the initial parameters values and dynamic evolution of the variables.

[13] All the simulations in the dissertation have been developed with the simulation platform *Laboratory for Simulation Development* - LSD. LSD can be downloaded from www.labsimdev.org.

Each consumer and firm is identified by numbers – consumer 1, consumer 2, all the way to consumer 13700 (maximum number of consumers); and producer 1, producer 2 and so on until producer 100.

First, on simulations 1 and 2, I will replicate Valente's model results and then I will gradually implementing the new features and evaluating the impacts of the addition. The evolution and configuration of the market will be assessed by the time series of the number of products from each firm in possession of consumers at a given time – the installed base of the products. In his model, Valente (2012) uses as decision strategy only the TTB heuristics and there is no change in structure of the environment other than modifications in the error parameter.

With this particular model framework, Valente (2012) does two experiments – one with highly intolerant to differences in qualities agents ($\tau$ = 0) and with a limited capacity to read products values even after a long period of learning ($\Delta = \Delta > 0$); and other with a positive level of tolerance ($\tau > 0$) and with perfect capacity to read products values ($\Delta$ = 0). All the other parameters are the same, including characteristics values, marketing strategies, number of products and so on. He finds out that these small changes in the parameters have a big difference on market dynamics and final configuration. These differences are going to be discussed after the replication.

TABLE 4 – INITIAL PARAMETERS VALUES

(Continues)

| Element | Description |
|---|---|
| t | Discrete time variable. Number of periods: 500 |
| n | Number of products: 100 |
| M | Number of characteristics: 10 |
| $v_X^i$ | Quality value for characteristic i in product X. Values drawn from a uniform random function in the range [90,110].Therefore, quality values mean is 100 for all characteristics. |

TABLE 4 – INITIAL PARAMETERS VALUES (Conclusion)

| Element | Description |
|---|---|
| $\delta$ | Exponent affecting the relevance of marketing in consumers' preferences. Set to 1. |
| $k_X^i$ | Marketing strategy index for characteristic i in product X. Values drawn from a uniform random function in the range [0.5,1.5]. |
| $\mathrm{N_t}$ | Total number of consumers: 13,700. This value descends from the dynamics of entry for new consumers. Each consumer enters the market with a number of new consumers to be introduced to the market. These "descendant" consumers will introduce the same number of consumers as the "parent" minus 1, assuming that more recent generations of consumers have fewer relations with people not already using the product. At the start of the simulation a single consumer (generation 0) brings 7 offspring (generation 1) into the market. Each of these introduces 6 new consumers of generation 2, and so on. Concerning the timing of entry, a parent introduces its offspring sequentially every few time steps chosen randomly in the range [1, 10]. |
| $\Delta_\mathrm{t}^\mathrm{i}$ | Perception error parameter. Each consumer at time of entry $t = 1$ is assigned constant initial value $\Delta_{\mathrm{t=1}}^{\mathrm{i}} = 200$. After the entry the variable changes according to the following dynamics: $\Delta_\mathrm{t}^\mathrm{i} = \Delta_{\mathrm{t=1}}^{\mathrm{i}} + 0.05 \times (\widehat{\Delta} - \Delta_{\mathrm{t=1}}^{\mathrm{i}})$ |
| $\tau_t$ | Level of tolerance: Each consumer at time of entry $t_e$ is assigned a initial value $\tau_{t=1}$. After the entry the variable changes during the initial 250 periods according to the following dynamics: $\mathrm{\tau_t^i} = \mathrm{\tau_{t=1}^i} - 0.00008$ |

SOURCE: Based on Valente (2012)

In simulations 3,4 and 5, I will change the heuristic used in the model. Instead of using TTB, agents in this simulation will use only TLL. There will be a variation of the perception deviations of agents, but all other parameters will be the same as the ones used in Valente's experiments. We can recall that the algorithm of TLL depends on an "exogenous" parameter: *m*, the number of products characteristics considered in the counting. A very frugal

TLL algorithm would use few characteristics and a cognitively demanding TLL would use all 10 characteristics in the counting. I will run simulations with different *m* and I will assess the results of this modification in the market configuration.

Then, in simulations 6 I will add Tallying as a possible strategy for consumers in the model wich already has Take-the-Best available as choice heuristic. I will assume a given *m* (number of characteristics used by TLL), $\Delta = 0$ and the tolerance level of the individuals will change following a simple linear dynamics. Changes on the structure of the environment during the simulation 7 allow us to assess the impact of both cognitive and structural changes at the same time. Furthermore, it enhances the realism of the model: there is no reason to believe consumers' tolerance levels will remain constant over time.

The next step is adding to the agents' adaptive toolbox the ITM heuristic. Obviously, it makes no sense to evaluate this heuristic alone in the model, the results would be trivial – the product chosen by the first consumer would be chosen by every other consumer entering the market and the final outcome would be a monopoly. In simulations 8, 9 and 10, I will focus on ITM's effects in the installed based dynamics making all other parameters but the total number of consumers constant over time. So, $\Delta = 0$ and $\tau > 0$ at all periods for all agents. A positive tolerance level will induce agents to use both TTB and TLL in throughout during all the periods.

Finally, I will repeat Valente's parameters setting but using all the adaptations in the structure of the environment and the descision strategies used by the consumers. In simulation 11 I will set ($\Delta = \Delta > 0$), in other words, there will be a dynamically changing perception error's parameter that will diminish but never reach zero. On simulation 12, the agents in the final period will perfectly read the characteristics values ($\Delta = 0$). These last experiments' outcomes can be compared with Valente's model results. The TABLE 5 summarizes the parameters settings of each experiment.

Since I defined the parameters for each experiment, on the next section I will analyze the results of the model simulations with these different initial settings. I will evaluate market impacts of these behavioral and environmental changes and compare the outcomes of this dissertation model with Valente's original experiments.

TABLE 5 – SIMULATION SETTINGS

| **Simulation** | $\mathbf{\Delta_t^i}$ **dynamics** | $\widehat{\mathbf{\Delta}}$ | $\boldsymbol{\eta}_\infty$ | **m** | $\boldsymbol{\tau_t}$ **dynamics** | $\boldsymbol{\tau_{t=1}}$ |
|---|---|---|---|---|---|---|
| 1 | Yes | 0 | 0 | 0 | No | 0.02 |
| 2 | Yes | 1 | 0 | 0 | No | 0 |
| 3 | Yes | 0 | 0 | 2 | No | 0 |
| 4 | Yes | 0 | 0 | 5 | No | 0 |
| 5 | Yes | 0 | 0 | 10 | No | 0 |
| 6 | Yes | 0 | 0 | 5 | No | 0.01 |
| 7 | Yes | 0 | 0 | 5 | Yes | 0.02 |
| 8 | No | 0 | 0.5 | 5 | No | 0.01 |
| 9 | No | 0 | 0.75 | 5 | No | 0.01 |
| 10 | No | 0 | 1 | 5 | No | 0.01 |
| 11 | Yes | 0 | 0.75 | 5 | Yes | 0.02 |
| 12 | Yes | 1 | 0.75 | 5 | Yes | 0.02 |

SOURCE: Own elaboration (2017)

# 4 ANALYSIS OF RESULTS AND DISCUSSION

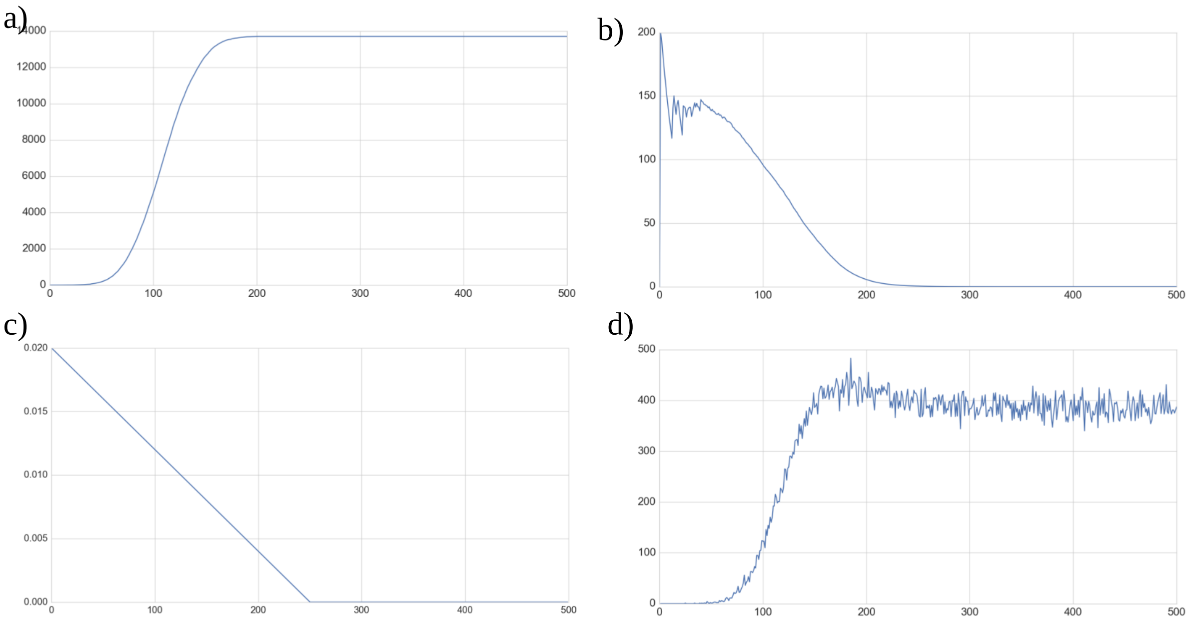
## 4.1 RESULTS

The experiments conducted in this dissertation produced various time series demonstrating consumer behavioral changes and the evolution of the market configuration. The analysis of consumer behavior will be focused on the number of agents using each heuristic and the market configuration will be assessed using the time series of the number of consumers for each product generated by each simulation setting. As stated in TABLE 4, the supply side is static: the products characteristic's values were drawn from a uniform random distribution and each product have the same real values in every simulation – there is no entry or exit of firms. This constant context present results that are common to all experiments, as they are produced by the same dynamic equations.

These common outcomes are presented in FIGURE 5. On the FIGURE 5a, there is the dynamics of consumer entry, with its typical s-shaped pattern of the "contagion" process. The average deviation from product's real value in the population due to perception errors is described on FIGURE 5b. The diminishing dynamics of the average errors represents the learning process in which consumer gradually acquires knowledge and the skills to accurately assess the products characteristics values. In some experiments (simulations 8, 9 and 10), this dynamic will be turned off and all agents will read perfectly characteristics values in order to focus the analysis on different aspects of the model.

The variation in the tolerance of the consumers to qualities differences change dynamics is showed in FIGURE 5c. The agents' tolerance diminishes accompanying the accumulation of knowledge and experience by their continuous use of the products – buyers become more "picky". As in the case of the perception errors, this dynamics also is not working on all simulations (it is in place only in simulations 7, 11 and 12). On the other experiments, the level of tolerance is constant. Finally, on FIGURE 5d there is the level of total sales. As explained in the section 2.3.1, this model is of semi-durable products which need to be replaced after a certain amount of time. Each consumer purchase one product when it enters the market and waits until it fails to purchase another to replace it. The time series on FIGURE 5d shows how many products are being replaced on every period. This semi-durable products lasts a random number of periods and that is what explains the noisy pattern on the series.

FIGURE 5 – GENERAL DYNAMICS OF THE SIMULATION RUNS



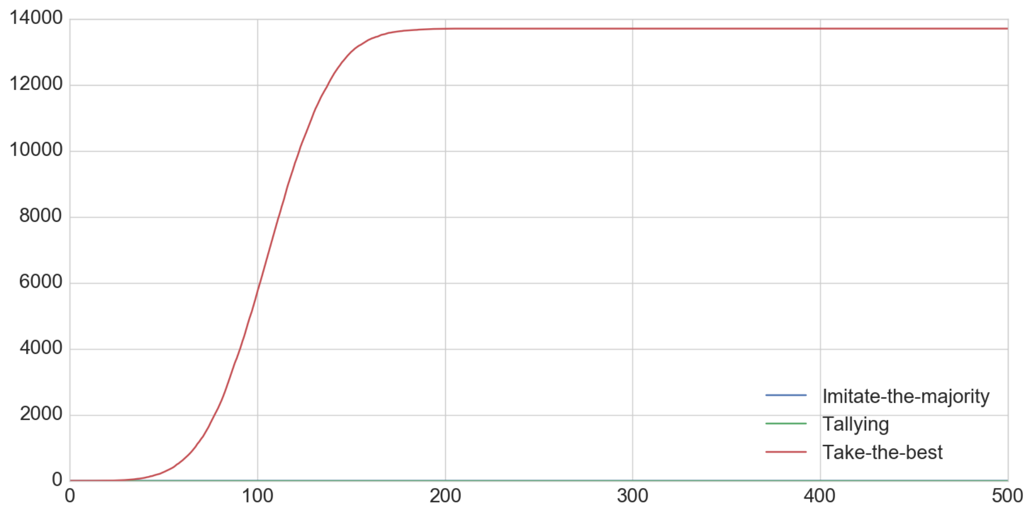

a) the dynamics of consumer entry; b) the average $\Delta_t^i$ for the whole population of consumers; c) the dynamics of the level of tolerance $\tau$ ; d) the level of total sales.

On the next section I will discuss the market configurations and consumer behavior of each experiment. The aim is to explain the patterns that emerge on the market configuration over time. I will start with Valente's original simulations.

### 4.1.1 Original experiments

On simulation 1 and 2, I replicate Valente's experiments. In these experiments, consumers only use the TTB heuristic (FIGURE 6), $\tau$ = 0.02 and $\widehat{\Delta}$ = 0 for the first simulation and $\tau$ = 0 and $\widehat{\Delta}$ = 1 for the second one. In other words, consumers on simulation 1 have a degree of tolerance which makes them indifferent to products that have a maximum difference of 2% on observed quality values and learn through experience how to read the true values of characteristics. Conversely, on simulation 2 consumers consumers are highly intolerant to differences in quality and never are able to assess the real products values. The results are presented on FIGURE 7 and FIGURE 8 where each line represents number of agents currently holding a specific product. Each product (and thus producer since each firm offers only one product) is identified with a different color and these colors are the same in all simulations runs.

FIGURE 6 – NUMBER OF AGENTS USING TAKE-THE-BEST



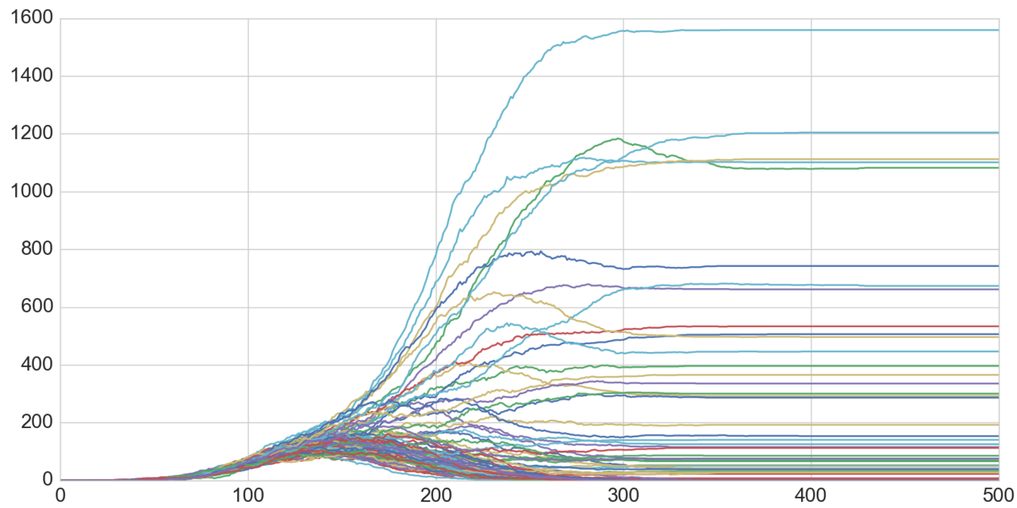

Source: Own elaboration (2017)

Valente (2012) calls the simulation 1 demand structure “complex segmentation”, where in the first time steps the high level of error of inexperienced buyers dominates the outcomes, so the products seem equal to each other and demand for them is almost equally distributed. On the second half of the simulation, the consumers have sufficient skills to assess the values of characteristics without errors and there market becomes segmented. On this stage, there are no more fluctuations because consumers systematically decide on the same products over time, because there are no more perception errors and the TTB always give the same results. The final configuration of this experiment is a market with various producers with a non-zero market share, with firms number 2, 36, 53, 54 and 96 having the highest proportion of the market[14].

Valente believes that the variety of products chosen by consumers is due to the variety on consumers preferences, because the TTB selection relies heavily on the ordering of the cues. Because the ordering (preferences) in this model is determined by a random market strategy vector (Table 4), this implies that preferences are equally distributed in the population. In other words, the probability of characteristic 1 being the first on the preference ranking of an consumer in the population is approximately the same as the other characteristics. Thus, the market demand is more evenly distributed.

[14] Producers are identified by numbers that range from 1 to 100. Each producer has the same line color assigned to it. The characteristics values of each producer are the same to all simulations.

FIGURE 7 – SIMULATION 1: COMPLEX MARKET SEGMENTATION

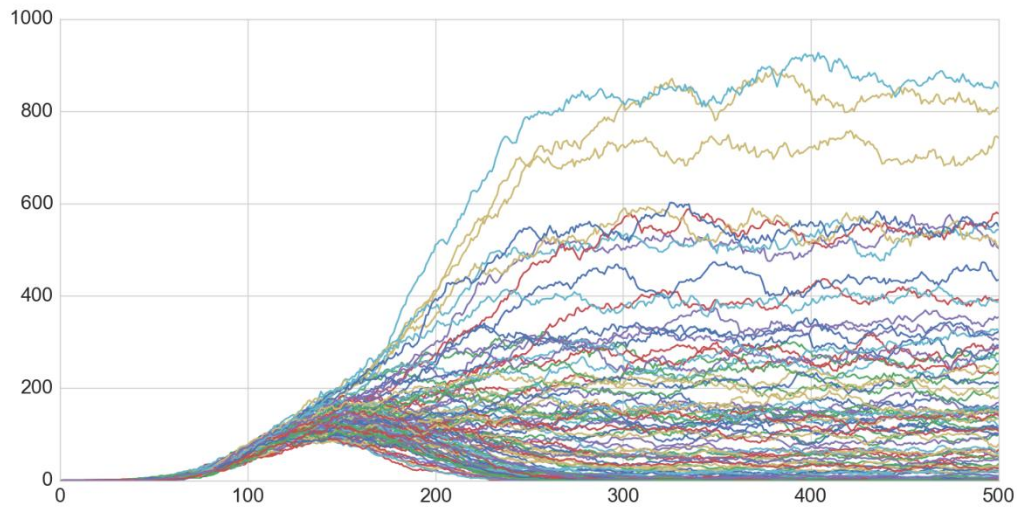



Source: Own elaboration (2017)

In simulation 2, there is also a complex market structure in which various firms have a non-zero market share. It starts the same way the previous simulation: the perception error prevails upon other factors and makes demand homogeneous. However, soon after the earlier stage of the simulation a different pattern emerges. The number of consumers currently using each product is noisy and fluctuates until the end of the experiment, with producers 29, 36 and 53 having the highest market share. Valente (2012) explains this pattern has two causes. First, the TTB with zero tolerance in a setting where the products values are randomly chosen real-values, only one characteristic is going to be evaluated – their values are not going to be the same, so only characteristic is enough to distinguish a product. The characteristic evaluated is the first on their preference ranking, which also is randomly chosen. Thus, the 10 firms with the best values on values on the 10 characteristics would have non-zero market share and the other would not be chosen.

Nevertheless, there is a second factor influencing the results: the perception errors are positive even in the latter stage of the simulation. Therefore, this complex pattern is caused by the random deviations in the reading of the real values, which induce the demand for products that otherwise would not be chosen. For Valente, this segmentation is caused by perception error, a very different explanation from simulation 1. The conclusions he draws from these experiments will be discussed later on this work. On the next section I will discuss the results using the TLL heuristic.

FIGURE 8 – SIMULATION 2: SEGMENTATION CAUSED BY PERCEPTION ERRORS




Source: Own elaboration (2017)

### 4.1.2 Experimenting with Tallying

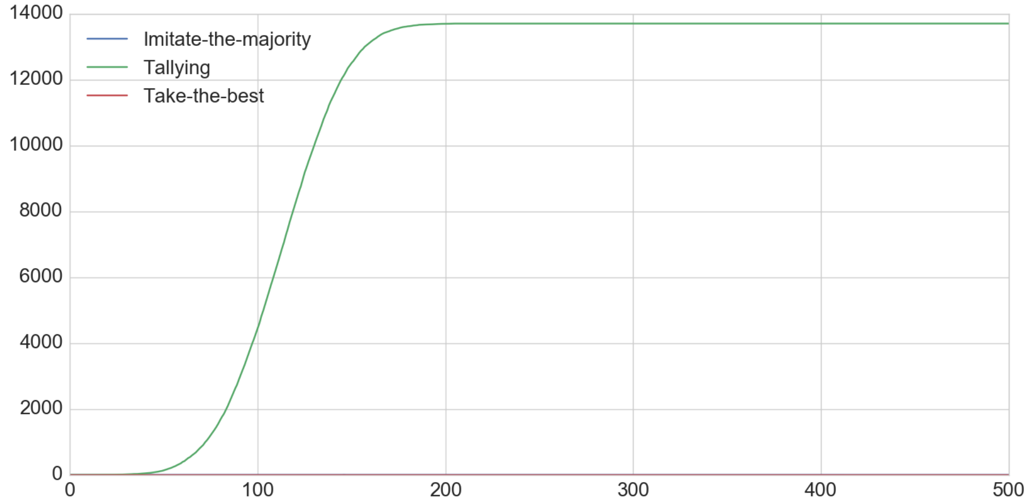
After the replication of Valente's results, I will adapt this model to use a different heuristics and study the impact of an alternative decision strategy on the results. In next experiments, I will only use the TLL heuristic (FIGURE 9). The TLL counts the number of positive cues and determines the product chosen as the one with the higher counting – in this case the cues are products' characteristics values. I already defined the criterion to define a positive cue: being a characteristic above the average, which in this case is 100. However, it still requires the definition of the number of characteristics to be evaluated as positive or not, the parameter $m$. In simulations 3, 4 and 5 I will test different number of characteristics taken in account by the TLL and investigate their impact on the demand structure of the market. As stated before, the characteristics of each product remain the same as in the other simulations.[15]

In the simulation 3 I examine a quite frugal TLL with m = 2. Only two characteristics randomly choosen from the pool of 10 characteristics per product will be assessed. The learning mechanism is working and for simplicity of the analysis, $\Delta$ and $\tau$ will be set to 0. The

[15] For example, the product from firm 1 has the same values in all simulations.

results presented in the FIGURE 10 are very interesting: the initial pattern remains the same, but on the last half of the simulation there is the emergence of market segmentation in groups with a persistent fluctuation pattern, even with no perception errors. This occurs because of TLL's search rule and the initial random search setting of characteristics value.

FIGURE 9 – NUMBER OF CONSUMERS USING TALLYING

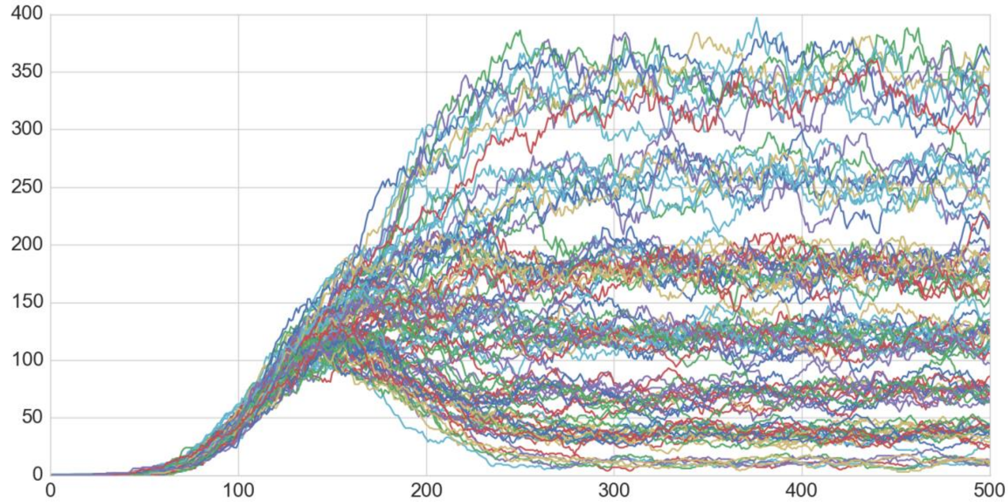



Source: Own elaboration (2017)

The products which have more values above the average will have a higher probability of having two positive cues, thus being chosen more often. Each one of the groups represents products with similar probability of having two positive cues. The fluctuation inside each niche is explained by the last step in the TLL algorithm: if options have the same tally, choose randomly. We had roughly seven "groups" of firms with similar number of consumers. The demand of each product is more evenly distributed because of the initial random setting of characteristics values which generated products with similar probabilities of having above average characteristics. So, the TLL is segmenting the marketing based on their superior probability of presenting a number of characteristics above the average. Let us now see what happens with this configuration if *m* – the number of characteristics used in the TLL algorithm – is increased.The producers of the group with highest market share were the firms 10,14,56,60,71,78,84,85,88 and 93.

In simulation 4, I use the same initial settings of the previous experiment, but I set m=5. Thus, I made TLL more cognitively demanding, in return inducing the demand of products with more qualities above the average. The outcome is a market much more concentrated and less diverse (FIGURE 11). We can identify only four niches in this experiment and the groups are better defined and are more divergent. Two firms stand out in the middle stage of the simulation, between the times steps 100 and 300. The peak on their demand is caused by the perception errors that are still occurring in that stage. This advantage quickly disappears after the consumers can perfectly observe products characteristics.

FIGURE 10 – SIMULATION 3: MARKETING SEGMENTATION IN GROUPS WITH TALLYING (m=2)

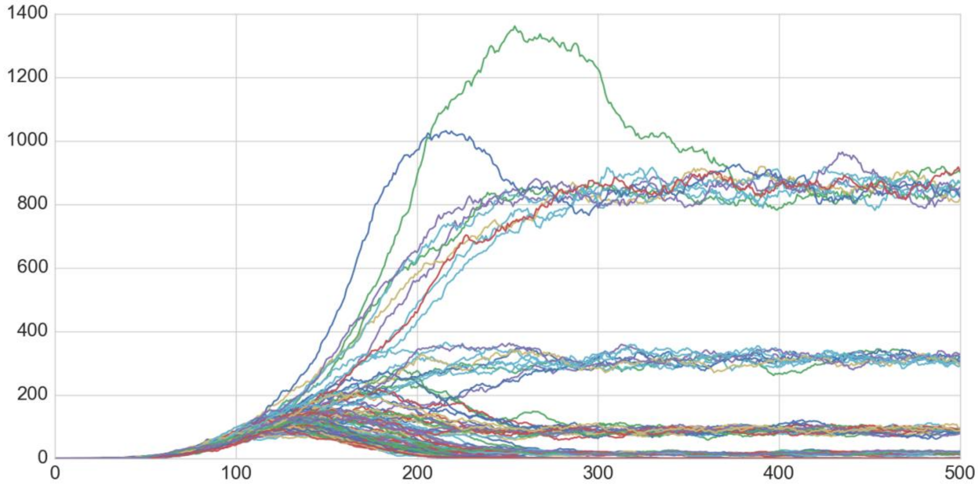



Source: Own elaboration (2017)

The quantity of products chosen in the most demanded firms oscillates around 900. In comparison, the group of firms with higher market shares in simulation 3 sells around 325 products. Interesting enough, the top ten producers in terms of market share are the same on both simulations – the producers identified by the numbers 10, 14, 56, 60, 71, 78, 84, 85, 88 and 93 are in the most demand groups in simulation 3 and 4. The TLL was capable of distinguish correctly between the even with a very frugal algorithm.

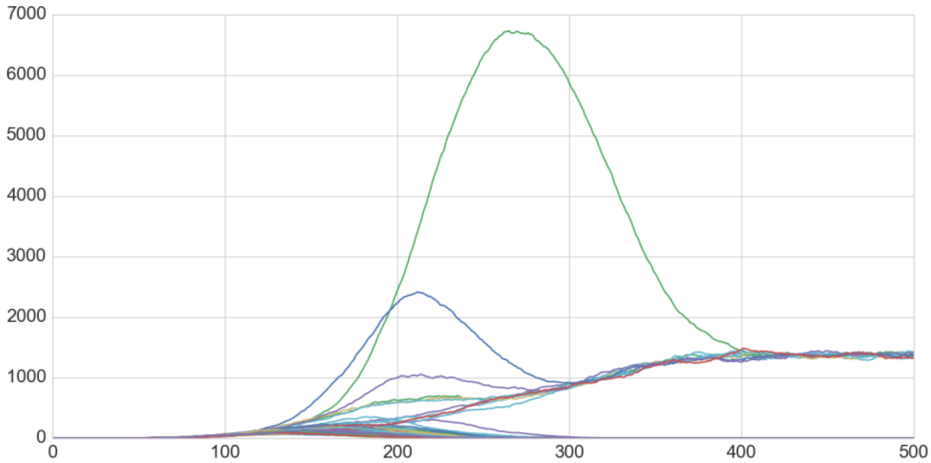
In the last experiment with the TLL, I will use the full power of this heuristic. In simulation 5, I set m=10 – the consumers will evaluate all products’ characteristics to determine a choice. In this extreme case, all the characteristics exhibited in the previous simulations are exacerbated, as we can see in FIGURE 12. The end market configuration is an oligopoly where only one group with few producers dominates the market while all the other firms have no demand for their products. Also, there are some peaks between the periods 100 and 300, also caused by the perception errors, though they are more prominent. These peaks in demand also disappear with the convergence of Δ to 0. Once more, the group with the highest market share is the same.

FIGURE 11 – SIMULATION 4: MARKETING SEGMENTATION IN GROUPS WITH TALLYING (m=5)




Source: Own elaboration (2017)

FIGURE 12 – SIMULATION 5: MARKETING SEGMENTATION IN NICHES WITH TALLYING (m=10)



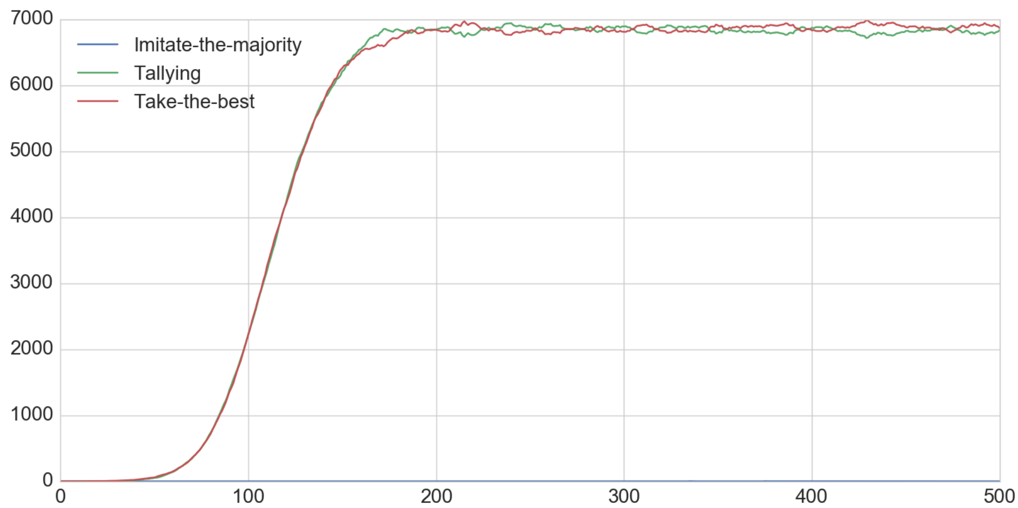

Source: Own elaboration (2017)

These results are expected – there are fewer producers with a high number of positive cues and the ones that reach the threshold will be chosen randomly every time a consumer replaces its product. Also as expected, the firms with a non-zero market share are the same 10 of the previous simulations and demand does not “leak” to products with less positive cues. With all these experiments, the patterns that emerge from the TLL use are already known. So, in the next section I will deal with a simulation where agents can use either the TTB or the TLL.

### 4.1.3 Using Take-the-best and Tallying

As we have seen the previous simulations, TTB and TLL produce very different results. In this section I propose to analyze what would happen if both of them were used. In one experiment I will introduce both heuristics in the adaptive toolbox of the consumers and they will have an equal probability of using either one of these decision strategies (FIGURE 13) – in this context, the tolerance level needs to be positive because it is the environmental trigger for the use of the heuristics. In the following simulation I will turn on the tolerance level dynamics established in the previous chapter – tolerance will starts higher and it will diminish over time linearly until it reaches zero and the consumer is intolerant to any difference in quality. The impact of this dynamic in the use of each heuristic is showed in FIGURE 14. I will also use a moderately frugal TLL, with m = 5. All the other settings are the same as the ones of the previous section.

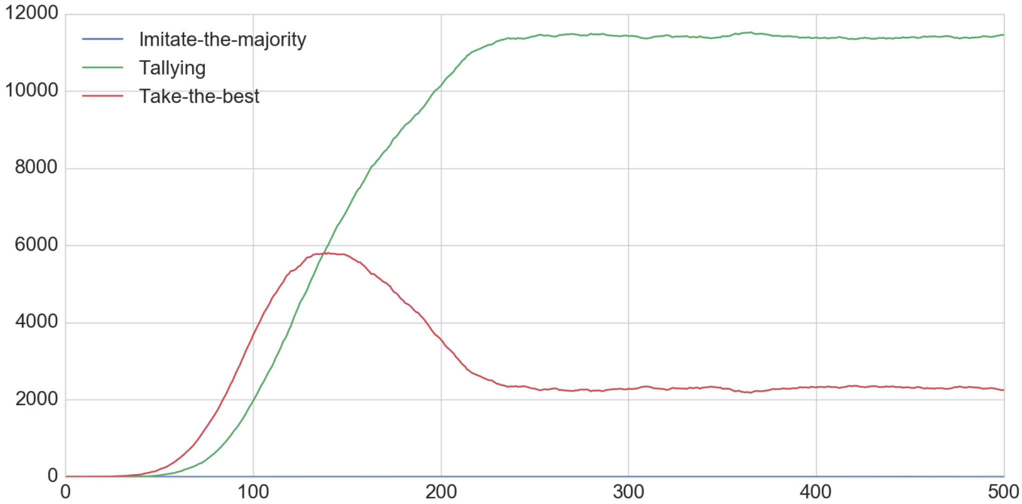
FIGURE 13 – HEURISTICS USED BY CONSUMERS (τ = 0.01)




Source: Own elaboration (2017)

The simulation 6 has the same initial pattern of the others simulations: small number of consumers with errors in value's evaluation prevailing over other factors. Then, the time step 200, there is a divergence in two groups. Some producers reach high market shares while others stagnate on a lower level. We have seen in section 5.1 that when $\tau > 0$ and $\Delta = 0$, TTB produce stable complex segmentation. However, the series present a noisy pattern and there is a gap between two groups of firms with roughly the same market share with the leaders being producers 2, 10, 14, 36, 53, 54, 56, 60, 71, 79, 84, 85, 88 and 96. These characteristics are probably due to the TLL heuristic. The constant changing between heuristics cause the noise and the gap is the result of the high market shares of firms with many positive cues. This can be confirmed by the prevalence of successful firms (2/3 of them) that also have high market shares in the experiment where consumers only use TLL.

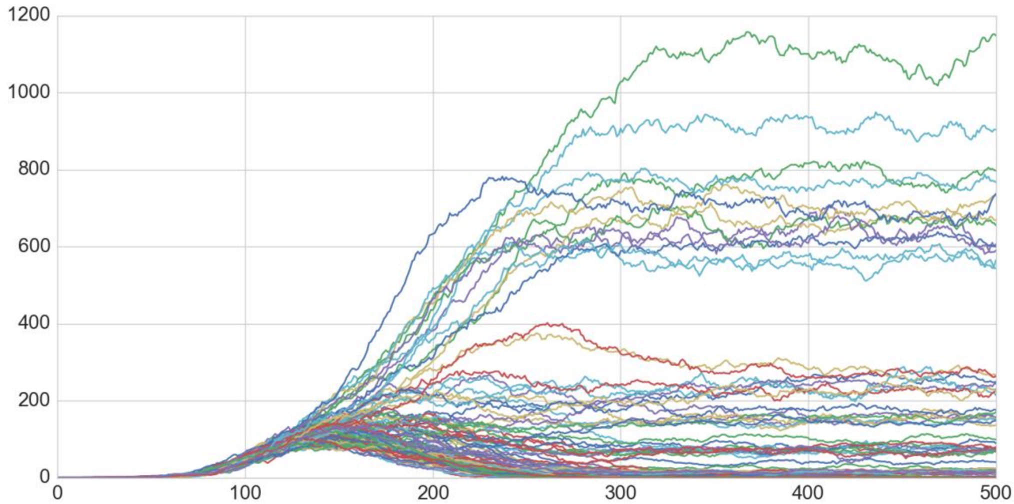
FIGURE 14 – HEURISTICS USED BY CONSUMERS ($\tau = 0.02 \rightarrow \tau = 0$)




Source: Own elaboration (2017)

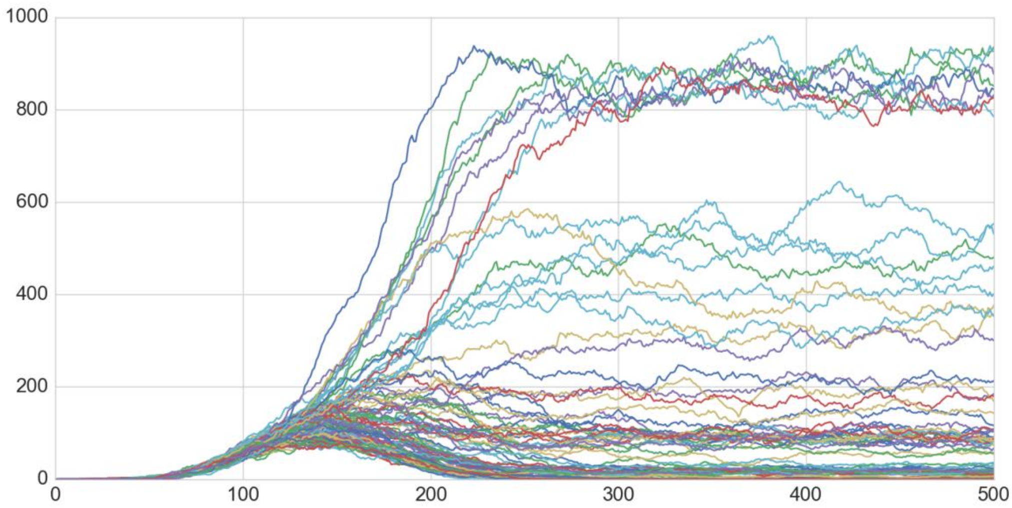
Simulation 7 presents a similar pattern. The difference is that the less successful group of producers is more numerous and has a higher market share than in the prior simulation. The firms with highest market share are 10, 14, 56, 60, 84, 85, 88 and 93. This is expected given that the number of TLL users is much higher than the TTB user in the final stage of the experiment. The TLL clearly dominates the end results, since all the producers with highest market shares are the same from the simulation with only the TLL. From these results, I can finally add the final heuristic to the pool of strategies of the individuals.

FIGURE 15 – SIMULATION 6: MARKET STRUCTURE WITH TAKE-THE-BEST AND TALLYING ($\tau = 0.01$)




Source: Own elaboration (2017)

FIGURE 16 – SIMULATION 7: MARKET STRUCTURE WITH TAKE-THE-BEST AND TALLYING
$(\tau = 0.02 \rightarrow \tau = 0)$

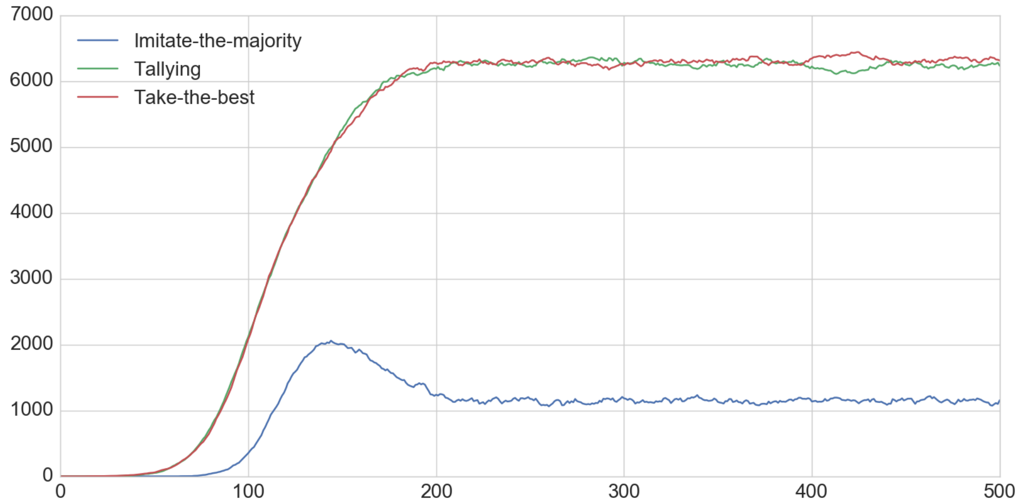



Source: Own elaboration (2017)

### 4.1.4 Including Imitate-the-majority

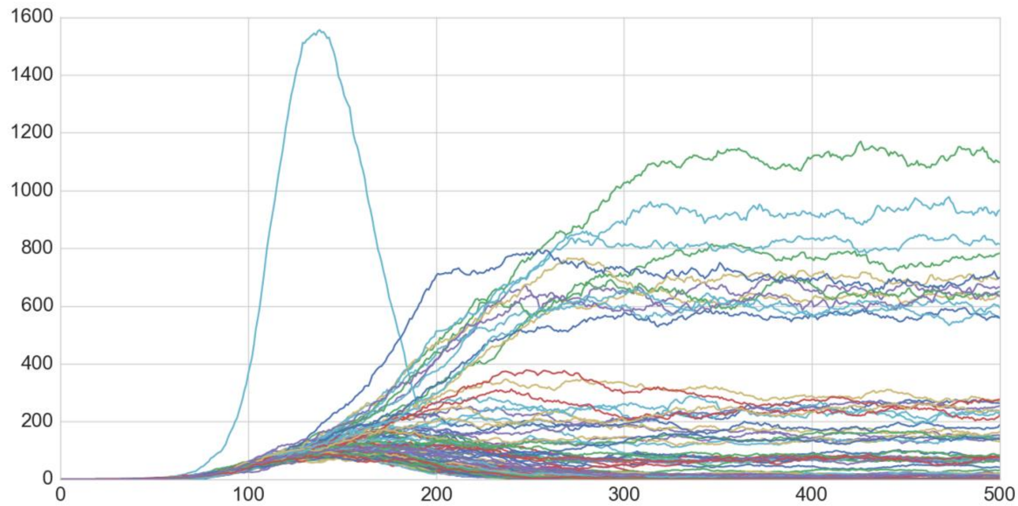
All these results given, it is time to include the ITM into the adaptive toolbox of the agents. With these experiments I aim to assess the impact of the ITM into the model. I will proceed in the following manner: I will gradually increase the share of final number of consumer which will use this social heuristics. The probability of using the ITM follows the consumers' entry dynamics in all experiments. What changes is the proportion of consumers relying on the ITM in the final stages of the simulation. This is made by manipulating the variable $\eta$, which in turn depends on $N_{max}$. I will gradually diminish $N_{max}$, thus increasing $\eta$ and the probability of using the ITM.

FIGURE 17– HEURISTICS USED BY CONSUMERS (τ = 0.01 and $\eta = 0.5$)




Source: Own elaboration (2017)

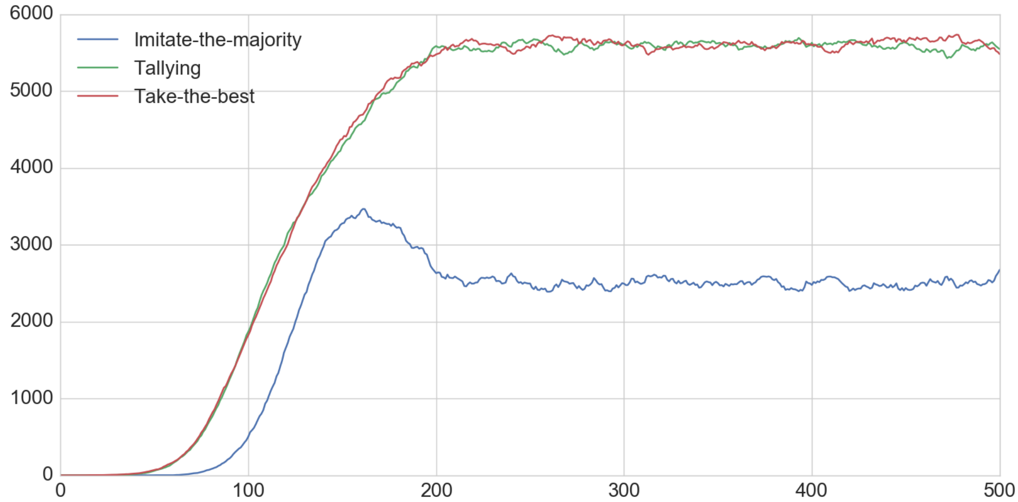
FIGURE 18 – SIMULATION 8: MARKET STRUCTURE (τ = 0.01 and $\eta = 0.5$)




Source: Own elaboration (2017)

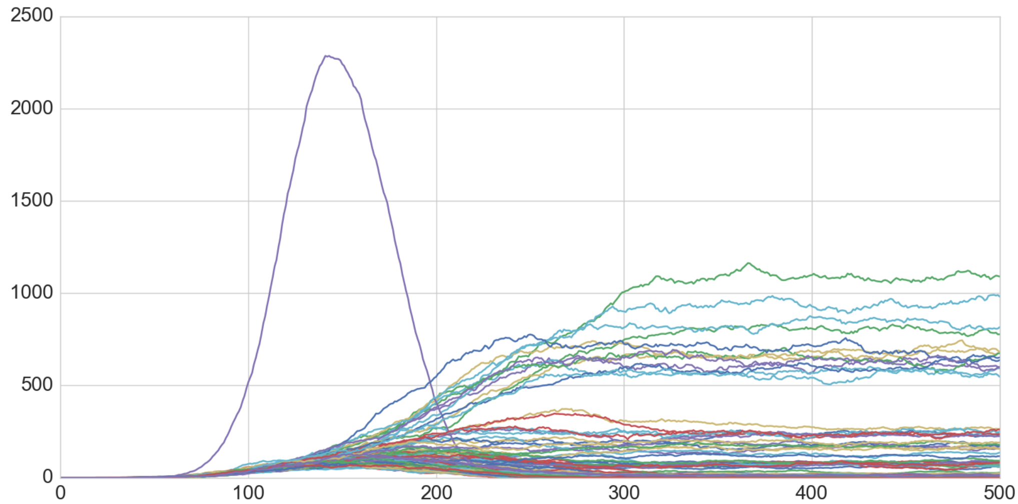
I will use in the experiments a TLL with m=5 and $\tau$ =0.01, which yields an equal probability of use of TTB and TLL. This setting is defined due to simplicity of analysis. In simulation 8 I will set the late stage $\eta = 0.5$, then in simulation 9 I will set $\eta = 0.75$ and finally in simulation 10 I will set $\eta = 1$.The resulting dynamics are presented in FIGURES 18, 20 and 22. With a low $\eta$, just a small proportion of the consumers population uses the ITM. This shares increases with a higher $\eta$ until it reaches 100% of the consumers using ITM in the most extreme case.

FIGURE 19– HEURISTICS USED BY CONSUMERS (τ = 0.01 and $\eta = 0.75$)




Source: Own elaboration (2017)

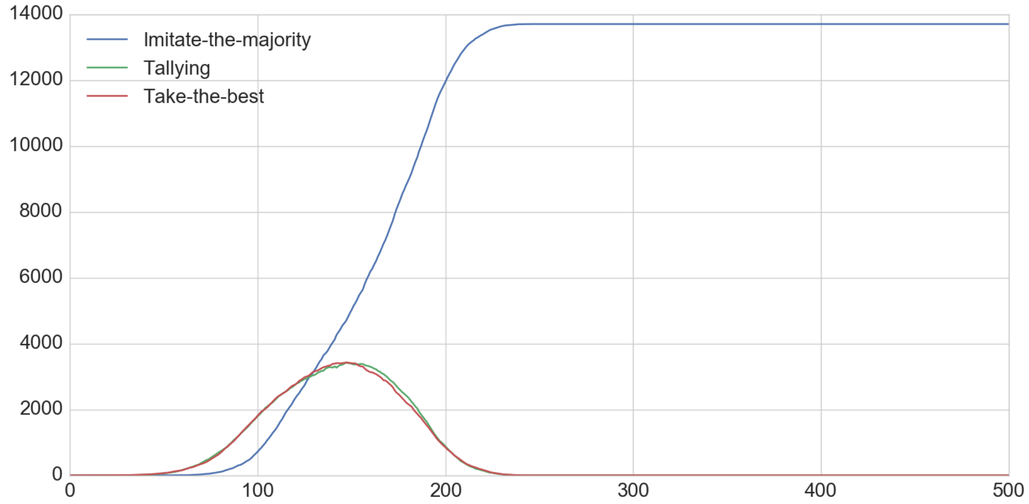
FIGURE 20 – SIMULATION 9: MARKET STRUCTURE (τ = 0.01 and $\eta = 0.75$)




Source: Own elaboration (2017)

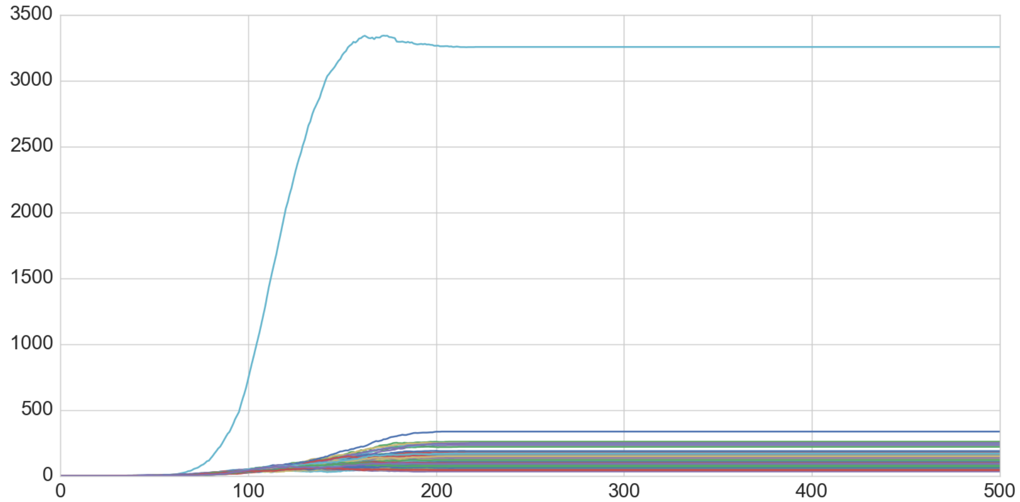
The first noticeable emerging property in the results with the ITM incorporated is a bell-shaped curve in the time series of a producer in the first half of the simulation. This feature it is explained by the structure of the environment in which the ITM is being used. As I have discussed before, in the first period the consumers are poorly trained to assess characteristics values, thus they treat most products as homogeneous. However, at the same time perception errors are high, the number of consumers is rapidly increasing, inducing the use of the ITM. So, any product that stands out in the first time steps have a substantial boost on their sales. The initial boost wears off though, because the consumers progressively learn to read the real values of the products and perceive the products the acquired are not the best on the market. The highest market shares in simulation 8 are from producers 2, 10, 14, 36, 53, 54, 56, 71, 79, 84, 85, 88 and 96.

FIGURE 21– HEURISTICS USED BY CONSUMERS (τ = 0.01 and $\eta = 1$)




Source: Own elaboration (2017)

FIGURE 22– SIMULATION 10: MARKET STRUCTURE (τ = 0.01 and $\eta = 1$)




Source: Own elaboration (2017)

This bell-shaped pattern occurs in simulation 8 and 9 on the first half of the experiment, when the ITM dominates the market outcomes. On the last half of the simulation, the perception errors are low enough so the other heuristics are able to prevail over the influence of the ITM. In fact, the ITM only reinforces the results of the other heuristics in the latter stages of the simulation. Even the leader firms in market share are the same. This situation does not repeat itself in the simulation 10. In this experiment, the producer 36 stands out in the beginning and maintains its lead until the end. This happens as a result of the positive feedbacks of the ITM algorithm. In the second half of this simulation, consumers stop using the nonsocial heuristics. Then, the ITM dominates and guarantees the leader maintain its position even with experienced consumers.

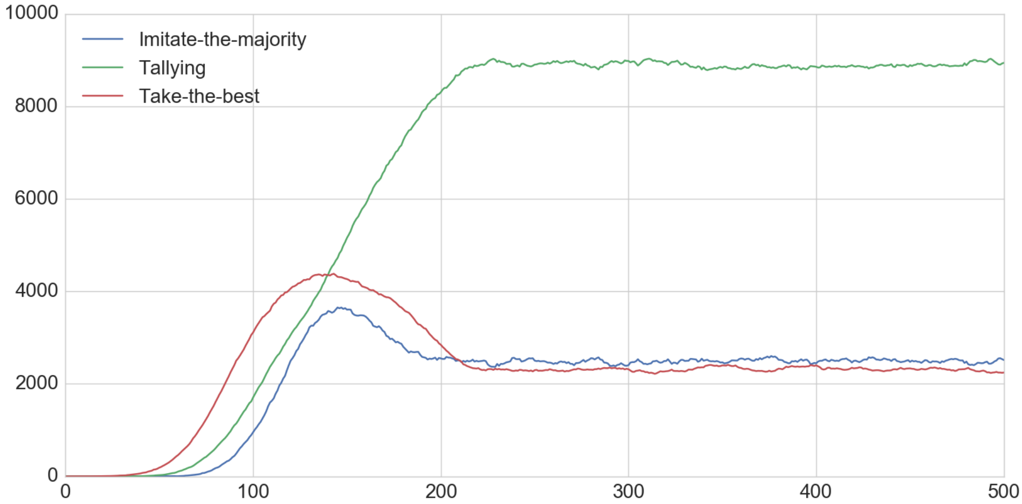
We could say that the use of ITM with less experienced consumers lead to an error in assessment of the best products and ITM was not ecologically rational. But as the learning process takes place, ITM becomes more adapted to the structure of the environment because it exploits the outcomes of the other two heuristics. The power of the ITM relies on the "outsourcing" of cognitive effort to other consumers. If these other consumers make are mistaking, then ITM gives suboptimal results. Conversely, when the ITM is used in a context where the majority is using ecologically rational heuristics, its outcome improves significantly.

### 4.1.5 Replicating the original experiment with the adapted model

The last experiments proposed in this dissertation will test similar settings of the original simulations in Valente (2012). As explained in the prior sections, Valente's experiments vary the value of two parameters, $\tau$ and $\Delta$. I will do the same with the model with all the adaptations – the adaptive toolbox and the dynamic structure of the environment. Then, I will compare the results with Valente's outcomes and verify if his conclusions hold in the exercise with our model.

In simulation 11 and 12 I will set $\Delta$=0 and (final) $\tau$=0.02 and $\Delta$=1 and (final) $\tau$=0, respectively. The common settings in this experiments are a moderate TLL with m=5; a low level of use of ITM with $\eta = 0.75$; and a dynamically changing level of tolerance $\tau$. The dynamics of heuristics used on both experiments is represented by FIGURE 23. With these settings, I mirror Valente's exercises to investigate the effects of changes in tolerance and perception in our model.

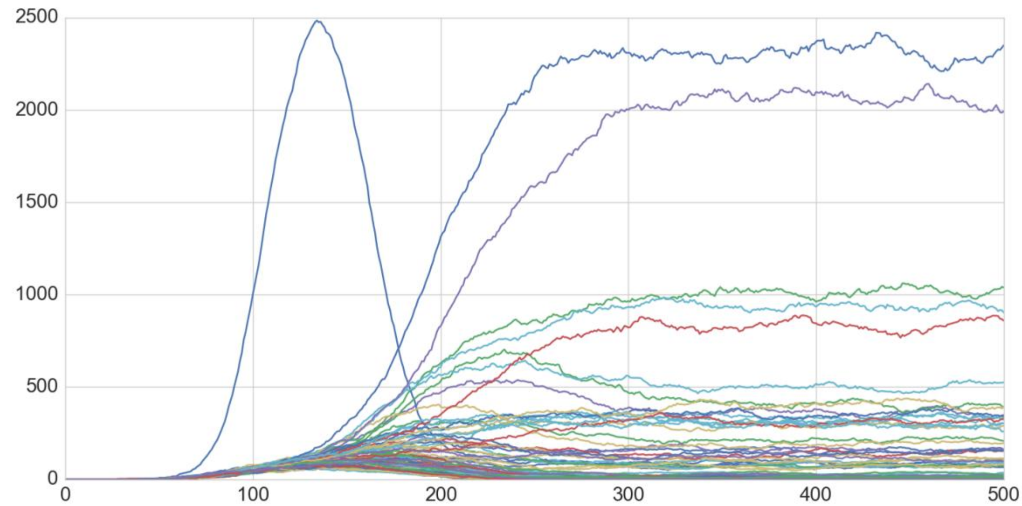
FIGURE 23– HEURISTICS USED BY CONSUMERS ($\tau = 0.04 \rightarrow \tau = 0.02$ and $\eta = 0.75$)




Source: Own elaboration (2017)

In simulation 11, we can see the bell-shaped pattern caused in the early periods of the experiment, the fluctuation in products chosen in latter stages and the segmentation of the structure of the market in different niches. Some of these features are easily explained by the factor already explored in previous sections. The bell-shaped curve is caused by the ITM, the market segmentation in niche is caused by the TLL. However, the fluctuation is not caused by the TTB, but by the randomness embedded in the definition of heuristics used. With Δ=0, the TTB yields flat time series because the algorithm always lead to the same choices. The final configuration is caused by the full unfolding of the dominant TLL heuristic, with firms 85 and 88 with top market share, followed by producers 14, 54,93.

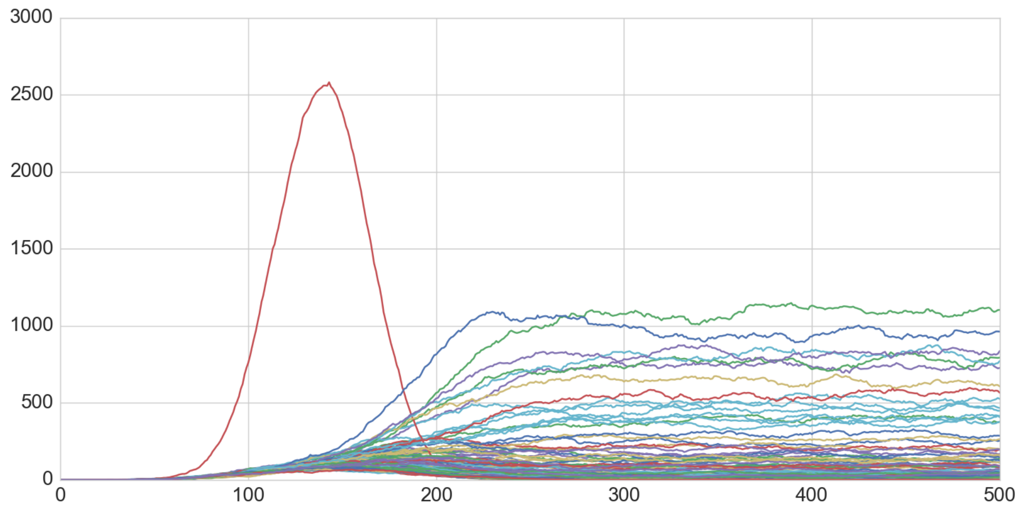
FIGURE 24– SIMULATION 11: MARKET STRUCTURE ($\tau = 0.04 \rightarrow \tau = 0.02$ and $\hat{\Delta} = 0$)




Source: Own elaboration (2017)

In simulation 12, the same bell-shaped pattern in the beginning of the experiment is present, but segmentation does not demonstrate a niche pattern. Furthermore, the market is remarkably less concentrated, even though the majority of consumers are using the TLL. Then, the only conclusion possible is that the sustained perception errors are causing the products to appear more similar and thus making difficult for the TLL or the TTB to differentiate several categories of products based on their qualities. The highest proportion of the market is held by firms 10, 14, 56, 60, 84, 85 and 88.

FIGURE 25 – SIMULATION 12: MARKET STRUCTURE ($\tau = 0.02 \rightarrow \tau = 0$ and $\widehat{\Delta} = 1$)




Source: Own elaboration (2017)

As we can conclude from the analysis of the demand structure of these two experiments, it is clear that the original findings of Valente’s simulation still holds for the adapted model presented in this dissertation. On both simulations 1 and 11, the market segmentation is caused by the internal mechanism of the dominant heuristics: the TTB on Valente’s model and the TLL on our model. On the other hand, simulations 2 and 12 have the same underlying cause for their market segmentation: perception errors drive the structure of the demand.

## 4.2 DISCUSSION

The results of the simulations suggest that the inclusion of other fast-and-frugal heuristics in Valente (2012) model had a significant impact on the dynamics without changing the general conclusion of his experiments. This is the result of the conservation of most of Valente’s model framework and the main evolutionary ideas incorporated in it. However, the different dynamics and market structures that emerged from our simulations suggests that the incorporation of different heuristics and the modeling of the structure of the environment is an advancement of the model insofar it brings more realism and sounder basis for its decision process mechanism. Furthermore, it does so without breaking the evolutionary economics assumptions identified in the literature of evolutionary consumption models.

The bounded rationality principle and the fundamental uncertainty hypothesis are respected in this dissertation model if we acknowledge the fast-and-frugal heuristics program interpretation of the term. Furthermore, agent heterogeneity naturally emerges from this approach to bounded rationality: as the agents are not perfectly adapted to their environments (GIGERENZER; GAISSMAIER, 2011), it is necessary to model the selection of heuristics in a manner that does not force all consumers to use the ecologically rational heuristics at all times. In our model, agents use different heuristics at different times.

Endogenous and path dependent preferences are retained from Valente's model, but with a significant difference – there are various preferences sets in our model. When a consumer use the TTB, their preference is defined by Valente's marketing mechanism. However, when the consumers use the TLL, this mechanism is not used and the preferences are defined by the amount of characteristics above the average. When the ITM is used, the agents' preferences are defined by the popularity of a product – consumers desire the most accepted product, not necessarily the ones with higher advertising nor the ones which more features above the average. In our framework consumers could be interpreted as having multiple motivations and preference formation mechanisms which change dynamically according to the structure of the environment.

The learning mechanism of Valente's model is preserved and a new one is included: the social learning strategy of the ITM, where agents learn from others how to consume. This is a simple way of modeling learning process, yet it had significantly altered the results – it lead to the consumers in the beginning of the simulation to temporally concentrate the market in one firm. An evolutionary economic interpretation of these results may use refer this dynamic with empirical analysis of industry life-cycles where an early market leader looses market share as the market develops.

It is also possible to interpret the results in a manner that indicates the presence of habits and routines. I have argued in section 2.3.2 that the ITM intrinsically incorporates the idea of habit as a propensity to behave. Furthermore, in simulation 10, all the consumer use ITM in the finals stages of the experiment and replace the products by the same they have last purchased, which suggests a routine behavior has emerged. However, I admit that the habits and routine aspects of the model are somewhat implicit and are open to other interpretation.

Nevertheless, the main finding of these simulations is the profound impact of the decision processes had in the market structure. Each simulation had a unique dynamic and a different set of producers as leaders. For instance, in simulation 11 the two firms with highest market share had between 2000 and 2500 products being held by consumers in the last stages of the simulation. In simulation 12, the market leaders barely reached 1000 products. The addition of the ITM drastically changed the dynamics of the initial periods of the market and the various level of frugality of the TLL promoted the emergence of a niche market segmentation that became more concentrated as the "strength" of the heuristic increased.

In sum, the results reinforce Valente (2012) conclusion: demand matters. The process consumers used to purchase products in our model influenced firms' performance and the industry life cycle. Consequently, it could be argued that the firms' ideal strategies in each scenario would have changed. Furthermore, in our model the changes in the information structure of the environment of decision induce and adaptive response of the consumer, which unveil the complexities faced by the firms in a situation where agents change their decision procedures.

# 5 CONCLUSION

Evolutionary economics is as well established approach in economics that has presented various theories to explain the most diverse economic phenomena. Nevertheless, I argue in this dissertation that the demand side of the theory is underdeveloped. In order to provide insights into demand side theorizing in evolutionary economics, this research investigates the consumption behavior in an evolutionary economics perspective. I identify typical assumptions in evolutionary economics in which a consumer theory may be built, present the fast-and-frugal heuristics research program – a psychological theory that may contribute to evolutionary research efforts in consumption behavior – and propose an agent based model of consumption in which the basic tenets respect both evolutionary economics and fast-and-frugal heuristics program principles.

After situating the research efforts into the evolutionary economics literature, I identified some typical features of an evolutionary theory which could be used to model consumer behavior. The features identified in this dissertation were: bounded rationality and heterogeneous agents; endogenous and path dependent preferences; fundamental uncertainty; learning; and routines and habits. These basic assumptions of evolutionary theory were identified through the use of bibliometric evidence (HODGSON; LAMBERG, 2016; SILVA; TEIXEIRA, 2009), surveys (SAFARZYNSKA; VAN DER BERGH, 2009; WITT, 2008) and a review of evolutionary economics consumption models.

In order to overcome the difficulties in modeling evolutionary consumption models, I introduced an approach in the psychological literature that could contribute to advance the evolutionary economics theories in consumption: the fast-and-frugal heuristics program (GIGERENZER; SELTEN, 2001). In this approach, which was inspired by Herbert Simon's bounded rationality, the cognitive mechanisms called heuristics play a major role in explaining human decision-making. Heuristics are rules of thumb, cognitive strategies that ignore information to make frugal and accurate decisions. These authors believe agents have an "adaptive toolbox", a collection of heuristics and their building blocks which provide the main decision strategies to the individuals. When a heuristic can exploit the decision environment to make accurate decisions, it is considered an ecologically rational strategy. I argue that this framework have strong synergy with evolutionary economics and can provide new insights to consumer theorizing efforts.

After reviewing the evolutionary economics investigations into consumer behavior and the fast-and-frugal heuristics approach, I develop an agent based model (ABM) featuring the main assumptions identified in each of these approaches. ABMs aim is to model adaptive systems and analyze their properties in a bottom up perspective (Pyka and Fagiolo, 2007). I argue that this is a modeling approach well suited to deal with an evolutionary economic phenomenon using simple heuristics. I propose a model framework – based on Valente (2012) – to analyze a semi-durable market evolution with agents using different decision strategies (i.e., heuristics) that can change depending on the structure of the environment in each stage of the market development.

Having developed an appropriate model, I investigate the implications of the inclusion of three heuristics (Take-the-best, Tallying and Imitate-the-majority) in the market structure and dynamics through a series of computer simulations. Based on these simulations, I confirm that the different heuristics decision process affect the dynamics of the market evolution, the firms' performance measured by sales and consequently the market concentration. I also replicate the experiments in Valente (2012) with the adapted model of this dissertation and reached similar results: the simulation of market configuration is determined by consumers' perception and decision strategies. These outcomes are in agreement with evolutionary economics literature in consumption models and the bounded rationality interpretation of the fast-and-frugal heuristics research program, which lead us to believe that the model presented achieve the aims proposed in this dissertation.

From an academic perspective, this research contributes to the growing literature on agent based models related to evolutionary economics. Furthermore, it also advances the interdisciplinary efforts in evolutionary economics providing microfoundations for a consumer theory based on the psychological literature that are compatible with the tenets of evolutionary economic theory. More important, this dissertation contributes to the understanding of the microfoundations of the demand side of evolutionary economics. Understanding the real-world strategies used by the consumers to decide which product they will purchase may enhance the comprehension of evolutionary economists of the demand-side drives that underlie phenomena like innovation, path dependency, consumer learning, and routine formation.

Although this research has achieved the goals proposed in the dissertation, there are still some limitations. First of all, a broader review of evolutionary economics could give more insights for the development of an agent based model of consumption. A more meticulous and systematic review could provide this broader view. In addition, due to time and computational constraints, the model presented in the dissertation was not tested for the robustness of the results. The robustness of ABMs outcomes are normally assessed by the variation of the initial settings and the random events programmed which could provide the data for the statistical analysis of the results. Moreover, although the model is explicitly designed to be a general theoretical model, it would be interesting to validate it empirically using data from real world market development. This would enhance the realism claims made in this dissertation and provide evidence to support this model framework.

In the future research the proposed framework can be expanded to accommodate more heuristics which could multiply the possible scenarios in which this model could be applied. It also would be interest to add more heterogeneity between agents implementing groups with different budget constraints, levels of tolerance and heuristics available to the consumers. Different preference formation mechanisms can be proposed based on the available in the cognitive and social psychology literature. The next step would be to improve the supply side with the insertion of innovations and a free entry dynamics which would make possible to analyze the impact of decision-process in a context where demand and supply interact. Moreover, this model could be adapted to be validated empirically with data of actual industry life-cycles.

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