AGENT-BASED APPROACHES TO THE STUDY OF HUMAN BEHAVIORS

Jean-Daniel Kant
To Jean-Pierre Barthélemy and to my father Michel Kant, in memoriam.
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<th>Description</th>
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<tr>
<td>ABM</td>
<td>Agent-Based Model</td>
</tr>
<tr>
<td>COBAN</td>
<td>Communication of Beliefs using Associative Networks</td>
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<tr>
<td>CODAGE</td>
<td>Cognitive Decision AGEnt</td>
</tr>
<tr>
<td>De-C GCM</td>
<td>Decentralized Garbage Can Model</td>
</tr>
<tr>
<td>FDC</td>
<td>Fixed Duration Contracts (CDD)</td>
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<tr>
<td>GC</td>
<td>Garbage Can</td>
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<tr>
<td>GCM</td>
<td>Garbage Can Model</td>
</tr>
<tr>
<td>HC</td>
<td>Human Capital</td>
</tr>
<tr>
<td>HSS</td>
<td>Human and Social Sciences</td>
</tr>
<tr>
<td>MAS</td>
<td>Multi Agent System</td>
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<tr>
<td>RALF</td>
<td>Reinforcement and Attentional Learning Framework</td>
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<tr>
<td>OEC</td>
<td>Open Duration Contracts (CDI)</td>
</tr>
<tr>
<td>OWA</td>
<td>Ordered Weighted Average</td>
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<tr>
<td>TA</td>
<td>Tree of Alternatives (in CODAGE)</td>
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<tr>
<td>WOWA</td>
<td>Weighted Ordered Weighted Average</td>
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INTRODUCTION

When one decides to begin the writing of his/her Habilitation, it is usually not with a happy smile. Not that we are lazy, but as academics, we are faced with the daily stream of all the tasks we have to complete, and having a break is not that easy. Moreover, what is the point of turning back on the past, to tell stories already finished, to devote time to things already done, when research is all about future and innovation?

Now that I have completed the exercise, I must admit I found it very stimulating to analyze in retrospect what I have done these last years. Broadly speaking, my work has actually tried to serve one purpose: to contribute to the study of the human systems’ behavior. By human system, I mean any system composed of one (individual) or several (collective) human beings, in interaction with each other or with some environment.

In this document, I will try to show how computational approaches – mostly multi-agent systems – could contribute to a better understanding of some human behaviors. Before going into more details, let me discuss first how this could be theoretically possible; in other words, how could Human and Social Sciences – the very sciences devoted to the study of human behavior – could benefit from Computer Science, and in what respect this contribution differs from the one provided by mathematical methods.

1.1 COMPUTER SCIENCE CONTRIBUTION TO HUMAN AND SOCIAL SCIENCES

First of all, what are the peculiarities of the Human and Social Sciences (HSS)? Their object is the realities of the human beings. According to Dépetleau, we have to face four main difficulties when we aim to study HSS (Dépelteau, 2010, p.78-93):

- **Complexity** – Human systems are complex systems, in the sense that they are unpredictable, made of a large number of heterogeneous elements and subject to many interactions, whether they are within a group or a society. There is a circular feedback loop between the (micro) level of the individuals and the (macro) level of social emergent phenomena. Each level is continuously undergoing transformations, the micro level transforms the macro level that will transform the micro level and so on. A complex system cannot be reduced to a simple one, the complexity is at the core (Morin, 1977, p. 377).

- **Subject and Object** – In the natural sciences, the subject (i.e. the researcher) and the object (the trees, the sea, the stars,...) are of different nature. With HSS, both subject and object are human. It is then difficult to avoid biases, subjectivity or prejudices, depending on our opinions, culture, beliefs... This is why Max Weber appealed for what he called an axiological neutrality (Weber, 1965). It implies to discriminate what comes from the empirical facts and what comes from our subjective judgment; the latter must not interfere with the former.

---

1In my work, the concept of emergence refers to the usual definition found in complex systems theory: the formation in a system – thanks to self-organization – of a pattern or feature or structure, which could not be reduced to a component or property of this system (e.g. Goldstein, 1999)
• **Freedom, scientific laws and determinism** – Unless s/he is constrained or imprisoned, a human being is free. This is a good news for humans but a bad one for the researcher in HSS. If the human is free, s/he is free to deviate from the scientific laws, which are in most cases too normative. This is particularly true when we produce general laws, based on a ideal (and imaginary) representative agent for instance.

• **Explanation and comprehension** – Humans act according to their objectives, these acts have *purposes* (most of the time). Science usually looks for *causalities*, it seeks to explain a particular phenomenon by finding its cause, using different modes of reasoning (induction, deduction, abduction, etc.). With HSS, we need to add comprehension to explanation, in order to study the *meanings* of the human actions, trying to produce a sort of *hermeneutics*.

Any model of human behaviors will have to face these difficulties, and I will use them to assess computational models, and especially agent-based models. But I need to define first what a computational model is and how it could contribute to HSS.

### 1.1.1 What is a computational model?

When I aim to propose a computational approach to HSS, it roughly means I intend to build computational models of human behaviors, and then simulate them. But what do we mean by computational model and in what respects does it differ from other types of models, like the mathematical ones?

First of all, there are many definitions of what a *model* is (Armatte, 2005). Broadly speaking, a model aims to (1) make intelligible a complex phenomenon, and/or (2) make possible experimentation, simulation and prediction. In the modern sciences, a model is thus both a theory (1) and a tool (2). Besides, a model is always a simplification of the reality, and is designed to answer a particular problematic. As underlined by Minsky, “*To an observer B, an object A* is a model of an object A to the extent that B can use A to answer questions that interest him about A.*” (Minsky, 1965). Here we introduce the concept of the usefulness of a model: it enables to learn something on the system we study.

How to define a *computational model*? Following Sun, we can state that “*Computational models (broadly defined) present process details using algorithmic descriptions. Mathematical models presents relationships between variables using mathematical equations. Verbal-conceptual models describe entities, relations, and processes in rather informal natural languages*” (Sun, 2008, p.2).

More precisely, a computational model must specify:

1. the atomic entities that form the system (e.g. actors)
2. the data exchanged by these entities (information, knowledge,...)
3. the data processing (perception, reasoning, decision,...)
4. the flows, the data exchanges between the entities

Here we focus on *information processing* processes. The computational model emphasizes the *behaviors*, which have to be made explicit in order to be implemented (programmed). This has a significant impact on modeling. When we model an individual behavior, we must detail what the agent will do, how it will decide, reason, etc. If we focus on collective behavior, we will detail the interaction between the agents. Eventually, we use an agent-based model (ABM) to make social structure emerge from these interactions. The ability to enable such an emergence is the very quality of ABMs that make them useful in social sciences (Gilbert and Troitzsch, 2005).

Another important feature of a computational model is to enable *experiments in silico*. When it is difficult, impossible or irrelevant to produce a formal model, we can start with
computational model – even simple and incomplete, simulate it, vary its parameters, analyze the results to progressively enrich the model. This approach is called Simulation Modeling. If we want to tell something relevant about real model, we must build a realistic model and first define what realistic actually means for a computational model. I will address this issue in the section 1.3 below, devoted to methodology. Now let me say some words about the type of computational models this work deals with: the agent-based models.

1.1.2 Agent-based models: the multi-agent paradigm

An agent-based model is made of computational agents. These agents interact with each other and forms a multi-agent system. An agent is an autonomous and proactive entity. It communicates with other agents (for instance through message sending), is driven by a set of drives, goals and satisfaction. The agent has its own resources and skills and can provide services. It is capable of perceiving (but only partially) its environment, and has a limited representation of this environment. It could also be able to learn. Finally, a multi-agent system usually reflects a certain form of organization (for more details on multi-agent systems, see e.g. Ferber, 1999; Wooldridge, 2002; El Fallah Seghrouchni, 2009).

The multi-agent paradigm has a lot of potential benefits: it brings heterogeneity into the system (the agents are heterogeneous), could implement any kind of interactions and organization, and emphasizes dynamics. Moreover, according to Epstein, agent-based models allow to provide a new way to tackle HSS by building a generative social science (Epstein, 1999). In this approach, every cognitive and social construct must emerge from the agents’ interactions, it has to be generated by the model and the simulation, instead of being given a priori. But this is not enough to provide an explanation of the real phenomenon. As underlined by Epstein, being able to generate a macro-structure from local interactions is only a necessary condition to be a candidate explanation, it must also do it in a realistic enough way at the micro-level.

This is the central issue of the micro-foundation of a model, I will come back to this issue below in section 1.3, where I detail the methodology I followed. Note that I defend here a quite demanding vision of what micro-foundation must be. Not only it prescribes to look at the individual behaviors (like in micro-economics) but these behaviors must be modeled in the most realistic possible way. To do so, I propose to

1. derive the model (and especially of the individual behaviors) from theories, facts, and data that are robust and empirically grounded;

2. use a data-driven approach, and validate the model on real data;

3. at the implementation level, ensure that the program stays compatible as much as possible with the conceptual model and do not violate its core principles (like bounded rationality). This comes from my psychomimetism theory (see 1.3 below).

Finally, beyond explanation and generativism, David et al. identified three forms of knowledge to account for a simulation: formal, empirical and intentional, and emphasize the role of intentionality of programming languages (David et al., 2005, 2006). The intentions of the programmer and the observer must be taken into account.

1.1.3 The (unavoidable) comparison with mathematical models

Mathematical models hold an important place in Science. Originated in Physics, they become quite popular in Social Sciences and dominate Economics. The acclimatisation of Science is a characteristic of modern sciences, and is viewed as a way to model the laws of Nature, and especially the causalities. Some might want to go further, as within the Vienna Circle that sees mathematics and mostly logics to be the only way to clean Science from its “metaphysical
misleading generalizations” (Armatte, 2005, p.88). Another quality the mathematical models possess lies in their ability to reconstruct a whole class of phenomena in Physics with only a reduced set of equations (Petitot, 1998). However, this re-constructive power is limited by the empirical imperative: the model must account for data and even more be grounded on reality. As stated by Albert Einstein – who used a lot of maths to develop his theories: “How can it be that mathematics, being after all a product of human thought which is independent of experience, is so admirably appropriate to the objects of reality? Is human reason, then, without experience, merely by taking thought, able to fathom the properties of real things? In my opinion the answer to this question is, briefly, this: as far as the propositions of mathematics refer to reality, they are not certain; and as far as they are certain, they do not refer to reality” (Einstein, 1921).

Of course, this appeal for realism in the models would apply for any kind of models, not only the mathematical ones. But because they could be normative and neglect the link with empirical reality, the mathematical models are particularly exposed to such a criticism.

This is the case in Economics, where the neoclassical models are often accused of being wrong, having nothing to do with the reality since they are grounded on false assumptions (rational expectations, omniscience, representative agent, efficient/perfect auto-organization, etc.), and showing deficiencies to predict the major economical events (like the 2007 crisis) (e.g. Fullbrook, 2004). To illustrate the differences between analytical (i.e. neoclassical) and ABM approaches in Economics, we compare them in Table 5.1 below.

<table>
<thead>
<tr>
<th>Information</th>
<th>Analytical</th>
<th>ABM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>global (omniscience)</td>
<td>local, network, ...</td>
</tr>
<tr>
<td>Representation</td>
<td>centralized (representative agent)</td>
<td>distributed</td>
</tr>
<tr>
<td>Decision</td>
<td>functions of numerical variables, equations</td>
<td>varying : variables, structures, objects, processes...</td>
</tr>
</tbody>
</table>
| Market               | neoclassical : utility optimization under constraints ; rational expectations (infinites), ... | cognitive approach, varying behaviors (e.g. bounded rationality, ...)
| Auto-organization    | efficient market (invisible hand) | by interactions (explicits), emergence, imperfections |

Table 1.1 – Comparing mathematical and agent-based models in Economics

To be fair, I presented the common and little old-fashioned version of neoclassical economics and some elements have been improved (multiple equilibriums in game theory, incomplete markets). But, to the best of my knowledge, no analytical model possesses all the ABM’ properties listed here. The most important quality of ABM lies in their ability to integrate various mechanisms from any kind (and different) source, various levels, and various properties (like the ones displayed in Table 5.1).

So who wins the battle? First of all, it is worth noticing that, as underlined by Miller and Page, we must distinguish the model from the tool (Miller and Page, 2007, p. 59). One can use a computer tool to implement and simulate a mathematical model. Conversely, mathematical techniques can be used to analyze an agent-based simulation or to describe an ABM. Thus, as you will notice, most of the models presented in this dissertation (WorkSim, Polias, HappyWork,...) are partly described with mathematical formula.

Now, let me discuss how mathematical and agent-based models may address the four issues that characterized the HSS and were presented in section 1.1 above.

Concerning complexity, there is a contradiction in terms to try to model a complex systems with only a set of some equations and a risk of reductionism, especially if the systems converges towards a unique equilibrium, analytically calculable: by definition, a complex system is unpredictable. Moreover, neoclassical models in Economics usually operate at an
aggregate level, using representative agents, and model mainly the consequences of the phenomena, not the causes: this is usually called black-box modeling. By contrast, the ABM can open the box and describe the behavior of agents at the micro-level in terms of information processing. Moreover, systems in SHS are adaptive systems, they adapt, learn, have a memory and these adaptation processes change the nature of system. Learning in multi-agent systems is a natural way to model adaptation, whether to produce new knowledge, or adapt a behavior to a changing environment (through reinforcement learning for instance). Note that several learning algorithms are based on mathematical theories (e.g. markovian learning) but here, the maths are used as a tool and this is a good example of fruitful cooperation between maths and ABMs.

Concerning the object and subject homology issue, entailing the need for axiological neutrality, the techniques of participatory simulations might help, where a human subject interacts with an ABM though an avatar that plays his own role. The method of companion modeling (Barreteau et al., 2014) allows to respect the point of view of the social actors, and the modeler can adopt a more neutral position.

Concerning human freedom, this supports the Einstein’s critics I mentioned above and as I already pointed out, any kind of model is concerned but normative approaches are more likely to differ from reality – by definition – and then from human behaviors. By contrast, one may adopt a descriptive approach that is by definition grounded on empirical facts and observations and is more likely to account for real behaviors. This is the approach I favor in my works and I will describe in section 1.3 below the methodology I propose to move in this direction.

Finally, concerning explanation and comprehension, modeling goals and meanings is a hard task. Mathematical models can tackle it with logics, based on the semantics of models. A way to model goals is given by the practical reasoning approach proposed by Bratman (1987), that gave rise to the famous BDI (Belief, Desires, Intentions) ABM. BDI is both a computational model (Rao and Georgeff, 1995) and a mathematical (logical) model (Cohen, 1990; Rao and Georgeff, 1991), another good example of the complementarities of the two approaches.

However, one may object that this discussion does not make sense, because computer objects are indeed mathematical objects and therefore there is no sense to distinguish and oppose them. This argument is based on the Church-Turing thesis (Kleene, 1967), stating that (1) every computable function is general recursive and (2; Kleene’s Theorem XXX) since every recursive function is computable by a Turing Machine, therefore every computable function could be computed by a Turing Machine or a recursive function, and then perfectly described by lambda-calculus. So, if every computer program could be perfectly translated into a mathematical system, what is the point to compare or oppose them ? There are at least two objections to this argument.

First of all, the Church-Turing thesis is only...a thesis, and has not been proven yet in general, for any type of function. If several computational models happened to be equivalent to a Turing Machine, there are some exceptions, like halting function (Copeland, 2003). Second, even if this thesis were true, that is if every computer program could be equivalent to some mathematical system, an equivalence (a kind of translation actually) is not an identity. Music can be translated into notes on a score, and reversely these notes can be played to hear the music. However, when a musician composes by writing notes directly on a score or by improvising on a piano, s/he uses two very different processes to create music, two different styles of composing. My claim is that is the same case for modeling : mathematical models and ABM are two very different styles of modeling and thinking. A mathematical model emphasizes global structures and relations, while ABMs forces us to model the underlying local processes that generate these structures, to decompose the human activities into processes and interactions.
1.2 THE MAIN PURPOSES OF THIS WORK

To sum up the precedent discussion, mathematical models and ABM differ in many respects but they could be often complementary to model human behaviors (see Kant, 2012, for some proposals). What really matters in fact is whether we adopt a normative or a descriptive approach. Moreover, another important quality of a model is its explanatory power. It is not sufficient to generate an observed macrostructure, the model must explain how and why this structure, the observed behavior occurred. The explanation must be constructed itself, not neglected or given per se, building a sort of “a constructivist (intuitionistic) philosophy on social science” (Epstein, 1999, p.43). When focusing too much on the results, on the consequences rather than the causes, mathematical models like the ones based on differential equations lack explanatory power (op. cit., p. 51).

So everything depends on our objectives and our criteria. In all the projects I conducted, I have favored a descriptive approach and tried to build models with as much explanatory power as possible. Consequently, the main questions I want to raise in this dissertation are the following:

P1 How could we design agent-based models of human behaviors that are descriptive and explanatory?

P2 How could these models account for real data?

P3 In what respect these models and their simulations could serve as decision-aid tools, for policy makers for instance?

P4 When tackling different types of behaviors and applications, could these models share common elements or are ad hoc models unavoidable?

Too many questions for a single dissertation you might think...And I will agree! My ambition is not to give a definitive answer to all of these issues, I only want to underline what has guided my work and preoccupations these last ten years, since I joined the MAS team of LIP6 in 2005. A part important of my approach was to define a methodology to help addressing these questions, so I will now present its main characteristics.

1.3 A METHODOLOGY TO STUDY HUMAN BEHAVIORS

First of all, we need to specify what the model is about, namely its domain \( D \) (e.g. labor market, opinion dynamics,...), the set \( B \) of the behaviors we want to describe and explain and the questions \( Q \) we want to ask to the simulation. My methodology lies on five main steps:

M1 Build a psycho/socio/econo-mimetic model of \( B \), using available facts and theories we have in \( D \).

M2 Perform a comprehensive sensitivity analysis of the model’s parameters, and derive a first typology of behavior (e.g. cognitive profiles), eventually to reduce the number of parameters.

M3 Calibrate the parameters for which we do not have an empirical value, using an available data set \( D_S \).

M4 Perform explanation analyses of the calibrated models, for instance by tracing agent’s decisions and the grounds of these decisions.

M5 Challenge and test the prediction abilities of the model, for instance by testing new policies, new variants, ...
Step M1 comes from the theory of psychomimetism I introduced Kant (1996, 1999). Psychomimetism prescribes some design principles for an artificial system aimed to model human cognition. It assumes that we have a cognitive model, i.e. a set of principles that describes the way the cognitive agent processes the information, and a description language, i.e. a way to represent the information. A psychomimetic artificial system has to:

PM1 implement all the principles of the cognitive model in order to perform numerical simulations of the model and validate it on experimental data.

PM2 produce structures, whether outputs or internal representations, that are interpretable in terms of elements of the description language

PM3 implement (e.g. with a learning mechanism) the processes that produced the structures prescribed by the design principle PM2

The design principle (PM1) emphasizes implementation. It means that the functional architecture of the artificial system and the way this system processes information are both compatible with the principles of the cognitive model. (PM2) emphasizes intelligibility. Instead of being a black box, a psychomimetic artificial system processes information meaningfully, so that an external observer could interpret its behavior and its outputs in terms of elements of the description language (e.g., symbols of natural language). (PM3) emphasizes what we call the structure-process coupling issue. Biology and psychology reveal that the representations used by a cognitive agent and the processes that have produced and transformed them are strongly interdependent. This implies that one should not study the representations involved in human cognition independently of the processes that produced these structures. (PM3) also emphasizes emergence and learning, a core process in human (and animal) intelligence.

The consequence of psychomimetism is that an artificial model is psychomimetic if it fully implements the set of cognitive principles (i.e. the theory) attached to it. For instance, if the bounded rationality concept, as introduced by Simon (1957), is part of these principles, then the artificial system must perform computations compatible with bounded rationality. In the case of decision, this banishes using models like SEU (Subjective Expected Utility; (Savage, 1954)) maximization, often found in economics, that imply infinite computations to explore all the consequences within the tree of alternatives. Bounded rationality implicates the idea that humans use heuristics instead of optimization process, and several researchers have proposed some naturalistic heuristics$^2$ for decision-making (e.g. Zsambok and Klein, 1996).

Steps M2 and M3 of the methodology are part of the classical techniques nowadays used in agent-based simulations. The estimation of parameters is an important stage for the empirical validation of agent-based models (e.g. Windrum et al., 2007). When we could find robust empirical data (from census, surveys, etc.), we use them. Otherwise, we could estimate the unknown parameters using an indirect estimation that minimize the distance between simulated moments and their empirical counterparts. In most cases, I use first-order moments when I could not find data on higher-order moments. I call this process calibration, following (Kydland and Prescott, 1996), even if I am aware that the distinction between calibration and estimation is controversial (Hansen and Heckman, 1996; Richiardi et al., 2006). The calibration method we use in our projects is the evolutionary algorithm CMA-ES (Hansen and Ostermeier, 2001). The sensitivity analysis is also an important part of validation, by studying the effects of variations of parameters, usually around the calibrated values. But there are

$^2$Note that the notion of heuristics has also been used by Kahneman and Tversky for their famous studies on heuristics and biases (Tversky and Kahneman, 1974), showing than humans differ from optimal behavior and violate most of the formal theories commonly used to model decisions, like probabilistic and logical reasoning.
many other techniques of sensitivity analysis, including random seeds and noise variations (see e.g. Richiardi et al., 2006, for details).

Steps M4 and M5 are consistent with the precedent section, the fact that we must go further than a descriptive approach. Explanation and prediction are central but difficult issues, and it is out of the scope of this dissertation to discuss them (see e.g. Elsenbroich, 2012). I will use the projects I conducted (and participated in) that are presented in this document to illustrate what could be done in this direction, as illustrative examples.

1.4 OVERVIEW OF THIS MANUSCRIPT

The aim of this document is to illustrate how this methodology could be applied to varying issues and domains, discuss the models, the simulation results, and the lesson learned (in the general discussion). I will focus here on collective behaviors and multi-agent models.

The chapter 2 focuses on social simulation, and introduces opinion and attitude dynamics, with two projects : COBAN on innovation diffusion and the second, Polias, on attitude formation and dynamics. Chapter 3 is also a model on attitude dynamics but in the special case of job satisfaction within a workplace (HappyWork project). This entails us to model firm organization and activities, among others. Chapter 4 is devoted to agent-based computational economics with the WorkSim project, a multi-agent model of the French labor market. This model is particularly challenging in terms of validation, because it has a large number of parameters (around 100). Finally, chapter 5 presents the general discussion of this dissertation, where I will synthesize the results obtained, and draw some perspectives for the future.

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3Due to lack of space, I will put aside the works on individual behavior I have also conducted these past years, including the psychomimetic neural network Categ_ART for cognitive decision-making and categorical judgment (PhD work, see e.g. (Kant, 1995, 1996)), the neuromimetic neural network RALF of rule formation based on a reinforcement learning inspired by the frontal lobe (Kant and Levine, 1997, 1998) and the CODAGE agent model (Kant and Thiriot, 2006; Kant and Domingue, 2007), which is aimed to reproduce the decision behavior for one human subject. Broadly speaking, the CODAGE agent is a macro-agent managed by a cognitive multi-agent architecture. The multi-agent system comprises a set of specialized agents, we call micro-agents in order to distinguish them from the CODAGE macro-agent they belong to, and a tree of alternatives to facilitate information sharing.
Social Behaviors: Innovation Diffusion and Attitude Dynamics

In this chapter, I will present two projects on social simulation. The first, COBAN (Communication of Beliefs using Associative Networks), simulates a process of innovation diffusion among a population. The second, Polias, models attitude dynamics. These models have many things in common: their cognition is based on beliefs, use a similar belief revision mechanism and includes a “persuasion” mechanism through communication. While COBAN goes deeper on this communication process by an explicit representation of arguments and beliefs’ exchange, Polias adds an emotional component to the cognitive one.

Before detailing these two approaches, let me present three core concepts we use here: beliefs, attitude and opinions.

2.1 Beliefs, Attitudes and Opinions

2.1.1 Beliefs

The first brick of knowledge representation, the atomic element in these models, is the belief. We could define it as the subjective component of human judgment, what an individual thinks to be true (like a true proposition in logic). A belief becomes knowledge only when the truth of a proposition becomes evident to the believer. A belief in someone or something (e.g. “I believe in freedom”) is basically different from a belief about something (e.g. “I believe that this country ensures free speech”) (Fishbein and Ajzen, 1975). In each case, belief could be conceptualized as an estimate of subjective probability or a true proposition. Moreover, beliefs vary in strength; they can refer to a specific event or a general situation; they could be about the past, the present and the future (expectations) (Wyer and Albarracín, 2005).

2.1.2 Attitudes

Attitude is a central concept, introduced in social psychology, to study human behavior. As many constructs in psychology, there are several ways to define it. Broadly speaking, it is “an overall evaluation of an object that is based on cognitive, affective and behavioral information” (Maio and Haddock, 2009, p.4). Allport suggested also that an attitude is a predisposition to act, being “a mental and neural state of readiness organized through experience, exerting a directive or dynamic influence upon the individual’s response to all objects and situations with which it is related” (Allport, 1935). Thus, an attitude is an evaluative judgment, and it has a valence to express a positive (in favor), neutral or negative (disfavor) of this object. It has also a strength, where one could slightly dislike spinach while another really hates it. This strength is at its core expressed qualitatively through language (as on opinion, see below), but computational
approaches need to convert it into numerical values, which is not an easy task\textsuperscript{1}. Moreover, when several people are interested in an object, and exert a social behavior on this object (attitude formation, exchange of opinions, etc.), this object will be called (according to social psychology) a \textit{social object}.

According to the \textit{multicomponent} approach (Zanna and Rempel, 1988; Eagly and Chaiken, 1993), attitudes have three components:

- A \textbf{cognitive} component, referring to the beliefs, thoughts and attributes associated with the object. This is the cognitive part of the attitude formation, and many models based in cognitive judgment theories may apply. Typically, the subject will weight the pros and cons, positive and negative consequences, and aggregate them.

- the \textbf{affective} component refers to feelings and emotions attached to the object, linked to physiological reactions, triggered by the confrontation with the social object (or representation of this object). Emotions (and mood) affect the cognitive judgment in terms of information processing\textsuperscript{2}. We therefore incorporated an emotional component in the Polias model (see section 2.3) below.

- the \textbf{behavioral} component is the link with past or future actions. Past actions influence present attitudes values: for instance having signed a petition in favor of animal rights tends to have a negative attitude toward bullfighting. Otherwise, this creates a cognitive dissonance (when there is a conflict between an action or an attitude; Festinger (1957)). Symmetrically, an attitude may influence future behaviors (think of buying or voting).

So it is clear now why the concept of attitude is so important to study human behavior, as it encompasses all these three major components of human psychology. In particular, the behavioral part could be useful in order to predict future actions, but this is never straightforward (because of unresolved dissonances) and is usually the most difficult part to model (Fazio, 1986, 1990). The attitude model in Polias has a cognitive and an emotional part, while HappyWork is mainly a cognitive model.

### 2.1.3 Opinions

\textit{Opinion} is often confused with attitude. A common definition is that an opinion is a \textit{verbalization} of a belief or an attitude (Thurstone, 1928). Therefore, it is only a partial reflection of an attitude, and for several reasons. First of all, there is always a bias when we communicate verbally to someone: for instance, we do not want to shock with firm or extreme opinions, we could hide ideas not commonly share by the majority (by fear of being rejected), etc. Second, even without this communication bias, our attitude is not always completely accessible, some parts or arguments that build it might not be fully known by ourself, making them difficult to verbalize.

In the COBAN model presented in the next section below, we introduce a model of opinion dynamics through the communication of beliefs.

\textsuperscript{1}This is a classical issue in psychology: how to encode numerically a qualitative judgment. There is a vast literature on attitude measurement (e.g. Maio and Haddock, 2009; Petty et al., 2009). Frequently, one asks subjects to fill questionnaires made of Likert scales, as it has been done in the data used in the HappyWork project (see section 3.1)

\textsuperscript{2}For instance, certainty-related emotions (happiness, anger, ...) make people to process information less carefully (and then with much readiness to be persuaded) than uncertainty-related emotions (surprise, fear,...) (Tiedens and Linton, 2001).
2.2 COBAN: AN AGENT-BASED MODEL TO STUDY THE DIFFUSION OF INNOVATIONS

The COBAN (COMMunication of Beliefs using Associative Networks) project was funded by Orange Labs, with the PhD of Samuel Thiriot (2006-2009). The aim was to propose an agent-based model to study diffusion of innovations. Diffusion of innovations is an interdisciplinary field that studies “the spread of new ideas, opinions, or products throughout a society” (Valente, 1995). Rogers defines diffusion as “the process by which an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 2003, p. 11)

Several models were built to study diffusion of innovations, including multi-agent based simulations, with different purposes. Explicative models aim to reach a better understanding of how individual interactions make collective dynamics appear. A great part of these models studies the decision/judgment level (adoption, opinion, perceived utility (Ellison and Fudenberg, 1995), payoff (Banerjee and Fudenberg, 2004), attitude, etc.). For instance, in the threshold model (e.g. Deffuant et al., 2005), social pressure makes individuals influenced by opinions of their neighbors. Several models also include the beliefs level, that is what individuals trust for a given object (one use “belief” rather than “knowledge” because these beliefs can be false or subjective). It is the case of models focused on informational cascades (see Roberts and Lattin (2000) for a review) or in the consumat approach (Janssen and Jager, 2003). In these models, beliefs are represented as single values or as a vector of values, and rarely aim to be matched against data collected on the field.

Predictive models aim to produce an estimation of the future diffusion rate of an innovation. The well-known model, and the most used in industry, is the Bass aggregative model (Bass, 1969). It includes parameters for adoption due to media messages, adoption due to interpersonal communication and an index of market potential for the new product. It permits to reproduce the classical S-curve of cumulated adoption.

Despite of the large amount of literature about diffusion of innovation, there still remain several problems that are not studied. The first lack resides in explicative power. Rogers (2003) underlines that models are not able to explain innovation failures (sometimes due to misunderstanding of what innovations are or to incompatibility with beliefs or values). Rogers also remarks that most of the said “innovations” launched in markets are in fact incremental products. In this case people already understand what the innovation is, how it works, so the diffusion becomes quicker. Such processes cannot be modeled without representing beliefs of the population about innovations. The second lack is about predictive power. The Bass model can predict the future adoption rate of an innovation only after its launch, based on the adoption data from innovators and early adopters. But at this time, costs are already engaged (for building the product, for communication, etc.). Obviously, the predictive interest of the model is highly lowered. So, firms use less formal methods to test new concepts, like interviews or focus groups, which provide some insights on subjective perception and expectations about the innovation. Here again, it seems that modelers cannot avoid to represent beliefs.

Our main concern is to be able to tackle real-world cases. For such purpose, we study how a modeler can represent individual beliefs in an agent-based simulation. For such a simulation, we need a model for knowledge representation that is complex enough to be explicative and representative, but also simple enough to make its parameters’ settings and data collection possible. We illustrate this approach with the simulation of iPod™diffusion using beliefs collected across forums.
2.2.1 The COBAN Model

2.2.1.1 Knowledge representation

Individual Associative Network The concept of associative network has been widely used in social sciences and artificial intelligence to model beliefs: Bayesian networks, causal networks, social representations represented as proximity networks, etc. A marketing methodology called the Means-end Chains Theory (MCT) (Reynolds and Gutman, 1988) proposes to formalize the perception of products as cognitive chains linking concrete attributes to perceived consequences for the individual and satisfaction of his values. As shown by the MCT, associative networks are relevant to represent the beliefs about products (an example is provided in Figure 2.1). These chains can be retrieved by semi-directed interviews, surveys or statistical data analysis. Messages like advertisement or consumer reviews can also be represented as chains (Reynolds et al., 1995), as shown in Figure 2.3.

Associative networks permit to represent several kinds of knowledge. We categorize knowledge as subjective or private. The subjective part of information is about the innovation itself, like product attributes (links 2-7) and perceived functional consequences of the product (e.g. 11,13). This kind of information is received or retrieved by individuals through mass medias or interpersonal communication. The private part of beliefs is about individuals themselves. These beliefs are more stable for an individual across time (Page et al., 2005). For instance, the belief “speed → time saving” is used for all technological innovations. Private beliefs can be heuristics, like “high price → high quality”. Private beliefs are provided as initial data by the modeler based on the population segmentation. A last kind of beliefs is about abstract judgments and is built by the individual itself based on its local information, as “product adopted by others”. This knowledge is represented in agents by simple computational rules held by each agent.

From the modeler viewpoint, concepts in the model are a finite set $C$, which is created based on data collection or expert hypothesis. Sometimes two or more concepts are incompatible: an agent cannot trust both of them in the same time for the same social object. Like in the evidence theory (e.g. Smets, 1994), we define frames of exclusivity called $\Theta^X$, with $X \subset C$. Some examples of frames are: (solid, breakable), (good connectivity, bad connectivity).

Formally, we define knowledge as directed associations between concepts. Mathematically, a belief is a binary relation in $C^2$. $C_1 b_{\sigma}^{a,t} C_2$ is the conviction held by an agent $a \in A$ at time $t$ that two concepts ($C_1$ and $C_2$) $\in C^2$ are associated with a given support $\sigma \in \Sigma$. The support represents the confidence of the agent on this belief (more details on support are provided below). In this model, existence of a link represents belief. No link means ignorance. Disbelief is modeled as the belief in the opposite concept. Each individual possesses his own set of beliefs; we name this set an Individual Associative Network (IAN).

Some concepts are considered as object of interest by the agents $A$ (agents will speak about them, they want to understand them, they can take decisions about these concepts). We use a psychosocial term (Moscovici, 1998) to design these objects of common interest: these concepts are social objects $O \subset C$. When we model the diffusion of innovations, social objects are innovations. A set of beliefs about a social object $o$ forms the representation $R_{o}^{X,t}$ of this object. This representation is the subgraph rooted in the social object. If a representation is shared between several agents, it becomes a social representation in the social psychology meaning, noted $SR_{o}^{X,t}$ with $o \in O$, $X \subset A$.

---


4 This taxonomy follows the one provided by Audenaert and Steenkamp’s studies on means-end chains theory (Audenaert and Steenkamp, 1997), and the discussion in the field of consumer value (Holbrook, 1999), which concludes that perceived value depends both on the intrinsic product properties and on the subjective perception of consumers.
Beliefs Revision Insights about persuasive communication are provided by social psychology (Moscovici, 1998). Persuasiveness of a communication depends on properties of the source like credibility, expertise, self-interest, structure of argumentation, messages order, etc. No formal model exists to compute the total persuasiveness of a communication based on these parameters. However, several formalisms are available to represent beliefs and their strength, mainly with probabilities or belief functions (see (Smets, 1998) for a comparative review). But, all of these models are normative and lead to results incompatible with observable evidence. They would require us to include quantitative valuation of beliefs (as probabilities or belief masses), which would make the model harder to validate, less representative and harder to manipulate. So, we developed a solution based only on the qualitative properties of beliefs.

The sources of informations are perceived as more or less credible by individuals. Broadly speaking, personal experience is stronger than other advices, themselves stronger than advertisement. We define a set $\Sigma$ that contains several levels of support (in other words: credibility, certainty, revisability, strength). Each source of information is categorized by the agents in one of these levels. Levels are defined operationally to fit observations from the population and the needs of the model. In COBAN, we use the following levels: no credibility is used for information from advertisement, plausible is used for advice from someone, indirect experience represents feedback of someone based on its personal experience. Personal experience represents the strongest level for beliefs acquired by the agent direct experience.

<table>
<thead>
<tr>
<th></th>
<th>no credibility</th>
<th>plausible</th>
<th>indirect experience</th>
<th>personal experience</th>
</tr>
</thead>
<tbody>
<tr>
<td>no credibility</td>
<td>0.9</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>plausible</td>
<td>1</td>
<td>0.9</td>
<td>0.01</td>
<td>0.001</td>
</tr>
<tr>
<td>indirect experience</td>
<td>1</td>
<td>1</td>
<td>0.9</td>
<td>0.001</td>
</tr>
<tr>
<td>personal experience</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.9</td>
</tr>
</tbody>
</table>

Table 2.1 – probability of revising a belief based on the support level of the previous belief $\sigma_{\text{old}}$ (top) and on the support level of the new information $\sigma_{\text{new}}$ (left column)

We assume that a stronger source erases the previous advice, because the new source is considered to be more credible. In some cases, however, it is possible for a strong belief (acquired by direct experience) to be modified by new weakly-supported information, because individuals accept to revise old beliefs, comply with social consensus, can be convinced by a good argumentation or another reason. That’s why we choose to model belief revision based on probabilities of revision between support categories $p(\text{revise}|\sigma_{\text{old}}, \sigma_{\text{new}})$. We built this function (Table 2.1) based on qualitative observations. A weak support has a low probability to modify a stronger support. However in long term, this probability becomes higher and higher, leading to invalidate old beliefs.
Retrieving from memory  We need to be able a retrieve the representation of a social object contained in an IAN. Retrieving a representation is done through a spreading activation process: start from the social object, then browse all the links connected to this node to build the representation $R^\alpha_t$. We assume an activation propagation inspired by evidence networks: the activation strength of a concept for an object is the strength of the weakest link in the chain that links the social object to this concept. When activation follows a link, it is filtered by the belief strength. For instance in Figure 2.1, activation of concept “time saving” for the social object “iPod” is “indirect experience”, which is the lowest support in the chain ($c_2$). If a node receives several levels of activation from its parents, the strongest activation is kept (i.e. the maximum value of activation, which is also an OR logical interpretation). In the example of Figure 2.1, “ease of use” has a support of “personal experience”. As a result, the activated representation contains the beliefs activated and their support.

In the particular case of incompatible beliefs, the activation process only keeps the strongest belief. For instance in Figure 2.1, the frame of exclusivity $\theta_{complexity} = \{ease \ of \ use, \ hard \ to \ use\}$ forbids both of these concepts to be trusted at the same time. The spreading activation process sets a low activation to “hard to use” and an higher to “ease of use”, so only the latter will be included in the activated representation.

### 2.2.1.2 Communication

As shown before by the agent-based modeling community, the social structure has a huge impact on the system dynamics (e.g. Valente, 1995)). As a consequence, we have to specify the channels that support communication, the structure of messages themselves, and the topics (social objects) agents are talking about.

A channel is a support of communication that transmits information from an information source to an audience. Historically mass media were controlled by firms for persuasive communication, while interpersonal channels were only used for uninterested communication. Today individuals’ reviews through specialized websites or forums could challenge traditional mass media, and interpersonal communication begins to be modified by individuals who are paid to propagate positive recommendations. To take this evolution into account, we propose to categorize channels based on their audience size and the determination of topics (Table 2.2). An unidirectional channel will always have a static topic (because the information source communicates about the object of its choice) while bidirectional channels allow interactive choice of topic. Modeling interactive topics implies modeling information research, and not only passive information reception.

A mass channel is connected to a great number of agents. The agent exposure defines

<table>
<thead>
<tr>
<th>interactive topic choice</th>
<th>big audience</th>
</tr>
</thead>
<tbody>
<tr>
<td>forums, search on internet</td>
<td></td>
</tr>
<tr>
<td>face-to-face</td>
<td>small audience</td>
</tr>
<tr>
<td>press, advertisement, direct experience</td>
<td>webslogs</td>
</tr>
</tbody>
</table>

Table 2.2 – taxonomy of channels
its probability to receive messages through this channel. An **interpersonal channel** represents the fact that two individuals can exchange information with a given exposure parameter (the probability for the agents to meet). A static-topic channel will only transmit passively messages, so the topic is determined by the information source. An interactive-topic choice channel asks both agents which topics they want to discuss about (the salient social objects set of each agent) and pick up randomly a social object in the union of the two sets.

**Messages** Each transmission of information (either from mass media or interpersonal) is a message. A message is intended to transmit information about a social object. A message is sent by a sender over a channel; audience will be determined by the channel itself. A communication campaign is composed of several messages broadcasted on channels during a given period.

The content of a message is a **transmissible associative network (TAN)**, which is made of associative links (see Figure 2.3 for example). A TAN typically embodies only a representation of a single social object. Sometimes - especially in the case of co-branding - the network can include several social objects and their associated representations. A TAN transmitted by an extrinsic information source is provided by the modeler. A TAN from an intrinsic information source is dynamically built by this agent.

![Figure 2.3 – Transcription of a consumer advice retrieved on a website (left) as a TAN (right)](image)

**2.2.1.3 Agents**

A consumer agent represents a unit of adoption. It embodies a belief base, a list of currently salient social objects and is linked to an agent profile. An agent profile contains the default exposure to mass channels, background knowledge, subjective production of knowledge. It also contains functions to evaluate attractiveness and decide adoption. It can also include some rules to create the subjective knowledge based on local information. For instance, the fact that others have adopted a product (belief number 1 in Figure 2.1) is modeled by a threshold on the observed relationships that possess the product.

The behavior process is represented in Figure 2.4. We designed multi-criteria functions to compute attractiveness and adoption, which take into consideration the support of beliefs. They are based on a **satisficing** heuristics (Simon, 1956). A function of attractiveness $f_{\text{Att}}(o): R^2_{o,t} \to \mathbb{R}$ computes how much an agent is interested by a social object based on its current representation. An object $o$ is attractive if $f_{\text{Att}}(o) \geq \text{threshold}_{\text{Att}}$. Adoption depends on the evaluation of both benefits and sacrifices of the innovations. Two functions are computed: $f_{\text{decide}}: R^2_{o,t} \to \{0, 1\}$ determines if the agent has enough information to decide, and the trade-off function $f_{\text{Tradeoff}}(o): R^2_{o,t} \to \mathbb{R}$ computes the perceived value of the innovation, based on benefits and drawbacks.
2.2.2 Simulation results

2.2.2.1 Data collection

We retrieved data from the publis/hed means-end chains analysis of iPod™ (Reppel et al., 2006) and from statistical analysis of reviews provided by consumers on specialized websites. This data is used to determine the content of interpersonal messages and to insert background knowledge into agents. Associative networks permit to represent background knowledge. For instance in Figure 2.1, the links (9,16) represent fears of late majority about technology: it’s hard to use and leads to waste of time.

We identified the following static-topic mass channels: TV advertisement, generalist and specialized press, experience with the product. We set exposure to each media from general statistics publis/hed about TV ads exposure, press reading, etc. We used as a social structure a small-world graph (a regular lattice with shortcuts as proposed in (Newman and Watts, 1999)). The exposure level to social interactions is retrieved from a study (Carl, 2006) about word-of-mouth, which quantifies on average 15 word-of-mouth episodes per week.

2.2.2.2 Agent profiles

We adopt the classical segmentation used in diffusion of innovations. Innovators like what is new, fun. They enjoy to spent time to learn how an innovation works. They are able to understand technological terms, and read specialized press nearly ones a week. They are more impulsive than others, and can adopt an innovation as soon as it is available. They easily speak about innovations. They like to be alone to possess new things, and an innovation already possessed by others loose its interest. Early adopters sometimes read specialized press. They like new thinks, they carefully study available information before buying. Individuals from early majority like to be on-trend, with new products. They already have a good knowledge about technology, but like to have feedback from first adopters before buying. Late majority individuals do not cares about the novelty of a product. They focus on the utilitarian aspect, do not like to loose time to learn new technologies. As part of their background knowledge, they believe that technological innovations are hard to use (as represented by beliefs 9,16 in Figure 2.1). They consider a piece of information as true only if it comes from someone else with direct experience. Laggards have a low exposure to press, and retrieve most of their information from interpersonal communication.

2.2.2.3 Simulation

The model is implemented with the Repast Framework. In this discrete-time simulation, each step represents one week.

Figure 2.5 shows the output of the model. Awareness starts before adoption due to announcement information transmitted about iPod™. Because an announcement is only transmitted in specialized press, mainly innovators and early adopters are aware of the product and can propagate word-of-mouth around them. Then the product is launched, with information in generalist press and TV advertisement. All the population becomes aware of the product and can adopt it. Early majority requires indirect information from previous users or independent reviews to adopt. Late majority needs indirect feedback to adopt. The last
2.2. COBAN: an agent-based model to study the diffusion of innovations

Figure 2.5 – Simulation of iPod™ diffusion in a population of 5000 agents

The curve in this figure shows that the diffusion is made quicker if another media (here: internet) permits to retrieve others’ advice quicker than face-to-face communication; this media is highly efficient because it permits to determine interactively topics and to retrieve credible information.

2.2.3 Observations

How to improve diffusion? In this model, advertisement on its own does not lead to adoption, but can make the product salient in individual minds and provoke adoption or word-of-mouth. The best idea to make diffusion quicker is to facilitate word-of-mouth, which is required to persuade late majority and laggards to adopt. A good timing, and attractive information, is required to stimulate word-of-mouth. If new information is sent when individuals are still looking for information, then this new information will be transmitted quickly through interpersonal communication. Observability, one of the factors mentioned by Rogers, also facilitates diffusion in this model. In the case of iPod™, the white earphones are easily identifiable, and are related to iPod™ based on advertisement campaigns. So potential adopters are aware of others’ adoption, leading them to follow this indirect recommendation. The importance of usage value, as in reality, is confirmed, because individuals who use the products are highly credible and can provoke adoption; it is of prime importance that they be satisfied by the product.

Social representations of the innovation emerge from the simulation. In the beginning of diffusion, we can observe collective representations shared by several agents (Figure 2.6): individuals who have already adopted possess a large amount of information provided by experience, while others only have a representation created from advertisement. Individuals who had no knowledge about mp3 players discover through word-of-mouth what are the criteria for evaluating the innovation. While late majority is initialized with no knowledge about mp3 players, all individuals end with general considerations about autonomy.
Figure 2.6 – Example of social representations. The left representation \( \text{SR}_{\text{early adopters},12} \) is shared by first adopters who have already an experience with iPod™. The right representation \( \text{SR}_{\text{latemajority},12} \) is held by several agents who just have information from advertisement, and know that iPod™ is already widely adopted.

or storage capacity. We also observe examples of incomprehension: an individual who has no knowledge about storage capacity is unable to understand what “10Gb” means, but he will learn it through interpersonal messages or well-designed advertisement (with the slogan “1000 songs in your pocket”).

2.3 POLIAS: DYNAMICS OF ATTITUDES WITHIN A POPULATION\(^5\)

In the Polias project, we propose a multi-agent model to better comprehend attitudes dynamics. Our goal is to propose a model that articulates the cognitive and emotional dimensions of attitudes within a population. This project is funded by Airbus Defence and Space (ADS), with the PhD of Kei-Léo Brousmiche (2012-2015), and has been led in collaboration with the Systems Design - Advanced Studies Team of ADS\(^6\) and with Nicolas Sabouret (LIMSI, Université Paris Sud). This ADS team proposed to illustrate our approach in the context of stabilization operations simulation: we study how so called “non-kinetic” actions (i.e. that do not rely on effective usage of force) alters population’s perception, attitudes and behaviors toward the actors involved: the UN Force, the insurgents (e.g. Talibans in Afghanistan, etc.).

2.3.1 Related works

Following the methodology of psychomimetism (better called here “psychosociomimetism”), we rooted our computational model into theories from social psychology. We briefly summarize them in the next section, following with a review of existing computational approaches (especially agent-based ones).

2.3.1.1 Attitude formation and change in social psychology

There are many models of attitude formation and change proposed in social psychology, since the introduction of this concept in 1935 by Allport (for recent reviews, see e.g. Crano and Prisline, 2006; Maio and Haddock, 2009; Bohner and Dickel, 2011). There is a consensus to view attitude formation and change as one dynamic process (referred to “attitude dynamics” in this document). Models differ whether attitudes are stable entities stored in long-term memory (like in Fazio’s et al. models Fazio, 2007), or, according to the constructionist view, “constructed on the spot” as evaluative judgments constructed from scratch, based on current available information (e.g. Schwarz, 2007). The main argument for this is to account for

\(^5\) Related Publications: (Brousmiche et al., 2014a,b, 2015; Brousmiche, 2015).

\(^6\) In particular, François Prenot-Guinard et Stéphane Fournier.
attitude changes when context varies. However, as summed up by Fazio (op. cit.), there are many empirical evidences that contradicts the constructionist view: pre-existent evaluations and attitude values have an impact on attitude. Moreover, the importance of prior learning is not taken into account by the constructionist perspective. This is why we adopted in Polias the Fazio’s approach with attitudes stored in memory.

There is also a debate on the way information is processed to compute the attitude. For several models, including ELM (Petty and Cacioppo, 1986) and HSM (Chaiken et al., 1989) models, a dual process underlies the attitude formation, where arguments (in a message) and external cues associated to the message (like source expertise) are processed differently. Also, in ELM and HSM, two processes co-exist depending on the motivation (high or low) and the ability (high or low) to process information. In the APE model (Gawronska and Bodenhausen, 2006), two mental processes coexist: an associative evaluation (like a connectionist network) that is implicit, occurs unintentionally and without awareness of the subject, and an explicit process, intentional and with awareness, which is based on logical reasoning. For other researchers, like Fazio, there is only one unique process, and the differences between implicit and explicit results mainly on two different ways of measuring the attitudes (Fazio, 2007). Again, we will take Fazio’s side, as there are many experimental evidences that support the unified perspective (Fazio, 2007; Bohner and Dickel, 2011), in accordance with an associationist perspective on cognition that underlies all my research (Kant, 1996).

Thus, to build our agent-based model, we departed from the object-evaluation associations framework introduced by Fazio and his colleagues in 1982, where attitudes are "associations between a given object and a given summary evaluation of the object – associations that can vary in strength and, hence, in their accessibility from memory" (Fazio, 2007). However, the number of associations is limited, as to comply with bounded rationality. The evaluation process could be analytic, or emotional, it can be based on past behaviors and experiences. The varying strength of the association enables variability in the attitudes for one person and across several individuals as well. The stronger the association is, the more it will impact other cognitions, behaviors and social processes. As stated by Fazio (op. cit.): “attitudes form the cornerstone of a truly functional system by which learning and memory guide behavior in a fruitful direction”.

2.3.1.2 Computational models of attitude dynamics

Let me now review some of the principal computational models that have been proposed for attitude dynamics. First of all, several connectionist models have been used to implement the psychosociological theories described above: dual processes (Monroe and Read, 2008) or unified models derived from Fazio’s framework (Eiser et al., 2003; Van Overwalle and Siebler, 2005). In (Eiser et al., 2003), they use a three-layers network (one hidden layer) coupled with a backpropagation (supervised) learning mechanism to train the network selecting eatable or non-eatable food, the activation output encodes the attitude value. As often with neural networks, the connection weights are difficult to interpret, the object attributes are not represented, and it is hard to see what are the beliefs that contribute to the attitude. Moreover, the backpropagation learning requires training samples, a data that is hard to collect (and to find in Nature). In (Van Overwalle and Siebler, 2005), an autoassociative network architecture with a linear activation update and the delta learning algorithm is proposed. There are three layers: object nodes, cognitive (attribute) nodes and two evaluative nodes (for positive and negative). This models integrates the object-evaluation associations proposed by Fazio, and is used to replicate and interpret several (human) experiments. However, this requires again a supervised learning, and therefore target output values. Moreover, these connectionist models are for individuals only and they do not model the role of human in-

Note that calibration requires target values too. But supervised learning requires attitude values for each object and each individual, while one could calibrate on aggregated data, like opinion polls in Polias.
teractions into the process of attitude formation. To take these interactions into account, we need multi-agent systems.

Many agent-based models of attitude treat the attitude formation process as a *black box*, and focus on how one individual’s attitude is influenced by others. The first models were inspired by statistical physics, with binary valued attitudes, and applied to voting (e.g. Galam, 2008). They usually view opinions and attitudes as the same thing. Then models appeared with attitudes of continuous values, like the well-known bounded confidence model (Defuant et al., 2000; Hegselmann and Krause, 2002), where two individuals (selected randomly) have attitude values close to each other (with a fixed threshold), each one modifies its attitude so that it gets closer to its peer’s (see e.g. for a review on these models Castellano et al., 2009). This is not a suitable approach for us because of its black-box nature: it models the consequences of attitude formation, not the formation process itself (the causes). Moreover, these models are not rooted in any socio-psychological theory, raising the question of their empirical plausibility (Chattoe-Brown, 2014).

There are however some agent-based models aimed to implement socio-psychological elements. Urbig and Malitz (2007) take inspiration from Fishbein and Ajzen (1975; 2005), where an attitude is composed of different impressions that are made of two elements: beliefs (also called cognitions) about the presence of some attributes and evaluations of these attributes (Ajzen, 1991). The attitude value is computed as the sum of the evaluations (that also includes a belief value) of the object’s features. The attitude revision is based on a variation of bounded confidence model, inheriting its shortcomings. Moreover, all the features contribute to the attitude calculus and are equally accessible (whatever this information is recent or old, important or not for the individual), which contradicts experimental findings and bounded rationality. Another model from Kottonau and Pahl-Wostl (PASS model; Kottonau and Pahl-Wostl, 2004) introduced several features similar to what we proposed in COBAN and Polias. This model simulates political attitudes and voting behavior. Like Polias, it models the formation and change of attitudes and the influence of the strength of attitudes on behavior. Like COBAN and Polais, interpersonal communication is modeled through exchange of messages, and the persuasion depends on the credibility of the source. However, these communication and persuasion mechanism differ from our works. In PASS, the accessibility of a message in memory is a measure of its probability to have an effect on the outcome of the attitude revision, whereas in Polias, it is derived from surprise and emotional response (see next section below).

### 2.3.2 The Polias model

Overall, we model in Polias the impacts on attitudes, within a population, of a series of actions (e.g. patrol, medical support, bombing) by some forces (e.g. United Nation force, terrorist or others) over time. These impacts that are (subjectively) evaluated by the individuals through an evolving attitude value toward each force at stake. The attitude depends on the belief the person has that this action 1) actually occurred and 2) produced an impact of a given payoff value (positive or negative). These beliefs are memorized and transmitted through other individuals, therefore potentially influencing their attitudes as well.

I will first present the static model, which describes the key concepts needed to construct the simulation: the different actors (the population represented by individuals grouped into different factions, and the Forces), the actions, their corresponding beliefs, the attitudes and finally the messages. Then I describe the attitude dynamics, including communication of beliefs and attitudes computation.

#### 2.3.2.1 Key elements

**Individuals** The individuals of the population are represented by computational agents and are characterized by a unique social group defined as a set of individuals sharing similar
characteristics or goals. We denote $SG = \{SG_1, SG_2, ..., SG_n\}$ the set of social groups and $Ind$ the set of all individuals. Each individual $i \in Ind$ is defined by a tuple

$$i = \langle sg, Blf, Cnt \rangle$$

with $sg \in SG$ the social group of the individual, $Blf$ the set of all the beliefs on actions present in the individual’s memory and $Cnt \subset Ind - \{i\}$ the set of all the contacts of the individual in a social network.

**Actors**  The actors represent objects that can act in the simulation and for which we want to analyze the attitudes evolution among the population. Each of them corresponds to a computational automaton executing its actions list given by the user (for instance, in the context of military interventions, the UN can secure a zone, the terrorists can perform a bombing attack ...). For each $actor \in Actors$, we denote $actionList_{actor}$ the ordered list of actions to be executed during the simulation.

**Social Objects**  We call social object an abstract or concrete, human or artificial entity on which people (at least two) exert a social behavior (attitude formation, opinion exchange, formation of social representation, etc.). Here, the social objects are: the actors and the social groups. We denote $SO \in SG \cup Actors$ the set of all social objects.

**Action Beliefs**  An action represents an accomplis/hed task by an $actor$ that impacts a beneficiary individual with a certain amount of quantified payoff. Individuals capture these actions either directly or indirectly through communication and add them into their belief base $Blf$. Besides these information are associated to a certain degree of credibility accorded to its source. We call these information action beliefs and denote them $a \in AB$:

$$a = \langle name, actor, coresp, date, bnf, pyf, \sigma \rangle$$

with name the unique name of the action; $actor \in Actors$ the actor which performed the action ; coResp $\in$ Actors the co-responsible actor of the action, if any ; $date \in \mathbb{N}$ the occurrence date of the action ; $bnf \in Ind$ the beneficiary individual of the action ; $pyf \in \mathbb{R}$ the objective payoff acquired by the subject which is negative when the action is harmful and positive when beneficial ; $\sigma$ the credibility of this impact’s information’s source with $\sigma \in \Sigma = \{\sigma_1, \sigma_2, ..., \sigma_k\}, k \in \mathbb{N}$, $\sigma_1 \prec \sigma_2 \prec ... \prec \sigma_k$ (see section 2.3.2.2 below).

**Attitudes**  For a given individual, each social object is associated to at least one attitude, negative when bad and positive when favorable. We must distinguish between two types of attitude :

- **Attitudes on Social Groups**  People have attitudes toward the different social groups that emanate from social tensions present within the population. We define a table $aTable_{|SG|\times|SG|}$ with values in $[-1,1]$, parameter of the simulation, which contains the inter social groups attitudes, that are considered fixed in our model. The attitude of an agent toward an social group follows this table:

$$\forall i \in Ind, \forall s \in SG, attSG(i,s) = aTable(i,sg,s)$$

Below, an example of attitudes’ configuration:

- **Attitudes on actors**  The heart of this model consists to simulate the dynamics of the attitudes of the population toward the actors that we denote $att(i,actor)$. We conceptualize this dynamic as the result of individual’s perceptions of the actors’ actions (cf. section 2.3.2.2 below).
Fig. 2.7 — Example of inter-social group attitudes configuration. Groups A et B are friends and both dislike C (and reciprocally).

Messages During a simulation, actors communicate on their actions to the population in which the information is propagated. These communications are emitted through messages defined by:

\[
m = \{\text{emitter}, \text{date}, a, \text{Adr}\}
\]

where \(\text{emitter} \in SO\) the social object associated to the emitter of the message; \(\text{date} \in \mathbb{N}\) the emission/reception date of the message; \(a \in Blf_{m,\text{emitter}}\) the action belief reported by the message and \(\text{Adr} \subset \text{Ind}\) the addresses of the message.

2.3.2.2 Attitude dynamics

Our model for attitude construction is depicted in Fig. 2.8 and based on action beliefs’ evaluations associated to the object, as proposed by Fazio (2007). The attitude toward an object is computed from a set of beliefs connected to it, weighted by an accessibility in memory factor (continuous value). As shown in Fig. 2.8, in the case of our applications, objects are forces, and beliefs are about actions that might have occurred.

Fig. 2.8 — Example of attitude in Fazio, 2007.

The attitude dynamics process unfolds mainly in 5 steps during one tick. (1) At first, the agent perceives an information that some action happened (whether it is the subject of this action or just witnesses it). (2) Then, it will evaluate the interest of this action, such interest will impact (as a weight) on both attitude computation and communication (to decide whether it wants to send this information). (3) The communication process is then triggered: the agent decides to send (or not) to its contacts the information it acquires during this time step. (4) When it receives messages from contacts, it updates its belief bases through a belief revision process. (5) Finally, the attitude values towards forces are updated. Let me now detail these steps.

(1) Action perception The agent could receive information in three different ways:

1. Direct perception: the agent either is subject to the action or directly witnesses it (e.g. the UN Force brings food to the village and the agent is a member of the village or was around when the action was done);
2.3. Polias : dynamics of attitudes within a population

2. **Actor communication**: an actor communicates about an action toward the population and the agent is one of the addressees (for instance, a force broadcasts propaganda messages or send leaflet);

3. **Intra-population communication**: the agent is given information about a previously perceived action by a neighbor in the social network, through a *message*.

**(2) Interest of an action** In order to determine what to base their attitude on and what to communicate to other individuals, agents estimate a model of *narrative interest* of the actions in their belief base. This interest is derived from Dessalles’s *Simplicity Theory* (Dessalles, 2006), a cognitive theory based on the observation that human individuals are highly sensitive to any discrepancy in complexity. Their interest is aroused by any situation which appears “too simple” to them (that is simpler to describe than to generate it)

An extension of the Simplicity Theory proposes to define the information’s narrative interest based on the emotion $E$ and the surprise level $S$ it causes to the individual (Dimulescu and Dessalles, 2009). We used the following formula to compute the interest:

$$I(i,a) = \alpha E(i,a) + (1 - \alpha)S(i,a) \quad (2.1)$$

We introduce a parameter $\alpha \in [0, 1]$ to weight emotion and surprise. Thus, important information are those who gives a high emotional level (e.g. “this tornado killed 1000 people”) and/or is unexpected (e.g. “there are never tornadoes in this area”).

Following (Dimulescu and Dessalles, 2009), the *emotional intensity* follows a logarithmic law in conformity with Weber-Fechner’s law of the stimuli (in our case, the action’s payoff $a.pyf$):

$$E(i,a) = \log\left(1 + \frac{|a.pyf|}{\xi}\right) \quad (2.2)$$

The parameter of sensitivity $\xi \in [0, 1]$ modulates the emotional response’s intensity value.

I detail in section A.2 of Appendix A how the surprise value $S(i,a)$ is computed.

**(3) Intra-population communication** Each agent can communicate through a given social network, and has a set of potential contacts (neighbors in the network). For each individual $i \in Ind$, for each action $a$ acquired during the current time step, the probability that agent $i$ sends a message about $a$ to a contact is given by:

$$p_{\text{send}}(i,a) = \begin{cases} 2^{I(a) - I_{\text{max}}} & \text{if } 2^{I(a) - I_{\text{max}}} > T_{\text{com}} \\ 0 & \text{otherwise} \end{cases} \quad (2.3)$$

where $T_{\text{com}} \in [0, 1]$ is a calibrated parameter. $I_{\text{max}}$ denotes the maximum of interest $I$, computed on the last $n\text{Step}^{10}$ (a fixed parameter of simulation). We choose a non-linear function for $p_{\text{send}}$, and it increases slower than linear, because we assume that the subjects are careful about what they transmit, and therefore, they will transmit only the information that have a sufficient interest

Note that the transmitted action contains only the impacts of the initial communication. For instance, if an actor performs the same action several times, agents will communicate only about the impacts of the last occurrence.

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8For details, see [http://www.simplicitytheory.org/](http://www.simplicitytheory.org/)

9On the other hand, in a region where a tornado happens several times a month, the impact of the deaths will be lowered.

10We introduce $n\text{Step} \in \mathbb{N}$, a fixed parameter to encode the number of time steps during which an information could remain the most important one (i.e. a dramatic event in the news). After $n\text{Step}$ steps, other information will be considered to become the most important one.

11It would be relevant to study the model’s behavior using other forms of sending probability, like faster than linear and linear. We plan to perform such an analysis in the short term.
(4) **Belief revision**  The belief revision mechanism is directly inspired by COBAN (cf. section 2.2.1.1 above). Here we take 3 possible levels of credibility: $\sigma_3$ (highest credibility) for direct experience, $\sigma_2$ for messages from families and friends, and $\sigma_1$ for others (unknown people, institutional message,...). Hence $\sigma_1 < \sigma_2 < \sigma_3$.

When an agent $i$ receives an incoming information in the form of an action belief $a_{in} \in AB$, of credibility $\sigma_s$, $s \in \{1, 2, 3\}$, it updates its belief base $Bl_f$ as follows:

1. If the action $a_{in}$ does not already exist in $Bl_f$ (i.e. there is no identical action with the same name, actor, beneficiary’s social group and date), the agent adds this action as a new belief. Its level of credibility is given by:

$$a_{in, \sigma} = \begin{cases} 
\sigma_3 & \text{if this is a direct observation} \\
\sigma_{\text{max}(s-1,1)} & \text{otherwise} 
\end{cases} (2.4)$$

When it is not a direct observation, the belief’s credibility is decreased by one level: when a friend tells me he observed an event ($\sigma_3$ for him), it is still a indirect observation for me ($\sigma_2$).

2. If an action $a_{ex}$ (with credibility $\sigma_s$) equivalent to $a_{in}$ exists in $Bl_f$ (i.e. they have the same name, actor, co-responsible, date, beneficiary, but differ by payoff), two situations can occur:

   (a) **Compatible case, reinforcement**
   
   if $|a_{ex, pyf} - a_{in, pyf}| \leq \varepsilon$ with $\varepsilon$ a fixed threshold, the beliefs are considered to be close enough to refer to the same action. In that case, the credibility value $a_{ex, \sigma}$ is updated as follows:

   $$a_{ex, \sigma} = \begin{cases} 
\sigma_3 & \text{if this is a direct observation} \\
\sigma_{\text{max}(s-1,\varepsilon)} & \text{otherwise} 
\end{cases} (2.5)$$

   For instance, if the existing credibility is $\sigma_1$ and a friend told me s/he saw an action ($\sigma_3$ for her), then the credibility for me is increased and becomes $\sigma_2$.

   (b) **Incompatible case, revision:**

   if $|a_{ex, pyf} - a_{in, pyf}| > \varepsilon$, the actions are incompatible. In that case, there is a probability that the agent replaces his belief $a_{ex}$ by $a_{in}$. This will depend on the revision probability value is given by Table 2.3, where $\pi_i \in [0, 1]$ with $i \in \{0,..,2\}$ are the model parameters for credibility revision. A random value is drawn from a uniform distribution: if it is greater then the revision probability, action belief $a_{ex}$ is replaced by $a_{in}$.

$$\begin{array}{cccc}
\sigma_3 & \sigma_2 & \sigma_1 \\
\sigma_3 & X & 1 - \pi_1 & 1 - \pi_0 \\
\sigma_2 & \pi_1 & \pi_2 & 1 - \pi_1 \\
\sigma_1 & \pi_0 & \pi_1 & \pi_2 \\
\end{array}$$

Table 2.3 – Generic table of credibility revision probabilities. By construction, a $\sigma_3$ level is never revised.

---

Note that the case $\sigma_3$ versus $\sigma_3$ is impossible since one cannot witness twice the same action occurrence (it will at least have a different date).
2.3. Polias: Dynamics of Attitudes within a Population

(5) Attitude update Whenever the reception of a new information about an action \(a\) done by an actor resulted in a belief revision in \(Bl_i\) or in a modification of the interest of an action belief, individual \(i\) will adapt its attitude toward actor based on its new mental state. S/he engages a three-stages process:

- **Evaluation** – The benefit of an action \(a\) is determined subjectively, i.e. in respect to agent \(i\)'s attitude and beliefs, using the evaluation model proposed by Ajzen and Fishbein (2005). This model combines payoff of the action for a beneficiary with the attitude of the individual toward this impacted beneficiary. In this way, an individual judging an action that is beneficial for him or for some of his “friends” (positive attitude), the overall benefit would be positive. Conversely, if the action is beneficial for his “enemy” (negative attitude), the action would have be evaluated with a negative value.

\[
eval(i, a) = \begin{cases} 
  a.pyf \times \text{sign}(\text{attSG}(i, a.bnfg.sg)) & \text{if } a.bnfg \in \text{Ind} \\
  a.pyf \times \text{sign}(\text{att}(i, a.bnfg)) & \text{if } a.bnfg \in \text{Act} 
\end{cases}
\]  

(2.6)

with \(\text{sign}(x) = \begin{cases} 
  1 & \text{if } x \geq 0 \\
  -1 & \text{sinon}
\end{cases}\)

- **Co-responsibility** Individuals tend to make responsible for an action other people, groups or institutions than the direct actor (Kelley, 1973; Jones and Harris, 1967). Hence, we introduce a co-responsibility mechanism that enables individual to attribute a fraction \(\rho \in [0, 1]\), parameter of the simulation, of an action payoff to the co-responsible. This mechanism occurs when an individual faces an action \(a\) in which (1) there is a co-responsible actor, (2) its impact is negative (i.e. there is no co-responsibility for beneficial actions) and (3) its evaluation is negative. In that specific case, the individual adds a belief \(a'\) with \(\text{actor}(a') = \text{coResp}(a)\) and \(\text{evaluation}(a') = \rho \times \text{evaluation}(a)\).

- **Attitude update** Once all the components of Fazio’s attitude model have been computed, the individual can finally construct his attitude. It corresponds to the aggregation of all actions’ evaluations for a given actor weighted by their corresponding accessibilities (i.e. interest value in our case). However, we propose that this aggregation proceeds in two steps. First, the agent aggregates all the action that share the same action type (e.g. patrol, health-care, etc.) for a given actor. Let \(\text{at}(i, \text{actor})\) be the list of all action types made by actor and \(\text{al}(i, \text{actor}, t)\) the list of all actions of type \(t\) performed by actor, in agent \(i\)'s belief base. The attitude \(\text{att}(i, \text{actor})\) of the individual \(i\) toward the actor is given at each time of the simulation by:

\[
\text{att}(i, \text{actor}) = \text{OWA}_{i \in \text{at}(i, \text{actor})} \left( \text{OWA}_{a \in \text{al}(i, \text{actor}, t)} (\eval(i, a) \times I(i, a)) \right)
\]  

(2.7)

We use an OWA aggregation here instead of a WOWA, because we assume than the agent has no particular preferences among the action types and among the actions (see e.g. (Yager, 1988; Ogryczak et al., 2012) on OWA aggregation and Appendix B for more details on aggregations).

2.3.2.3 Model’s parameters

We summarize in Table A.1 (section A.1 in Appendix A) the parameters of Polias model, where we distinguish the parameters at the individual levels (both cognitive and emotional) from the social ones.
2.3.3 Simulation results

The model has been implemented in Java under Repast.

2.3.3.1 Model’s dynamics

Several Sensitivity analyses have been conducted to study the model’s dynamics and the impact of the parameters. Let me summarize the main results (for details, see (Brousmiche, 2015, ch. 4) :

- When $\alpha$ or $\xi$ increases, the attitude increases. $\xi$ plays the role of a scaling factor, triggering the strength of the emotional response.

- $\alpha$ sets the balance between emotion and interest. We can define 3 cognitive profiles: poorly emotional ($\alpha = 0.1$), balanced ($\alpha = 0.5$) and highly emotional ($\alpha = 0.9$).

- When they face events affecting other social groups (than their own), poorly emotional agents (and balanced ones, to a lesser extent) will react less steeply and less rapidly than highly emotional agent. This is because, when the emotion weight is low, the interest weights a lot, and interest decreases with the social distance between the agent and the one affected by the event (cf. section A.2 in Appendix A).

- We obtain a classic S-form shape of adoption curve, and the adoption rate increases with $T_{com}$.

- The adoption increases with the revision probabilities $\pi_0$ and $\pi_1$ (we keep $\pi_2 = 0.5$ for all simulations), and also with the density of the social network (we vary the mean degree $k$ of a Watts and Strogatz (1998) small-world network).

For the aggregation operators used to compute the final attitude value (cf. eq. 2.7), we choose the following, in order to limit the number of parameters to calibrate:

\[
\text{attitude}(i, \text{actor}) = \sum_{t \in \text{at}(i, \text{actor})} \left( \sum_{a \in \text{al}(i, \text{actor}, t)} \frac{\text{eval}(a, i) \times \text{interest}(a, i))}{|\text{al}(i, \text{actor}, t)|} \right) \right)
\] (2.8)

2.3.3.2 Case study from field data

Scenario Through our cooperation with Airbus Defence and Space, we have been given an access to polls results about opinions of the population toward the different present Forces (foreign Force and Taliban) in an area of Afghanistan where French forces conducted stabilization operations. In the course of the NATO intervention in Afghanistan to stabilize the country, the French Forces were tasked to maintain security in the regions of Kapisa and Surobi between 2008 and 2012. As part of a more comprehensive maneuver, their actions were meant to complement conventional security operations by positively influencing the population and its key individuals through communication, reconstruction and humanitarian actions. Through a set of six interviews with all the successive officers in charge (3 colonels and 3 commanders) from the Joint Command for Human Terrain Actions, we managed to rebuild the sequence of the events that took place during their tenures, originating both from the NATO and from the Taliban insurgents. This sequence takes the shape of a scenario (see figure 2.9).

Each action is characterized by a reach, a frequency and a payoff: how many people were directly affected by the action, how many times per week if it is frequent, how each individual
is impacted. These values were defined based on subjective assessments of domain’s subject matter experts.

We can observe that both Forces have a constant background activity toward the population composed of non-kinetic actions. However, the Red Force activity is heavily decreased during winter which corresponds to the second period on the scenario. One reason is that local Taliban leaders leave the region to avoid the arid climate. On the Blue Force side, the activity decreases constantly due to the political decision taken after the big human losses on the first period (suicide attack of Joybar on July 13th 2011, which caused considerable human casualties among the Blue Forces).

Figure 2.9 – Scenario of Blue and Red Forces actions, and opinion polls

In order to follow the progress of population’s sentiments and to link them to foreign Forces activities, the French Ministry of Defense financed opinion polls in Afghan regions where the French forces were operating. Those surveys were conducted by Afghan contractors between February 2011 and September 2012 with an interval of approximately 6 months issuing into four measure points P1, P2, P3 and P4 of the opinion of the population of Kapisa toward (1) the Blue Force and (2) the Red Force on the period corresponding to our scenario. The results are displayed in Table 2.4 below.

Simulation settings and initialization We input the action sequence presented in the scenario of both Red and Blue Forces into the simulation scheduler; one tick corresponds to one
day. The simulation covers the period between the first and last opinion polls in 554 ticks.
The two agents corresponding to each Force will then operate their actions according to the
scenario. The artificial population representing the inhabitants of Kapisa is composed of
500 agents connected by an interaction network based on a small-world topology (Milgram,
1967) with a degree of 4 (i.e. each individual has 4 neighbors in average).

Before running the actual simulation, we initialize the population with a personal history
for each individual and an attitude corresponding to the value given by P1. Indeed, one of
our model’s originality resides in the fact that the attitude depends on the agent’s cognitive
state characterized by its beliefs and accessibility values. Thus, we must give individuals an
initial belief with a certain reach and payoff for both attitudes toward Red and Blue Forces.
These beliefs represent the interactions with Forces preceding to the simulation span. An-
other subtle point in our model is that individuals are surprised when they witness a totally
new action, resulting in an overestimation of the action’s impact. In order to habituate them
to certain regular actions (such as patrols, preaches, radio broadcasts etc.) we need to run
an initialization scenario before the actual one in which the population is confronted to these
actions, until we reach a stable point (approximately 200 ticks). This scenario is depicted in
Figure 2.10 below.

<table>
<thead>
<tr>
<th>Polls dates</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;The Blue Force contributes to security&quot;</td>
<td>40</td>
<td>32</td>
<td>24</td>
<td>19</td>
</tr>
<tr>
<td>&quot;The Red Force is the principal vector of insecurity&quot;</td>
<td>27</td>
<td>60</td>
<td>27</td>
<td>37</td>
</tr>
</tbody>
</table>

Table 2.4 – Percentage of the population favorable with two questions at different dates

Calibration method Once the simulation is properly initialized, we calibrate the model
parameters using each opinion polls results as objectives. We have four points to calibrate
per Force, thus totaling 8 points of calibration. 8 model parameters are shared among all
individuals of the population:
- $a$, the weight of emotional sensibility toward the surprise factor
- $\xi$, the level of sensibility to a stimuli (i.e. payoff)
- $\rho$, the co-responsibility factor of Blue Forces for harmful Red actions
- $T_{com}$, the communication threshold
- 4 parameters of initialization actions to attain the first point P1

\[^{13}\text{We must add in the initialization scenario a positive action done by the Red Force, and a negative action done by the Blue Force This is to balance the habituation effects where most of the time the Blue Force actions are positive and negative for the Red Force. We have to set for each of these two additional actions a payoff and a reach, so a total of 4 values.}\]
2.3. Polias : dynamics of attitudes within a population

The other parameters are set to the following values: \( \pi_0 = 0.9, \pi_1 = 0.75, \theta T_0 = 10, \epsilon = 0 \). The social network is a Watts and Strogatz (1998) small-world network, with mean degree \( k = 4 \).

We define our fitness function as the sum of differences' squares between each point of the opinion poll results and its corresponding percentage of favorable individuals in the simulation. We choose to minimize this fitness using the evolutionary algorithm CMA-ES that is one of the most powerful calibration method to solve this kind of problem Hansen and Ostermeier (2001) and that we have successfully tested and used in the WorkSim project (see section 4.3.1 in chapter 4 for more details). Once the fitness stops progressing over 500 iterations, we interrupt the calibration process and save the parameters. Each calibration iteration is based on the average output on over 20 simulations replica since the model is stochastic. It took about 36 hours on a grid made of 20 processors (4GHz Intel Xeon).

**Calibration results** The figure 2.11 shows the results of our model once its parameters have been calibrated. Plain curves represent the objectives to reach that are based on the collected opinion poll results dashed curves correspond to the simulation results, with \( \alpha = 0.77, \zeta = 0.01, \rho = 0.21 \) and \( T_{com} = 0.15 \) (as obtained by the calibration). Hence, the individuals appear to be quite emotional, and blame the Blue Force to be co-responsible for 21% of the negative effects.

We can observe that the attitude dynamics tendencies are well reproduced. The average difference between results and objective points is 2.9% with a maximum of 6% for the P2 and P4 blue points. This gap between survey and simulation results could be explained by several factors. First, the established scenario is based on subjective assessments of some Blue Force officers and do not capture all the military events that took place on the terrain. Furthermore, the parameters of action’s models (i.e. payoffs, frequency and reach) have been assessed based on qualitative appraisal of subject matter experts since there is no scientific method to assess them. Second, the sampling of the opinion survey could not be maintained through the survey process, due to the dynamics of the conflict: certain villages could not be accessed constantly over time due to their dangerousness. Moreover, as it was pointed earlier, the questionnaire did not directly ask the opinion toward Red Force which might increase the gap between our model outputs and the polls results. Finally, our field data is limited to the context of military events. Even if our study concerns attitudes toward Forces in the military/security context, other events might also have influenced these attitudes such

**Figure 2.11 – Simulation results compared to opinion polls**
as economic or daily activities. In view of these limitations, the reproduction of the general tendencies of attitude dynamics between each polls seems encouraging.

**Attitude Dynamics** Finally, we proceed to an automatic classification of individual attitudes, using a Kohonen neural network (Kohonen, 1982) made of 9 neurons (3x3 grid). The input vector are the attitude values at each point P1,..P4 and for both forces, therefore 8 values for each of the 500 agents. The results are displayed in the Figure 2.12. A one can see, we can identify three groups:

- The pro-Blue group (cells 8 and 9), where initial attitudes are favorable to the blues, and increase through the simulation and the attitudes towards red forces move from neutral to negative. It represents 122 agents.

- The anti-Blue group (cells 2 and 3), with initial attitudes are unfavorable to the blues, and decrease through the simulation, while the attitudes towards red forces move from slightly positive to neutral. It contains 299 agents.

- The neutral group (cells 1,4,5,7), whose attitudes are close to zero, slightly decreasing for both forces during the simulation. This groups is made of 79 agents.

![Classification of attitudes with a 3x3 Kohonen map](image)

**Figure 2.12 – Classification of attitudes with a 3x3 Kohonen map**

This is a work in progress. More work needs to be done to further analyze this classification, to characterize more finely the members of each group and to analyze the behaviors of typical agents in order to account for this scenario and the polls data. More details will be found in the final version of Brousmiche (2015).

### 2.4 Conclusion of this Chapter

In this chapter, I presented two models devoted to opinion and attitude dynamics. COBAN emphasizes knowledge representation by introducing a compact and original opinion representation through Individual Belief Associative Networks. It also introduces an original communication mechanism based on Transmission Networks and a belief revision mechanism based on credibilities. The model has been validated on real data and has shown its efficiency to account for the innovation diffusion. In particular, the knowledge incorporated into the belief networks can be used to explain the diffusion (success and failure), to make social representation and learning emerge.
Representing knowledge as associative networks permits to create models which can be tested against real data, and to represent both messages and individual knowledge in a computationally tractable way. This representation is highly manipulable, even for non-experts. Implicitly it allows to model misunderstanding of information, word-of-mouth or launch of related innovation in a more plausible way - in fact models that were expected by Rogers. Hence we could build models that represent the whole adoption process, from awareness to decision.

One limitation of such social simulation is that it depends on the social networks used to model interaction. A change in the network could produce quite different outcomes. This is why Samuel Thiriot also proposed an automatic generator of such a network, given various social rules observed in the real population (Thiriot and Kant, 2008a). It is based on bayesian networks and is now available as an open-source software\textsuperscript{14}. Polias is a comprehensive agent-based generative model of attitudes. Strongly grounded on social psychology, it integrates a cognitive and an emotional component, combined with a communication mechanism inspired from COBAN. It has a relatively small number of parameters (8), and has been calibrate to account for real field data. Polias is a generic model of attitude formation, and could be applied to any application domain.

In the very next future, one interesting step would be to combine these two models and merge them into a complete opinion and attitude dynamics model, taking advantages from both models. The knowledge representation with beliefs in COBAN could help to understand the individual attitude and to characterize more finely the classification of a population. We should also add a behavioral component to the attitude generation. Learning (from the past) mechanisms could also be incorporated to link an attitude with past behaviors and their consequences. Finally, some contextual mechanisms could be added, while we know that an opinion or attitude will differ depending on the context (e.g. professional, personal, political, ...) we are when we use it. With context, we open in some way the door to multi-level modeling, another possible perspective for this kind of research (I will come back to this in the general discussion of this thesis).

Finally, one may question the axiological neutrality of this kind of models. For instance, in Polias, deciding whether a payoff of an action is positive or negative depends on your point of view, on what side you are on. This is partially captured in Equation 2.6, but should be investigated further\textsuperscript{15}. Furthermore, ethical issues might be raised, as being able to model opinions and attitudes could lead to an instrument of ideological manipulation or propaganda, if it falls into the wrong hands.

\textsuperscript{14}\url{http://sourceforge.net/projects/yang-j/}.
\textsuperscript{15}For instance, by impacting not only the sign but the value of attitudes on Social Groups $attSG$ in Equation 2.6.
3 HAPPYWORK: JOB SATISFACTION AND ACTIVITY AT THE WORKPLACE

The HappyWork project aims to model and simulate job satisfaction within a firm. It is funded by Technologia, the leader counseling firm in France specialized in psychosocial risks, with the PhD of Kevin Chapuis (2012-2016).

Work is the activity in which people spend most of their daytime. According to opinion survey regarding life domains, job often comes at the top ranking in terms of subjective importance (Clark, 2010) and job satisfaction is one of the strongest predictor of overall happiness (Diener et al., 1999). Moreover, the interest in job satisfaction has recently increased when more firms and governments realize the importance of work-related illnesses. Many reports (e.g. Valeyre et al., 2009) point out the increasing number of psychosocial risks at work, including musculoskeletal disorders, depression or burn-out. These clinical consequences are usually associated with typical behavioral patterns - e.g. absenteeism, withdrawal behavior, quitting or job dissatisfaction (Harrison et al., 2006) - that not only affect the firm but also send a warning sign about employees’ psychophysical condition.

The two first sections introduce our satisfaction model, followed by some simulation results. Then, I will present our activity model, to describe what agents are doing when working, and how it will affect the work conditions, and therefore the job satisfaction. In other words, an activity model is essential to model job satisfaction dynamics.

3.1 DYNAMICS OF ATTITUDES TOWARD JOB WITHIN A FIRM

3.1.1 What is Job Satisfaction?

Job satisfaction is roughly about “how people feel about their jobs and different aspects of their jobs [...] the extent to which they like (satisfaction) or dislike (dissatisfaction) their jobs.” (Spector, 1997). The seminal work of Locke (1968) goes further to explain the content of this feeling, that is “the pleasurable emotional state [i.e. job satisfaction] resulting from the appraisal of one’s job achieving or facilitating one’s values”. Although there is a relative consensus about the nature of job satisfaction, there are many controversies regarding the content and area of influence of this subjective reactions to job conditions. In HappyWork, we follow an attitudinal approach: job satisfaction is mostly conceptualized as an attitude toward the job (Spector, 1997). Let me now describe the cognitive, emotional and behavioral components of job satisfaction.

Cognitive dimension – It focuses on information processing based on job features (Fisher, 2010). Among many of these cognitive approaches, we find Value-Based Evaluation (moral or physical values Locke, 1968), Needs-Based Judgment (e.g. the Job Characteristics Model (Hackman and Lawler, 1971)), Social Information Processing, which emphasizes the influence of context (social environment) and consequences of past choices (Salancik and Pfeffer, 1978), input/output based judgment, e.g. the Cornell Model (Hulin et al., 1985), where

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1Related publications: (Chapuis and Kant, 2014a,b; Chapuis, 2016)
job evaluation is based on contributions (e.g. skills, time, effort,...), outcomes (salary, conditions,...) and environmental factors. Overall, the job attitude is computed through a comparative evaluation of job features, i.e. an aggregation of perceived discrepancies between job features and a set of standards (referents) (Dalal, 2012). These referents could be alternative situations (lived in the past, by others or even mentally experienced (Levy-garboua and Montmarquette, 2004)) or abstract standards (values, needs, etc.).

**Affective dimension** – It includes affective response at work (Judge et al., 2012), emotional responses to job events (Weiss and Cropanzano, 1996), personality bias and interaction between affective and cognitive evaluation while at work (Weiss, 2002). However, several authors warn about the speculative content of mechanisms involved in emotion at work, and their links with cognitive reaction to job events and features. Emotion and cognition are intimately related to one another, but no consensus emerges on their respective roles in job satisfaction formation (Judge and Klinger, 2008).

**Behavioral dimension** – It concerns how job attitude influences the subject’s behavior and actions. Therefore, it is of great interest since a good understanding of the relation between attitude and behavior can provide insights to improve organization outcomes (Ajzen, 2011). Note that this component is mostly studied as a consequence rather than as an antecedent of job satisfaction: for instance, one will study if a very unsatisfied employee will under-perform or be ill more frequently (Harrison et al., 2006).

### 3.1.2 Related agent-based works

We have already reviewed the agent-based approaches for attitude dynamics in section 2.3.1 of chapter 2. However, to our knowledge, no agent-based model has been proposed for job satisfaction. Though we view it as an attitude, we also claim that job satisfaction has several peculiarities that require a specific model (and then distinct from Polias). Again, we follow psychomimetism and implement well-founded psycho-sociological theories. As for agent interactions, we go beyond diffusion or communication by modeling a complete social comparison process, as it as been shown by the literature to be a crucial component of job attitude (Festinger, 1954). Finally, our mid-term / long-term goal is to provide a decision-aid tool for managers that aim to improve job satisfaction within their firms. Therefore, we need a rich and realistic enough model. In particular we must incorporate the elements (e.g. job conditions,...) we find in actual firm organization and that a manager will seek to adjust.

### 3.1.3 Our approach to job satisfaction : the HappyWork framework

As stated before, we follow here an attitudinal approach. Moreover, we will focus only on the cognitive dimension of job attitude, for two main reasons. First, most of the surveys and data available on job satisfaction only capture the cognitive dimension (Weiss, 2002). The affective one is difficult to measure and to model at the moment (Fisher, 2010). To tackle the behavioral dimension, we must first model the activities at work : this is the very purpose of our DeC-GCM model presented in section 3.4 below.

Our approach for job satisfaction, the *HappyWork framework*, is based on subjective feature evaluation and comparison process with standards. If we take the point of view of organizational psychology and econometrics, the features will be the characteristics of the job, and concern the job at different levels, like work load, demand for creativity, autonomy, salary, etc. They are subjective perceptions of the job and could be accessible through surveys.

Defining standards is a difficult task, as there is no accepted consensus on their type and content. In Locke’s value-percept model (Locke, 1976), standards are personal values; in

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2The only other model would be (Tarvid, 2014), but job satisfaction takes only a minor role in this model, being reduced to a single utility function (weighted average of four attributes).
Cornell’s model (Smith et al., 1969) standards are past experiences and social values. Michalos (1985) tried to synthesize these approaches in his multi-discrepancy theory (MDT). He proposed that satisfaction is inversely related to perceived discrepancies between what we have and various standards, including what we want (desire discrepancy), the best we had in the past (past comparison discrepancy), and what relevant others have (social comparison discrepancy).

From our review of this literature, we have selected two types of standards and hence two types of comparison:

- a **social comparison** where a subject compares his/her job situation with some other individuals (denoted as social referents).

- an **historical comparison** where a subject compares his/her current job situation with past situations (denoted as past referents).

To these comparison processes, we add a **third component**: the **direct effect** that represents a direct evaluation of job features. This component is intended to capture individuals and environment differences, a subjective component where one will judge directly his working conditions, salary, interaction of work activity with private and family life, etc.

The Happywork framework is summarized in the Figure 3.1 below.

![Figure 3.1 – The HappyWork Framework: cognitive process of job evaluation resulting in job satisfaction](image)

At first, agent $a$ acquires information about the job and comparison standards: a job feature perceptions vector $RQ(a)$, the job features for referent $r$ $RQ(r)$ and past job features $RQ(h)$. Once the three cognitive sub-processes (social, historical and direct) have been performed, a final aggregation can be done to obtain the overall job satisfaction (corresponding to the answer to a question like: “overall, are you satisfied with your job?”).

Finally, in HappyWork, we promote a **data-driven approach**, in order to account for real data deriving from field surveys. Thanks to our partner Technologia, we were able to use some of their questionnaires and surveys to feed our agents at initialization, and study their job satisfaction dynamics (see section 3.3 below on data collection).
3.2 **AGENT-BASED MODEL OF JOB SATISFACTION**

3.2.1 **Model inputs and initialization**

Let \( A \) be the set of agents in the simulation. Let \( Q = \{q_1, \ldots, q_n\} \) be the set of job characteristics, these characteristics being sorted into a set of job dimensions \( D = \{d_1, \ldots, d_k\} \). \( Q \) and \( D \) will be provided by the questionnaire we aim to study. Every agent \( a \in A \) is initialized with values \( RQ(a) = [q_{1a}, \ldots, q_{na}] \) that encode its subjective job features as responses to the questionnaire on each feature \( q_i \). The questionnaires under study are made of ordered Likert scales\(^4\), so the numerical encoding is straightforward (e.g. 1 for very unsatisfied, 2 for unsatisfied, etc.).

3.2.2 **Discrepancy evaluation**

The social comparison implies a computation of the differences \( \Delta(a, r) \) between an agent \( a \) and one of his referent \( r \). We have:

\[
\Delta(a, r) = [\delta(a, r, q_1), \ldots, \delta(a, r, q_n)]
\]

\[
\delta(a, r, q_i) = \frac{q_{ia} - q_{ir}}{\text{max}(q_i) - \text{min}(q_i)}
\]

(3.1)

where \( \delta(a, r, q_i) \in [-1; 1] \) computes the discrepancy between \( a \) and \( r \) on feature \( q_i \), \( \text{min}(q_i) \) and \( \text{max}(q_i) \) being respectively the minimal and maximal values for question \( q_i \) given by the questionnaire.

3.2.3 **Social comparison**

To design the social comparison process, we take our inspiration from Mussweiler’s Selective Accessibility Model (SAM) (Mussweiler, 2003). According to Mussweiler, people compare with each other using three main processes: (i) the subject \( a \) uses a set \( RS(a) \) of referents to compare with; (ii) for each referent \( r \in RS(a) \), if \( a \) feels similar enough with \( r \), then it engages the comparison process; and in that latter case, (iii) the impact of the comparison is computed either by assimilation or contrast, two different sub-processes I will detail below.

1) **Referent selection.** Classical definition of social referent encompasses closeness and similarity (Suls et al., 2002). Referents in work organization could be identified as individuals we interact with, colleagues and generally people in close environment (Greenberg et al., 2007). In absence of data on the real social network, we assign for each subject \( a \) a set of referents \( RS(a) \), of cardinality \( NR \). \( RS(a) \) is made of first-degree neighbors in the social network.

2) **Similarity hypothesis–testing (anchoring).** At this stage, agent \( a \) must decide whether it is close enough to referent \( r \). To do so, \( a \) computes \( \text{mode}(a, r) \in [0, 1] \) as the proportion of features on which \( a \) and \( r \) have different values, using the following algorithm 1 below, where \( \beta \in [0, 1] \) is a calibrated parameter.

Hence, \( \text{mode} = 0 \) means a complete similarity, and \( \text{mode} = 1 \) a complete dissimilarity. Following Mussweiler (2003), \( \text{mode}(a, r) \) is not computed on the entire job feature set. In

---

\(^3\)Dimensions are groupings of features in order to study a job from a certain angle. Among the dimensions, we have those proposed by Karasek (a widely used questionnaire to assess psychosocial risks and job satisfaction): psychological demand, decision latitude and social support Karasek (1979).

\(^4\)A Likert scale (Likert, 1932) is a psychometric scale commonly involved in research that employs questionnaires (usually with 4 or 5 levels). A typical five-level ordered Likert scale, where the items are ordered along satisfaction: Strongly Unsatisfied / Unsatisfied / Neither satisfied nor unsatisfied / Satisfied / Strongly Satisfied.
fact, people typically select few salient information about their referents to engage in a basic, spontaneous, and preliminary comparison process: this is an anchoring\textsuperscript{5} . We denote this salient feature set $SF(Q)$, it is made of readily accessible job features, like employment conditions. If $mode(a, r)$ exceeds a given deflection threshold $\sigma^{D}$, the comparison target is too dissimilar. In this case the referent is deflected and no comparison occurs. Otherwise, the similarity hypothesis is supported and $a$ moves to the third step.

3) **Assimilation and contrast outcomes.** According to SAM theory, comparison outcome depends on comparison content and “on what information is cognitively accessible “. Content is defined by the direction of comparison, namely downward when $a$ compares itself with someone $r$ feels to be worse off on characteristic $q$ – in our case when $\delta(a, r, q) > 0$ – or upward comparison for the opposite – when $\delta(a, r, q) < 0$. Accessible information is conceived in SAM as priming stimulus focusing on similarity or dissimilarity (Mussweiler, 2003). The model posits that if someone is primed to insist on similarities with the comparison target, then assimilation process occurs. This happen when $mode(a, r) < \sigma^{A}$, where $\sigma^{A} \in [0, 1]$ denotes an assimilation threshold (i.e. the maximum proportion of differences to be considered similar). Otherwise, when $mode(a, r) \geq \sigma^{A}$, a contrast sub-process is triggered.

Moreover, assimilation process makes the subject $a$ feel to be in the same situation as the referent. Hence, if the referent is in a better condition, $a$ foresees it will be better off soon and, this comparison will have a positive impact on its comparison process. Symmetrically, comparing with someone worse leads to a negative impact on job satisfaction (“my situation will deteriorate soon ”) (Wheeler and Suls, 2007). Contrast typically render opposite consequences, that is a positive/negative impact when comparing with someone better/worse (“I feel different than my referent, and then happy when I’m better, unhappy when I’m worse ”). This could be summarized in Table 3.1 below, where $IC(a, r, q)$ is the outcome of $a$’s comparison with referent $r$ on feature $q$. $IC(a, r, q) > 0$ (resp. $< 0$) means that $a$’s comparison with $r$ will tend to increase (resp. decrease) $a$’s satisfaction on feature $q$.

<table>
<thead>
<tr>
<th>Assimilation</th>
<th>Contrast</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r$ is better ; $\delta(a, r, q) &lt; 0$</td>
<td>$IC(a, r, q) &gt; 0$</td>
</tr>
<tr>
<td>$r$ is worse ; $\delta(a, r, q) &gt; 0$</td>
<td>$IC(a, r, q) &lt; 0$</td>
</tr>
</tbody>
</table>

To encode these effects, contrast outcome is computed as the difference itself : $IC(a, r, q) = \delta(a, r, q, i)$. Symmetrically, assimilation could be given by $IC(a, r, q, i) = -\delta(a, r, q, i)$. However, several socio-psychologists (Wheeler and Suls, 2007) have found that assimilation process often exhibits mixed effects (assimilation and contrast), even when the subject feels very close to comparison target. In other words, assimilation process may contain a certain proportion of contrast – denoted $\alpha^{c} \in [0, 1]$ in our model. In fact, $\alpha^{c}$ will

\textsuperscript{5}Anchoring refers here to a general judgment theory in cognitive psychology, the anchoring and adjustment heuristics (Tversky and Kahneman, 1974).
weight the assimilation and contrast components within the comparison:

\[
IC(a, r, q_i) = (1 - \alpha^c) \times (-\delta(a, r, q_i)) + \alpha^c \times \delta(a, r, q_i) = (2\alpha^c - 1)\delta(a, r, q_i)
\]

The overall comparison process is summarized in the following algorithm:

**Algorithm 2** Impact of feature comparison

1: if \( \text{mode}(a, r) \geq \sigma^D \) then STOP (no comparison) [Deflection]

2: else if \( \text{mode}(a, r) < \sigma^A \) then

   \[
   IC(a, r, q_i) = (2\alpha^c - 1)\delta(a, r, q_i)
   \] [Assimilation] (3.2)

3: else if \( \sigma^A \leq \text{mode}(a, r) < \sigma^D \) then

   \[
   IC(a, r, q_i) = \delta(a, r, q_i)
   \] [Contrast] (3.3)

4: end if

The final social comparison outcome for agent \( a \) is computed from its \( IC(a, r, q) \) values. This is done through a sequence of multi-criteria aggregations. At first, we use a WOWA (weighted ordered weighted average) aggregation along the features of each dimension to obtain the aggregated comparison impact \( ICD(a, r, d) \) on each dimension \( d \in D \). Then, to get \( \text{CompSoc}(a, d) \) – the overall comparison impact on dimension \( d \), all the referents \( r \in RS(a) \) will be aggregated using an ordered weighted average (OWA) operator:

\[
\text{SocSat}(a, d) = \text{OWA}_{\text{w}}_{r \in \text{RS}(a)} \left( \text{WOWA}_{w, p} \left( IC(a, r, q_i) \right) \right)
\] (3.4)

For the OWA weights \( \text{w} \), we will have to choose between the three proposed profiles (neutral, optimistic or pessimistic; see Appendix B for details). For the WOWA-specific weight \( p \), to use the same weights as defined by Karasek (Karasek et al., 1998), because the questionnaires in our data set were built according to the Karasek model (Karasek, 1979), a wide-spread used model to design questionnaires on job satisfaction.

### 3.2.4 Historical comparison

The historical comparison process accounts for the importance of previous events and situations in the past: is the subject better off now compared to how s/he was before, or worse? To model this, we take our inspirations from Kahneman’s peak-end model (Kahneman, 2000). Like in the social comparison process, agent \( a \) will compute a discrepancy vector for all the features \( q_i \): \( \Delta(a, h) = [\delta(a, h, q_1), \ldots, \delta(a, h, q_n)] \).

How to choose the referents \( h \)? According to peak-end, they will be: (peak) the situation that corresponds to the most intense satisfaction – most positive or most negative, and (end) the last situations experienced by the subject. We denote \( IS_h(t) \) the individual situation vector that encodes all the feature values for agent \( a \) at time \( t \), and \( t_{\text{max}} \) records the time (a tick number in the simulation) when the satisfaction was maximal in absolute value. The historical referent set \( RH(a) \) is given by:

\[
RH(a) = \bigcup_{RH_{\text{peak}(a)}} \{h_0\} \cup \bigcup_{RH_{\text{end}(a)}} \{h_1, h_2, \ldots, h_{f_a}\}
\] (3.5)

with \( h_0 = IS_h(t_{\text{max}}) \) and \( \forall i \in \{1, \ldots, f_a\} \), \( h_i = IS_h(t - i) \), \( f_a \) is the size of the memory (in tick numbers) for the historical comparison. This size must be limited to account for bounded rationality.
The impact of historical comparison \( IC(a, h, q) \in [-1;1] \) is given by the discrepancy between current and past value for feature \( q \):

\[
\forall h \in RH(a) \quad IC(a, h, q) = \delta(a, h, q) \quad (3.6)
\]

Then we aggregate the impact features \( q \) to produce impacts for each dimension \( d \):

\[
ICH(a, h, d) = \text{WOWA}_{w,p} (IC(a, h, q)) \quad (3.7)
\]

For this aggregation, again, the \( p \) weights will be based on in the Karasek model (see previous section above).

Finally, we need to aggregate on referents \( h \) for each dimension \( d \):

\[
HistSat(a, d) = \text{WOWA}_{w',p'} \left( IC(a, h, d) \right) \quad (3.8)
\]

In the spirit of peak-end theory, the \( p' \) weight of the peak will be 0.5 and the other 0.5 will be divided among the past referents. The weights of past events in the WOWA aggregator will decrease over time, so that the most recent will have a stronger impact. Let \( r_a \) be this decrease rate, compute the decrease using a formula from Levy-Garboua & Montmarquette (2004; p.138):

\[
p'_{0} = \frac{1}{2}, \quad \forall i \in \{1,2, \ldots f_a\} \quad p'_{i} = \frac{1/((1+r_a)^i)}{2 \cdot \sum_{j=1}^{f_a} 1/(1+r_a)^j} \quad (3.9)
\]

### 3.2.5 Direct Impact

The last component of the aggregation process. First, we need to convert each feature value to an impact on satisfaction. The final satisfaction value is in \([-1,1]\), so we need to transpose the Likert values into \([-1,1]\):

\[
Val_{q_i}(a) = \left( \frac{2 \cdot (q_{ia} - \min(q_i))}{\max(q_i) - \min(q_i)} \right) - 1 \quad (3.10)
\]

where \( Val_{q_i}(a) \) is the translated value for \( q_{ia} \).

Finally, to compute the direct impact for each dimension \( d \), we apply a weighted mean, using again the weight vector \( \Gamma^{Q} \) defined by Karasek in (Karasek et al., 1998):

\[
DirectSat(a, d) = \sum_{\forall q \in d} Val_q(a) \cdot p_q \quad (3.11)
\]

\( p_q \) values are taken from the corresponding Karasek's \( \Gamma^{Q} \) vector values.

### 3.2.6 Final Aggregation

First of all, for one given dimension \( d \) we need to aggregate the three processes (social, historical and direct). The satisfaction on dimension \( d \) \( sat(a, d) \in [-1,1] \) aggregates the three processes:

\[
sat(a, d) = \text{WOWA}_{w,\Gamma} \left( SocSat(a, d), HistSat(a, d), DirectSat(a, d) \right) \quad (3.12)
\]

We apply a set of weights \( \Gamma = \{\gamma^S, \gamma^H, \gamma^D\} \) (calibrated parameters) corresponding to the three processes in this WOWA.

Finally, we aggregate all the dimensions to obtain the global satisfaction value:
\[ Sat(a) = \text{WOWA}_{\Lambda, \Delta}(\text{sat}(a,d)) \]  
where \( \Lambda = \{\lambda_1, ..., \lambda_k\} \) weight the different dimensions in the WOWA

We summarize in Table C.1 (section C.1.1 of Appendix C) the parameters for the satisfaction model.

### 3.3 Simulation results for job satisfaction

The satisfaction model was implemented in Java. Unless specified, the parameter values are set to their baseline values (displayed in C.1.1).

#### 3.3.1 Data collection

Thanks to our partner Technologia, we had access to survey data concerning a big French industrial company in 2011. There were 195 respondents and we extracted 37 features from the initial 113 questions. 27 features correspond to the three-dimensional model of Karasek (1998): psychological demand (9 questions), decision latitude (9 questions) and social support (9 questions). Then we add questions on: salary, working hours, number of subordinates, status, position, management, seniority, age, gender, and degree. All these questions are made of Likert scales. We also added the question on job satisfaction (4-levels Likert) that give the satisfaction level declared by each respondent. We show in Figure 3.2 below an extract of the original survey (in French).

![Survey Sample](image)

**Figure 3.2 – Survey Sample. Q1=“In my work, I have to learn new things”. Q21=“My manager helps me to accomplish my task”. Q139=“What is your salary (excluding bonuses)?”. Answer 1 is complete disagreement, Answer 4 full agreement.**

#### 3.3.2 Sensitivity analysis

We conducted several sensitivity analyses of the satisfaction model, and I will present here the main results. We have \( n = 100 \) agents, connected with a small-world network, with an average number of referents \( R_N \simeq 9 \) (cf. Table C.1) The dynamics derives here from the social referents: a fraction \( R_N^c = 20\% \) is randomly changed every tick. The results are averaged over 50 simulations of 10 ticks.

**Social comparison** We study the impact of the three parameters of the social comparison process: the assimilation threshold \( \sigma^A \), the deflection threshold \( \sigma^D \) and the weighted part of contrast effect within assimilation \( \alpha^c \). In Figures 3.3, we display the impact of \( \sigma^A \) and \( \sigma^D \).
3.3. Simulation results for job satisfaction

As one can see, when $\sigma_A$ increases, the number of comparisons by assimilation increases, and when $\sigma_A$ decreases, the number of comparisons by contrast increases. When $\sigma_A > 0.5$ there is a majority of comparisons by assimilation. Otherwise, the comparisons by contrast dominate. Moreover, the number of deflections increases with $\sigma_D$, especially when $\sigma_D > 0.5$.

Finally, for given pair of $\sigma_A$ and $\sigma_D$ values, when $\alpha_C > 0.5$ and $\sigma_A < 0.5$ the comparison process turns into a contrast one.

**Impact of aggregations**  In our model, we have two types of aggregations:

- An aggregation on characteristics ($q_i$) or dimensions ($d$), in equations 3.4, 3.7 and 3.13. It captures how a subject judge his condition of work, salary, etc. For all these aggregations, we set the OWA weight parameter $\kappa$ (from equation B.1) to a single control value $\kappa^A$.

- An aggregation on referents, whether social (colleagues, friends,...) in equation 3.4 or historical (past situations, equation 3.8). Similarly, these aggregation are controlled by the parameter $\kappa^R$ for the value of their $\kappa$.

Recall that a high value of $\kappa$ will make the subject optimistic becomes more sensitive to the highest values or to the smallest one for a pessimistic. In other words, when $\kappa$ is high, the optimistic becomes even more optimistic and the pessimistic more pessimistic.

To facilitate the calibration of the $\kappa$ values, we introduce a transformation of the $\kappa$ variable $k = f(\kappa)$:

$$
k = \begin{cases}
\kappa & \text{for optimistic profile} \\
1 & \text{for neutral} \\
-\kappa & \text{for pessimistic}
\end{cases}
$$

(3.14)

Note that $\kappa \geq 1$, so $k \leq -1$ or $k \geq 1$.

We display in Figure 3.4 the variations of the aggregated satisfaction with $k^A$ and $k^R$.

We notice that the aggregation has a strong impact on aggregated satisfaction, and not surprisingly the pessimistic individuals are much less satisfied (satisfaction = -0.98 for $k^R = k^A = -8$) than the optimistic (satisfaction = 0.99 for $k^R = k^A = 8$). Overall, the level of satisfaction is very sensitive to the parameters of the OWA aggregations.

We conducted other analyses, including the impact of the type of comparison (social,
historical, and direct). To do so, we vary the
parameters the weights $\gamma^D$ and $\gamma^H/\gamma^S$. We
notice in Figure 3.5 below that the direct process has a significant impact on average satis-
faction (increasing). Moreover, a high weight on social comparison diminishes the minimum satis-
faction. Finally, the historical process has a slow impact here because the working condi-
tions remain static in this experiment, and therefore reduces the interest of this mechanism.

![Figure 3.5](image)

(a) Variation of minimum sat-
isfaction with weights $\gamma^D$ and $\gamma^H/\gamma^S$
(b) Variation of average satis-
ification with weights $\gamma^D$ and $\gamma^H/\gamma^S$
(c) Variation of maximum sat-
isfaction with weights $\gamma^D$ and $\gamma^H/\gamma^S$

**Figure 3.5 – Effects of types of comparisons in job satisfaction**

**Cognitive Profiles**  From the sensitivity analyses, we deducted a set of cognitive profiles that
not only serve as a first basis to obtain a typology of the observed behaviors, but also facilitate
the calibration process by reducing the size of the parameters’ space. Here we reduce the
parameters to three variables (three types of profile), described in the Table 3.2 below (see
(Chapuis, 2016), ch. 4 for details).

<table>
<thead>
<tr>
<th>Comparison Profile Type</th>
<th>$\sigma_A$</th>
<th>$\alpha_C$</th>
<th>$\sigma_D$</th>
<th>$\beta^S$</th>
</tr>
</thead>
<tbody>
<tr>
<td>High Assimilation (HA)</td>
<td>0.6</td>
<td>0.2</td>
<td>0.5</td>
<td>0.4</td>
</tr>
<tr>
<td>Moderate Assimilation (MA)</td>
<td>0.4</td>
<td>0.3</td>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>High Contrast (HC)</td>
<td>0.2</td>
<td>0.6</td>
<td>0.8</td>
<td>0.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>State of Mind Profile Type</th>
<th>Feature Agreg.</th>
<th>Referent Agreg.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\kappa^A$</td>
<td>$\kappa^R$</td>
</tr>
<tr>
<td>Pessimistic</td>
<td>Pessimistic</td>
<td>2</td>
</tr>
<tr>
<td>Neutral</td>
<td>Neutral</td>
<td>1</td>
</tr>
<tr>
<td>Optimistic</td>
<td>Optimistic</td>
<td>2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Orientation Profile Type</th>
<th>$\gamma^S$</th>
<th>$\gamma^H$</th>
<th>$\gamma^L$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social Comparison Orientation (SCO)</td>
<td>1</td>
<td>1/3</td>
<td>1/3</td>
</tr>
<tr>
<td>Historical Comparison Orientation (HCO)</td>
<td>1/3</td>
<td>1</td>
<td>1/3</td>
</tr>
<tr>
<td>Direct Orientation (DO)</td>
<td>1/3</td>
<td>1/3</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 3.2 – Cognitive profiles
3.3.3 Impact of cognitive profiles on job satisfaction

Finally, we study the impact of these cognitive profiles on job satisfaction. To do so, we simulated an improvement policy, aimed to improve some some characteristics of the most unsatisfied agents. More precisely, at each tick, we select the 25% least satisfied agents (first quartile) and for each of these agents, we increased the 3 lowest job characteristics (out of 24 - 12.5%), using the following protocol : 10 ticks for an initialization phase, 10 iterations of improvement phase (each lasting 8 ticks, so 80 ticks in total) and 10 iterations for a last stabilization (100 ticks for the whole simulation). During each improvement phase, the three characteristics are increased by a value randomly drawn in \([0,1]\) from a uniform distribution. The parameters are set at their baseline values (cf. section C.1.1 in appendix C), with a neutral state of mind.

3.3.3.1 Impact of Comparison Profiles on satisfaction

The results are displayed in Figure 3.6 below.

![Figure 3.6](image)

Figure 3.6 – Global satisfaction \(\text{Sat}(a)\) averaged by quartile groups, from the least satisfied (Q1 group) in red to the most satisfied (Q4) in green.

We obtained contrasting results according to profiles. With strong assimilation (HA), the agents are almost insensitive to the improvement policy, except for least satisfied Q1 for which we observe a slight decrease in their global satisfaction. This could be explained by the effect of downwards comparison in case of assimilation. The improved agents have more chance to have higher features than others, which entails a negative impact on satisfaction\(^6\)

---

\(^{6}\)This kind of behavior has been studied within the framework of justice theory. If an employee considers that s/he is overpaid compared to others and that this is unfair, it may generate a negative attitude towards her/his job and the firm (e.g. Colquitt et al., 2001).
In case of profiles with contrast (MA and HC), we observe a common trend (amplified in HC, where contrast is stronger): a net increase for $Q_1$, slight increase for $Q_2$, and inversely symmetrical for $Q_3$ (slight decrease) and $Q_4$ (net decrease). In that case, the policy keeps improving the least satisfied ($Q_1$ and $Q_2$), these individuals feel better off comparatively to their referents, as their characteristics improves. This is the opposite for $Q_3$ and $Q_4$: they feel not as greater as before when their referents eventually improved their situation, and their satisfaction slightly decreases. Thus, these results are mainly explained by the social comparison component.

In figure 3.7 below, we study the transitions flows between the quantile groups. They are consistent with the results on average satisfaction I just discussed above. With a high assimilation profile, we got the highest proportion of indivuals remaining in their original group (highest values on the matrix diagonal): 73% (32/44) of least satisfied remain so after the policy, so did 77% of the most satisfied. This percentage is much lower in mixed or high contrast profile: 38% (remaining in $Q_1$) and 56% (in $Q_4$) for MA, and 46% (remaining in $Q_1$) and 58% (in $Q_4$) for HC. This confirms that the policy had more effect on mixed and contrast agents than HA ones.

![Gross flows matrices](image)

**Figure 3.7 – Gross flows matrices, measuring transitions between quantile groups.** The rows display the originating groups (t=0) and the columns the destination (t=100). For instance, in the HA profile, we have 12 agents that moved from $Q_2$ to $Q_3$.

Furthermore, we computed the sum of the upward flows, when the quantile group is upgraded and therefore the satisfaction increased (i.e. from $Q_i$ to $Q_j$, with $i > j$; the inferior diagonal of matrices in Figure 3.6, and below), and did the same for downward flows (superior diagonal and above). These measured are depicted in Table 3.3 below.

As one can see, high assimilation gives almost a zero-sum game: the number of upward flows almost equals sum of the downward ones. The balance is a little better for both MA and HC: 3 more improvements that deteriorations, the main difference is that moderate assimilation shifted the balance upward: 3 more improvements but 3 more deteriorations.

To summarize, the main result we can derive at this stage from these results for the so-
3.3. Simulation results for job satisfaction

Table 3.3 – Sum of upward and downward flows the from matrices in Figure 3.7, with a neutral aggregation and equal proportion of orientation profiles ($\Gamma_1 = \Gamma_2 = \Gamma_3 = 1/3$).

<table>
<thead>
<tr>
<th></th>
<th>HA</th>
<th>MA</th>
<th>HC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upward</td>
<td>35</td>
<td>57</td>
<td>54</td>
</tr>
<tr>
<td>Downward</td>
<td>34</td>
<td>54</td>
<td>51</td>
</tr>
</tbody>
</table>

The sum of upward flows indicates improvements, while the sum of downward flows indicates deterioration.

3.3.3.2 Impacts on other profiles

Due to lack of space, I will briefly summarize the simulations results of the impacts of the two other profiles.

**State of mind profile**

First of all, we noticed that at the start of the simulation, before the improvement policy is applied, the initial values of pessimistic agents’ satisfactions are shifted downwards for all the quartile category, compared to the neutral agents (lower satisfaction systematically), while optimistic satisfaction are shifted upwards, and this is consistent with the sensitivity analysis described in section 3.3.2 above. About the gross transition flows, we performed the same type of computations as above for the upward and downward flows, they are displayed in Table 3.4.

<table>
<thead>
<tr>
<th></th>
<th>HA</th>
<th>MA</th>
<th>HC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Upward</td>
<td>24</td>
<td>52</td>
<td>53</td>
</tr>
<tr>
<td>Downward</td>
<td>25</td>
<td>45</td>
<td>49</td>
</tr>
</tbody>
</table>

Table 3.4 – Sum of upward and downward flows the from matrices in Figure 3.7, with a pessimistic and optimistic aggregation and equal proportion of orientation profiles ($\Gamma_1 = \Gamma_2 = \Gamma_3 = 1/3$).

As one can see, the results are similar to the neutral profile, with the noticeable exception of high assimilation, for which we observed a stronger resistance to the policy (higher percentage of agents remaining in the same quartile group). This higher resistance is also observed for optimistic agents, as well as a zero balance for HA and MA. The only positive balance is given for high contrast agents, but smaller (+3) than pessimistic HC (+4) and MA (+7). Overall, the policy seems to work better on pessimistic agents, where the improvement of the lowest characteristics compensates their overweighting on these lowest values.

**Orientation profile**

Finally, we performed analysis of 27 profiles, resulting from the combination of all cognitive profiles displayed in Table 3.3. The detailed results could be found in
(Chapuis, 2016, chap. 5). If we focus on the impact of orientation profiles, we find that agents with Direct Orientation DO profile show the highest improvements in their satisfaction, and noticeably for all quantile groups and every comparison profiles. Historical Comparison HCO agents obtained a more contrasting result, with a satisfaction near 0 at the end of the policy, and a number of improvements that almost equals the number of deteriorations. Finally, for SCO agents (social comparison), we obtain very similar but amplified results than what we described in the paragraphs above.

### 3.3.4 Validation on real data

We followed the same methodology used in Polias and WorkSim and calibrated the satisfaction model using CMA-ES. We focus on a set of survey data of 100 agents, for which we know their overall job satisfaction at three distinct periods, thanks to our partner Technologia. Indeed, in these data, the subjects declared explicitly their level of satisfaction at the end of the questionnaire, at three dates we denote $T_0$, $T_1$, and $T_2$. For this dataset, we have 300 targets (the satisfaction at the three dates) and 300 parameters to calibrate (the 3 Cognitive Profiles for each individual). In terms of calibration, with so many targets and parameters, we attain the limits of CMA-ES. With 100 agents, the global error rate reaches 20% (235/300 targets reached) and 63% of the agents for which their 3 satisfaction values is perfectly found without error. Therefore, the results must be cautiously interpreted, taking this precision rate into account.

The nature of the data could also explain the difficulty we have to reach the targets: these targets are measures of satisfaction at three different times. As one can see in figure 3.8 (right), the overall satisfaction increased at $T_2$ and then decreased at $T_3$ but we had unfortunately no information on what actually happened in the firm between $T_1$ and $T_2$ and between $T_2$ and $T_3$, and could not modify the working conditions accordingly. Hence, our calibration algorithm found a continuous increase between $T_1$ and $T_3$, which is obviously not the case in reality.

Nevertheless, we tried to understand these changes in satisfaction during these 2 time intervals, using our satisfaction model. This is a work in progress, and so far we only have preliminary results. For instance, we analyzed in Figure 3.9 (right) the calibrated values for 3 groups of agents: agents with a declared satisfaction value that increased between $T_0$ and $T_2$ (green line), a second with a decreasing satisfaction (red line) and the third with a stable satisfaction (blue line). Notice that we are dealing here with a declared satisfaction (a data), not a computed one from the simulation. As one can see, the agents from the green group with an increased satisfaction are quite pessimistic ($k = -0.17$), use compar-
3.4 Activity Model

ison (whether social with $\gamma^S = 0.58$ or historical, $\gamma^H = 0.61$), while the direct effect is significantly lower ($\gamma^D = 0.4$). When we analyze from the dataset the job characteristics of these “green” agents, we noticed that these features actually increased from $T_0$ to $T_2$, creating many positive impacts when they compare their situations with their past or with their referents (contrast mode mixed with a moderate assimilation, $\alpha^C = 0.3$ and $\sigma_A = 0.3$). Agents with stable satisfaction (blue line) had stable characteristics between $T_0$ and $T_2$. They favor social comparison ($\gamma^S = 0.73$ while $\gamma^H = 0.38$ and $\gamma^D = 0.46$). Their clear trend towards assimilation ($\sigma_A = 0.44$) in terms of comparison profile might explain the stability of their satisfaction, as positive impact have more ambivalent effects in assimilation, especially with a significant contrast component ($\alpha^C = 0.32$). They are the most optimistic in the dataset ($k = 0.2$). Finally, the agents with degraded satisfaction (red group) are the most pessimistic ($k = -0.31$), favor social comparison ($\gamma^S = 0.68$) with a high tendency for contrast comparison ($\alpha^C = 0.42$, $\sigma_A = 0.34$ et $\sigma_D = 0.68$). The job characteristics decreased from $T_0$ to $T_2$ for the agents of this group, because of pessimism that made them focus on the lowest values, and contrast that made them feel that their situation is much worse than their referents.

In the next section, I will present our activity model, De-C GCM. Indeed, once we have modeled job satisfaction as an attitude towards work conditions, we need to make these conditions evolve with time in order to make this model active. Moreover, we want the dynamics to be endogenous, and we therefore need to build a model of activity at work. This is a vast subject, vast enough to devote at least an entire PhD to it, so we seek to keep the model as simple as possible to feed our satisfaction process.

3.4 Activity Model

During the HappyWork project, we had to build a second model: a model of work activity within a firm. There are some – not many though – agent-based computational models of work activity and firm organizations (e.g. Chang and Harrington, 2006; Sibertin-Blanc et al., 2013; Sibertin-Blanc and Teran Villegas, 2014). Some of them view the firm as a problem resolution entity (Cohen et al., 1972; Gibbons and Roberts, 2013; Lomi and Harrison, 2012). Among them, we chose to follow the Garbage Can approach, from the seminal paper of Cohen et al.(1972), and its extensions (Fioretti and Lomi, 2008, 2010; Cowan et al., 2013). Originally, the Garbage Can Model (GCM) deals with four types of entities: employees viewed as decision-makers, the problems to be solved, decision opportunities and possible solutions (to solve the problems).

3.4.1 The organization: problem solving, structure and social relationships

In De-C GCM, the firm is an entity that proposes specific solutions to encountered problems: in short, organization is a problem solving entity (Cowan et al., 2013). The resolution is delegated to the components (i.e. agents) of the organization through an allocation or division of labor mechanism (Cohen et al., 1972) (Lomi and Harrison, 2012). Thus, within the firm, there is a set of incoming problems – denoted as $P$, with $GC_{max}$ the maximum number of problem the firm can consider simultaneously – which are allocated to able agents. Let $n$ be the number of agents in the firm.

---

7Decentralized Garbage Can Model
3.4.1.1 The Firm as a problem solving entity

Each problem \( p \in P \) has an expected duration \( d_p \) (in hours), the expected time for the agents to solve it. Moreover, all the problems are not identical, they differ by their type \( \tau \in \{ \tau_1, ..., \tau_m \} \), where \( m \) is the number of problem types in the firm. For instance, it could be a technical problem, financial, or a management issue, etc. Furthermore, the organization estimates the energy level per hour required to solve the problem, denoted \( E_{p0} \). For sake of simplicity, this required energy is supposed to be the same for all problems in \( P \), and is a parameter of the simulation.

For each problem entering the organization, the type is randomly drawn from a uniform distribution. The duration demand \( d_p \) cannot exceed one work day (7 hours here) and depends on how many agent could work on the same problem. Hence:

\[
d_p = \text{rand}(0, 7) \times \sum_{i=1}^{n} a_{\tau_i, \tau_p}
\] (3.15)

with \( \text{rand}(0, 7) \) a real number between 0 and 7 draws from a uniform distribution. \( a_{\tau_i, \tau_p} \) is equal to 1 if agent \( a \) can address problem of type \( \tau_p \) and null otherwise.

3.4.1.2 Binding agents and problems

Thus, like in the original GCM, agents and problems are binded together according to an allocation matrix \( A_T = (a_{\tau_i, \tau}) \) \( 1 \leq i \leq n, 1 \leq \tau \leq m \), with \( a_{\tau_i, \tau_p} \) as defined above. This matrix is generated using a two-steps algorithm that generalizes Cowan et al. (2013):

1. Then we draw \( m_a \), the number of different types agent \( a \) may have to deal with. It is drawn between 1 and \( m \) with a probability \( N_T(j) \) to have \( m_a = j \) given by:

\[
N_T(j) = \frac{w_j}{\sum_{k=1}^{m} w_k} \quad \text{where} \quad w_j = \frac{1}{(1 + | j - \mu_\tau \times m |)^{v_\tau}} \quad \forall j = \{1, 2, \ldots, m\} \quad (3.16)
\]

with \( \mu_\tau \) the expected value of \( j \), and \( v_\tau \in [0, 5] \) a parameter of the generation process. The higher \( v_\tau \) is, the greater chance to have \( m_a = \mu_\tau \).

2. We need now to draw \( m_a \) problem type indexes in \( \{1, \ldots, m\} \). To do so, we follow a power rule: the probability to associate an agent with problem type \( i \) is given by:

\[
IT(i) = \frac{i^{T_id}}{\sum_{j=1}^{m} j^{T_id}}
\] (3.17)

where \( T_id \in [0, 5] \) is the third generation parameter.

Based on these two probabilistic rules, we are able to generate various types of allocation matrices, from a completely random to a near upper triangular one for instance.

**Responsibilities** The allocation matrix \( A_T \) gives a list of problem types for each agent to deal with. Based on this access structure, we can compute a responsibility value \( z_i \) for each agent \( i \). To do so, and following (Cowan et al., 2013), we introduce a modified version of the allocation matrix denoted \( O_S = (y_{ij})_{1 \leq i \leq n, 1 \leq j \leq m} \) (organizational structure), and displayed in Figure 3.10 below. The \( y_{ij} \) values are given by:

\[
y_{ij} = \frac{1}{\sum_{k=1}^{m} a_{\tau_k, j}}
\] (3.18)
3.4. Activity Model

![Figure 3.10 – The modified access structure OS with 10 agents and 10 problem types](image)

For one particular problem type \( j \), \( y_{ij} \) is the inverse of the number of agents responsible for \( j \). The responsibility degree for one agent \( i \) will be given by the sum of all \( y \) values he is concerned with:

\[
z_i = \sum_{j=1}^{n} y_{ij}
\]

(3.19)

In the example of Figure 3.10, we have \( z_1 \approx 2.76, z_2 \approx 1.56 \), etc.

**Problem Hierarchy and Sharing**  We can characterize the organization with two parameters from OS matrices. The first is problem hierarchy (vertical relationship): “two agents \( a \) and \( a' \) have a problem hierarchical relationship if \( a \) is responsible for every problem that \( a' \) is responsible for, plus some extra problem(s)” (Cowan et al., 2013, p. 8). In other words:

\[
a \succ_{ph} a' \iff T_a \supset T_{a'}
\]

(3.20)

where \( T_a \) denotes the set of problem types the agent \( a \) is responsible for. In the matrix of Figure 3.10, \( A_1 \succ_{ph} A_2, A_8 \succ_{ph} A_{10} \), etc. This concept of hierarchy focus exclusively on embedded problem solving responsibility and on whether this embedding is hierarchical or not.

The second characterization of the organization is sharing (horizontal relationship). This relation is bidirectional and measures the extent to which two agents share responsibilities. Formally, sharing between agent \( a \) and \( a' \) is defined as the ratio of the number of problem types in common to the sum of their problem types:

\[
\text{share}(a, a') = \frac{|T_a \cap T_{a'}|}{|T_a \cup T_{a'}|}
\]

(3.21)

For instance, in Figure 3.10, \( \text{share}(A_1, A_2) = 3/9, \text{share}(A_7, A_8) = 1/4 \), etc.

---

8. \( E_0 \) represents a certain requirement on quality and productivity of work expected by the firm.

9. This way of viewing hierarchical relationships with in firm is questionable, as there are many other ways to characterize them. Moreover, the CEO (like agent \( A_1 \) in Figure 3.10) tends to be at the top of the matrix (top of the hierarchy), so s/he will be the person with the maximum number of problems to solve. If \( T_1 \) represents “firm strategy” and \( T_{10} \) “changing a bulb”, it is doubtful that the CEO will be in charge of tasks like \( T_{10} \), even if the normalization used to compute the responsibility weights could drastically reduce this weight for the CEO if many employees are in charge of tasks like \( T_{10} \). Nevertheless, I believe that this link between the level one has in the firm’s hierarchy and the number of problems one has to address is not straightforward (it could even be at the opposite) and I am then aware of the limitations of what Cowan et al. proposed. However, we decided to follow them as a first approach, for sake of simplicity.
3.4.1.3 Problem generation

The $GC_{\text{max}}$ problems are generated using the following probability function $PG(\tau_j)$ to generate a problem of type $\tau_j$:

$$PG(\tau_j) = \frac{w(\tau_j)}{\sum_{k=1}^{m} w(\tau_k)}$$

With $w(\tau_j) = \left( \sum_{i=1}^{n} (a_{\tau_i,j} \times z_{a_i}) \right)^{\mathcal{P}^{\text{id}}}$ and $\mathcal{P}^{\text{id}} \in [0, 2]$

When $\mathcal{P}^{\text{id}}$ is high, it increases the probability to generate a type bound with agents of large number of responsibilities $z_a$. When $\mathcal{P}^{\text{id}} = 0$, we get an uniform distribution.

Once the type is sorted, we set the total expected duration of the problem $d_p$, drawn for a uniform distribution in the interval $[d_{\text{min}}, d_{\text{max}}]$ (Fioretti and Lomi, 2008).

3.4.1.4 Demand allocation

Once the organization structure $OS$ is given, the main task of the organization is to allocate incoming problems (stored in the garbage can $GC$) to the agents. A policy must be defined to determine how this demand is split between responsible agents.

For a problem $p$ with type $\tau_j$ and demand duration $d_p$, the firm will allocate a duration of work $d_p(a)$ on problem $p$ for all agent $a$ responsible for this problem:

$$\forall a \in \mathcal{A}_{\tau_j} \quad d_p(a) = d_p \cdot \frac{1/\exp(|\tau_j|/\zeta)}{\sum_{a' \in \mathcal{A}_{\tau_j}} 1/\exp(|\tau_{a'}|/\zeta)}$$

$\mathcal{A}_{\tau_j}$ is the set of agents responsible for problem type $\tau_j$. The parameter $\zeta \in [0, +\infty]$ triggers the allocation. The higher $\zeta$, the closer to an equal repartition the allocation is. When $\zeta$ is low (close to 0), the demand is concentrated to the agents with low responsibilities (low value of $|\tau_a|$).

A problem leaves the organization only when it is considered to be solved. That is the case when all responsible agents $a$ have spent $d_p(a)$ hours to work on this problem.

3.4.1.5 Social Network Generation

Once we have defined an organization with the allocation matrix $\mathcal{A}T$, we can build a social network that represent the individual interactions, based on this organization. In general, social networks in firms are close to small-worlds (Uzzi et al., 2007). To generate the social network corresponding to a given allocation matrix, we follow Cowan et al. (2013), and define layers in the network. Any agent who dominates (using the order relation of equation 3.20) no other agent is on the bottom layer of the hierarchy. And then, recursively, an agent is in layer $l$ if, of the agents he dominates, the highest is in layer $l-1$. We depict in Figure 3.11 some typical layered organizations.

Once the layers are created, each layer will be generated as a small world, from the Watts & Strogatz (1998) model (for details, see Chapuis, 2016, ch.6).

3.4.2 The worker agent: decision process, work potential and recovery mechanism

An agent at work has essentially to decide (i) on which problem it wants to work and (ii) on many time and energy it will devote to solve this problem. The decision process inspired by the Effort-Recovery and COR psychological theories (Meijaman and Mulder, 1998) (Hobfoll, 1989) (Demerouti et al., 2012).
3.4. Activity Model

3.4.2.1 Decision modalities

An agent considers work as a resolution problem activity. If no problem is assigned to the agent, then it decides to apply a predefined **routine** procedure. It consists of a basic activity, comprising exact available time and low effort spending:

\[
DS_a(t) = Dw_a(t) \\
ES_a(t) = Ew_a(t) \cdot \theta^R
\]

where \( \theta^R \in [0, 1] \) represents the fraction of energy spent for the routine process.

When problems are assigned to the agent, it will always try to reach resolution. In the case it cannot solve the considered problem, the decision is blocked.

**Agent desk and problem ordering**  All assigned problem from organization are stacked on agent’s desk \( GC_a \). Agents work on problem sequentially, so problems contained in the \( GC_a \) are ordered according to agent preference, defined by weights \( pw_a(p, t) \) for agent \( a \), problem \( p \) and time (tick) \( t \):

\[
pw_a(p, t) = (2 \rho_a - 1) \times d_p(a) + \ln(1 + t - t_p)
\]

where \( t_p \) denotes the time when problem \( p \) first appears in the \( GC \) and \( \rho_a \) a parameter in \([0, 1]\). When \( \rho_a = 0 \), agent will always tackle lower demanding (i.e. lower duration) problem first; when \( \rho_a = 1 \), agent will start with the most demanding ones first; and when \( \rho_a \approx 0.5 \), the agent will consider older problems first.

The agent’s desk is sorted in ascending order of problem’s weights \( pw_a(p, t) \). The agent processes them sequentially until no more problem remains or one leads to a blocked decision (see below).

**Resolution decision**  Agent’s decision first consists of evaluating time and energy it will spend to solve the problem for resolution and if available applying its own potential to solve problem. To do so, it computes the **resolution cost** \( EE_a(p, t) \) that is, for agent \( a \) at time (tick) \( t \), the required energy to solve problem \( p \). It is based on problem-associated demand \( Ep_0 \) (see section 3.4.1.1), and on an agent **efficiency factor** \( eff_{a,p} \), that measures the ability the agent \( a \)
has to solve the problem \( p \). For sake of simplicity, \( \textit{eff}_{a,p} \) is randomly drawn in \([0.5, 2]\) from an uniform distribution. Lastly, required energy also depends on responsibility degree \( z_a \). The overall evaluation is computed as follows:

\[
EE_a(p, t) = \frac{Ep_0}{1 + \ln \left( 1 + \frac{|GC_a|}{z_a + \Gamma_z / \lambda_q} \right)} \times \textit{eff}_{a,p} \times d_p(a, t) \tag{3.26}
\]

Hence, the required energy decreases with factor \( \frac{|GC_a|}{z_a + \Gamma_z / \lambda_q} \), which encodes the “net” size of agent’s desk, as the ratio of size \( |GC_a| \) to the responsibility degree. If the responsibility \( z_a \) is high, so will be the energy. This means that an agent will tend to decrease its effort as problems accumulate, but less quickly if it has many responsibilities in the organization. There is a balance between the agent’s constraints and the organization’s needs.

Resolution is straightforward from that point: if the agent has enough available time and energy to solve the problem, resolution occurs and this consumes its related time and energy. Formally, agent daily consumption is given by two variables \( DS_a(t) \) and \( ES_a(t) \), respectively for time and energy. They are reset to 0 at each beginning of a working day. Let \( Dw_a(t) \in [0, 24] \) and \( Ew_a(t) > 0 \) be the maximum potential amount the agent \( a \) can spend on duration and energy respectively (see section 3.4.2.2 below for details on their computation).

Resolution is made possible if these two conditions are satisfied:

\[
Dw_a(t) - DS_a(t) \geq d_p(a, t) \tag{3.27}
\]
\[
Ew_a(t) - ES_a(t) \geq EE_a(p, t) \tag{3.28}
\]

**Blocked decision** If agent cannot reach problem’s resolution, i.e. if the time (eq.3.27) or energy (eq.3.28) condition is not satisfied, decision process is blocked. The agent will try to do its best to reach the resolution. At first, it considers to spend all the time it has left, i.e. \( DE_a(p, t) = Dw_a(t) - DS_a(t) \). On this basis it anticipates the corresponding level of required energy, base on a similar equation to equation 3.26:

\[
DE^*_a(p, t) = \frac{Ew(t)/1 + \ln \left( 1 + \frac{|GC_a|}{z_a + \Gamma_z / \lambda_q} \right)}{Ew_a(t) - ES_a(t)} \times \textit{eff}_{a,p} \tag{3.29}
\]

If it has enough energy, i.e. if \( Ew_a(t) - ES_a(t) \geq EE^*_a(p, t) \), it spends \( DE^*_a(p, t) \) and \( EE^*_a(p, t) \) to work on \( p \). Otherwise, it reverses the perspective and envisages to spent a time according to the energy \( Ew_a(t) - ES_a(t) \) it has left. This duration is given by:

\[
DE^*_a(p, t) = \frac{Ew(t)/1 + \ln \left( 1 + \frac{|GC_a|}{z_a + \Gamma_z / \lambda_q} \right)}{Ew_a(t) - ES_a(t)} \times \textit{eff}_{a,p} \tag{3.30}
\]

In that case, the agent spends the energy \( Ew_a(t) - ES_a(t) \) and time \( DE^*_a(p, t) \) to work on \( p \).

### 3.4.2.2 Energy spending and recovery

The agent’s potential evolves dynamically. Available time \( Dw_a(t) \) is reset to 7 hours at the beginning of each tick.\(^{10}\)

For the energy dynamics, we start from Effort-Recovery theory (Meijaman and Mulder, 1998). First, spending time and energy triggered a physiological and psychological reaction identified as a load:

\[
\text{Load}_a(t) = \frac{DS_a(t)}{\lambda^a} \times \ln \left( 1 + \frac{ES_a(t)}{Ew_a(t)} \right) \tag{3.31}
\]

\(^{10}\)Thus, the daily working time is 7 hours in the firm, or 35 hours a week, the legal working time in France.
Following the COR model (Hobfoll, 1989), we model functional load reaction to be compensated by available work resources, like help from colleagues help or a well-designed work procedure: \( \lambda_{f} \) encodes the amount of resource an agent can access in order to decrease its load reaction. It is also correlated to effort duration and energy amount.

When the effort has stopped, the agent can enter a recovery process:

\[
\text{Recovery}_{a}(t) = \lambda_{R} \cdot (24 - DS_{a}(t))
\] (3.32)

The most important determinant of recovery from work is the off-work activities (i.e. sleeping, family time, resting, sport, etc. (Demerouti et al., 2009, 2012)). The \( \lambda_{R} \) parameter is the recovery rate for agent \( a \), and it encodes the effect of these off-work activities.

Effort has consequences in the mid and long term, and it is accumulated by the agent. This accumulation process is modeled with the variable of load accumulation \( Acc_{a}(t) \) given by:

\[
Acc_{a}(t + 1) = Acc_{a}(t) + Load_{a}(t) - Recovery_{a}(t)
\] (3.33)

When \( Load_{a}(t) > Recovery_{a}(t) \), \( Acc_{a} \) decreases and could eventually become negative: that may be an early warning of burn-out.

Finally, the charge could be used to compute the new level of energy potential for agent \( a \):

\[
E_{w_{a}}(t + 1) = EB_{a} \times \frac{1}{1 + Acc_{a}(t) \cdot \psi_{a}}
\] (3.34)

where the maximum value is represented by agent’s energy basic level \( EB_{a} \) and minimum value 0. \( \psi_{a} \) encodes the sensitivity to an accumulation of effort old. The higher \( \psi_{a} \) is, the less the agent will be impacted by negatives consequences of effort, and vice-versa.

### 3.4.2.3 Energy and duration updates

At the end of each tick \( t \), the energy levels and duration levels are updated:

\[
ES_{a}(t + 1) = ES_{a}(t) + EE_{a}(p, t)
\] (3.35)

And

\[
DS_{a}(t + 1) = DS_{a}(t) + DE_{a}(p, t)
\]

\[
d_{p}(t + 1) = d_{p}(t) - DE_{a}(p, t)
\]

\[
d_{p}(a, t + 1) = d_{p}(a, t) - DE_{a}(p, t)
\] (3.36)

We summarize in Tables C.2 and C.3 (section C.1.2 of Appendix C) the parameters for our activity model De-C GCM.

### 3.5 SIMULATION RESULTS FOR THE ACTIVITY MODEL

In this section we investigate the De-C GCM dynamics and focus on organizational structure\(^{11}\). Parameters related to the number – \( \mu_{\tau} \) – and variability – \( \nu_{\tau} \) – of agent responsibilities, along with problem allocation (see sec. 3.4.1.2) – \( T^{id} \) – are considered. Based upon this analysis we will define some schematic organizations, and assess the performance of these schemes. Simulations are run for 200 ticks and outputs are aggregated over 100 runs.

\(^{11}\)Another part of sensitivity analysis concerns the individual cognitive parameters, including effort and recovery. These analyzes can be found in (Chapuis, 2016, ch.5, section III).
3.5.1 Typology of organizational structures

From sensitivity analyses, we have extracted a typology based on 4 typical organizations, summarized in Table below. They are given by the generation parameter $\mu, \nu, T^{id}$, and could be analyzed to another set of indicators:

- $H_0$, the number of hierarchical relationships (in the sense of problem hierarchy defined by equ. 3.20);
- $S_0$, the number of vertical relationships\(^{12}\);
- $Sv_0$, the proportion of shared responsibilities. $Sv_0 = \sum_{i=1}^{n} \left( \sum_{j=1}^{n} share(a_i, a_j) \right)$, with $share(a_i, a_j)$ defined in equ. 3.21.
- $T_0, T^{min}_a$ and $T^{max}_a$ are respectively the mean, minimum and maximum number of problem types the agents are responsible for.

<table>
<thead>
<tr>
<th>Type</th>
<th>$\mu$</th>
<th>$\nu$</th>
<th>$T^{id}$</th>
<th>$H_0$</th>
<th>$S_0$</th>
<th>$Sv_0$</th>
<th>$T_0$</th>
<th>$T^{min}_a$</th>
<th>$T^{max}_a$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Versatile</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>84</td>
<td>39</td>
<td>2</td>
<td>1</td>
<td>4</td>
<td></td>
</tr>
<tr>
<td>Specialized</td>
<td>0.04</td>
<td>10</td>
<td>2</td>
<td>2529</td>
<td>382</td>
<td>4</td>
<td>4</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>Pyramidal</td>
<td>0.04</td>
<td>1.5</td>
<td>0</td>
<td>56</td>
<td>2292</td>
<td>397</td>
<td>8</td>
<td>3</td>
<td>75</td>
</tr>
<tr>
<td>Triangular</td>
<td>0.02</td>
<td>1.5</td>
<td>2</td>
<td>337</td>
<td>2274</td>
<td>363</td>
<td>7</td>
<td>7</td>
<td>77</td>
</tr>
</tbody>
</table>

Table 3.5 – Four typical organizations described by some indicators

To analyze the main differences between these organizations, we can start by studying the responsibility distributions depicted in Figure 3.12, combined with the data of Table 3.5 (see also the Figures C.1 and C.2 in Appendix C):

- The **Versatile** firm has no hierarchy and very low sharing. Agents are responsible for only 2 problem types on average. All types of problem are assigned to 1 or 2 agents. Because sharing is very low, each agent has its own role, the firm is a collection of separated teams made of few people. This could be the case of a service provider, for instance.

- The **Specialized** firm has also no hierarchy but much more sharing (2529 pairs). It divides the problem types into 2 groups. A first group (20% of the problem types) that is shared by 10 agents on average (right part of Fig. 3.12b) represents the common activity of the firms, i.e. the main processes shared by most of the employees (e.g. meeting, reporting, interacting with clients,...). The second group of problem types is shared by very few agents (4 on average), including a subgroup of 20 % of problem types for which only one agent is responsible. This second group represents the specialized tasks of the organization. However, one can notice in Fig. 3.12b that these specialized agents are also the ones with the most responsibilities (at the top of the matrix), the least specialized agents focus on the main activities. For instance, this could be a firm with few experts or creators, and many implementers (like a design company).

- The **pyramidal** firm has a some hierarchy (though limited, with $H_0 = 56$ and the highest sharing index (2922 pairs). In Figure C.2c, we see that the first decile of agents covers most of the problem types : they cumulate 375 responsibilities. However, Figure C.2d shows that distribution of agents per problem type is uniform (as for the versatile

\(^{12}\)The number of agents that share a set of responsibilities. Formally, this would be, for the agents $i$ and $j$, when $T_{ai} \cap T_{aj} \neq \emptyset$ and $T_{ai} \subset T_{aj}$ and $T_{aj} \supset T_{ai}$.
3.5. Simulation results for the activity model

3.5.1 Versatile

(a) Versatile

(b) Specialized

(c) Pyramidal

(d) Triangular

Figure 3.12 – Four types of allocation matrix, averaged over 100 organization generations and for n = 100 agents and m = 100 problem types. In the Y-axis, the agents are ranked by increasing order of responsibilities (the top agent has the highest number of responsibilities). X-axis denotes the problem types, ranked by index number. For each generation, we draw a dot in the (x,y) plan for each agent y responsible the problem type x. Hence, a darker color indicates more frequent responsibilities.

firm). The top managers addresses almost all the problems, but these problems are potentially tackled by all their subordinates. We have here a vertical hierarchy with no specialization, it is a sort of mix of versatile and triangular behaviors. This could be a start-up company.

• The triangular firm has the strongest hierarchy index, combined with high sharing. It represents the typical vertical organizations, where the top manager addresses all the problems, his/her subordinate many problems but few, and so on. At the bottom of the hierarchy (bottom of matrix in Fig. img:Tr), agents are responsible of few problems. As shown in Fig. it is a mix of strong hierarchy and specialization: the top managers are specialized in the tasks than their subordinates cannot tackle. This could be find in varying types of firms, from multinational companies to family businesses.

We can summarize these observations in the Table 3.6 below.

3.5.2 Impact of organization on firm’s performance

Now that we have defined four types of organization, we can study how one type of organization impacts the firm’s performance.
### Table 3.6 – Four typical organizations described by some indicators

<table>
<thead>
<tr>
<th>Type</th>
<th>Vertical Hierarchy</th>
<th>Responsibility Sharing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Versatile</td>
<td>None</td>
<td>None (Full division of labor)</td>
</tr>
<tr>
<td>Specialized</td>
<td>None</td>
<td>Partial: core business + specialization</td>
</tr>
<tr>
<td>Pyramidal</td>
<td>Moderate (functional)</td>
<td>Strong division of labor + specialization (top managers)</td>
</tr>
<tr>
<td>Triangular</td>
<td>Strong (linear)</td>
<td>Partial: core business + hierarchical specialization</td>
</tr>
</tbody>
</table>

3.5.2.1 Response to external demand

The first experiment studies the response to an increase of external demand. We depict in Figure 3.13 below the time needed to solve all of the problems in the Garbage Can. To vary the demand, we change the size of the GC, \( GC_{\text{max}} \), varying from 100 to 10000.

The triangular clearly gives the poorest performances: it takes 75 ticks to solve 100 problems, while the others take 25 for the specialized, 27 for the pyramidal, 32 for the versatile. The same ranking is observed for 10 000, from 3500 ticks needed by the triangular and less than 1000 for the specialized and the versatile. The time increase with the size of demand is slower than linear, showing some economies of scale. The best performance is given by the versatile (30 more time needed from 100 to 10000), followed by the specialized (36), the triangular (47) and the pyramidal.

Thus, the most hierarchical organizations are the least efficient. This is mainly because they have many agents with high responsibilities, entailing a congestion, where problems are blocked because these high responsible agents are too busy. Pyramidal performs a little better than triangular because it is a little more versatile: pyramidal agents can address almost any type of problem (uniform distribution in Fig. C.2d), while this distribution is heterogeneous and hierarchical (see Fig. C.2b), loosing versatility and then adaptability.

3.5.2.2 Response to internal demand

We study here how organizations react when the charge of problems increases, that is when problems need more time (increasing \( d_{\text{max}} \)) or more energy (increasing \( E_{P0} \)). The results are displayed in Figures 3.14 below.

We obtain the same ranking as external responses. The most efficient is again the specialized and the triangular is the worst. The congestion effect, due to a non-uniform distribution of problem types, could explain these differences.

3.5.3 Impact of problem allocation

In this experiment, we study the effects of internal organization. First, we vary the main parameter of problem generation, \( P_{id} \). When \( P_{id} \) is high, it increases the probability to generate a type associated with a larger number of responsibilities (\( z_{a} \)). When \( P_{id} = 0 \), we get an uniform distribution (cf. section 3.4.1.3). The results can be found in Figure 3.15, when we display the resolve time variation with \( P_{id} \).
3.5. Simulation results for the activity model

When $P_{id}$ is low ($< 2.3$), we found our traditional ranking of resolve times: Triangular > Pyramidal > Versatile > Specialized. But when $P_{id} > 3.2$, while the performances of pyramidal and specialized remain (almost) the same, the curves of triangular and versatile reverse, the former becoming among the best and the latter the worst. This is not very surprising when we recall that a high value $P_{id}$ implies to generate problems types concentrated (specialized) on the agents with the highest responsibilities.

While this is in total accordance with the principles that built the triangular organization, it is a total contradiction with the philosophy of versatile firms, where type allocation is uniform. This is why its performance drastically drops when we select this kind of allocation.

Another parameter that triggers problem allocation to agents is $\zeta$. The higher $\zeta$, the closer we have an equal allocation. When $\zeta$ is low (close to 0), the demand is concentrated to the agents with low responsibilities (cf. section 3.4.1.4). The results can be found in Figure 4.6, where we display the resolve time variation with $\zeta$.

Again, we find a reversal of fortune: the pyramidal that was performing the best for $\zeta = 0.5$ becomes the second worst when $\zeta > 64$, while the specialized and versatile remain insensitive to a change of $\zeta$, and the triangular performs less well when $\zeta$ increases. Again, the hierarchical organizations, namely triangular and pyramidal, favor specialization of types, which is more in accordance with low $\zeta$ where agents with low responsibilities receive more demand than the others. We have already pointed out that hierarchical firms suffer from congestion, because their most respon-
sible agents are overstretched. A lower $\zeta$ brings more balance to the distribution of tasks within the firm.

These last two experiments bring up a very important point. A performance of a given organization slightly differ with the values of collateral parameters. In other words, it can be “optimized” and any comparison between organizations must ideally be made using their optimized versions. We tried to do so for the parameters $P^id$ and $\zeta$: we chose their values to give the best possible performance (measured with the resolve time). The results are summarized in Table 3.7. As one can see, there is a substantial difference between the baseline and the optimized versions. When optimized, the performances of the hierarchical firms (pyramidal and triangular) are much improved, becoming closer to the specialized organization that remains the best one of the four. By contrast, the promising versatile could not be improved enough and become now the worst. Of course, it does not mean we could not improve the versatile firm with a different subset of parameters.

Moreover, other indicator than resolve time might be used to characterize the organization and their differences. One important issue concerns the impact on the employees. How does an organization affect the cognitive behavior of the individuals at work? How does it impact the way an employee manage his/her effort facing an increase of demand for instance? Does certain organization favor the occurrence of burnouts? These issues are part of our work in progress and some elements of response might be found in (Chapuis, 2016, ch. 5).

<table>
<thead>
<tr>
<th>Organization</th>
<th>Baseline</th>
<th>Best</th>
<th>$P^{id}$</th>
<th>$\zeta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specialized</td>
<td>66</td>
<td>30</td>
<td>3.2</td>
<td>4</td>
</tr>
<tr>
<td>Pyramidal</td>
<td>108</td>
<td>38</td>
<td>0.8</td>
<td>8</td>
</tr>
<tr>
<td>Triangular</td>
<td>228</td>
<td>42</td>
<td>6.4</td>
<td>16</td>
</tr>
<tr>
<td>Versatile</td>
<td>77</td>
<td>71</td>
<td>0</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 3.7 – Organization performances (in resolve time)

### 3.6 Conclusion of this Chapter

In this chapter, I presented the HappyWork project. It includes two agent-based models: job satisfaction and activity. To our knowledge, it is the first comprehensive model of job satisfaction, it is strongly grounded on social psychological and has been validated on real data.

It is also the first to use multi-agent systems to study the effects of cognitive profile on an improvement policy of job conditions. Of course, our results have to be confirmed with other policies and simulations. But we believe it shows a solid trend and this is a major finding of HappyWork at this stage: 

*subjects have quite different behaviors according to their cognitive profile and the success or failure of an improvement policy depends on this profile.* This must be taken into account by policy makers when they design their policies.

We also proposed De-C GCM, an agent based model of work organization. Our work has extended the GCM to include more cognitively based decision making. On the other hand we also provided an agent-based model of the Effort-Recovery theory. We have explored the main parameters of worker decision and organizational design, and we obtained a second major finding: 

*the type of organization has a significant impact on firm’s performance.*

Each of these two models could be improved. For instance, in order to take all the dimensions of attitudes into account, we could add an emotional component to the satisfaction model, and eventually a behavioral one (but this would be more difficult, because of the high variety of possible behaviors associated to job satisfaction). We could also add a anticipation...
mechanism, where the agents not only look in the past or present but also into its future ("will my situation be better off in the future?").

Concerning the activity model, we could add more interactions between agents and introduce teams, allowing one agent, when it is overloaded, to redirect a part of its tasks to other agents from its team. A more decentralized allocation of tasks could also be proposed, where this function could be transferred to managers.

However, the first priority would be to unify the satisfaction and activity models into a single model of an organized firm, because there is a natural mutual dependence between the two models: an organization impacts the job satisfaction, and job satisfaction impacts the workers’ activities, which may have in return an impact on organization (at least on its performance). We lacked time to process this unification within the three years of K. Chapuis’s PhD, and this would be a quite exciting challenge for this project in the future.
4 Economic Behaviors: The Case of the Labor Market

The last chapter of this habilitation is devoted to the application of multi-agent systems to Economics. The WorkSim project\(^1\) aims to model and simulate labor markets. It is funded by the “PDI SYtèmes Complexes”\(^2\) PhD program, with the PhD of Olivier Goudet (2012-2015) and was before funded by the Région Île-De-France with the previous PhD of Zach Lewkovicz (2006-2010). It is jointly led by Pr. Gérard Ballot (Université Paris 2).

It belongs to the recent tradition of agent-based models used in Economics, also referred as Agent-Based Computational Economics (ACE; Tesfatsion, 2006). The main idea is to account for the complexity of economical processes. While orthodox models see economic systems as a set of homogeneous agents with (almost) unlimited capacities of computation and memory (think about the rational anticipation models for instance), the ABM approach promotes heterogeneity and bounded rationality. Thus, WorkSim is another good occasion to apply our psychomimetic methodology, that is to:

- account for bounded rationality, heterogeneity, learning and rich interactions;
- avoid black-box modeling and describe explicitly the cognitive processes involved at the microeconomic level;
- implement economic theories that have been confronted with data (stylized facts, econometric studies, studies, etc.).

The presented version of WorkSim here aims to analyze the French labor market in 2011\(^3\), but the contributions to the methodology we implemented enable researchers to use it for other countries as well.

In next section, I will present the theoretical framework and related models. Section 4.2 will develop the model, and section 4.3 the analyses and simulation results.

4.1 Theoretical Framework and State of the Art

The model WorkSim is a novel tool of analysis for labor markets. The first objective of the model is to reproduce the gross flows between the important states: employment (distinguishing fixed term contracts and open ended contracts), unemployment and inactivity, and the ratios of individuals in these states. The novelty of the model is that it simulates the flows on the basis of the rational decisions of individual heterogeneous agents. Once the model is calibrated, the second objective is to characterize the nature of the labor market under study. This is done, first by examining the patterns of flows and stocks at the aggregate level and at the levels of different categories of labor, and second by sensitivity experiments, modifying some exogenous parameters and variables such as the demand for the good. Finally the model once calibrated is a tool for experimenting labor market policies, including changes in

\(^1\)Related Publications: (Lewkovicz and Kant, 2007b,a, 2008; Lewkovicz, 2010; Ballot et al., 2013; Goudet et al., 2014; Ballot et al., 2015; Goudet et al., 2015; Goudet, 2015; Ballot et al., 2016).

\(^2\)Jointly Funded by UPMC and IRD.

\(^3\)The most recent year for which we have full statistical data we need for calibration.
the labor law. The multi-agent methodology is the perfect tool for such a research program, since it can model institutions precisely, and account for heterogeneity and individual interactions. Simulation results enable us to compute aggregate variables such as the flows and the stocks, and finally the individual careers and the main types of trajectories.

However, the labor market is complex and this means that the modeling progresses only by steps. The present version is consistent as a stock-flow model and more detailed than other existing stock-flow models of the labor market, analytic, econometric, or multi-agent. The model builds on the experience of model ARTEMIS proposed by Ballot (1981; 1988; 2002) and a preliminary version of WorkSim by Lewkovicz and Kant (Lewkovicz and Kant, 2007a, 2008; Lewkovicz, 2010).

4.1.1 Extending Search Theory

WorkSim like ARTEMIS is grounded in the concept of search (Phelps, 1970). Search Theory studies how economic actors find a partner for their transactions (here a company with a job). The search concept is necessary to distinguish the two states of “unemployed” and “inactive” on the basis of rational decisions of agents. There is indeed a flow from unemployment to inactivity, because the value in terms of unemployment utility (expected gains from search minus time foregone) may become lower than the utility of inactivity (including welfare and free time). In that case, the individual stops search and becomes inactive. This is distinct from the fact that part of the inactive persons do not want to work because they have some other resources and value non-working time (caring for children). In WorkSim the basic concept of search is extended in three directions, in order to build a general theory of mobility:

1. **Search is done also by firms** that symmetrically look for workers who are high in the productivity distribution. They prefer to keep a job vacant than hire a worker with a poor productivity. A stopping rule taking the form of a minimum productivity requirement or hiring standard follows. Moreover, the addition of the costs of search may render the job unprofitable (and then it will be suppressed).

2. **The search calculus is extended to all voluntary decisions by workers** such as quits and on-the-job search (i.e. looking for a new job while remaining employed). The firms take into account the search costs of replacement when they consider firing a worker, for lack of productivity. Finally the hiring decision is the result of the sequential decisions of the worker who applies and the firm which selects and hires. Moreover, unlike matching models, **we do not use any matching function** – like in the canonical model of Mortensen and Pissarides (1994) – as it is an aggregate artifact, likely not to be robust to large changes in the labor market, and with weaker microeconomic foundations than our double search decisions. The model definitely belongs to the pure search models, fully taking into account the heterogeneity of jobs and workers.

3. **Our model integrates wage rigidities** with the realistic assumption that firms have often several jobs. It allows for the differentiation between demand shocks and productivity shocks, while existing search models do not often deal with this topic. The model then contains some Keynesian features. Demand shocks explain part-time, dismissals, and job creations in the model, while productivity changes explain dismissals, promotions and some hires. This distinction has also some importance since the model deals only with the labor market, with no feedback on the goods market. **The demand for the goods is exogenous.** To make things simple and coherent, we assume that each firm produces

---

4For evidence of the bias introduced by a matching function as a result of an employment policy, see (Neugart, 2008).

5The wages are rigid because it is usually difficult for a firm to reduce wages, due to labor agreements, fears for lost productivity or competition with other firms to hire employees.
a variety of a unique good with horizontal differentiation, and hence a unique exogenous price. However, each firm faces stochastic shocks on its demand, which can be seen as fluctuations of consumers' preferences.

However, a major difference between WorkSim and the analytical search models relies on our utilization of the concept of Simon's bounded rationality to model the decisions (Simon, 1955). Two major arguments can be given:

1. First, dynamic programming algorithms used to solve the decision problem in analytical search theory cannot be used in a model in which heterogeneous agents move sequentially into many states over time and compete.

2. Second, according to bounded rationality theory, real agents have limited capacities in terms of computation and memory. They might therefore use simple rules, but a very important behavioral addition in our approach is that they can revise their decisions or even their rules thanks to learning and collecting information. This continuous learning is in fact very coherent with search theory. However, in order to compute equilibrium, analytical models assume perfect rationality and individuals have a lot of information such as the true distribution of wages, and firms the true distribution of productivities. By contrast, in WorkSim, we model “simple” decision rules - that comply with bounded rationality, partial information and learning processes.

4.1.2 Related Agent-based models

The contributions to the multi-agent literature on labor markets must also be assessed. This literature is thin but has a long history. Bergmann (1974) has developed a simple search model by both sides of the market and obtained simultaneously vacant jobs and unemployment. Eliasson (1977) built a Keynesian and Schumpeterian micro-to-macro model which treats only firms as individual agents but the number of workers in a firm can vary and unemployment is computed. ARTEMIS, the ancestor of WorkSim, is the first multi-agent model to have modeled the gross flows between the three main states of the individuals, with the addition of on-the-job search as a state. This was also done within an institutional framework, notably with a temporary help firm, and firing costs. The model generates a temporary segmentation of the young workers. Then, a negative demand shock affects very differently the categories of labor, precluding the progressive integration of young workers in the internal labor markets. This will lead to a permanent segmentation with serious life cycle consequences.

The years 2000 have mainly seen multi-agents models aiming at theoretical research (see Neugart and Richiardi (2012) for a recent review), such as introducing networks, a logical way to consider search in some contexts (Tassier and Menczer, 2001). Richiardi (2004; 2006) modeled the matching process between workers and firms with on-the-job search, entrepreneurial decisions and endogenous wage determination. The model is able to reproduce a number of stylized facts generally accepted in labor economics, and, most interestingly, important stylized facts such as a negatively sloped wage curve, and a constant returns to scale matching function emerge only out-of-equilibrium. Hence, these results question equilibrium models when they take these regularities for granted.

Neugart (2008) developed an agent-based labor market model with sector-specific skill requirements. In the model, firms are hit by asymmetric shocks, and unemployed worker have to invest in their human capital in order to qualify for job openings. The government steps in and subsidizes the workers' training costs. This model is used to evaluate the aggregate impact of labor market policies.

Barlet et al. (2009) simulate the French labor market for year 2006. They distinguish individuals and jobs but not firms as such although there is labor demand side, with creations
and destructions of jobs based on a desired margin and demand. Fixed duration (CDD) and open ended (CDI) contracts are also distinguished. The flows are obtained from transition rates, often exogenous, but the dismissals are determined by the destruction of jobs. The model is calibrated using an indirect inference method, and is then used to study the effects of the rise of the minimum wage and a lowering of the social charges on the firms.

WorkSim goes beyond the existing multi-agent literature on the labor markets in three directions:

1. It is the only ABM labor model to be grounded in a double stock-flow accounting, one for the individuals, one for the jobs, and most of the important flows are considered. This accounting is the equivalent of the financial stock-flow accounting for ACE macroeconomic models, a guarantee of coherence. It also allows for a easy description of the labor market dynamics at the aggregate and any disaggregation level of interest, and the highlighting of the competition between categories of labor (young, adults, seniors...).

2. It models the institutions and the labor law at their level of direct impact (the microeconomic level), since they are rules of the game that agents know and take into account in their decisions. The diverse forms of labor contracts, with very extreme differences, are probably the major feature of the French labor market, and they are at the heart of the model, since they modify the flows.

3. Most of the gross flows are generated by bounded rational decisions based on an enlarged search theory, and the effects of shocks we will study then integrate the agents responses and interactions within the rules of the game and the accounting constraints. Our multi-agent model then provides a tool to explore rigorously the complex system constituted by the labor market.

4.2 MODEL DESCRIPTION

4.2.1 The agents in WorkSim

In WorkSim, the agents are heterogeneous. They have specific attributes determined once and for all at their creation and internal variables that evolve all along the simulation. The agents attributes and variables are shown in Appendix D, section D.3. There are two types of agents: Private Firms and Individuals. At its creation, each firm starts with at least one worker to run the company, representing the managing director. The Individuals are grouped in households and the simulation evolves in a closed population. The individuals can marry each other, have children, and therefore the decisions of one member of the household may have an impact on the other members.

The agents under 15 or over 65 years belong to these households but are not instantiated as full agents and do not take decisions in the model. However, these non-instantiated agents indirectly participate through the economic decisions of the other members of the household (e.g. the number of dependent children is taken into account in decisions of transition to inactivity, the retirement pension is included in household income). The individuals under 15 years become full agents in the model at the age of 15, and some remain in the school system while others enter the labor market.

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6The diversity of contracts exists in many other countries and our model could be adapted to simulate other labor markets.

7The managing director works full time for the firm, and at the three occupations. The director never leaves the firm, except to retire or when the firm goes bankrupt.
4.2. Environment

In addition to these agents, the model uses three artifacts:

- **JobAds**, which receives job offers from the firms and job applications from the job seekers. Dissemination of information, however, is based on the job search process described in more detail below (see sections 4.2.8.4 and 4.2.9), according to the principles of search theory.

- A “**Statistical Institute**” that calculates statistics from the simulation and disseminates some information (e.g. tension on the labor market). The information is imperfect for agents, and we could specify what information is being broadcasted.

- A **Public Sector** that recruits (exogenously) employees, collects payroll taxes on businesses.

4.2.3 Institutional Framework

Moreover, it also includes one institutional module. One distinctive feature of the WorkSim model is to integrate a fairly complete and flexible institutional framework that includes (1) the necessary elements of the French labor law, including two types of contract: fixed duration contracts (FDC) and open ended contracts (OEC), dismissals on personal and on economic grounds, redundancy payments, ...), and (2) government decisions (minimum wages, welfare benefits, ...).

4.2.4 Individuals

In WorkSim, the individuals \(i\) are characterized by the following attributes:

- **Gender**: female or male.

- **Age**, denoted \(age_i\) and counted in weeks (a tick represents one week in the simulation).

- Preferences for free time: see section 4.2.9.1 below.

- **State** in the labor market. The possible states are: inactive, unemployed, employed and not searching for another job (denoted ENS), employed and seeking a new job (denoted OTJS, for On-The-Job Searchers), student or retired.

- **Occupation**, denoted \(q\) in this chapter. The number of possible occupations is denoted \(n_q\). In our simulations, we consider 3 levels: 1 = blue collar or employee, 2 = middle level job, 3 = executive. Of course, an individual can change its occupation during the simulation (upward or downward).

- **Productivity kernel** \(kProd_i\): it represents the “innate” abilities of the individual \(i\). \(kProd_i \sim \text{Max}(0, \mathcal{N}(1, \sigma_{coreProd}))\) with standard deviation \(\sigma_{coreProd} \in [0, 1]\) is an exogenous calibrated parameter.

---

8Artifacts in multi-agent systems are the passive (non-proactive) entities providing the services and functions that make individual agents work together (Omicini et al., 2008), and must be distinguished from proactive autonomous entities like the individuals or the firms.

9Main FDC (CDD) Features: maximum duration of 18 months including the possibility to be renewed once, small probationary period, allowance at the end of the contract: 10% of total gross salary. Cannot be broken without heavy penalties (paying the remaining salary part).

10Main OEC (CDI) Features: no duration limit, probationary period, no firing costs for the first year, no termination costs if quitting, variable firing costs when firing.

11In this chapter, \(\mathcal{N}(\mu, \sigma)\) denotes a normal law distribution, with mean \(\mu\) and standard deviation \(\sigma\).
• Condition factor \(\text{cond}_i, t\) that represents the physical condition, the motivation and satisfaction for \(i\). It evolves with time following a random walk:
\[
\text{cond}_{i,t+1} = \text{Max}(\text{minC}, \text{Min}(\text{maxC}, \text{cond}_{i,t} + N(1, \sigma_C)))
\]
(4.1)

Hence \(\forall t, \text{cond}_{i,t} \in [\text{minC}, \text{maxC}].\) \(\text{minC}\) et \(\text{maxC}\) are two exogenous parameters and \(\sigma_C \in [0, 0.3]\) is calibrated.

• Human capitals (HC) \(\text{HC}^{\text{gen}}_{i,t}\), \(\text{HC}^{\text{occ}}_{i,q,t}\), \(\text{HC}^{\text{spec}}_{i,p,t}\) respectively for the general, related to the occupational level \(q\), and specific to the firm and job \(p\) human capitals).

The general HC represents the abilities useful for all jobs, like problem solving or knowledge of a foreign language. It increases with experience (one more unit per tick) and also with training. It decreases at each tick if \(i\) is unemployed by a percentage \(L_{xp}\) after \(T_{xp}\) ticks (loss of skills). \(L_{xp} \in [0, 0.1]\) and \(T_{xp} \in [0, 100]\) are two calibrated parameters.

The occupational HC is related to the occupational level, and represents abilities specific to this level: machinery or team leading for instance. Like the general HC, it increases with experience (one more unit per tick) and also with training, and decreases at each tick if \(i\) is unemployed by a percentage \(L_{xp}\) after \(T_{xp}\) ticks.

The specific HC is related to the position and the firm. It represents abilities specific to the job in the firm, like a particular process or a software to use. It equals the number of ticks the employee spends in the job. It is reset to zero when s/he leaves the job.

4.2.5 Demand

The only production factor is the labor, like in many labor market models. There is one good, and each firm produces a certain amount of its own variety of this good. The price \(P\) is then unique (horizontal differentiation) and fixed at the arbitrary value of 1. Each firm of the \(N\) firms in our model responds to a quantity demanded of this good \(D_{j,t}\), which fluctuates randomly due to variations in consumers preferences. However, the global demand \(D_{tot}\) is held constant because we aim to study our economy in a steady state.

At time \(t = 0\), the market share of a firm \(j\) is given by
\[
\text{MS}_{j,t=0} = \frac{D_{j,t=0}}{D_{tot}}
\]

We assume that the distribution of this global demand varies between firms. Then we apply a stochastic shock on this market share for each firm at each period (random walk) using the following normal law:
\[
\forall t, \text{MS}_{j,t} = \text{Max}(0, \text{MS}_{j,t-1} \times (1 + N(\mu_{\text{MS},j,t}, \sigma_{\text{MS},j,t})))
\]
with \(\mu_{\text{MS},j,t}\) and \(\sigma_{\text{MS},j,t}\), two parameters of trend and deviation of this market share specific to each firm. These coefficients are randomly drawn every year for each firm according

\[\text{12The Human Capital represents the skills acquired through experience by the individual during her career. “Loosely speaking, human capital corresponds to any stock of knowledge or characteristics the worker has (either innate or acquired) that contributes to her/his “productivity”” (Acemoglu and Autor, 2011.). According to human capital theory, an investment on training increases human capital and therefore productivity (Becker, 1964). Becker distinguished between general and specific to the firm (and by extension here in WorkSim, specific to the job) human capital. There is also a human capital specific to the occupation, where a worker or a lawyer will acquire specific skills that will remain until if s/he leaves her occupation. There are many evidences that support all these three types of human capitals (e.g. Kambourov and Manovskii, 2009; Crook et al., 2011).}\]
to normal laws $\mathcal{N}(0, \sigma_{\text{trend}})$ and $|\mathcal{N}(0, \sigma_{\text{deviation}})|$. The first date of revaluation for a firm is random, then the revaluations take place every year after this date.

The demand of each firm $j$ is recalculated each period according to the evolution of this market share:

$$D_{j,t} = \frac{MS_{j,t}}{\sum_{k=1}^{N} MS_{k,t}} \times D^{\text{tot}}$$ (4.2)

Moreover, each firm has a specific organization and needs labor for each of occupation $q$:

$$D_{j,q,t} = D_{j,t} \times \psi_{j,q}$$ (4.3)

with $\psi_{j,q}$ the share of demand of the firm $j$ allocated to the occupation $q$. When creating a firm these shares are randomly drawn from a standard normal distribution with a mean $\mu_{\psi}$, which depends on the occupation of the job, and a standard deviation $\sigma_{\psi}$.

### 4.2.6 Jobs

Each firm $j$ has a specific job of managing director noted $p_0$ and a list $(p_{q,1}, p_{q,2}, ..., p_{q,m_{j,q}})$ of $m_{j,q}$ jobs per occupation $q$. A job can be in 3 different states: each job $p$ of the occupation $q$ is characterized by specific attributes determined once for all at its creation: filled, vacant or pending. A pending job is typically an FDC contract that ended, but cannot be renewed immediately, because of the waiting period. The firm does not want to destroy the job, if there is still a potential demand margin for it, so it becomes a pending job, until the waiting period will be finished. So we have here an important feature of WorkSim: unlike other models, we distinguish the job and the contract, several employees (and therefore several contracts) may have occupied the same job since its creation.

Each job $p$ of the occupation $q$ is characterized by specific attributes determined once for all at its creation:

- a vector of required human capitals $[HC_{\text{gen}}^\text{req}, HC_{\text{occ}}^\text{req}, HC_{\text{spec}}^\text{req}]$, respectively for the general, related to the occupational level $q$, and specific to the firm and job $p$ human capitals. They represent the minimum skills required to work on this job and are randomly drawn according to uniform distributions respectively between 0 and $\text{MaxHC}_{\text{gen}}^\text{req}$, $\text{MaxHC}_{\text{occ}}^\text{req}$ and $\text{MaxHC}_{\text{spec}}^\text{req}$. We will see in the next section that an individual can acquire these skills with experience and training.

- The duration of work, measured by the number of hours required per week for the job $p$, $H_{p,W}$. This number of hours is randomly drawn at the time of creation of the job. It has a probability $PrMid$ to be equal to 23.2 hours (part-time job) and $1 - PrMid$ to be equal to 39.6 hours (full-time job), from the actual work duration measured by DARES.

- A hourly base production equals to the hourly base production for all jobs in the firm at occupation $q$. It is randomly drawn at the creation of the firm $j$ within bounds from a standard normal distribution with a mean $\mu_q$, which depends on the occupation level of the job, and a standard deviation $\sigma_q$:

$$QH_{j,q}^{\text{base}} = \text{Max}(0, \mu_q \times \mathcal{N}(1, \sigma_q))$$

This drawing models the differences in production efficiency (technology, organization...) between the firms.

- A hourly base salary determined from the base production in the job for all jobs in the firm at occupation $q$:

$$SH_{j,q}^{\text{base}} = QH_{j,q}^{\text{base}} \times P \times (1 - \zeta)$$ (4.4)
with $P = 1$ the exogenous price of the (unique) good and $\zeta \in [0, 1]$, an exogenous parameter that represents the share of the base productivity value kept by the firm (in order to pay expenses, taxes, interests, dividends, etc.). The weekly base salary will be simply given by

$$S_{j,p,q}^{\text{base}} = S_{j,q}^{\text{base}} \times H_p W_p$$ (4.5)

- A level of amenity. This represents non-monetary features perceived by the individual on the job (social recognition, working environment,...). A hourly base amenity randomly drawn at the creation of the firm as a percentage $PrA$ of the base salary for all occupation level $q$ according to $AH_{j,q} \sim \mathcal{N}(0, \sigma_A \times S_{j,q}^{\text{base}})$. $\sigma_A$ is an exogenous parameter. The weekly base amenity of the job is then $A_{j,p,q} = AH_{j,q} \times H_p W_p$. Note that the amenity could be positive or negative$^{13}$.

### 4.2.7 Simulation cycle in the WorkSim Model

The simulation cycle includes four main steps, as shown in Figure 1 below:

1. Firm decisions: contracts and vacancies management, evaluations, job creation / destruction;
2. Individual decisions: labor market entrances and exits, job search;
3. Firm decisions: applications and promotions management;
4. Demography: household dynamics, retirements, aging.

---

$^{13}$The amenity is a proxy for all the factors that make the work pleasant or painful. We consider the work time per period when we calculate this amenity to avoid a bias, and above all, the amenity is fully revealed to the employee only after hiring. This amenity discovery could cause some early quitting, as it is happening in reality. Thus, in terms of imperfect information, there is a kind of symmetrical process between amenity discovery for the employee and employee’s productivity discovery for the employer. The main difference is that we assume the employee to be promptly informed of the amenity of the firm, while the productivity of the employee is measured only very gradually (the probationary period is too short to reveal the real productivity).
The length of one period in the simulation cycle corresponds to one week in the real world, in order to take into account the many very short term contracts that are found in the French labor market. 46% of all hires are on Fixed Duration Contracts that last one week or less in 2010 (ACOSS, 2011). Moreover, when statistics are needed, we took 2011 as a reference year, for which we could find the most recent and complete statistical data and sources.

4.2.8 Firm decisions

I have regrouped in Appendix D, section D.1 the main economic computations a firm has to perform during one simulation period: benefit, job features including the production base and the salary base, employee productivity (that will depend on its human capitals) based on imperfect information, cost of an employee.

Before describing the job creation process, let me describe the demand anticipation mechanism that is the core of these job creation process and the endogenous choice between the different contracts: FDC and OEC.

Three possible scenarios The central idea that governs job creation relies on the way the firm will estimate the future demand. If the demand is going to increase, a new job might be profitable, but not if there is a decrease in the demand.

Hence, the firm will compute three scenarios – pessimistic, neutral and optimistic, which are depicted in the Figure 4.2 below. We see in this Figure that in the pessimistic scenario of demand evolution, the demand of the firm is below its production with the new job after a certain time. As the firm cannot sell more goods than its demand, it may result in a loss because the firm has to continue to pay a salary. In this example, we see that it may be more profitable for the firm to choose a contract with a shorter expected duration like a 3 months FDC. Indeed, the firm will have the option to end this contract after 3 months in case of a negative scenario or to renew it if it goes well. However with a shorter contract it is more difficult to amortize the cost of hiring and training a new employee. It therefore appears a trade-off depending on the level of uncertainty of future demand and how the firm perceives the risks.

Note that, because of bounded rationality, the firms anticipates with a finite horizon only.

![Figure 4.2 – Demand and risk anticipation of the firms](image-url)
4.2.8.1 Job creations (step 1 in Figure 1)

The job creation proceeds in three steps:

1. First, the firm checks if there is a sufficient demand margin to create a new job. Here it considers the actual (not anticipated) demand margin $DM$ (defined by eq. D.14 in Appendix D): if $DM_{j,q,t} > DT$, where $DT \in [0, 1000]$ is the demand margin threshold (calibrated parameter), then the firm moves to the next step. Otherwise, no job is created.

2. If there is in the firm a pending job in the occupation $q$, the firm considers to hire a new person for this job (taking into account the eventual waiting period). Therefore the pending job becomes a vacant job. Otherwise, it moves to the next step.

3. Here, $DM_{j,q,t} > DT$ and there are no pending jobs in occupation $q$. Hence, the firm considers to create a new job $p$ of the occupation $q$. The characteristics of this new job are randomly drawn. From these job features, the firm must decide which type of contract suits better. This choice process between OEC and FDC is the core of the job creation process, and is described in the next paragraph.

Evaluation of a contract  During a prospecting phase, the firm receives information about $NPros$ job seekers of the occupation $q$, who have applied to a job with a FDC and $NPros$ job seekers of the occupation $q$ who have applied to a job with an OEC during the last period. The expected profit per period $\Phi_{i,j,p,q,c,t}^{\text{per}}$ for a candidate $i$ on a job $p$ with a contract $c$, given in D.30 and computed with the algorithm presented in section D.2 – this profit depends on the anticipated demand. The OEC contract is compared with several FDC with different fixed terms: 1 week, 1 month, 2 months, 6 months, 12 months, 18 months. Then the firm chooses to create the contract $c$ with the best average positive profit.

Then each contract $c$ will be evaluated on a set of $NPU$ potential candidates. These candidates are unemployed job seekers and JobAds sends to the firm their productivity level and human capitals. From this date, the firm computes the average profit per period:

$$\Phi_{j,p,q,c,t}^{\text{avg}} = \frac{\sum_{i \in E_q} \Phi_{i,j,p,q,c,t}^{\text{per}}}{NPU}$$ (4.6)

The firm will choose the contract $c^*$ that give the highest positive profit. If all the profits are negative, no new job is created.

If a job is created, the demand margin is updated, it will be diminished by the expected production of the new job: $DM_{j,q,t} \leftarrow DM_{j,q,t} - Q_{j,p,q,c,t}^{\text{avg}}$ with:

$$Q_{j,p,q,c,t}^{\text{avg}} = \frac{\sum_{i \in E_q} Q_{i,j,p,q,c,t}^{\text{est}}}{NPU}$$ (4.7)

The firm continues to consider creating new job as long as $DM_{j,q,t} > DT$.

4.2.8.2 Job destruction (step 2 in Figure 1)

By contrast, when there is a significant reduction in its demand in one occupation (in our model, this is when $DM_{j,q,t} < -DT$), the firm reacts in the short-term by trying to remove its vacancies. In the medium run (on a yearly basis), if this low cost adjustment is not sufficient, the firm considers the possibility to dismiss workers.

Moreover, independently of the demand level, the vacancies that remain unfilled and have a vacancy duration greater than a fixed threshold – a parameter that will differ for FDC and OEC – are destroyed.
4.2. Model Description

**Short-term adjustment: vacancy removals** In each period, when $DM_{j,q,t} < -DT$, the company randomly draws one of its vacancies and removes it. $DM_{j,q,t}$ is increased by $Q_{avg,j,p,q,c,t,creat}$. This process is repeated for all the remaining vacancies as long as overproduction remains (i.e. as long as $DM_{j,q,t} < -DT$ and there are still vacancies to be removed).

**Medium-term adjustments: economic dismissals** An evaluation of the financial viability of the company is performed on a yearly basis (52 periods in the simulation). The first date of the balance sheet is drawn randomly, then this financial reporting occurs every year from this date. The company calculates its yearly return that is computed as the ratio of the yearly profit over the total labor cost\(^{14}\). If this return falls below a certain profitability threshold (a fixed parameter $PT$, that will be calibrated), the firm can justify an economic dismissal procedure:

- All remaining vacancies are removed.
- After all the vacancies being removed, if $DM_{j,q,t} < -DT$ still holds, the firm consider to dismiss employees. It randomly sorts one employee, computes the associated profit $\Phi_{tot,i,j,p,q,c,t}$ and the firing cost $EFC$. If $\Phi_{tot,i,j,p,q,c,t} < -EFC$, the firm dismiss the employee. This process is repeated until $DM_{j,q,t} > -DT$ or if all employees have been evaluated.

If a company has no employee anymore, and if the managing director left alone does not make a sufficient return, the firm is considered to be bankrupt and is removed from the simulation. The managing director becomes unemployed. However, we want to keep the number of firms constant\(^{15}\). Hence, when a bankruptcy has occurred, we randomly select an active agent in the simulation to create a new firm and manage it. S/he will be the only producer in the firm (until s/he starts to recruit).

**4.2.8.3 Employee evaluations (step 3 in Figure 1)**

In each period, the firm examines if some employees have to be evaluated. This individual evaluation may occur:

1. At the end of the probationary period for FDC and OEC;
2. Every year, at the anniversary date of the contract, for OEC employee.
3. At the end of FDC contract to decide if it should be renewed;
4. At the end of FDC contract, if the transformation of FDC to OEC is to be considered;

**Dismissal for personal reasons** The process takes in two steps:

1. First, the firm evaluates if there is a case for considering the dismissal. That could be the case if the employee’s production is below the firm’s requirement. Thus, there is a chance that the firm considers to fire this employee for personal reasons if the annual production of the employee $Q_{real,i,j,p,q,c,t}$ satisfies: $Q_{real,i,j,p,q,c,t} < \rho \times Q_{required,p,q}$ where $Q_{required,p,q}$ is the required level of production and $\rho$ an exogenous parameter in $[0.7, 0.9]$.

---

\(^{14}\)The labor cost represents here the capital funds the firm has to pay in advance. Hence, the return is the ratio of the profit over this capital.

\(^{15}\)We keep the number of firms constant for two main reasons. First, we do not aim to model the process of firm creation, way too complex and out of the scope of WorkSim. Second, we are looking for a steady-state with a scale-up for year 2011, to apply and assess policies, and this will not be possible if the number of firms evolves constantly.
\( \rho \) encodes the tolerance the firm has with underproduction, or the maximum margin risk it accepts to take.\(^{16} \)

2. Then the firm decides whether such a dismissal is profitable (on economic grounds).

### 4.2.8.4 Hiring phase and promotions (step 7-8 in Figure 1)

Once the firm has chosen which contract \( c \) to create, a hiring norm must be computed to evaluate the candidates. This hiring norm is the profitability threshold below which it prefers to refuse a candidate. To do so, it uses the positive expected profits \( \Phi^\text{avg}_{i,j,p,q,c,t} \) calculated for each of the \( N_{\text{Pros}} \) candidates during the prospecting phase (eq. 4.6 above) and compute the average \( \Phi_{\text{Moy}} \), the minimum \( \Phi_{\text{Min}} \) and the maximum \( \Phi_{\text{Max}} \) values.

The hiring norm of the firm is given by:

\[
HN_{\text{Norm}}_{i,j,p,q,t=\text{crea}} = \left( \Phi_{\text{Moy}}^{\text{per}} + N_1 \times (\Phi_{\text{Max}}^{\text{per}} - \Phi_{\text{Min}}^{\text{per}}) \right) \frac{N(d_c)}{H(TIGH_{q,t}=\text{crea})} \tag{4.8}
\]

- \( N_1 \) will be calibrated in \([0, 1]\). The hiring norm increases with \( \Phi_{\text{Max}}^{\text{per}} - \Phi_{\text{Min}}^{\text{per}} \), so the firm favors a large dispersion of candidates’ qualities in order to increase the probability to get better candidates, as prescribed by search theory.

- \( N(d_c) = N_2 + N_3 \times d_c \), an increasing function of the duration of the contract \( d_c \) proposed for the job. \( N_2 \) et \( N_3 \) are two calibrated parameters in \([0, 1]\). We assume that the firm will be more demanding for longer contracts, as they imply to keep the employee for a longer time.

- \( TIGH_{q,t} = \text{crea} \) is the tightness on the labor market at the time of job creation and is given by \( TIGH_{q,t} = V_{q,t}/U_{q,t} \) with \( V_{q,t} \) the vacancy rate and \( U_{q,t} \) the unemployment rate at time \( t \) for the occupation \( q \). The higher this tension, the more the firms have to lower their requirements if they hope to find a candidate. \( H \) is a logistic function with values between 0.8 and 1.2 and given by \( H(x) = 0.8 + \frac{0.4}{1+20xe^{-3x}} \).

This hiring norm is then decreased by a percentage \( N_4 \) in each period until the job is filled, but never drops below 0.

Hiring takes place in three steps:

1. **Receiving applications** – The firm receives applications from external and internal applicants.

2. **Selection and potential hiring** – A two-steps process takes place:
   
   (a) First, the firm computes a score for each candidate (internal or external), given by the expected profit per period \( \Phi_{i,j,p,q,c,t}^{\text{per}} \) (section D.2.1.4, eq. D.30). Then the best candidate (highest score) is selected.

   (b) Thereafter, the firm checks if this candidate exceeds the hiring norm. If this is the case, the candidate is hired, otherwise, the job remains vacant.

3. **Internal promotion** – If the best candidate hired is an internal candidate of the company, it is a promotion. The employee acquires the occupation level of the job.

\(^{16}\)If \( \rho \) is too high, it will create a lot of firings and the firm will have a higher chance to face trials and higher chance to lose if it underestimated the real employee’s productivity.
4.2.9 Individual decisions (step 4-6 in Figure 1)

The individuals take decisions in each period of the simulation. This decision process is modeled with a state machine, where one individual will be in one particular state: inactive, unemployed, employed and not searching for another job, employed and seeking a new job, student or retired. The transitions between these states can be caused by individual choices (for example: to look for a job, to quit a job...), by external events (firing, death...), or eventually by a sequence of multiple decisions (e.g. applying for a job, and the firm hires the candidate).

4.2.9.1 Utility functions

Each individual uses a utility function, to decide whether s/he should stay in her/his current state or move to another one. The utility function has the generic form of a Cobb-Douglas function:

\[ U = (\text{Income} + \text{Amenity} + \text{Stability})^{1-\alpha} \text{(Free Time)}^{\alpha} \]  

(4.9)

It is a weighted aggregation of four factors:

1. **Income**: weekly income of the household in euros, divided by the number of consumption units (an adult counts for 1, a child 0.5)
2. **Amenity**: non-monetary features perceived by the individual (social recognition, working environment, job hardness...), cf. section 4.2.6 above.
3. **Stability**: criteria reflecting the preference of the individual for stability, i.e. for a job with the long contract duration. The maximum value is given for a permanent job (OEC). This stability is converted here into a percentage of salary and is expressed in euros;
4. **Free time**: free time per week available for the individual outside her/his working hours and search time. Our definition is a broad one since it includes time devoted for instance to sleep, eating, washing, domestic duties, and notably caring for the children.

The parameter \( \alpha_{i,t} \in [0, 1] \) encodes the preference of the individual for free time or work.

\[
\alpha_{i,t} = \min(0.95, \alpha_i^\text{base} \times (1 + \alpha_i^{\text{old}} \times (\text{age}_{i,t} - 15) \times F_{i,t}^{w}))
\]

(4.10)

- \( \alpha_i^\text{base} \) is drawn at the creation of the agent according to a normal distribution with mean \( \alpha_0 \) and standard deviation \( \sigma_{\alpha\text{pha}} \) (and with a minimum of zero).
- \( \alpha_i^{\text{old}} \) encodes an effect of age: like in several economic models (Dubois and Koubi, 2015; Jaaidane and Gary-Bobo, 2015), we assume that age will increase the disutility of time spent at work.
- \( F^w \) only concerns women with children (so equals 1 otherwise). As in the ARTEMIS model (Ballot, 2002), \( \alpha \) is different between men and women with children, because gender roles in the household has some impact\(^{17}\).

\[ F_w = 1 + \alpha_{\text{child}}^w \times n_{i,t}^\text{child} \]

where \( n_{i,t}^\text{child} \) counts the number of children. Moreover, for young women (under 25), \( \alpha_{\text{child}}^w \) is multiplied by an additional factor \((1 + \alpha_{y}^w)\), to take into account the overload for young women (with young children).

\(^{17}\)In fact, and even if societies are constantly evolving on that issue. French women in 2011 have devoted more time than men for housework and the education of children. According to INSEE’s inquiry on time use, on average, women devote 45mn daily to care for children, while men spend only 19mn on such an activity. Indeed, in 2011, the full-time employment rate of French women living in a couple with three children or more was 39.8% and 87% for men in the same situation (INSEE, 2011c)
$\alpha^0, \sigma_{\text{alpha}}, \alpha^{\text{old}}, \alpha^{\text{child}}$ are calibrated parameters in $[0, 1]$ and $\alpha^{yw}$ is calibrated in $[0, 20]$.

### 4.2.9.2 Overview of the decision-making process

The decision-making process of individuals is sequential and summed up in the state transition diagram depicted in Figure 4.3. At each tick, the individual agent computes the utility of its current state and the utilities of each reachable state. Each utility is evaluated using the generic form given by equation 4.9 above, and instantiated with the relevant values of income, amenity, stability and free time. For some transitions, a factor $ICHANG \in [1, 2]$ is applied that represent the psychological cost facing change (calibrated parameter). When $ICHANG > 1$, the new state’s utility must be even greater to win the decision.

![Figure 4.3 – UML State diagram describing the main transitions of individuals and their decision-making process.](image)

**Figure 4.3** – UML State diagram describing the main transitions of individuals and their decision-making process. Each utility is calculated according to the equation 4.9. Legend: UTTINA: utility to be inactive. UTNEW: utility of a new job, estimated through prospecting. UTUEM: utility to be unemployed. UTRES: utility of reservation. UTOJS: utility of the OJS (On-the-Job-Search) state. UTEMP: utility to be employed. UTQUI: utility to quit. ICHANG: psychological cost to change state (calibrated exogenous parameter). EMPLOY measures the employability of the inactive. Dotted arrows represent decisions that do not fully depend on the agent (i.e. taken by the firm.)

### 4.2.9.3 Decision to look for a job

A job search could be long and psychologically costly if it does not lead to a success. Therefore the inactive agent will first try to assess her/his employability $EMPLOY$. Employability measures to capacity for someone to get a job, according to her/his skills, degree, career and current state. In WorkSim, it is given by $Q_{i,t}^{eff} \times H(TIGH)$, where the product of the indi-
individual’s productivity (based only on general human capital) is modulated by the tension in labor market (with function $H$ being the same than in equation 4.8 above).}

### 4.2.9.4 Decision of student and public servant agent

Given the variety of possible situations, we found difficult to model the behavior of students in this first version of WorkSim. We adopted a “black-box” approach, simply aiming to reproduce the flow of students towards activity on the labor market in 2011. Furthermore, the public servant agents (21.3% of the agents) do not take decisions and are just present in order to reproduce demographic and employment statistics. When they retire, they are replaced according to a rate 1:1 (to be in a steady state) by youths who are finishing their studies and are randomly drawn in their cohort.

### 4.2.9.5 Job search process

After describing the different decision mechanisms, let me now detail the overall job search process:

1. Each period in the model (one week in the reality), a job seeker receives from JobAds a list of $NV_{i,t}$ vacancies matching her occupation or a level above. We assume that these incoming job offers occur at a mean frequency that is known and independent of the time elapsed since the last offer. Therefore, we model the incoming of new job offers with a Poisson law: at time $t$, this number of vacancies $NV_{i,t}$ is drawn from a Poisson distribution with parameter $\lambda_t = NSJ_t \times H(TIGH_t)$, where $NSJ_t$ is the average number of vacancies received by the unemployed at each period, and $H$ is the same function of tightness as above.

2. The individual sends an application for the first offer whose utility is above his/her reservation utility $UTRES_{i,t}$. If there is no job offer corresponding to her/his occupation or if all of her/his applications are rejected, s/he lowers her/his reservation utility $UTRES_{i,t}$. Thus, at the end of each period, the reservation utility is updated:

$$UTRES_{i,t} = UTRES_{i,t-1} \times (1 - Ru_3) + Ru_4 \times (UTUEM_{i,t} - UTUEM_{i,t-1}) \quad (4.11)$$

where $Ru_3 \in [0, 0.005]$ is a calibrated parameter and $Ru_4$ a fixed parameter (0.5). The first part of the equation accounts for the diminution with time and second one is driven by a modification of $UTUEM$, that is the utility for the unemployed (for instance a decrease of revenue will lower $UTUEM$ and therefore $UTRES$, as the urge to find the job increases).

---

18Indeed, a high tension $TIGH = V/U$ corresponds to a high number of vacant jobs and/or to a low unemployment rate, and is therefore always favorable to job seekers.

19Reservation utility is an important concept in labor economics. It is the equivalent of the hiring norm, for the individual, as it represents the minimum level of utility to make it acceptable to an agent. It does not remain constant, but dynamically evolves during the agent’s life, to adapt to situation changes. So, the equation will vary, depending on the agent’s state (see eq. 4.11).
The job-search process is summarized by the sequence diagram in Figure 4.4 below.

![Sequence Diagram](image)

**Figure 4.4 – UML sequence diagram of the job-search process in WorkSim**

4.3 SIMULATION ANALYSES AND RESULTS

In this section, I will summarize the main results from the simulations we conducted with WorkSim. First of all, following the methodology I presented in the introduction of this thesis, we conducted an automatic calibration procedure in order to ground the model on real data and to find the values of parameters that have to be calibrated. As described in section D.4 of Appendix D, we have a total of 91 parameters in the present version of WorkSim: 31 are fixed and 60 are to be calibrated (24 for the individuals, and 36 for the firms).

4.3.1 Calibration

**Scaling** First of all, we must set the number of agents in the simulation. It must be large enough to account sufficiently for real behaviors, but not exceed our computational power. We choose not to exceed 10000 agents in order to cope with our computational resources, especially during the calibration procedure. To do so, we start from the real firm distribution by size (i.e. number of employees) in France in 2011. We scale up this distribution by a reduction factor of 4700 and obtain 808 firms, for a total of 4411 employees. Then, we add public servants in a proportion of 21.3% and the numbers of “inactive”, “unemployed”, “retired” and “student” agents corresponding to 2011 statistics. We obtain a total of 8713 individual agents and it corresponds to the 40.79 million individuals in the age range 15-64 with a reduction factor of 4682 (which...
is well in line with the reduction factor for the firms). Finally, we have then 8713 individuals and 808 firm agents, for a total of 9521 agents in the simulation.

**Calibration procedure** To calibrate the 60 model parameters, we chose to use a calibration process. It minimizes a *fitness* function that is the weighted sum of the relative spreads between the outputs of our model and the real targets of the French labor market in 2011 (source INSEE/DARES). We have chosen 63 targets grouped in 10 different categories: unemployment rates (7 targets), activity rates (6), salaries (14), job flows (12), FDC (4), long-term unemployment (3), mobility (between occupations; 12), additional (part-time, vacancies, on-the-job, training costs). In most cases, we have a target per occupation or age range.

To minimize our fitness function, we choose the evolutionary algorithm CMA-ES (Hansen and Ostermeier, 2001), which is one of the most powerful algorithms to solve this kind of problem (Auger and Hansen, 2012). CMA-ES means Covariance Matrix Adaptation Evolution Strategy. The principle of this evolutionary algorithm is to test step by step new generations of points in the parameters space. Each new generation of points is drawn stochastically according to the results obtained with the previous generation of points. The mean and the covariance matrix of the distribution of the new randomly drawn points are updated incrementally in order to move towards the best results obtained by previous generations, as shown in Figure 4.5 below.

![Figure 4.5 – Example of optimization with CMA-ES on 2 parameters. The lighter zones correspond to lower fitness values.](image)

At each iteration, the CMA-ES algorithm sets the values of all the 60 parameters. Then, to cope with the stochasticity we have in the model, 48 simulations are run (they are usually called *replications* in a calibration process) with a different seed for the random generator, and the outputs are averaged over these 48 simulations to obtain the fitness value of the iteration. We stop the calibration when the fitness does not improve (same minimum value) for 500 iterations.

Moreover, a simulation needs some time to stabilize. To overcome possible instabilities, we use the following protocol: at time t=0, we initialize the model (including the 31 fixed parameters) with statistics for year 2011. Then we run the calibration for 2 years (i.e. each replication is run for 104 ticks), in order to let the model reach a more stable state. At this point (t=104), we save the totality of the model (the states and variables of all the agents, a complete serialization of the system). To ensure the model is stable enough, we run a
second calibration for another 2 years (from t=104 to 208) and obtain from this calibration the parameters of what we called the baseline simulation\textsuperscript{21}.

**Computational power needs** The calibration process is very costly in terms of computational resources, because the total number of simulations could be very high: it is given by the product of the number of iterations by the number of replications. With WorkSim, it took 2000 iterations to converge, and as stated above each iteration is made of 48 replications\textsuperscript{22}. So we run 2000 × 48 = 96000 simulations. Each simulation takes about one minute overall and the whole calibration process will take one or two days (depending on the number of available cores) to be completed.

**Results of the calibration on the main targets** The values of the calibrated parameters are shown in sections D.4.2 and D.4.3 of Appendix D. We obtain an average relative spread between all the outputs of our model and the real targets of 9.6%. These spreads can be deemed satisfactory for such a large non-linear model. We deal with a multi-objective optimization problem with many targets and parameters, and these problems are known to be hard to solve.

Let me now examine the calibrated value for some key parameters. By definition, these values are difficult to assess, because there is no reference point in the real life (if there was one, we would have use it in the model!).

For the individuals, the preference for free time $\alpha_0$ est is relatively small: 0.07. However, as shown in equation 4.10, this parameter is multiplied by other factors, $\alpha_{old}$, $\alpha_{base}$, with these values, the real value of free time preference is 0.28.

From equation 4.9, we find that the elasticities of U respectively to work ($W = Income + Amenity + Stability$) and free time (denoted $L = FreeTime$) are: $e_{UL}(W, L) = 1 - \alpha$ and $e_{UL}(W, L) = \alpha$; and the marginal rate of substitution of free time to work is $\tau_{L,W} = (\frac{1}{\alpha} - 1) \frac{L}{W}$ (these are the classical properties of a Cobb-Douglas function). Here, there is indeed a preference for work, with $e_{UL} = 0.72$, $e_{UL} = 0.28$ and $\tau_{L,W} = 2.56 \times \frac{L}{W}$: if we increase the time of work by 30%, the utility will increase by 21.6%; with the same increase in free time, the utility only increases by 8.4%. This is coherent with the fact that French people place a great importance to work in their life, according to several studies and polls (e.g. Davoine and Meda, 2009).

The psychological cost of change $ICHANG$ is calibrated to 1.26. That implies that 26% of increase in utility is necessary to change to a new state.

Concerning the firms, the share of base productivity value kept by the firm $\zeta$ equals 71%, which implies that 29% of the production value is given for the salary. This seems rather low, but it does not include labor costs (social security, taxes) and the salary in WorkSim is a net salary. Using a multiplication factor of 1.8, we obtain that gross salaries correspond to 50% of the production. But the most notable result concerns the scenario coefficients $\omega$: we found that the pessimistic scenario weights $\omega_{-1} = 78.9\%$ of the total weight, while the neutral weights $\omega_0 = 14.5\%$ and the positive scenario weights only $\omega_{+1} = 6.6\%$. The French firms appear to be very pessimistic about their future, they tend not to create long-term jobs as they appear to be too risky (because of anticipated insufficient demand). This is one of the main results of our simulations, and could be one important explanation of the high level of unemployment in France.

\textsuperscript{21}To measure the stability, we can compute the median drift for all the 69 targets, from 104 to 208 ticks. We obtained 4.2 \%, which we considered to be acceptable
\textsuperscript{22}We chose 48, as it is the number of maximum cores available in the LIP6 computer grid. Hence, each replication could be run in parallel, and then averaged to get the result of one iteration.
4.3. Simulation analyses and results

4.3.2 Sensitivity analyses

Once we have studied the values of the calibrated parameters, it is important to study the dynamics around these calibrated values. That is the role of sensitivity analyses, that are now commonly used in multi-agent simulations. Here we change one parameter at a time, keeping the other parameters set to their baseline values (fixed or calibrated, see section D.4 of Appendix D). We performed several analyses on free time \( \alpha \), change factor \( ICHANG \), etc. (see (Goudet, 2015) for more details).

Two parameters appeared to have a strong effect on unemployment. First, the share of base productivity value kept by the firm \( \zeta \) produces a sort of bell curve for the employment rate, as depicted in Figure 4.6 below: when \( \zeta \) is decreasing below 0.78, the employment rate decreases because the firms are reluctant to create jobs with lower margin, and therefore the unemployment rate rises (when \( \zeta = 0.4 \), it reaches 35%). When \( \zeta \) increases over 0.78, the employment rate decreases because the salaries are decreasing and that discourages the individuals and they become inactive. This discouragement makes the unemployment slightly decrease. Note that in reality, \( \zeta \) will emerge from the negotiation results between unions and managements.

![Figure 4.6 – Sensitivity of the share of base productivity value kept by the firm \( \zeta \)](image)

The second strong effect is produced by the scenario weights. As shown in Figure 4.7 (top), when \( \omega_{-1} \) increases, the unemployment rate rapidly increases, from 5% to 11%, although the total demand is kept constant. The explanation is partly given by the bottom figure in Figure 4.7: when the firm is very pessimistic, it creates a lot of FDC, and more and more very short FDC (1 week duration): more than 30% of hirings are on these short contracts when \( \omega_{-1} \geq 0.8 \). These effects are not surprising per se. What is really surprising is the amplitude of this effect and above all, the fact that the calibrated value \( \omega_{-1} = 0.8 \) is on the worst part of the curve, giving almost the highest unemployment, FDC and very short FDC hirings. According to WorkSim, the French labor market badly suffers from the pessimism of its firms, and this is one of the major finding of this work.

Finally, we measured the impact of shocks on the global demand \( D_{tot} \). Results are shown in Figure 4.8. When the demand increases (positive shock, demand factor greater than 1), unemployment decreases to reach its structural value (6.5%), despite a high number of vacancies, due to the mismatch between labor offer and demand. With a negative shock (factor lower than 1), the unemployment rises rapidly: a decrease of demand by 30% doubles the unemployment rate from 10% to 20%. Finally, we found that the number of entries \( OEC \) increases with demand (see bottom figure): when demand is doubled, it almost equals the
number of entries in FDC. The entries in FDC increases when demand decreases, except when demand is too low (Factor less than 0.8): in that case, the firms stop creating FDC as well.

### 4.3.3 Flow analysis: persistent segmentation in the French labor market

We also studied the weekly gross flows diagrams we derive directly from our simulations. The flows are depicted in the section D.5 of annexe D. In the diagram for all individuals (Figure D.2), the labor market is characterized by high rates of rotation between the states of “unemployed” and “Employee in FDC”. The probability to exit from unemployment to get an OEC is only 4.54%, while it is 18.37% to get a FDC. The strongest flow is from FDC to unemployment (28.94%), while the entry from FDC to OEC is only 4.44%. This strongly illustrates the segmentation (or dualism) that characterizes the French labor market between a population of well-protected employees under OEC (the biggest stock), with a very low probability to become unemployed, and a precarious population (3 times smaller) of employees that are unemployed or in FDC and move between these two states. When we analyze the diagrams by age (Figures D.3,D.4,D.5), we find the same segmentation for the young, but more surprisingly also for the intermediates (25-49 yo) and the seniors (50-64 yo). This strong segmentation is persistent with age, and this is another major finding of our simulations. The conversions of FDC in OEC rate are not very strong and recruitment in OEC neither, so that precariousness does not disappear.
4.3. Simulation analyses and results

4.3.4 Assessment of some labor public policies

We conducted several simulation of labor policies, and most of them were new (never implemented). In fact, one of the major purpose of WorkSim is to aid politicians on employment and labor, by simulating and understanding the effects of one particular policy.

Because the choice between contracts (OEC and FDC) is at the core of our model, several policies targeting the contracts were simulated. We also tested a fiscal policy (reduction of charges) and one involving the reduction of working time. Let me summarize the main results of these simulations.

**Forbidding fixed duration contracts** Because of the strong segmentation in the French Labor market, with a lot of flows between FDC and unemployment and very few to enter into a more stable OEC, one might want to forbid the FDC and have only OEC contracts. We experimented this forbidding in WorkSim, where only OEC and few customary FDC contracts remained. We measured the impact after 2 and 4 years. Two years after the forbidding, there is a significant rise of unemployment rate (+2.61), especially among young people and employees or workers. After 4 ans, the unemployment rate decreases, and the impact drops to +0.42, because part of the individuals get hired on a OEC. But the unemployment rate decreases also because of the discouragement of 420 000 that leave the labor market (the activity rate drops by 1.03 point). More over, the long-term unemployment strongly increases (20.4 points after 2 ans, and still 11.1 points more after 4 years). Thus, not only the forbidding of

---

**Figure 4.8 – Sensitivity to demand shocks. x-axis displays the demand factor \(df \in [0, 7; 2]\), where the total demand \(D_{tot}\) becomes \(df \times D_{ref}^{tot}\).**
FDC failed to reduce the segmentation but it actually increased it\textsuperscript{23}. FDC and OEC are not substitutable but complementary, as suggested elsewhere (Bunel, 2007).

**Firing costs and legal justification** Another option to reduce unemployment would be to ease the creation of OEC (instead of FDC). Many firm leaders and employers’ syndicate complain about the level of firing costs on one hand, and about the difficulty to fire an employee when the demand becomes insufficient, on the other hand. Therefore we conducted experiments to study these issues.

In a first experiment, we vary the level of firing costs, and multiply them by a factor between 0 and 50. Surprisingly, we found a very small effect on unemployment. The unemployment rate increase only by 1 point when we multiply the firing costs by 50. When the cost increases, the firms replace OEC hirings by FDC hirings. Moreover, when the cost is null, the unemployment remains around 9.5\%, because hiring in OEC remain low.

So, maybe this is not about the cost of firing, but about the difficulty to fire someone, when the demand is low. Therefore, we conducted a second experiment, where we remove the legal justification attached to firings. When it is the economic interest for the firm to fire an employee, it does so. Moreover, this possibility is integrated into the anticipation mechanism that is part of the decision process to create an OEC job. The results are shown in Table 4.1. With this variant, unemployment rate drops by 1.89 points, and the decrease is particularly important for the youth, with a drop of 9.71 points. However, we observe an increase of 1.48 for the seniors. When we look at the unemployment rate per occupation, we find the variant to be quite beneficial for the blue collars/employees category (+3.1 points) at the detriment of the two other occupations (+0.78 for middle levels and +0.87 for executives). This could partly due to the fact that the firms mainly use OEC to hire: the entry rate in OEC goes from 9.156 \% to 30.78 \%; while the entry rate in FDC drops from 38.3 \% to 6.26 \%. The share of FDCs drops from 10.33 to 1.74 \%. As a counterpart, the OEC become more precarious: the economic firing rate increases from 0.44 \% to 26.13 \% and the average seniority in OEC decreases from 4.76 to 2.23 years, and the probability to lose a job increases by 65 \% (from 8.7 \% to 14.4 \%).

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Reference</th>
<th>Variante</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate (%)</td>
<td>9.78</td>
<td>7.89</td>
<td>-1.89***</td>
</tr>
<tr>
<td>Unemployment rate 15-24 ans (%)</td>
<td>20.88</td>
<td>11.17</td>
<td>-9.71***</td>
</tr>
<tr>
<td>Unemployment rate 25-49 ans (%)</td>
<td>8.4</td>
<td>7.03</td>
<td>-1.37***</td>
</tr>
<tr>
<td>Unemployment rate 50-64 ans (%)</td>
<td>6.84</td>
<td>8.32</td>
<td>+1.48***</td>
</tr>
<tr>
<td>Unemployment rate Blue collars/employees (%)</td>
<td>10.84</td>
<td>7.74</td>
<td>-3.1***</td>
</tr>
<tr>
<td>Unemployment rate Middle Levels (%)</td>
<td>6.71</td>
<td>7.49</td>
<td>+0.78***</td>
</tr>
<tr>
<td>Unemployment rate Executives (%)</td>
<td>4.64</td>
<td>5.51</td>
<td>+0.87***</td>
</tr>
<tr>
<td>Activity rate (%)</td>
<td>66.93</td>
<td>67.48</td>
<td>+0.55***</td>
</tr>
<tr>
<td>Number of employed individuals (in thousands)</td>
<td>24 629</td>
<td>25 355</td>
<td>+726***</td>
</tr>
<tr>
<td>Average individual’s utility</td>
<td>196.3</td>
<td>202</td>
<td>+5.7***</td>
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<td>Annual average firm benefit (in thousands euros)</td>
<td>189</td>
<td>197</td>
<td>+8***</td>
</tr>
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<td>Long-term unemployment rate (%)</td>
<td>34.6</td>
<td>31.9</td>
<td>-2.7***</td>
</tr>
<tr>
<td>Probability to loose one’s job within a year</td>
<td>0.087</td>
<td>0.144</td>
<td>+0.057***</td>
</tr>
</tbody>
</table>

*Table 4.1 – Removal of legal justification in case of firing.*

\textsuperscript{23}There are several processes involved in FDCs, and they have opposing consequences on unemployment: buffer-stock, screening, experience and stepping stone are more likely to have a positive effect, while churning (the fact that workers are sent to unemployment frequently) is rather negative. It is very difficult to quantify these effects. WorkSim is the first agent-based model to account for all these five effects. Our results for the FDC forbidding could be explained by the fact that the reduction of churning is not large enough to compensate the loss of buffer stock and stepping stone effects (for definitions and more details, see Goudet \textit{et al.,} 2014; Goudet, 2015).
Thus, the removal of legal justification improves the situations of the most fragile categories (namely the youth, the blue collars, the employees) as most of them was hired in FDC and now get an OEC. This is a the detriment of the other categories that were hired in OEC and now face shorter OEC and more frequent firings. Globally, the individual utilities slightly increase, as do the firm benefits. Moreover, when the economy faces negative demand shocks, we found that this variant policy performed much worse than the baseline simulation, as depicted in Figure 4.9, where the total demand $D_{tot}$ is multiplied by a factor between 0.5 and 2. When this factor decreases below 0.8, the unemployment rate increases much faster in the variant simulation (in red) than in the baseline one (in blue; 10 more points for the variant than the baseline when the factor is 0.5). However, the structural employment (when the demand is multiplied by 2) is higher in the baseline than the variant (6.5% vs 5%). To sump up, this policy is not yet the ideal solution to improve employment: even it is costless and created 726 000 jobs in our simulation, that was at the price of a significant higher precariousness, and shows less resilience when the demand gets weaker. But it is a path to solve the most important issue in the French Labor Market: how improving the situation of the outsiders without degrading the situation of the insiders? We think that this variant results might suggest to consider the merge of OEC and FDC into a unified contract (“contrat unique”) and the implementation of “Flexicurity” Cahuc and Kramarz (2004); Boyer (2006).

Reduction of charges The level of social charges on employment are frequently discussed, especially by employers’ syndicates. In fact, in 2003, the minister F. Fillon has passed a law that reduces the charges paid by the firms on employment, for salaries lower than 1.6 times the minimum wage (SMIC). The decrease will be 26% for firms will 20 employees or more, and 28.1% for the others. To study the effect of this measure, we compared the results of the baseline simulation with a new simulation where these charge reductions are removed. We measured a drop of 0.72 points in unemployment rate, and a gain of 233 000 more jobs, thanks to the charges reduction. The firms also increase their benefits. However, it might me more efficient to target the policy on smaller wages, as advocated by several economists (e.g. Cahuc and Carcillo, 2014). Therefore, we vary the maximum wage to receive to policy, from 1.2 SMIC to 2.2 SMIC. The results are displayed in the Table 4.2 below. It appeared that the 1.2 SMIC target gives the most effective policy: smallest

\[\text{Table 4.2} \]

---

\[\text{As noted above, the baseline simulation is performed with parameters set to their calibrated values (the values summarized in sections D.4.2 and D.4.3).}\]
unemployment rate (9.55%), 298 000 more jobs, 253 000 less unemployed and also the lowest costs.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>1.2 SMIC</th>
<th>1.3 SMIC</th>
<th>1.6 SMIC</th>
<th>2.2 SMIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate (%)</td>
<td>9.55</td>
<td>9.66</td>
<td>9.78</td>
<td>9.83</td>
</tr>
<tr>
<td>Number of created jobs (in thousands)</td>
<td>298</td>
<td>266</td>
<td>233</td>
<td>217</td>
</tr>
<tr>
<td>Number of avoided unemployed (in thousands)</td>
<td>253</td>
<td>228</td>
<td>192</td>
<td>180</td>
</tr>
<tr>
<td>Gross cost per created jobs (in euros)</td>
<td>86138</td>
<td>94361</td>
<td>110 729</td>
<td>119 816</td>
</tr>
<tr>
<td>Gross cost per avoided unemployed (in euros)</td>
<td>101 581</td>
<td>110 088</td>
<td>134 375</td>
<td>144 445</td>
</tr>
</tbody>
</table>

Table 4.2 – Charge Reductions. The baseline simulation corresponds to the 1.6 SMIC column (in italics).

**Reduction of working time**  In 1998, France experienced a significant reduction of working time, from 40 to 35 hours per week. This measure created 350 000 jobs, for a total cost 13 billions euros for the State Romagnan (2014). However 35h is the legal time, but the time actually worked is higher (39.6 hours in 2011), as workers can work overtime. With WorkSim, we wanted to experiment a full reduction: what happen if all the workers in the labor market work only 32 hours a week (and no more)? Remember that in WorkSim, we did not integrate overtime, so everyone works $H_p W_p$ hours per week. So we simply set $H_p W_p = 32$ and we reduced the part-time working time from 23.2h to 18.7h (in proportion). The results are displayed in Table 4.3 below. We observe an important drop in the unemployment rate (from 9.78 to 6.64 %), for every age categories and every qualification (decrease around 3 points). The long-term unemployment also diminishes (-5.9 points). There are 877 000 fewer unemployed, and 1.2 millions of more jobs, because of a rise of the activity rate, as the job situation improved. Furthermore, we observe a decrease in the salary (184 € per month in average, -9 %), because of the time reduction, and a slight decrease in the individuals’ utility (-5.2, that is -2.6 %). On the firms’ side, there is a slight decrease in the benefits (-11 or -5.8 %), because the average worker’s production decreased (from 6793 to 5471 per month), which entailed a loss of revenue (higher that the loss of costs). In terms of equity, this policy brings some balance, because individuals with the lowest utilities (first decile) show an increase of 4.9 % of their utilities. However, it is worth noting that, even though the situation of employment has much improved, the segmentation remains, with few individuals having access to OEC and the majority of entries being in FDC (the entry rate in OEC increases from 9.31 to 10.34, and the one in FDC decreases from 37.62 to 37.24). The reduction of time is indeed a promising approach but not a miraculous one. Moreover, several important effects of this policy are not taken into account by this version of WorkSim, but should be for a more precise assessment: effect in the household consumption (or the increasing free time and the decrease of salary), effect of the loss of production and benefits, organizational issues in the firms.

4.4 **CONCLUSION OF THIS CHAPTER**

WorkSim is the first and oldest project (9 years) I have created and been working on since I joined the MAS team of LIP6 in 2005. The work seems to have reached a certain level of maturity, we have a comprehensive model of the labor market, and implemented numerous mechanisms that were not integrated together before within a single labor market model: both sides of the market, detailed decision processes under bounded rationality, learning and anticipation, endogenous contract choices, human capitals, endogenous salaries and productivities. The stock-flow accounting of individuals, based on gross flows, is complete and endogenous. It can be supplemented by a stock-flow accounting of jobs (and even jobs within the company) for further analysis. The institutional environment is modeled and based on labor law, which sets constraints on the possible decisions.
4.4. Conclusion of this chapter

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Référence</th>
<th>Variante</th>
<th>Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment rate (%)</td>
<td>9.78</td>
<td>6.64</td>
<td>-3.14**</td>
</tr>
<tr>
<td>Unemployment rate 15-24 ans (%)</td>
<td>20.88</td>
<td>16.89</td>
<td>-3.99**</td>
</tr>
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<td>Unemployment rate 25-49 ans (%)</td>
<td>8.4</td>
<td>5.33</td>
<td>-3.07**</td>
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<td>Unemployment rate 50-64 ans (%)</td>
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<td>4.09</td>
<td>-2.75**</td>
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<td>Unemployment rate Blue collars/employees (%)</td>
<td>10.84</td>
<td>6.47</td>
<td>-4.37**</td>
</tr>
<tr>
<td>Unemployment rate Middle level (%)</td>
<td>6.71</td>
<td>4.26</td>
<td>-2.45**</td>
</tr>
<tr>
<td>Unemployment rate Executives (%)</td>
<td>4.64</td>
<td>3.83</td>
<td>-0.81**</td>
</tr>
<tr>
<td>Long-term unemployment rate (%)</td>
<td>34.6</td>
<td>28.7</td>
<td>-5.9**</td>
</tr>
<tr>
<td>Activity rate (%)</td>
<td>66.93</td>
<td>67.9</td>
<td>+0.97**</td>
</tr>
<tr>
<td>Employment rate (%)</td>
<td>60.38</td>
<td>63.39</td>
<td>+3.01**</td>
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<td>Number of employed individuals (in thousands)</td>
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<td>25 857</td>
<td>+1 228**</td>
</tr>
<tr>
<td>Number of unemployed individuals (in thousands)</td>
<td>2 672</td>
<td>1 795</td>
<td>-877**</td>
</tr>
<tr>
<td>Monthly net salary (full-time equivalent, in euros)</td>
<td>2036</td>
<td>1855</td>
<td>-184**</td>
</tr>
<tr>
<td>Average individual’s utility</td>
<td>196.3</td>
<td>191.1</td>
<td>-5.2**</td>
</tr>
<tr>
<td>Annual average firm benefit (in thousands euros)</td>
<td>189</td>
<td>178</td>
<td>-11**</td>
</tr>
<tr>
<td>Share of part-time jobs (%)</td>
<td>21.04</td>
<td>19.92</td>
<td>-1.12**</td>
</tr>
<tr>
<td>Turnover rate (%)</td>
<td>45.26</td>
<td>40.02</td>
<td>-5.24**</td>
</tr>
<tr>
<td>Average number of spells in FDC</td>
<td>1.97</td>
<td>1.92</td>
<td>-0.05**</td>
</tr>
</tbody>
</table>

Table 4.3 – Reduction of working time

WorkSim is calibrated on a large number of targets of the French labor market in 2011, by using a powerful algorithm which has not already been used in economic models. It reproduces well enough these targets to conduct some economic analyses. Moreover, it reproduces well the gross flows measured by different statistical sources and with different types of measures. This gives us an estimation of the model accuracy, and is part of the model’s validation process.

We conducted several analyzes and policy evaluations. These helped us to identify core mechanisms in the French Labor Market: segmentation, importance of firms’ pessimism, among others. Labor policies appeared to have contrasting results in terms of employment improvements, utilities, benefits and costs.

This is indeed a “work in progress” and there is room for improvements. At first, the model can be extended in several directions: adding temporary employment agencies, social networks, and training (more detailed) for instance. We can also integrate more organizational elements (some of them could take inspiration from the activity model in HappyWork), including skills and tasks.

Second, WorkSim needs to be plugged into an agent-based macro-economical framework, in order to have consumption, production and financial effects as well. Third, tools to help analyzing and explaining the simulations are still to be developed further: visualization (improving the graphical interface in WorkSim), analyses of the agents’ decisions, automatic classification of agents’ trajectories to study individuals’ careers (cohort analysis). Another issue is the link with econometrics, to improve the agents’ micro-foundation and enhance the validation process.
5 General discussion and perspectives

In this final chapter, I present the general conclusion and perspectives of this work. In the conclusion section of each previous chapters, I have already highlighted the main contributions and drawn the perspectives of each corresponding project. Therefore, I will focus here on more general issues. In particular, I will show in section 5.1 how I have managed to tackle the research issues stated in the introduction section. Then I will highlight to contribution to multi-agents systems (section 5.2) and conclude in section 5.3 with the general future directions.

5.1 Methodological assessment

In this manuscript, I presented four projects aimed to design agent-based models and simulations of complex human behaviors. They show how ABM could be used to deal with major economic and societal issues: opinions and attitudes, job satisfaction and (un)employment. These projects are also (partial) answers to the questions (P1)-(P4) I raised in the introduction. They are intended to be very descriptive: following psychomimetism, all of the models are deeply grounded into psychological, psychosocial or economical theories, and these theories are empirically grounded. In that respect, one could qualify them as “realistic”, though such a qualification is always delicate to assess. At least, they are descriptive (P1) in a realistic way since they follow psychomimetic, use empirically grounded theories and are calibrated on real data (P2).

These models also incorporate some explanatory mechanism (P1). For instance, in COBAN we introduced explicit representations of beliefs (as Individual Belief Associative Network) that enable us to extract social representations of groups of subjects (see Figure 2.6). These interpretations give relevant explanations on what criteria a subject will adopt (or not) a social object. In HappyWork and WorkSim, the simulation produces endogenous flows that could also serve as a basis for behavior explanations. In WorkSim, we have traced the decisions made by the agents, to understand for instance the reasons why they enter or leave unemployment (Lewkovicz, 2010, ch. 7). We also found that the high level of pessimism within the firms might be a potential explanatory factor of the high unemployment in France.

About, the ability to serve as a decision-aid tool (P3), the WorkSim model is probably the best I have done so far into that direction. Several labor policies have been tested and assessed, all of them being very current and widely discussed by French decisions makers and opinion makers. These results could guide policy makers to decide what are the most promising policies and where to put the effort. HappyWork, though not yet completed, has also a interesting potential in terms of decision-aiding, as it could tell us which type of work organization is susceptible to increase job satisfaction. Do these examples mean that we could use these tools right away to make real decisions ? In this kind of matter, one has to be very cautious. A model of a complex system is by definition incomplete. For instance, WorkSim needs to be coupled with a macroeconomic model. About validation, a calibrated model is
Chapter 5. General discussion and Perspectives

certainly better than a purely normative model, but this is not sufficient. Calibration and estimation raise a number of questioning, especially concerning their robustness. For instance, the solution of calibration is not necessarily unique, making difficult (if not impossible) to interpret the calibrated values. There are many other issues involved in the validation processes (e.g. Windrum et al., 2007; Moss, 2008) and further work needs to be done to assess the robustness of our results when we simulate new labor policies: after all, this is a prediction task and we know that robust predictions are the most difficult to produce.

Finally, it is not obvious that we have succeeded to avoid the major flaw in agent-based modeling (and in computer science in general): what I called *ad hocism* (P4), this “tendency to establish temporary, chiefly improvisational policies and procedures to deal with specific problems”¹.

At first glance, all the four models I presented look quite different. To compare these models, we can for instance use an extract of the questionnaire proposed by Richiardi et al. (2006). The results are displayed in Table 5.1 below.

<table>
<thead>
<tr>
<th></th>
<th>COBAN</th>
<th>Polias</th>
<th>HappyWork</th>
<th>WorkSim</th>
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<td>Goal</td>
<td>Empirical and Theoretical</td>
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<tr>
<td>Testable with real data</td>
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<td></td>
<td></td>
<td></td>
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<td>Evolution of population</td>
<td>Static</td>
<td>Dynamic</td>
<td>Static</td>
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<td>boundedly-rational</td>
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<td>Social comparison - social network / task sharing - firm organization</td>
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</table>

Table 5.1 – Comparison of the four project, using part 2 (Structure of the model) of the questionnaire in (Richiardi et al., 2006).

As one can see, though these models are obviously different in content, they do share common design principles. They are different modeling solutions to (quite) different issues, but are based on the same methodology. However, this might not be enough to completely avoid *ad hocism*. Ideally, one single model or single architecture should be used for a maximum number of projects if we believe that *ad hocism* is a bad thing². In the future, I will consider to move these models closer together. For instance, I could certainly merge COBAN and Polias, to obtain a unified model of opinions and attitude. Likewise, it would make sense to incorporate HappyWork into WorkSim, first because we know that job satisfaction has a direct impact on productivity and therefore on employment, and also because it will give to WorkSim a model of activity at work and firm organization.

¹Quoted from the Free Online Dictionary [http://www.thefreedictionary.com/ad+hocism](http://www.thefreedictionary.com/ad+hocism)

²Note that some researchers advocate that, on the contrary, *ad hocism* is an excellent thing, a source of creativity (e.g. Jencks and Silver, 2013).
5.2 CONTRIBUTIONS TO MULTI-AGENT SYSTEMS

Whether unified or not, these models propose original mechanisms that could be reused to any kind of multi-agent systems, especially systems made of cognitive agents:

- **Knowledge** representation with compact Individual Associative Belief networks (COBAN, section 2.2.1.1)
- **Communication** based on transmission of symbolic messages, through TAN (COBAN, section 2.2.1.2)
- **Belief revision** mechanism (COBAN and Polias, sections 2.2.1.1 and 2.3.2.2)
- **Interest** of an event or information, based on surprise and emotion (Polias, section 2.3.2.2)
- **Tasks** representation and allocation within an organization (HappyWork, section 3.4.1)
- **Anticipation** in finite horizon, compatible with bounded rationality (WorkSim, section D.2.0.1)
- **Decision** mechanism based on state machine and satisficing heuristics (WorkSim, section 4.2.9)

Moreover, the calibration protocol presented in WorkSim (section 4.3.1) and also used in Polias and HappyWork may be of use to adjust a multi-agent system to real data, and could be even a alternative to supervised learning.

So, again, the question remains whether these cognitive mechanisms should and could be unified. To pursue our fight against ad hocism, it would be of interest to bring together this unified model with comparable agent architectures that have been used (e.g. GAMA (Taillard et al., 2010), IODA (Kubera et al., 2008, 2011) or ATOM for financial systems (Mathieu and Brandouy, 2010)). There is also the important issue of whether multi-level models might be needed to model complex behaviors and organizations (e.g. Mathieu and Picault, 2011; Picault, 2013).

5.3 FUTURE DIRECTIONS

Talking about the future, what would be the other perspectives of this work? First of all, as I indicated at each conclusion chapter of this dissertation, each project has its own agenda. Beyond these agendas, I suggest the following future directions:

**Formal analyses** – One major obstacle to the development of multi-agent simulations to study human behavior lies in the difficulties to analyze these systems. A possible way would be to use formal models for such an analysis. Several approaches are inspired statistical physics (e.g. Di Guilmi et al., 2012) or dynamical systems (Treuil et al., 2008), using continuous models based on differential equations. However, artificial intelligence is more inclined to develop discrete models, whether in logic (widely used to analyze some cognitive agent model, like BDI) or in discrete mathematics with the decision theory. I suggest that we should also explore the way of using these kinds of discrete models, which allows us in particular to describe the symbolic structures involved in cognition, to analyze agent-based models and simulations of human behavior.

**Validation** – Finally it is necessary to put more efforts towards the central issue of validation. I suggest two directions, among others. First of all, I would like to investigate the link with econometrics, which has developed a great knowledge for parameter estimation. Econometric models are usually more precise but less complete than agent-based models, so there is
certainly a path for mutual benefit. A second direction to facilitate the micro-foundation of ABM is the participatory simulation. This is a path to direct estimation of parameters, where they are learned through the interactions between the subject and the agent-based simulation. Many techniques might be used: reinforcement learning (like in RALF), preference elicitation like in decision-aid, etc. Of course, many difficulties await us in that way, like how to choose the subjects (it is too costly to have too many but they have to be representative enough of the population we model). Not to forget the experimental biases this kind of method entails (e.g. North and Macal, 2007, pp.184-186). Nevertheless, it constitutes a promising approach to study human behaviors, an approach where artificial intelligence could play a central role.

\footnote{Some researchers have already started to study the links between econometrics and ABM (e.g. Shu-Heng et al., 2012).}


Einstein, A. *Geometry and experience*. In *Lecture before the Prussian Academy of Sciences, January 1921*.


INSEE. Une photographie du marché du travail en 2011. 2011d.


Locke, Edwin A. What is job satisfaction, Septembre 1968.


Tarvid, A. Job satisfaction as a unified mechanism for agent behaviour on a labour market with referral hiring. In *Advances in Computational Social Science and Social Simulation*, Barcelona, 2014.


Appendices
A

POLIAS: APPENDIX

A.1 POLIAS PARAMETERS

<table>
<thead>
<tr>
<th>Name</th>
<th>Value Domain</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>[0,1]</td>
<td>Emotion / Surprise weight</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>[0,1]</td>
<td>Emotional sensitivity to stimuli</td>
</tr>
<tr>
<td>$UT_0$</td>
<td>$\mathbb{R}^+$</td>
<td>Generation complexity of a new event</td>
</tr>
<tr>
<td>$\rho$</td>
<td>[0,1]</td>
<td>Degree of co-responsibility</td>
</tr>
<tr>
<td>$T_{\text{com}}$</td>
<td>$\mathbb{R}^+$</td>
<td>Interest threshold to send a message</td>
</tr>
<tr>
<td>$\epsilon$</td>
<td>[0,1]</td>
<td>Compatibility threshold</td>
</tr>
<tr>
<td>$\pi_0, \pi_1, \pi_2$</td>
<td>[0,1]</td>
<td>Credibility revision probabilities</td>
</tr>
<tr>
<td>payoff</td>
<td>$\mathbb{R}$</td>
<td>Action payoffs</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Name</th>
<th>Value Domain</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$.Table</td>
<td>[0,1]</td>
<td>Attitudes between social groups</td>
</tr>
<tr>
<td>SN</td>
<td>graph</td>
<td>A social networks for the individuals</td>
</tr>
</tbody>
</table>

Table A.1 – Polias parameters summary

A.2 COMPUTING SURPRISE VALUES

In the Simplicity Theory, several dimensions are considered for the computation of surprise (e.g. geographical distance, recency etc). In our model, we use two dimensions: the temporal distance and the social distance. Hence, the surprise value is the sum of a temporal component $S_{\text{time}}$ (where an infrequent event will have more impact than an usual one) and a social component $S_{\text{social}}$, which is a temporal component combined with a personal perspective (i.e. events that affected the individual’s social network):

$$S = S_{\text{time}} + S_{\text{social}}$$  \hspace{1cm} (A.1)

The temporal surprise is given by the relative impact of the Raw temporal unexpectedness $U_{\text{time}}$raw diminished by the level $U_{\text{time}}$perso of this unexpectedness from the person’s view:

$$S_{\text{time}} = U_{\text{time}}^{\text{raw}} - U_{\text{time}}^{\text{perso}}$$  \hspace{1cm} (A.2)

Similarly, for the social surprise:

$$S_{\text{social}} = U_{\text{social}}^{\text{raw}} - U_{\text{social}}^{\text{perso}}$$  \hspace{1cm} (A.3)

This leads to four unexpectedness values: $U_{\text{time}}^{\text{raw}}$, $U_{\text{social}}^{\text{raw}}$, $U_{\text{time}}^{\text{perso}}$ and $U_{\text{social}}^{\text{perso}}$. In all four cases, the unexpectedness of the event (in our model, the action) can be defined by the discrepancy between its generation complexity and its description complexity: $U_x = C_x - C_d^x$ with $x$ the dimension. The description complexity $C_d$ must be understood in the meaning of Shannon’s information theory (Shannon and Weaver, 1949), i.e. the size of the smallest computational program that could generate this event.
Raw temporal distance ($U_{\text{raw}}^{\text{time}}$) The temporal complexity of generation refers to the probability that the action occurs at a given time. This notion could be interpreted as the usual time gap between two occurrences of the action: the more the action is rare, the bigger the gap is, the less it is probable, the more it is unexpected.

Therefore we define the usual time gap using the difference between the occurrence date $a.\text{date}$ of the action $a$ and its last occurrence date $a_{\text{old}}.\text{date}$: $C^{\text{time}}_{\text{w}} = \log_2(a.\text{date} - a_{\text{old}}.\text{date})$.

The temporal complexity of description corresponds simply to the elapsed time between the action and the current time $t$: $C^{\text{time}}_{\text{d}} = \log_2(t - a.\text{date})$.

Thus, the unexpectedness level for the temporal dimension is given by $C^{\text{time}}_{\text{w}} - C^{\text{time}}_{\text{d}}$, that is:

$$U_{\text{raw}}^{\text{time}}(a) = \begin{cases} 
\log_2(a.\text{date} - a_{\text{old}}.\text{date}) - \log_2(t - a.\text{date}) & \text{if } a_{\text{old}} \neq \emptyset \\
UT_0 - \log_2(t - a.\text{date}) & \text{otherwise}
\end{cases}$$

where $UT_0 \geq 0$ denotes the generation complexity of an event encountered for the first time.

Raw social distance ($U_{\text{raw}}^{\text{social}}$) The social complexity of generation refers to the probability that the action occurs on a beneficiary who belongs to a particular social group. We define it with $C^{\text{social}}_{\text{w}} = -\log_2(\frac{\text{nbOccSG}(a, i, sg)}{\text{nbOcc}(a)})$ with $\text{nbOccSG}(a, i, sg)$ the occurrence number of the action $a$ whose beneficiary is a member of the same social group $i, sg$ as the agent.

The description complexity $C^{\text{social}}_{\text{d}}$ corresponding to the social distance between the individual and the beneficiary of the action depends on two factors: the distance in the social graph and the average degree in the graph. Indeed, the higher the degree, the more complex it will be to describe a single step in the graph (in terms of information theory) and this influence is linear. However, the distance in the graph has an exponential impact on the social distance generation (since it requires to describe all possibilities at each node). Thus, $C^{\text{social}}_{\text{d}} = \log_2(v^d)$ with $v$ the degree of the graph and $d$ the shortest distance between $i$ and $a.bnf$ in the graph.

Hence we obtain the following formula:

$$U_{\text{raw}}^{\text{social}}(a) = -\log_2\left(\frac{\text{nbOccSG}(a, i, sg)}{\text{nbOcc}(a)}\right) - \log_2(v^d)$$

(A.5)

Personal temporal distance $U_{\text{perso}}^{\text{time}}$ and personal social distance $U_{\text{perso}}^{\text{social}}$ The personal unexpectedness is based on the last occurrence of the action $a$ which has personally affected the individual, i.e. the last occurrence of the action (with the same name and actor) for which $a.bnf$ is the agent $i$ itself. We denote $a_{\text{perso}}$ this particular occurrence.

The computation of the unexpectedness values is the same as above (eq. A.4), except that the search of experienced occurrences in the belief base is limited to actions with $i$ as the beneficiary:

$$U_{\text{perso}}^{\text{time}}(a) = \log_2(a.\text{date} - a_{\text{perso}}.\text{date}) - \log_2(t - a.\text{date}) = \log_2\left(\frac{a.\text{date} - a_{\text{perso}}.\text{date}}{t - a.\text{date}}\right)$$

(A.6)

$$U_{\text{perso}}^{\text{social}}(a) = -\log_2\left(\frac{\text{nbOccSG}(a_{\text{perso}}, i)}{\text{nbOcc}(a)}\right)$$

(A.7)

where $a_{\text{perso}}.\text{date}$ denotes the date of the last time the action happened to the subject, and $\text{nbOccSG}(a_{\text{perso}}, i)$ the number of occurrences for this action. In the case where the individual has never personally experienced the action, $U_{\text{perso}} = 0$. 
To sum up, the surprise values are given by:

\[ S_{\text{time}}(a) = \begin{cases} \log_2 \left( \frac{a.\text{date} - a_{\text{old}}.\text{date}}{t-\text{a.date}} \right) - \log_2 \left( \frac{a.\text{date} - a_{\text{perso}.\text{date}}}{t-\text{a.date}} \right) & \text{if } a_{\text{old}} \neq \emptyset \\ UT_0 - \log_2(t - a.\text{date}) - \log_2 \left( \frac{a.\text{date} - a_{\text{perso}.\text{date}}}{t-\text{a.date}} \right) & \text{otherwise} \end{cases} \]

Likewise:

\[ S_{\text{social}}(a) = -\log_2 \left( \frac{\text{nbOcc}_{SG}(a,i.sg)}{\text{nbOcc}(a)} \right) - \log_2(v^d) + \log_2 \left( \frac{\text{nbOcc}_{SG}(a_{\text{perso}},i)}{\text{nbOcc}(a)} \right) \]

That is:

\[ S_{\text{time}}(a) = \begin{cases} \log_2 \left( \frac{a.\text{date} - a_{\text{old}}.\text{date}}{a.\text{date} - a_{\text{perso}.\text{date}}} \right) & \text{if } a_{\text{old}} \neq \emptyset \\ UT_0 - \log_2(a.\text{date} - a_{\text{perso}.\text{date}}) & \text{otherwise} \end{cases} \quad (A.8) \]

and

\[ S_{\text{social}}(a) = \log_2 \left( \frac{\text{nbOcc}_{SG}(a_{\text{perso}},i)}{v^d \times \text{nbOcc}_{SG}(a,i.sg)} \right) \quad (A.9) \]

Thus, \( S_{\text{time}} \) will increase when the event is infrequent (\( a.\text{date} - a_{\text{old}}.\text{date} \) increases) and/or it happens recently to the individual (\( a.\text{date} - a_{\text{perso}.\text{date}} \) is small).

\( S_{\text{social}} \) will increase when the event happens more frequently to me than in general (\( \text{nbOcc}_{SG}(a_{\text{perso}},i) \) increases) and/or it concerns someone close to the individual in the social network (small \( v^d \)).
A NOTE ON AGGREGATIONS

As in many decision models, we use multi-criteria aggregations\(^1\) at several stages in our models. For sake of simplicity, we favor weighted average operators, OWA (Yager, 1988) and WOWA (Torra, 1997).

B.1 OWA PARAMETERS

When there are no preferences for the values to be aggregated, we use a simple OWA (Ordered Weighted Average) with the following settings. In our models, the aggregations are usually performed along some variable \(x\), and the OWA aggregation has the generic form (Ogryczak et al., 2012) described in the following equation B.1:

\[
\text{OWA}_w(F(x)) = \sum_{i=1}^{n} (w_i \cdot F(x_{\sigma(i)}))
\]

(B.1)

where \(F\) is a function on a set of values \(x\) in a discrete set \(X = \{x_1, x_2, \ldots, x_n\}\) of the values to be aggregated, \(n = |X|\) and the values \(F(x_i)\) are re-ordered using the permutation \(\sigma\) so that \(F(x_{\sigma(1)}) \leq F(x_{\sigma(2)}) \leq \cdots \leq F(x_{\sigma(n)})\) (increasing order).

\(w_i\) are positive or null weights and verify \(\sum_{i=1}^{n} w_i = 1\). To compute them, we define three possible aggregation profiles (Fuller, 1996):

- **Neutral** \(w_i = \frac{1}{n}\)
- **Pessimistic** \(w_i = \left(\frac{i}{n}\right)^{\kappa} - \left(\frac{i-1}{n}\right)^{\kappa}\)
- **Optimistic** \(w_i = \left(\frac{n-i+1}{n}\right)^{\kappa} - \left(\frac{n-i}{n}\right)^{\kappa}\)

(B.2)

with \(\kappa > 1\). These weight functions are depicted in Figures B.1 below for some \(\kappa\) values.

The Neutral profile corresponds to the classical average operator. When \(\kappa\) increases, the pessimistic agent is more sensitive to the smallest values, and the optimistic to the highest ones. Therefore the choice of the aggregation profile and its associated strength (\(\kappa\)) may have an important impact on the results, and should be treated with care, by conducting deep sensitivity analyses to measure such an impact.

---

\(^1\)See e.g. (Grabisch and Perny, 2003) for a review on multi-criteria aggregation.
Appendix B. A note on aggregations

Figure B.1 – OWA weight \( w_i \) functions (of index \( i \)) for \( n = 10 \) and \( \kappa = 2 \) (black line), 5 (blue), 10 (green) and 20 (red).

B.2 WOWA PARAMETERS

When the individual show some preferences (importance) on certain features to base her/his decision on, a WOWA (Weighted Ordered Weighted Average) aggregation is more suitable, under the condition that we have some information to compute the feature weights (and this is unfortunately not always the case !).

Let \( w \) be the vector of OWA weights, and \( p = (p_1, ..., p_n) \) be the importance weighting vector, such that \( p_i \geq 0 \) and \( \sum_{i=1}^{n} p_i = 1 \).

The generic form of WOWA (Ogryczak et al., 2012) follows the equation B.4:

\[
WOWA_{w,p}(F(x)) = \sum_{i=1}^{n} \left( \pi_i(w,p) \cdot F(x_{\sigma(i)}) \right)
\]  

(B.3)

where the weights \( \pi \) are defined as:

\[
\pi_i(w,p) = \phi_w(p_i + \sum_{k<\sigma(i)} p_{\sigma(k)}) - \phi_w(\sum_{k<\sigma(i)} p_{\sigma(k)})
\]  

(B.4)

and \( \phi_w \) is a monotone increasing function that interpolates points \( \left( \frac{1}{n}, \sum_{k<i} w_k \right) \) together with \( (0,0) \) (Torra, 2000), and \( \sigma \) denoting the ordering permutation (like in the OWA above)\(^2\).

\(^2\)We used this library to implement our WOWAs: http://www.mdai.cat/ifao/wowa.php?llenguaj=ja.
C

HAPPYWORK: APPENDIX

C.1 HAPPYWORK PARAMETERS

C.1.1 Satisfaction model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Baseline value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>IS((a))</td>
<td>(q_{1a}, \ldots, q_{na})</td>
<td>questionnaire</td>
<td>Characteristics</td>
</tr>
<tr>
<td>SF((Q))</td>
<td>(q_{1f}, \ldots, q_{msf})</td>
<td>Ad hoc</td>
<td>Salient Characteristics</td>
</tr>
<tr>
<td>(\sigma_A)</td>
<td>0, 1</td>
<td>0.4</td>
<td>Assimilation threshold</td>
</tr>
<tr>
<td>(\sigma_D)</td>
<td>0, 1</td>
<td>0.8</td>
<td>Deflection threshold</td>
</tr>
<tr>
<td>(\alpha^c)</td>
<td>0, 1</td>
<td>0.3</td>
<td>Contrast weight</td>
</tr>
<tr>
<td>(\beta^s)</td>
<td>0, 1</td>
<td>0</td>
<td>Similarity threshold</td>
</tr>
<tr>
<td>(f)</td>
<td>N</td>
<td>8</td>
<td>Memory size (in ticks)</td>
</tr>
<tr>
<td>(r)</td>
<td>0, 1</td>
<td>0.5</td>
<td>Memory decrease rate</td>
</tr>
<tr>
<td>(\Gamma)</td>
<td>(1/3, 1/3, 1/3)</td>
<td>WOWA Weights on processes</td>
<td></td>
</tr>
<tr>
<td>(\Lambda)</td>
<td>(1/k, \ldots, 1/k)</td>
<td>WOWA Weights on dimensions</td>
<td></td>
</tr>
</tbody>
</table>

| Network |
|---|---|---|---|
| \(RN\) | 2, \(n\) | \(2 \times \ln(n)\) | Average number of referents |
| \(RN^c\) | 0, 1 | 0.2 | Proportion of occasional referents |

Table C.1 – 12 parameters for the satisfaction model

C.1.2 Activity model

C.1.2.1 Parameters of the organization

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Baseline value</th>
<th>Description</th>
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</thead>
<tbody>
<tr>
<td>(n)</td>
<td>(N^+)</td>
<td>100</td>
<td>Number of problem types</td>
</tr>
<tr>
<td>(\mu_\tau)</td>
<td>0, 1</td>
<td>(1/25)</td>
<td>Average number of types per agent</td>
</tr>
<tr>
<td>(\nu_\tau)</td>
<td>0, 5</td>
<td>1</td>
<td>Number of types narrowness</td>
</tr>
<tr>
<td>(\tau^{id})</td>
<td>0, 2</td>
<td>2</td>
<td>Problem generation</td>
</tr>
</tbody>
</table>

| Garbage Can |
|---|---|---|---|
| \(GC^{max}\) | N | \(n\) | GC size |
| \(\theta^{id}\) | 0, 2 | 1 | Responsibility weight in problem generation |
| \(\zeta\) | \(L\) | 50 | Individual demand allocation |
| \(E_{P0}\) | \(N^+\) | 20 | Base energy cost (in hours) |
| \(d_{max}\) | \(R\) | 4 | Maximum resolution duration |

Table C.2 – De-C GCM: 9 organization parameters
C.1.2.2 Parameters of the individual

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Baseline value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
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<td>$\lambda^L$</td>
<td>$\mathbb{R}^*_+$</td>
<td>0.5</td>
<td>Load</td>
</tr>
<tr>
<td>$\lambda^R$</td>
<td>$\mathbb{R}^*_+$</td>
<td>0.5</td>
<td>Recovery</td>
</tr>
<tr>
<td>$\psi$</td>
<td>$\mathbb{R}^*_+$</td>
<td>0.64</td>
<td>Sensibility to Charge</td>
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</table>

*Effort-Recovery model*

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Definition</th>
<th>Baseline value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\rho$</td>
<td>$[0, 1]$</td>
<td>0.5</td>
<td>Desk ranking preference</td>
</tr>
<tr>
<td>$\theta^R$</td>
<td>$[0, 1]$</td>
<td>0</td>
<td>Energy fraction for routine tasks</td>
</tr>
</tbody>
</table>

*Decision process*

Table C.3 – De-C GCM : 6 individual parameters

C.2 TYPOLOGY OF ORGANIZATIONS

To help us analyzing the organizations, we display in the Figures C.1 and C.2 below the distribution of responsibilities per agent (left column) and the distribution of responsible agents per problem type (right column).

![Distribution of responsibilities per agent (left column) and distribution of responsible agents per problem type (right column).](image)

Figure C.1 – Distribution of responsibilities per agent (left column) and distribution of responsible agents per problem type (right column).
C.2. Typology of organizations

Figure C.2 – Distribution of responsibilities per agent (left column) and distribution of responsible agents per problem type (right column).
D WorkSim: Appendix

D.1 Key Economic Computations in the WorkSim Model

We describe here some key economic computations in WorkSim on the firm side.

D.1.1 Firm Benefit

At each step of our simulation – one week in the reality, we suppose that each firm \( j \) with \( n_{j,q} \) employees at the occupation level cannot sell more goods than its demand quantity \( D_{j,q,t} \) and its production \( Q_{j,q,t}^{eff} \). \( Q_{j,q,t}^{eff} \) is the sum of the production of all these \( n_{j,q} \) employees. The good is produced before the firm knows its demand, so that the firm pays the wages and the other costs even if the good is not sold. The good cannot be stored and any excess of offer is lost. The income of the firm \( j \) at time \( t \) is given by:

\[
R_{j,t}^{eff} = P \times \sum_{q=1}^{n_q} \min(Q_{j,q,t}^{eff}, D_{j,q,t})
\]  
(D.1)

where \( n_q \) is the number of occupation levels in the market.

The regular global cost of the firm is:

\[
C_{j,t}^{eff} = \sum_{i=1}^{n_j} C_{i,j,p,t}^{eff}
\]  
(D.2)

where \( C_{i,j,p,t}^{eff} \) is the effective salary cost of the employee \( i \) in a job \( p \) in the firm \( j \) at time \( t \) and \( n_j \) the total number of employees in the firm \( j \).

The profit of the firm at time \( t \) is given by:

\[
\Phi_{j,t}^{eff} = R_{j,t}^{eff} - C_{j,t}^{eff}
\]  
(D.3)

This profit is stored in the history of the firm in order to perform a yearly balance (cf. section 4.2.8.2).

D.1.2 Effective production of an employee \( i \) in a job \( p \) : \( Q_{i,p,q,t}^{eff} \)

There is a base productivity attached to each job, and the employee’s characteristics and effort will modulate its value. Moreover, the employer has only an imperfect and evolving information on individual productivity\(^1\).

\(^1\)In this productivity differentiation, we find an essential difference with the ARTEMIS model, where individuals were distinguished only by a cost of personal training financed by the firm to reach the same productivity after hiring and training. Compared with the previous version of WorkSim (Lewkovicz and Kant, 2008), the present version introduces experience factors and imperfect information.
The effective productivity of an individual $i$ at job $p$ is given by:

$$Q_{i,p,q,t}^{\text{eff}} = Q_{i,p,q,t}^{\text{base}} \times k\text{Prod}_i \times \text{cond}_{i,t} \times F_{\beta}(H_{i,t}^{\text{gen}}, H_{q,t}^{\text{occ}}) \times F_{\lambda}(H_{i,p,t}^{\text{spec}})$$  \hspace{1cm} (D.4)

The effective productivity is based on four complementary factors: (1) the base production in the job, (2) the core productivity of the employee and her condition, (3) the general human capital and the human capital of the employee in the occupation level of the job she holds, and (4) the specific human capital in the job $^2$:

1. The base production $Q_{i,p,q,t}^{\text{base}}$ for the job $p$ in occupation $q$ is given by

   $$Q_{i,p,q}^{\text{base}} = QH_{i,q}^{\text{base}} \times H\text{p}_{p,i}$$

2. $k\text{Prod}_i$ and $\text{cond}_{i,t}$ are the productivity kernel and the condition factors;

3. We have for the general and occupation factor$^3$:

   $$F_{\beta}(H_{i,t}^{\text{gen}}, H_{q,t}^{\text{occ}}) = 1 + \beta \times H_{i,t}^{\text{gen}} - \beta' \times (H_{i,t}^{\text{gen}})^2 + \beta_q \times H_{q,t}^{\text{occ}} - \beta'_q \times (H_{q,t}^{\text{occ}})^2$$  \hspace{1cm} (D.5)

4. For the the job-specific production factor$^3$:

   $$F_{\lambda}(H_{i,p,t}^{\text{spec}}) = 1 + \lambda \times H_{i,p,t}^{\text{spec}} - \lambda' \times (H_{i,p,t}^{\text{spec}})^2$$  \hspace{1cm} (D.6)

$\beta, \beta', \beta_q, \beta'_q, \lambda$ et $\lambda'$ are calibrated exogenous parameters in $[0,0.1]$.

### D.1.3 Employee productivity estimation

One key theoretical options of WorkSim model is that an employer never knows perfectly the productivity of an employee. This hypothesis is in the line of (Jovanovic, 1979), and was the basis of important developments in labor economics. This hypothesis has multiple potential effects on the functioning of the labor market. We assume that the company does not have any a priori knowledge about the precise levels of real productivity for each of its employees. Therefore, it is only able to assess a level of estimated productivity:

$$Q_{i,p,q,t}^{\text{est}} = Q_{i,p,q,t}^{\text{eff}} \times \sigma_{i,p,q,t}^{\text{Eval}}$$  \hspace{1cm} (D.7)

$\sigma_{i,p,q,t}^{\text{Eval}}$ represents the degree of uncertainty of the company in the evaluation of its employees. It depends on the seniority $\text{Sen}_{i,p,t}$ of the employee at her job $p$ in the firm and is drawn from the following distribution when the employee is hired, and also at each employee evaluation:

$$\sigma_{i,p,q,t}^{\text{Eval}} = \text{Max}(0, N(1, \sigma_0 \times (1 - \delta_{\sigma} \times \text{Sen}_{i,p,t})))$$  \hspace{1cm} (D.8)

with $\sigma_0$ and $\delta_{\sigma}$ two exogenous parameters$^4$.

---

$^2$These complementaries are justified by various economic studies. The complementarity in terms of performance between a technological level of a job (related to implicit physical capital associated) and a level of human capital used is a common accepted fact (Leiponen, 2005), even if it should be finely-shaded. The complementarity between general human capital and specific human capital has the following theoretical basis: the general human capital of an individual allows him to better utilize her specific knowledge (Ballot and Taymaz, 1997; Acemoglu and Pischke, 1998).

$^3$ $F_{\beta}$ and $F_{\lambda}$ follow a type of concave function $F(x) = 1 + ax - bx^2$, where $a > 0$, $b > 0$ and $b \ll a$, in order to obtain a diminishing return (increasing $F$, decreasing $F'$) for each HC on the employee’s productivity. This diminishing return was observed in studies for France (e.g. Befify et al., 2006).

$^4$Note that when the firm only has one employee, the firm knows its global production $Q_{i,t}$ and does not have any doubt on her effective production; therefore $\sigma_{i,p,q,t}^{\text{Eval}} = 0$. 

---
D.2.0.1 Demand anticipation

**Impact on firm demand** In section 4.2.5 above, we described how the demand of each firm is determined through its market share evolution. However we suppose that the firm

$$\text{Effective cost of an employee } i \text{ in firm } j = C_{i,p,q,t}^{\text{eff}}$$

**Weekly starting salary** The salary $S_{i,p,q,t=\text{hiring}}^{\text{eff}}$ of an employee $i$ in firm $j$ at level of occupation $q$ at time $t = \text{hiring}$ is given by:

$$S_{i,p,q,t=\text{hiring}}^{\text{eff}} = \text{Max}(\text{SMIC}, S_{i,p,q}^{\text{base}} \times F_{\beta}(HC_{i,t}^{\text{gen}}, HC_{i,t}^{\text{occ}}) \times F_{\lambda^*}(HC_{i,p,t}^{\text{spec}}) \times G(U_{q,t=\text{publish}}))$$

(D.9)

SMIC is the minimum hourly wage in France, net of the employee’s contribution to social security. The starting salary is the weekly base salary of the job $S_{i,p,q}^{\text{base}}$ (cf. section 4.2.6, eq. 4.5) modulated by the factors of human capitals of the employee $HC_{i,t}^{\text{gen}}$, $HC_{i,t}^{\text{occ}}$ and $F_{\lambda^*}(HC_{i,p,t}^{\text{spec}})$, which is the productivity gain actor related to the experience in the job that affects the salary. The function $F_{\lambda^*}$ is given by:

$$F_{\lambda^*}(HC_{i,p,t}^{\text{spec}}) = 1 + S_\ast^* \times (\lambda \times HC_{i,p,t}^{\text{spec}} - \lambda^* \times (HC_{i,p,t}^{\text{spec}})^2)$$

(D.10)

with $S_\ast^* \in [0, 1]$, an exogenous calibrated parameter.

A final factor affecting wages is the global unemployment rate $U_{q,t=\text{publish}}$ at the time of publication and at the level of qualification $q$ of the job offer by the firm. We consider that the relation $G$ is isoelastic, according to the literature on the wage curve (Blanchflower and Oswald, 1994), and take $G(x) = k_q \times x^\omega$, where $\omega$ is an exogenous parameter, set as its standard value of -0.1, and $k_q = \left(\frac{1}{U_{q,\text{ref}}}\right)^\omega$. $U_{q,\text{ref}}$ is set as the global unemployment rate for the reference year we study for the level of qualification $q$.

This weekly salary of employee $i$ in firm $j$ is reviewed annually at her/his birthday date of her arrival in the company according to the same equation D.9.

**Effective cost of an employee** The effective cost of an employee $i$ on a job $p$, $C_{i,p,q,t}^{\text{eff}}$, include her salary $S_{i,p,q,t}^{\text{eff}}$ and payroll charges.

$$C_{i,p,q,t}^{\text{eff}} = S_{i,p,q,t}^{\text{eff}} \times SalC$$

(D.11)

$SalC$ corresponds to the payroll charges to salary (social security contributions).

D.2 Profit evaluation algorithms

D.2.0.1 Demand anticipation

**Impact on firm demand** In section 4.2.5 above, we described how the demand of each firm is determined through its market share evolution. However we suppose that the firm

---

5As for “Salaires minimum interprofessionnel de croissance”. In 2011, the monthly net minimum wage for a full-time job was 1,072 €.

6Due to important considerations of equity in terms of human resource management (e.g. (Adams, 1963)), the employer cannot discriminate between employees who have the same experience. A feeling of unfairness could generate decreases in effort and productivity for the employees who feel unequally treated (efficiency wage concept). Moreover, in terms of theoretical consistency, it is necessary to choose a posted salary and not a salary negotiated on the basis of a matching value. The matching theory usually chooses the latter, but the search theory involves the assumption of a distribution of salaries offered by companies, which leads job seekers to identify interesting jobs and apply for them (or not).

7In France, we have $SalC = (1 + EmpC) \times (1 + FirmC)$, where EmpC is the employee’s contribution and FirmC is the firm’s contribution. There are both percentages computed on the gross salary. For 2011, in France EmpC = 0.22 and FirmC = 0.42. Source: INSEE http://www.insee.fr/fr/themes/detail.asp?ref_id=ir-sls2010&page=irweb/sls2010/dd/sls20103.htm.
does not know the coefficients $\mu_{MS,j,t}$ and $\sigma_{MS,j,t}$ involved in this mechanism. The firm only observes the evolution of its demand period after period. From its history of demand during the last year (52 periods of one week in the model), the firm learns the coefficient of trend and deviation of its demand $\hat{\mu}_j$ and $\hat{\sigma}_j$. These two coefficients are estimated from a linear regression on its demand history according to this model:

$$D_{j,t} = \alpha_j + \mu_j \times t + \epsilon_t$$

with $\epsilon_t$ the random error with mean 0 and standard deviation $\sigma_j$.

Once the firm has estimated these coefficients $\hat{\mu}_j$ and $\hat{\sigma}_j$, it anticipates that its demand will be modified by a random shock $\delta \sim \mathcal{N}(\hat{\mu}_j, \hat{\sigma}_j)$ each period. Then the firm can deduce a modification of its demand at a horizon $d$ as the sum of these $d$ small independent shocks:

$$\Delta \sim \mathcal{N}(d \times \hat{\mu}_j, \sqrt{d} \times \hat{\sigma}_j)$$

This impact at horizon $d$ has 99% chance to be in the interval $[d \times \hat{\mu}_j - 3 \times \sqrt{d} \times \hat{\sigma}_j, d \times \hat{\mu}_j + 3 \times \sqrt{d} \times \hat{\sigma}_j]$.

To simplify the calculations of our agent firm, we assume that the firm only evaluates 3 scenarios of its demand evolution corresponding to the lower limit, the center, and the upper limit of this interval:

$$l^\text{tot}(\theta, d) = d \times \hat{\mu}_j + 3 \times \theta \times \sqrt{d} \times \hat{\sigma}_j$$

with $\theta = -1$ in the pessimistic scenario, $\theta = 0$ in the neutral scenario and $\theta = +1$ in the optimistic scenario.

The firm deduces a potential impact after $d$ period on its demand per occupation $q$ in the scenario $\theta$, $l^\text{tot}_q(\theta, d) = \psi_{j,q} \times (d \times \hat{\mu}_j + 3 \times \theta \times \sqrt{d} \times \hat{\sigma}_j)$, with $\psi_{j,q}$ the share of demand of the firm $j$ allocated to the occupation $q$ (cf. equation 4.3).

**Demand margin calculation** Now the anticipated demand margin $AD_{j,q,t}$ (that is the net demand at time $t$ for firm $j$ and qualification $q$) can be computed by

$$AD_{j,q,t}(d, \theta) = (D_{j,q,t} + l^\text{tot}_q(\theta, d)) - (Q_{j,q,t}^p + B_{j,q,t}(d))$$

It is the difference between:

- the anticipated demand as the sum of the firm demand $D_{j,q,t} “corrected”$ by the anticipation factor $l^\text{tot}_q$,
- and the anticipated production capacity, given by the sum of the current total effective production of the firm $Q_{j,q,t}$ and the current expected production of vacant jobs (to be filled) of the firm $Q_{j,q,t}^p$, diminished by a buffer $B_{j,q,t}(d)$ that represents a demand margin the firm could have in the future if it ends its short contracts (the employees that will not work anymore for the firm at time $d$; see figure D.1 below). $B_{j,q,t}(d)$ is the sum of the estimated productions of the jobs in the firm whose contracts have an expected duration shorter than $d$:
  - FDC with a fixed term shorter than $d$
  - expected retirement of employees in OEC before $d$ periods.

Let the demand margin $DM$ be given by:

$$DM_{j,q,t} = D_{j,q,t} - (Q_{j,q,t}^p + Q_{j,q,t}^s)$$

Thus, we can rewrite eq. D.13 as follows:
D.2. Profit evaluation algorithms

\[ AD_{i,q,t}(\theta,d) = DM_{i,q,t} + t_{q,t}^{\text{total}}(\theta,d) + B_{i,q,t}(d) \]  \hspace{1cm} (D.15)

In this form, we see that the buffer is an additional demand margin for the firm.

Figure D.1 – Demand and risk anticipation : Buffer

D.2.0.2 Employee Profit Evaluation

A profit evaluation algorithm is used by the firm to evaluate an employee \( i \) on a job \( p \) with a contract \( c \) with a set of potential duration \( D_c^{\text{possible}} \). This set of possible durations represents the different options of duration a firm may have with a contract. For example for a contract with an initial duration of \( D^{\text{init}}_c \), but renewable once with the same duration, the set of possible duration is \( D_c^{\text{possible}} = \{ D^{\text{init}}_c, 2 \times D^{\text{init}}_c \} \), and during the anticipation with a given scenario of demand evolution the firm will only retain the best option.

This unique algorithm will be used at different moments in the model :

- during the job creation process to assess the expected profit with a potential candidate on a job with a new contract (cf. section 4.2.8.1 below)
- during the evaluations of employees already in the firm : end of probationary period, personal and economic firing (cf. section 4.2.8.2)
- during the hiring process to evaluate the hiring norm and the expected profit with the candidates (cf. section 4.2.8.4)

The algorithm will be implemented with different parameters depending on the type of contract and is described in the next section.

D.2.1 Evaluation of the profit per period with a employee \( i \) on a job \( p \) with a contract \( c \) of duration \( d_c \) : \( \Phi_{i,j,p,q,t} \)

In order to evaluate this profit, the firm takes into account up to five phases :

1. A possible phase of hiring if the employee evaluated is not already on the job. The job is vacant during a period \( d_v \) and the firm has to pay a vacancy cost \( VC \). When the firm evaluates the profit with an employee already on the job, we have \( d_v = 0 \) and \( c_v = 0 \).

2. An eventual training phase, in order to transmit to the new employee the required Human Capitals (required HC). This training has a cost denoted \( TC \)
3. The actual phase of the contract from the period $d_v$ to $d_v + d_c$.

4. A possible advance notice period of the duration $d_n$ if the contract is an OEC and the firm needs to fire the employee. During this period, the employee does not produce, but the firm continues to pay a salary for the employee. It results to an additional cost $c_n$.

5. A possible waiting period $d_w$ in the case of a temporary contract. During this phase, the job is in the state pending and the firm does not perceive any profit.

Let me now detail the computation of the total profit.

D.2.1.1 Vacancy costs

The discounted vacancy cost for a duration $d_v$ is given by:

$$ VC = \sum_{d=1}^{d_v} \frac{c_v}{(1 + r)^d} $$  \hspace{1cm} (D.16)

with $r$ the discount rate (fixed parameter).

D.2.1.2 Training costs

For the discounted training cost, we have:

$$ TC = \frac{TrC^{spec} + TrC^{gen} + TrC^{occ}}{(1 + r)^{d_c}} $$  \hspace{1cm} (D.17)

with $TrC^{spec}$ the specific training cost, $TrC^{gen}$ the general training cost and $TrC^{occ}$ the training cost related to the occupation. We suppose that these costs are proportional to the amount of human capital we must transmit to the employee to reach the required levels:

$$ TrC^{spec} = PTr^{spec} \times S_{p,q}^{\text{base}} \times HC_{\text{spec}}^{\text{Req}} $$ \hspace{1cm} (D.18)

$$ TrC^{gen} = PTr^{gen} \times S_{p,q}^{\text{base}} \times \text{Max}(0, HC_{\text{gen}}^{\text{Req}}, HC_{i,t}^{\text{gen}}) $$ \hspace{1cm} (D.19)

$$ TrC^{occ} = PTr^{occ} \times S_{p,q}^{\text{base}} \times \text{Max}(0, HC_{\text{occ}}^{\text{Req}}, HC_{i,q}^{\text{occ}}, HC_{i,q}^{\text{occ}}) $$ \hspace{1cm} (D.20)

with $PTr^{spec}$, $PTr^{gen}$ and $PTr^{occ}$ three calibrated parameters in $[0, 10]$.

D.2.1.3 Contract profit for scenario $\theta$

Following equations D.4 and D.7, the expected production of a new employee after $d$ periods is:

$$ Q_{i,j,p,q,t}^{\text{est}}(d) = \sigma_0 \times Q_{p,q}^{\text{base}} \times kProd_i \times cond_{i,t} \times F_\beta(HC_{i,t}^{\text{gen}}(d), HC_{i,q}^{\text{occ}}(d)) \times F_\lambda(HC_{i,p,t}^{\text{spec}}(d)) $$ \hspace{1cm} (D.21)

and the salary (cf. eq. D.9):

$$ S_{i,j,p,q,t}(d) = \text{Max}(SMIC_{p,q} \times F_\beta(HC_{i,t}^{\text{gen}}(d), HC_{i,q}^{\text{occ}}(d)) \times F_\lambda(HC_{i,p,t}^{\text{spec}}(d)) \times G(U_{q,t})) $$ \hspace{1cm} (D.22)

Hence, the weekly profit, after $d$ periods spent after $d_v$ et for a scenario $\theta$, is:
\[
\Phi_{i,j,p,q,t}(\theta,d) = P \times \max(0, \min\left(\Phi_{i,j,p,q,t}^{est}(d), AD_{j,q,t}(\theta,d + d_v)\right)) - S_{i,j,p,q,t}(d) \times (1 + \text{BenC}) \times (1 + \text{SalC})
\]  

\[\text{(D.23)}\]

If we cumulate this profit for the period from \(d_v\) to \(d\), applying a discount factor \(d\), we get for this cumulated profit :

\[
\Phi_{i,j,p,q,c,f}(\theta,d_c) = \left(\sum_{d=1}^{d_c} \frac{\Phi_{i,j,p,q,t}(\theta,d))}{(1 + \rho)^{d+1}}\right) \frac{\text{EndC}_c(d_c)}{(1 + \rho)^{d_c+1}}
\]

\[\text{(D.24)}\]

with \(\text{EndC}_c(d_c)\), the cost to end the contract (different for OEC and FDC).

Then, the firm choose the best duration, that is the one that give the highest profit:

\[
\Phi_{i,j,p,q,c,t}^*(\theta) = \max_{d_{option} \in D_{c,f}^{option}} \Phi_{i,j,p,q,c,f}(\theta,d_{option})
\]

\[\text{(D.25)}\]

with \(D_{c,f}^{option}\) the set of possible durations\(^8\)

The net profit per period for a contract \(c\) with a duration \(d_c\) in scenario \(\theta\) is then :

\[
\Phi_{i,j,p,q,c,t}^{net}(\theta) = \Phi_{i,j,p,q,c,t}^*(\theta) - VC - TC
\]

\[\text{(D.26)}\]

### D.2.1.4 Total and per period profits

Finally, the firm computes the final (total) profit as the average profit for the 3 scenarios of demand \(\theta \in \{-1, 0, 1\}\) :

\[
\Phi_{i,j,p,q,c,t}^{tot} = \omega_{-1} \times \Phi_{i,j,p,q,c,t}^{net}(\theta = -1) + \omega_0 \times \Phi_{i,j,p,q,c,t}^{net}(\theta = 0) + \omega_{+1} \times \Phi_{i,j,p,q,c,t}^{net}(\theta = +1)
\]

\[\text{(D.27)}\]

with \(\omega_{-1}, \omega_0\) and \(\omega_{+1}\) the weighting coefficients of the firm for each of the 3 scenarios. \(\omega_{-1} + \omega_0 + \omega_{+1} = 1\). The values of these coefficients represent the greater or lesser pessimism of the firm during the evaluation process.

To compute the profit per period (in order to compare contracts with different durations for the same position), we need to compute the total duration of the contract \(d_{tot}\) :

Let’s put :

\[
d(\theta) = d_v + d^*(\theta) + d_w + d_n
\]

\[\text{(D.28)}\]

Then \(d_{tot}\) will average \(d\) on the three possible scenarios :

\[
d_{tot} = \omega_{-1} \times d(\theta = -1) + \omega_0 \times d(\theta = 0) + \omega_{+1} \times d(\theta = +1)
\]

\[\text{(D.29)}\]

Finally we derive the profit per period :

\[
\Phi_{i,j,p,q,c,t}^{per} = \frac{\Phi_{i,j,p,q,c,t}^{tot}}{d_{tot}}
\]

\[\text{(D.30)}\]

\(^8\)For an FDC, as stated in section 4.2.8.1, \(D_{c,f}^{option}\) = \{1 week, 1 month, 2 months, 6 months, 12 months, 18 months\}. For OEC, we assume that the firm estimates a potential average duration \(d_{learned}\) by learning and \(D_{c,f}^{option} = \{d_{learned}\}\).
D.3 **Summary of Agents’ Attributes**

<table>
<thead>
<tr>
<th><strong>Individuals</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific attributes of individuals</td>
<td></td>
</tr>
<tr>
<td>• gender</td>
<td></td>
</tr>
<tr>
<td>• base alpha parameter (preference of the individual for free time or work when entering the labor market)</td>
<td></td>
</tr>
<tr>
<td>• initial occupation level when enter the labor market</td>
<td></td>
</tr>
<tr>
<td>Internal variables of individuals</td>
<td></td>
</tr>
<tr>
<td>• age between and 65, which evolves during the simulation</td>
<td></td>
</tr>
<tr>
<td>• current occupation level (which can change if the individual receive a promotion)</td>
<td></td>
</tr>
<tr>
<td>• the state on the labor market: employed, OTJS (person employed and looking for an other job), unemployed, inactive, student, retired</td>
<td></td>
</tr>
<tr>
<td>• the firm, the job, the contract and the salary if employed</td>
<td></td>
</tr>
<tr>
<td>• salary history during all the career</td>
<td></td>
</tr>
<tr>
<td>• matrimonial status</td>
<td></td>
</tr>
<tr>
<td>• list of information about states and incomes of the other members of her household (partner and children). The model evolves in closed population, then the others members of the household are agents in the model.</td>
<td></td>
</tr>
<tr>
<td>• current alpha parameter (preference of the individual for free time or work), evolving during the simulation</td>
<td></td>
</tr>
<tr>
<td>• human capital, general experience on labor market and specific experience in a job of a firm</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th><strong>Private Firms</strong></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Specific attributes of private firms</td>
<td></td>
</tr>
<tr>
<td>• base productivity and base salary of its jobs by occupation level</td>
<td></td>
</tr>
<tr>
<td>• amenity of its jobs by occupation level: non-monetary characteristics evaluated imperfectly by the employed (e.g. working conditions....)</td>
<td></td>
</tr>
<tr>
<td>• share retained by the firm on employee’s productivity value</td>
<td></td>
</tr>
<tr>
<td>Internal variables of private firms</td>
<td></td>
</tr>
<tr>
<td>• lists of employees, jobs and contracts</td>
<td></td>
</tr>
<tr>
<td>• list of vacancies</td>
<td></td>
</tr>
<tr>
<td>• yearly balance of profit and loss</td>
<td></td>
</tr>
<tr>
<td>• demand margin</td>
<td></td>
</tr>
</tbody>
</table>
D.4 Parameters values for WorkSim

In this section, we give the values for all the 91 parameters in WorkSim: 31 are fixed and 60 are calibrated (24 for the individuals, and 36 for the firms).

D.4.1 Fixed Parameters (31)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSJ</td>
<td>Duration of one job offer search (search and apply)</td>
<td>8 hours</td>
<td>a priori</td>
</tr>
<tr>
<td>Ta</td>
<td>Free Time per week</td>
<td>91 hours</td>
<td>(INSEE, 2011a)</td>
</tr>
<tr>
<td>R_H4</td>
<td>Reservation utility parameter 4</td>
<td>0.5</td>
<td>a priori</td>
</tr>
<tr>
<td>σ_q</td>
<td>Standard deviation of firm productivities</td>
<td>0.1</td>
<td>a priori</td>
</tr>
<tr>
<td>σ_qΨ</td>
<td>Standard deviation of demand share per occupation level</td>
<td>0.1</td>
<td>a priori</td>
</tr>
<tr>
<td>σ_alpha</td>
<td>Standard deviation of Free Time preference distribution</td>
<td>0.1</td>
<td>a priori</td>
</tr>
<tr>
<td>λ</td>
<td>Sensitivity to specific human capital</td>
<td>0.00038</td>
<td>a priori</td>
</tr>
<tr>
<td>λ′</td>
<td>Decreasing factor of Sensitivity to specific human capital</td>
<td>5 × 10⁻⁸</td>
<td>a priori</td>
</tr>
<tr>
<td>σ_A</td>
<td>Amenity ratio</td>
<td>0.5</td>
<td>a priori</td>
</tr>
<tr>
<td>PrSt</td>
<td>Stability ratio</td>
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<td>a priori</td>
</tr>
<tr>
<td>minC</td>
<td>Minimum condition factor</td>
<td>0.5</td>
<td>a priori</td>
</tr>
<tr>
<td>maxC</td>
<td>Maximum condition factor</td>
<td>1.5</td>
<td>a priori</td>
</tr>
<tr>
<td>NPU</td>
<td>Number of job seekers known by a firm (each month)</td>
<td>3</td>
<td>a priori</td>
</tr>
<tr>
<td>NPJ</td>
<td>Number of occupied jobs known by an individual (each month)</td>
<td>3</td>
<td>a priori</td>
</tr>
<tr>
<td>NSJ_U</td>
<td>Average number of offers sought by an unemployed (each week)</td>
<td>4</td>
<td>a priori</td>
</tr>
<tr>
<td>NSJ_O</td>
<td>Average number of offers sought by an OTJS (each week)</td>
<td>2</td>
<td>a priori</td>
</tr>
<tr>
<td>r</td>
<td>Annual discount factor</td>
<td>3%</td>
<td>a priori</td>
</tr>
<tr>
<td>ω</td>
<td>Sensibility of salary to unemployment, per occupation level</td>
<td>-0.1</td>
<td>(Nijkamp and Poot, 2005)</td>
</tr>
<tr>
<td>PD</td>
<td>Maximum Time before suppressing a pending job</td>
<td>3 months</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,1w</td>
<td>Maximum Time before suppressing a vacant FDC (of 1 week)</td>
<td>3 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,1m</td>
<td>Maximum Time before suppressing a vacant FDC (of 1 month)</td>
<td>6 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,2m</td>
<td>Maximum Time before suppressing a vacant FDC (of 2 months)</td>
<td>8 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,3m</td>
<td>Maximum Time before suppressing a vacant FDC (of 3 months)</td>
<td>10 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,6m</td>
<td>Maximum Time before suppressing a vacant FDC (of 6 months)</td>
<td>13 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,12m</td>
<td>Maximum Time before suppressing a vacant FDC (of 12 months)</td>
<td>17 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDD,18m</td>
<td>Maximum Time before suppressing a vacant FDC (of 18 months)</td>
<td>20 weeks</td>
<td>a priori</td>
</tr>
<tr>
<td>VD_CDI</td>
<td>Maximum Time before suppressing a vacant OEC</td>
<td>6 months</td>
<td>a priori</td>
</tr>
<tr>
<td>PrApP</td>
<td>Probability of a claim to the labor court (personal dismissal)</td>
<td>0.17</td>
<td>(Serverin and Valentin, 2009)</td>
</tr>
<tr>
<td>PrApE</td>
<td>Probability of a claim to the labor court (economic dismissal)</td>
<td>0.0112</td>
<td>(Serverin and Valentin, 2009)</td>
</tr>
<tr>
<td>PrSE</td>
<td>Probability of winning a case in labor court</td>
<td>0.645</td>
<td>(Munoz Perez and Serverin, 2005)</td>
</tr>
<tr>
<td>Psm</td>
<td>Probability of serious misconduct (weekly)</td>
<td>0.00001</td>
<td>a priori</td>
</tr>
</tbody>
</table>
## D.4.2 Calibrated Parameters for the individual (24)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Interval</th>
<th>Calibrated Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha^0$</td>
<td>Average base factor for individual preference for free time</td>
<td>[0,1]</td>
<td>0.07</td>
</tr>
<tr>
<td>$\alpha^{old}$</td>
<td>Sensitivity of preference for free time to age</td>
<td>[0,1]</td>
<td>0.108</td>
</tr>
<tr>
<td>$\alpha^{child}$</td>
<td>Sensitivity of preference for free time to number of children</td>
<td>[0,1]</td>
<td>0.193</td>
</tr>
<tr>
<td>$\alpha^{yw}$</td>
<td>Additional Factor for young women (preference for free time)</td>
<td>[0,20]</td>
<td>11.6</td>
</tr>
<tr>
<td>$\sigma_{coreProd}$</td>
<td>Standard deviation of the productivity kernel distribution</td>
<td>[0,1]</td>
<td>0.193</td>
</tr>
<tr>
<td>$T_{xp}$</td>
<td>Time in period before loss in human capital</td>
<td>[0,100]</td>
<td>33</td>
</tr>
<tr>
<td>$L_{xp}$</td>
<td>Share of human capital lost each period after $T_{xp}$ periods out of employment</td>
<td>[0,0.1]</td>
<td>0.93%</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Sensitivity factor to general human capital</td>
<td>[0,0.1]</td>
<td>0.00396</td>
</tr>
<tr>
<td>$\beta'$</td>
<td>Second sensitivity factor to general human capital</td>
<td>[0,0.1]</td>
<td>$6.42 \times 10^{-7}$</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>Second Sensitivity factor to human capital in the occupation level Employee/Worker</td>
<td>[0,0.1]</td>
<td>0.00151</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>Second Sensitivity factor to human capital in the occupation level Middle level</td>
<td>[0,0.1]</td>
<td>0.0023</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>Second Sensitivity factor to human capital in the occupation level Executive</td>
<td>[0,0.1]</td>
<td>0.00394</td>
</tr>
<tr>
<td>$\beta'_0$</td>
<td>Second sensitivity factor to human capital in the occupation level Employee/Worker</td>
<td>[0,0.1]</td>
<td>$5.87 \times 10^{-7}$</td>
</tr>
<tr>
<td>$\beta'_1$</td>
<td>Second sensitivity factor to human capital in the occupation level Middle level</td>
<td>[0,0.1]</td>
<td>$3.88 \times 10^{-9}$</td>
</tr>
<tr>
<td>$\beta'_2$</td>
<td>Second sensitivity factor to human capital in the occupation level Executive</td>
<td>[0,0.1]</td>
<td>$7.22 \times 10^{-8}$</td>
</tr>
<tr>
<td>$ET$</td>
<td>Employability Threshold</td>
<td>[0,1000]</td>
<td>124</td>
</tr>
<tr>
<td>$ICHANG$</td>
<td>Psychological cost of change</td>
<td>[1,2]</td>
<td>1.26</td>
</tr>
<tr>
<td>$Ru_1$</td>
<td>Reservation utility parameter 1</td>
<td>[0,2]</td>
<td>0.99</td>
</tr>
<tr>
<td>$Ru'_1$</td>
<td>Reservation utility parameter : on-the-job-search</td>
<td>[0,2]</td>
<td>1.49</td>
</tr>
<tr>
<td>$Ru_2$</td>
<td>Reservation utility parameter 2</td>
<td>[0,1]</td>
<td>0.158</td>
</tr>
<tr>
<td>$Ru_3$</td>
<td>Decrease of reservation utility at each period (in %)</td>
<td>[0,0.005]</td>
<td>0.0043</td>
</tr>
<tr>
<td>$FailT$</td>
<td>Number of periods after which an employed seeks jobs with lower occupational level</td>
<td>[0,1000]</td>
<td>191</td>
</tr>
<tr>
<td>$PrBQ$</td>
<td>Probability to receive an offer with higher occupational level</td>
<td>[0,1]</td>
<td>0.014</td>
</tr>
<tr>
<td>$\sigma_C$</td>
<td>Condition Factor parameter</td>
<td>[0,0.3]</td>
<td>0.092</td>
</tr>
</tbody>
</table>
# D.4. Parameters values for WorkSim

## D.4.3 Calibrated Parameters for the firm (36)

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Interval</th>
<th>Calibrated Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_0$</td>
<td>Base hourly productivity for employee/workers</td>
<td>[0, 100]</td>
<td>4.92</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>Base hourly productivity for middle level</td>
<td>[0, 100]</td>
<td>5.53</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>Base hourly productivity for executive</td>
<td>[0, 100]</td>
<td>6.88</td>
</tr>
<tr>
<td>$\zeta$</td>
<td>Share of base productivity value kept by the firm</td>
<td>[0, 1]</td>
<td>0.71</td>
</tr>
<tr>
<td>$PT$</td>
<td>Profitability Threshold</td>
<td>[0, 1]</td>
<td>0.22%</td>
</tr>
<tr>
<td>$\mu \psi_0$</td>
<td>Mean share of the firm demand allocated for employee/worker positions</td>
<td>[0, 1]</td>
<td>33.5%</td>
</tr>
<tr>
<td>$\mu \psi_1$</td>
<td>Mean share of the firm demand allocated for middle level positions</td>
<td>[0, 1]</td>
<td>28.1%</td>
</tr>
<tr>
<td>$\mu \psi_2$</td>
<td>Mean share of the firm demand allocated for executive positions</td>
<td>[0, 1]</td>
<td>38.4%</td>
</tr>
<tr>
<td>$\mu_{max}$</td>
<td>Maximum of the market share trend factor</td>
<td>[0, 0.3]</td>
<td>0.0052</td>
</tr>
<tr>
<td>$\mu_{alea}$</td>
<td>Standard deviation of the market share trend factor</td>
<td>[0, 0.1]</td>
<td>0.0020</td>
</tr>
<tr>
<td>$\sigma_{max}$</td>
<td>Maximum of the market share random factor</td>
<td>[0, 0.3]</td>
<td>0.037</td>
</tr>
<tr>
<td>$\sigma_{alea}$</td>
<td>Standard deviation of the market share random factor</td>
<td>[0, 0.1]</td>
<td>0.0033</td>
</tr>
<tr>
<td>$PrMid$</td>
<td>Probability for a new job to be a part-time job</td>
<td>[0, 1]</td>
<td>0.287</td>
</tr>
<tr>
<td>$MaxHC_{general_Req}$</td>
<td>Maximum level of required general human capital</td>
<td>[0, 10000]</td>
<td>1517</td>
</tr>
<tr>
<td>$MaxHC_{occ_Req}$</td>
<td>Maximum level of required human capital at a given occupation level</td>
<td>[0, 10000]</td>
<td>8.5</td>
</tr>
<tr>
<td>$MaxHC_{spec_Req}$</td>
<td>Maximum level of specific human capital</td>
<td>[0, 10000]</td>
<td>127</td>
</tr>
<tr>
<td>$PT_{\psi_{gen}}$</td>
<td>Sensibility to general human capital</td>
<td>[0, 10]</td>
<td>0.117</td>
</tr>
<tr>
<td>$PT_{\psi_{occup}}$</td>
<td>Sensibility to human capital at a given occupation level</td>
<td>[0, 10]</td>
<td>1.51</td>
</tr>
<tr>
<td>$PT_{\psi_{spec}}$</td>
<td>Sensibility to specific human capital</td>
<td>[0, 10]</td>
<td>0.0228</td>
</tr>
<tr>
<td>$\sigma_0$</td>
<td>Standard deviation of productivity estimation</td>
<td>[0, 0.5]</td>
<td>0.224</td>
</tr>
<tr>
<td>$\delta_c$</td>
<td>Decreasing factor of $\sigma_0$ with seniority</td>
<td>[0, 0.01]</td>
<td>0.0032</td>
</tr>
<tr>
<td>$\omega_{-1}$</td>
<td>Weighting coefficient for pessimistic scenario</td>
<td>[0, 1]</td>
<td>78.9%</td>
</tr>
<tr>
<td>$\omega_0$</td>
<td>Weighting coefficient for neutral scenario</td>
<td>[0, 1]</td>
<td>14.5%</td>
</tr>
<tr>
<td>$\omega_{+1}$</td>
<td>Weighting coefficient for optimistic scenario</td>
<td>[0, 1]</td>
<td>6.6%</td>
</tr>
<tr>
<td>$N_1$</td>
<td>Hiring Norm parameter 1</td>
<td>[0, 1]</td>
<td>0.38</td>
</tr>
<tr>
<td>$N_2$</td>
<td>Hiring Norm parameter 2</td>
<td>[0, 1]</td>
<td>0.017</td>
</tr>
<tr>
<td>$N_3$</td>
<td>Hiring Norm parameter 3</td>
<td>[0, 1]</td>
<td>$4.73 \times 10^{-5}$</td>
</tr>
<tr>
<td>$N_4$</td>
<td>Hiring Norm parameter 4</td>
<td>[0, 0.2]</td>
<td>11.7%</td>
</tr>
<tr>
<td>$SF$</td>
<td>Share of firms with very short (1 week) FDC</td>
<td>[0, 1]</td>
<td>15.7%</td>
</tr>
<tr>
<td>$InitV$</td>
<td>Initial market share (to create the initial vacancies)</td>
<td>[0, 1]</td>
<td>0.113</td>
</tr>
<tr>
<td>$PrCVac_{CDD}$</td>
<td>Vacancy cost parameter (OEC)</td>
<td>[0, 10]</td>
<td>0.784</td>
</tr>
<tr>
<td>$PrCVac_{CDI}$</td>
<td>Vacancy cost parameter (FDC)</td>
<td>[0, 10]</td>
<td>5.7</td>
</tr>
<tr>
<td>$S^*_\lambda$</td>
<td>Impact on salary of the productivity due to specific human capital</td>
<td>[0, 1]</td>
<td>0.636</td>
</tr>
<tr>
<td>$\rho$</td>
<td>Dismissal for personal reason parameter</td>
<td>[0.7, 0.9]</td>
<td>0.8</td>
</tr>
<tr>
<td>$DT$</td>
<td>Demand Threshold to create a new job</td>
<td>[0, 1000]</td>
<td>413</td>
</tr>
<tr>
<td>$SenT$</td>
<td>Minimum seniority level required for a promotion</td>
<td>[0, 1000]</td>
<td>556</td>
</tr>
</tbody>
</table>
D.5 Flow Diagrams

We present the flow diagram for all individuals (figure D.2) and by age group (15-24, 25-49 and 50-64 years old), translated at the national level. Each type of flow is measured in two ways. First the numbers associated with the arrows indicate the number of agents in thousands who move from one state to another during the basic period, a week. The thickness of an arrow in the diagram shows the strength of a flow compared to the other flows. Second the percentage in brackets indicates the proportion of agents of a group who change state. This is computed as the ratio of the gross flow between two states on the number of the agents in the a state of origin. It can be labeled as the probability of transition from a state to another over a period. These probabilities are very low because they are calculated on a weekly basis but they can be perfectly compared between one another and the relative probabilities can be interpreted in economic terms.
Figure D.2 – Gross flows (all)
Figure D.3 – Gross flows of the 15-24 yo
Figure D.4 – Gross flows of the 25-49 yo
Figure D.5 – Gross flows of the 50-64 yo
Titre Agent-based approaches to the study of human behaviors

Résumé Mes recherches portent sur l’apport de l’informatique – et plus particulièrement des systèmes multi-agents (SMA) – pour étudier les comportements humains. Les systèmes humains sont étudiés aussi bien au niveau des comportements individuels que collectifs, en modélisant notamment les interactions d’un sujet humain avec les autres et avec son environnement. Les systèmes humains ont des particularités, qui rendent leur étude difficile : ils sont complexes par nature ; à la fois sujet et objet quand un autre humain les étudie, ce qui rend plus difficile de conserver une neutralité axiologique (au sens de M. Weber) ; libres de ne pas suivre les lois scientifiques, surtout si elles sont trop générales ; enfin les humains agissent suivant des buts et mettent du sens dans leurs actions, un modèle doit donc être capable de produire une explication et compréhension de ces comportements. Pour aborder ces difficultés, je propose une méthodologie, fondée sur la théorie du psychomimétisme : (1) établir le modèle agent (et notamment des comportements individuels) à partir des théories, des faits et des données de sciences humaines et sociales (SHS, e.g. psychologie, sociologie, économie, etc.) qui soient robustes et fondés empiriquement ; (2) utiliser une approche centrée sur les données, et valider le modèle sur des données réelles ; et (3) au niveau de l’implémentation, s’assurer que le programme soit compatible avec le modèle conceptuel et ne viole pas ses principes de base (par exemple, comme la rationalité limitée). Plusieurs projets de divers domaines illustreront mon approche, tous à base de SMA: Coban (marketing, psychologie) est un modèle de dynamique d’opinions, et de diffusion de l’innovation (par exemple, le lancement d’un nouveau produit). Polias (psychologie sociale) un modèle de dynamique d’attitudes (par exemple, celles d’une population prise au milieu d’un conflit armé). Happywork propose un modèle agents de la satisfaction au travail d’un employé, incluant un modèle des activités de l’employé au travail au sein d’une entreprise. WorkSim est un l’un des modèles les plus complets du marché du travail français, et sera utilisé pour évaluer diverses politiques publiques (réduction de charges, réduction du temps de travail, etc.). Pour chaque projet, je présenterai le modèle, la procédure de validation (tous les modèles sont calibrés sur des données réelles) et les résultats de simulation, afin d’évaluer les apports de ces différentes contributions.

Mots-clés Modélisation et simulation de systèmes complexes, simulation multi-agents, sciences humaines et sociales, psychomimétisme, opinions, attitudes, satisfaction au travail, marché du travail

Title Agent-based approaches to the study of human behaviors

Abstract Broadly speaking, my work aims to contribute to the study of the human systems’ behavior. By human system, I mean any system composed of one (individual) or several (collective) human beings, in interaction with each other or with some environment. I will show how computational approaches – mostly multi-agent systems – could contribute to a better understanding of some human behaviors. Human systems are by nature complex, delicate to study for a human (studying another human; the axiological neutrality at stake), free not to follow scientific rules and needs to account for explanation and meanings of their actions. To address all these peculiarities, I propose a general methodology, based on my psychomimetism theory, to (1) derive the computational model (and especially of the individual behaviors) from theories, facts, and data from Human and Social Sciences (HSS; psychology, sociology, economics, etc.) that are robust and empirically grounded; (2) use a data-driven approach, and validate the model on real data; and (3) at the implementation level, ensure that the program stays compatible as much as possible with the conceptual model and do not violate its core principles (e.g. like bounded rationality). Several projects from various
fields will illustrate my approach, all of them agent-based: Coban (marketing, psychology) is a model dynamics of opinions, diffusion of innovation (e.g. the launch of a new product) and Polias (social psychology) a model of attitude dynamics (e.g. for a population in the middle of the war conflict). HappyWork proposes an agent-based model of job satisfaction for an employee, including a model of employee’s activities at work within a firm. WorkSim is a one of the most comprehensive agent-based model of the French labor market, and will be used to assess various labor policies. For each project, I will present the model, the validation procedure (all models are calibrated on real data) and simulation simulations, in order the assess the benefits of these contributions.

**Keywords**  Modeling and simulation of complex systems, multi-agent simulation, human and social sciences, psychomimetism, opinions, attitudes, job satisfaction, labor market