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Master's Thesis

An agent-based model of price formation in the international trade of rice

Exploring new pathways to prevent global food crises

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Abstract

The food crisis of 2008 saw the price of rice tripled in a few months. Rice being the staple food of half of the world population, tens of millions faced malnourishment, poverty or social unrest. While mainstream economic theories and models remain unable to provide a unified account of the reasons of the crisis, recent research identifies internal dynamics emerging from the local interactions and behaviours of economic agents as more convincing drivers of the price dynamics. From existing descriptions of the international trade markets in term of a dynamical network of heterogeneous country nodes, agent-based models (ABM) appear as a suitable alternative for the modeling of complex out-of-equilibrium price dynamics. Assuming that the price of rice in the domestic market of each trading country arises from the transmission of price information between trading agents and price-monitoring international institutions (PMI), responsible for monitoring the trade markets, we developed an ABM of domestic and global price formation in the international trade network (ITN) of rice. Calibrated and validated against empirical data, our model was able to simulate a price spike in the global price of rice comparable to empirical time-series, as well as realistic changes in the trading strategy of the countries. The high sensitivity of countries' domestic markets to price information and the aggregation of the global price by the PMI were identified as internal drivers of crisis-like price dynamics. Finally, a higher sensitivity of domestic markets to changes in trade policies increased the instability of the global price. Thus, our model provides computational evidence of the ability of a fully deterministic model to simulate crisis-like behaviour in the ITN based on internal mechanisms of information transmission, in the absence of external shocks. It also confirms the high sensitivity of the trade network to external shocks to the domestic prices. Besides, for specific values of its parameters, the model showed specific price behaviours in line with ideal cases of mainstream economic theories. Finally, we identified several strategies to prevent or mitigate the development of global food price crises and compared them to existing policy recommendations.

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Contents

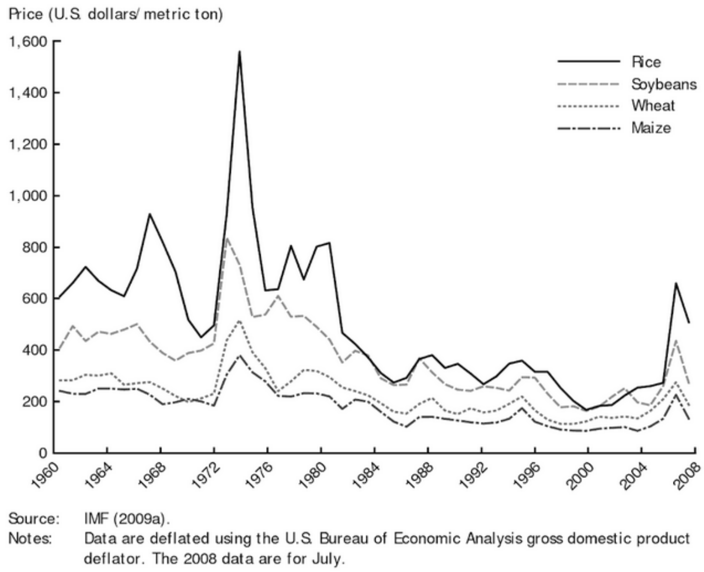
Chapter 1

Introduction

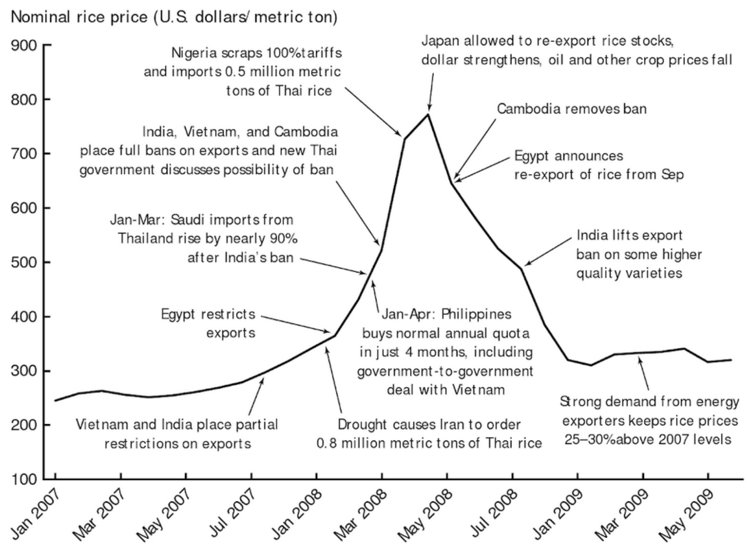
1.1 Background

After a 25 years-long period of declining food prices, reaching all-time lows, the prices of cereals rose sharply in a short period of time triggering a global food crisis spanning from 2006 to mid-2008 (Timmer, 2009; Demeke et al., 2009) (see Figure 1.1(a)). Consumed by almost half of the world population as a staple food, rice was the most severally impacted commodity and saw its price tripled between August and May 2008 (Trostle, 2008; Headey, 2011; Timmer, 2009). Thus, although world food crises remain rare (the previous one being in 1972-74)(Timmer, 2010), they bear severe consequences. The surge in cereal prices in 2007-08 is thought to have driven 130 million people into poverty and led to an increase of 75 million in the malnourished world population (Headey, 2011). The crisis also triggered waves of social unrest in about 20 different countries resulting from "consumers anger and fear over high food prices" (Trostle, 2008; Rutten et al., 2013). Therefore, preventing instabilities in food prices is necessary to ensure the economic access of all households to sufficient food supplies which is one dimension of food security (Timmer, 2012). It justifies to focus on gaining understanding of the drivers and mechanisms underlying food price dynamics.

A large body of literature has tried to explain the crisis using mainstream economic theory and models (Headey and Fan, 2008; Rosegrant et al., 2008; Mittal et al., 2009; Trostle, 2008; Mitchel, 2008; Timmer, 2010; Headey, 2011). Grounded in the General Equilibrium theory (FAO, 2004b), these models assume that the behaviour of supply, demand and price results in an equilibrium state of the whole economy that can be deduced from the aggregate contribution of each of its actors (Walras, 1954; Farmer and Foley, 2009). In this framework, crises are caused by external shocks to supply or demand from which the economy adjusts by moving to a new equilibrium price. The specifics of this new equilibrium state inform models (Farmer and Foley, 2009; Kirman, 2010). Calibrated on empirical data, models are no longer valid in case of large change and show no predictive power regarding crises (Abbott, 2012; Headey and Fan, 2010; Headey, 2011; Farmer and Foley, 2009). Thus, mainstream analyses of the crisis consist of identifying the external shocks that could have caused the observed change in price. However, the lack of agreement in the literature on the relative role of the external factors of the 2008 food crisis (e.g. extreme weather events, oil price shocks, long-term increase in demand, economic shock) sheds light on the limitations of this approach (Headey and Fan, 2010; Sornette, 2003; Kirman, 2010).



(a) Trend in real international prices of key cereals, 1960 to mid-2008, adapted from Headey and Fan (2010). The figure shows two main peaks corresponding to the last two global food price crisis in 1972 and 2008. In between, the global price of cereals followed a decreasing trend. Rice shows the largest variations.



(b) The effects of export restrictions on rice prices, adapted from Headey and Fan (2010). The main changes in the trend of the global price have been associated to the change of trading policy of large importers and exporters of rice.

Figure 1.1: International price of rice and national policies of the major importers and exporters during the 2008 price crises

In spite of these limitations, General Equilibrium's analyses of supply, demand, and price are used to inform economic agents choices and governments' policies in agricultural markets (Rosegrant et al., 2008; Bchir et al., 2002; Kirman, 2010; Chen and Saghaian, 2016). Consequently, they influence the evolution of the price of rice. Therefore, understanding the formation and evolution of rice prices requires to identify the key conclusions of these analysis which motivate trader choices and governments' change of policies. Because of highly incomplete and imperfect information about short-run supply, demand and stocks in the rice markets, traders and countries use prices as proxies for these factors (Timmer, 2012). It is also the case for price-monitoring international institutions (PMI) specialized in reviewing, spreading and promoting trade-relevant information within the international trade network (ITN), such as the Food and Agriculture Organisation of the United States (FAO), the Agricultural Market Information Service (AMIS) and the United States Department of Agriculture (USDA)[1]. Since price changes in markets are thought to reveal supply and demand information (Milgrom and Stokey, 1982), importers, exporters and institutions constantly monitor them. These price trends motivate the change of national trade policies (Chen and Saghaian, 2016). In the General Equilibrium framework, prices on international markets for the same commodity are supposed to follow the law of one price (LOP). According to the LOP, a commodity has a single price, in common currency unit, throughout the world (Isard, 1977; Listorti and Esposti, 2012; Barrett and Li, 2002; Deuss, 2017). The adjustment of this price is ensured by trade which transfers the excess supply or demand from one market to the other until equilibrium is reached. Thus, trade is the main vector of price transmission throughout the ITN (Listorti and Esposti, 2012; Gotz et al., 2012). The remaining differences in price between markets is explained by the costs of trade that adds up to the initial price (such as transport costs or tariffs, that is, taxes on imports or exports), or by trade restrictions which prevent the transfer of excess supply or demand from one market to another (Listorti and Esposti, 2012). Otherwise, any price change in the domestic market of a country due to a local demand or supply shock would generate an equal price change in the domestic markets of its trading partners (Listorti and Esposti, 2012).

Because it is thought that less trade prevents price transmission between markets, anti-trade policies (hoarding of stocks, aggressive imports, exports restrictions and bans, change in tariffs) are used by governments to isolate their domestic markets from the price variations of their trading partners and from the world markets (Trostle, 2008; Tadasse et al., 2016). However, since these policies reduce the supplies available for trade or increase the demand, the General Equilibrium theory predicts a mechanical increase in the international price (Porteous, 2017). Thus, it is thought that the implementation of a protectionist policy by a country generates a price increase in the domestic markets of its trading partners. Consequently, information about new anti-trade policies spread the fear of a price rise within the markets and motivate more countries to implement protectionist policies. It is thought that if a sufficiently large share of the market collectively enforces anti-trade policies, the world's price volatility[2] increases (Anderson and Nelgen, 2012b,a; Ivanic and Martin, 2014; Durevall and van der Weide, 2014). This effect is described in the literature as the multiplier effect and is supported by multiple empirical studies for a large group of agricultural commodities (Giordani et al., 2016, 2014; Gotz et al., 2012; Abeysinghe and Forbes, 2005; Fair et al., 2017). Departing from traditional economic analysis, which only considers external shocks as triggers for the crisis, more recent economic literature identified it as an internal driver of the food prices dynamics in the ITN (Tadasse et al., 2016; Rutten et al., 2013). Since the rice price crisis saw a large increase of protectionism during the price spike, and its decrease during the price fall (see Figure 1.1(b)), it has sometimes be considered the most important driver of the food crisis (Headey and Fan, 2010; Demeke et al., 2009).

Even though the multiplier effect provides a convincing account of the unfolding of the food crisis and explains the reasoning of national governments, we argue that it does not identify the correct underlying mechanism of the price rise. In fact, the literature on agricultural trade reports evidence of price and volatility transmission between markets even in the absence of trade as a result of information transmission between international and domestic markets of grains (Ceballos et al., 2017; Myers and Jayne, 2011; Brooks and Matthews, 2015; Wright, 2011; Stephens et al., 2012; Gotz et al., 2012). Thereby, it has been argued that information carries price changes and anxiety from the world to the domestic market more efficiently than physical trade flows and outweighs the dampening spatial price equilibrium effect predicted by the LOP (Gotz et al., 2012). As a consequence, imperfect market information can impede price transmission (Brooks and Matthews, 2015) and, conversely, foreign market news can cause volatility spillovers from one market to the next (Ito et al., 1992; Gotz et al., 2012; Myers and Jayne, 2011). In addition, more attention is given to larger price movements, which increases price information flows. Therefore, an initial price increase could theoretically be amplified by the

[1] In 1998, it was stated that "Providing information on agricultural markets, costs, and prices is a primary function of public sector agricultural economists employed by the USDA and by land grant universities." (Salin et al., 1998). Similarly, the AMIS was created by the G20 to improve market transparency in response to the 2007-08 price spike (Brooks and Matthews, 2015).

[2] Price's fluctuations around its equilibrium value.

announcement effect of major market players moving to protectionism even in the absence of trade. Since traditional economic theories identify trade as the main driver of price change, the expected impact of this information is likely to be the largest for direct trading partners of the country which undergoes a price or a policy change. Since prior work identified the existence of two-ways micro-level (local buyers and sellers) to macro-level (international markets) feedbacks within the economy (Tesfatsion, 2002), we suggest that information flows between neighbouring countries in the ITN, and PMI. This way, it sets up positive feedback loops of information which spread and amplify local price shocks through the ITN. It is known that such positive feedback loops can generate interdependent or 'cascading' failures within networks from a single local shock (Helbing, 2012). Thereby, statistically independent local price shocks can scale-up to the level of the whole economy causing global price bubbles and crashes (Helbing, 2012; Tesfatsion, 2002). The growth in connectivity and trade flows of the ITN during the last 20 years suggest an increase of its complexity[3] that may be associated with higher systemic risks (Puma, 2019), whcih supports this hypothesis. Thus, in addition to identifying the initial external price shocks that cause food crises, it appears crucial to understand the role of internal information feedback loops in order to mitigate the systemic risks that can give rise to food crises (Tadasse et al., 2016).

Research shows that the economy, and the ITN more specifically, exhibits emergent behaviours characteristic of a dynamical adaptive network with heterogeneous node attributes (Schweitzer et al., 2009). Since agent-based computing can be used to simulate global or emergent phenomena in complex heterogeneous adaptive systems (Niazi and Hussain, 2011), its application to economic modeling has been increasingly supported in the literature (Tesfatsion, 2002; Arthur, 2006; Farmer and Foley, 2009; Fagiolo et al., 2017). More specifically, agent-based models (ABM) appear as the most suited modeling tool to investigate price dynamics in the international trade of rice (Bonabeau, 2002; Tesfatsion, 2002). ABM represent real-life systems as a collection of autonomous decision-making entities, called agents, which individually assess a situation and make decisions on the basis of a set of rules (Bonabeau, 2002). Since the modern economy is made up of millions of individuals interacting together directly and indirectly, based on both local and global information (Kirman, 2010), ABM have already been used for economic modeling, giving rise to the field of agent-based computational economics (Tesfatsion, 2002). Nowadays, ABM are considered valid and effective competitors of standard General Equilibrium models in macroeconomics (Fagiolo et al., 2017). Since they are dynamical out-of-equilibrium models, they are able to explain a wide range of non-linear behaviours such as bubbles and crashes that equilibrium models cannot account for (Arthur, 2006; Farmer and Foley, 2009).

This perspective fueled the research on the resilience of (food trade) networks, their ability to absorb shocks, which confirmed the importance of their interconnectedness, structure and modularity in the spread, amplification and absorption of shocks, but also the role of individual properties of its nodes such as the national income per capita (Battiston et al., 2012; Helbing, 2012; Lee et al., 2011; Torreggiani et al., 2017; Gao et al., 2016; Distefano et al., 2018; Dolfing et al., 2019). In the field of finance, ABM of adaptive agents reacting to different streams of news have shown to be able to generate price bubbles in a financial market (Harras and Sornette, 2011). In this context, three sources of information were simulated: private information, information shared by a market player, and publicly released information. These three information sources can also be found in economic markets. First, local production and demand information are used to inform domestic markets (Headey and Fan, 2010). Second, governments closely monitor global and domestic food prices to inform their policy (Godfray et al., 2010). Finally, we already mentioned the role of the PMI in communicating price information with the rest of the ITN. Thus, we argue that the dynamics of price within the ITN of rice is governed by the same three sources of information: private, local and global. These three channels of information flow define the network structure of the information feedback loops that may be responsible for price transmission and shock amplification throughout the ITN of rice.

In this information network, we argue that a major role is attributed to the PMI. The increasing size and complexity of economic networks made individuals and decision makers increasingly reliant on the reports and summary statistics released by trade-related institutions (Kirman, 2010). However,

[3]The global food system has been described as a prototypical complex system (Puma, 2019), that is, a system in which large networks of components with no central control and simple rules of operation give rise to complex collective behaviour, sophisticated information processing, and adaptation via learning or evolution (Mitchell, 2009).

this communication suffers from important limitations due to analysts' use of aggregate measures, their imperfect knowledge of the world and their reliance on General Equilibrium models. In the case of rice market, the value of the international price communicated by the FAO and the IMF are based on export prices of a few main export markets (the United States, Thailand, Vietnam, India and Pakistan in the case of the FAO, with a focus on Thailand (FAO, 2004a, 2007b,c,a, 2002), Thailand and Vietnam for the World Bank (WB, 2019) and only Thailand for the IMF (IMF, 2019)) which may not always be representative of the system as a whole. Thus, even though these institutions were created in order to increase the predictability and stability of the trade system (Headey, 2011), it remains unclear whether or not they may contribute to price shocks' amplifications within the food trade system.

1.2 Hypothesis and research question

This research is based on the hypothesis that the price inflation during the first half of a price bubble is caused by information feedback loops within the ITN. Assuming that information is transmitted between trading partners and with PMI based on the strength of their trade relationships, we propose the following scenario as an explanation of the unfolding of a price crisis. An initial price increase on the market of one of the main exporters gets amplified by three different feedback loops. First, this information sends signals of a decrease in supply (or increase in demand) on the domestic markets which motivates market players to adopt anti-trade policies which further increase the price. Second, the information about this initial price increase is transferred to the domestic markets of its trading partners whose similar hoarding and buying behaviours lead to a price increase on their domestic markets as well. Thus, the initial price trend in the first country spreads to the second country and, by the same mechanism, feeds back to the country where it first originated. Finally, in the case of the biggest exporters, the trend followed by their domestic market is monitored by the PMI in order to estimate the evolution of the global price of the commodity traded. Once processed and aggregated over the most important export markets, this global price information is sent back to the entire network, including these main exporters. Eventually, the main exporters receive and process information coming from their domestic markets three times: once directly as raw information, a second time once processed by their trading partners, and a third time once processed by the PMI. Thereby, a small increase in the price of one of the main exporter gets amplified and spreads within the network, triggering a global food crisis. In addition, the change of trading policy of the countries which thrive to protect their domestic market from the global price spike further amplifies the price movements of their trading partners, and eventually of the global trade market itself.

This work investigates the role of information transmission in the triggering of price crises in international food markets. More specifically, it focuses on the relative contribution of each information feedback loop in the transmission and reinforcement of local price variations to the global prices. It will investigate the question of whether it is possible to prevent food price crises or reduce their severity by modifying the strength of these three feedback loops or the processing of market information done by the PMI.

1.3 Goal of the research

We aim to develop an ABM of price dynamics in the international trade of rice, capable of generating the price dynamics and changes in trade policies observed in the wake of the rice price crisis of 2008. Our model should be comparable to empirical price-time series and reported governments' change of trade policy during the crisis. Once the model has been validated against existing price and policy data, our goal is to explore different ways to aggregate price information at the institutional level and quantify their impact on the price dynamics. This way, we expect to identify the role of institutional communication in the spread and absorption of price shocks as well as potential new strategies to mitigate a price surge.

1.4 Contributions

The main contributions of this work are the following:

- developing an agent-based model of price transmission based on information transmission in the ITN;
- proposing a validation measure and a benchmark performance for ABM of the rice price crisis of 2008;
- proving that realistic price dynamics can be caused by internal drivers of the trade system, even in the absence of external shocks;
- linking price dynamics that can be generated by the model to existing mainstream economic theories;
- identifying new potential drivers of large price variations and corresponding strategies to prevent them.

1.5 Outline

This thesis is structured in the following way. Chapter 2 presents agent-based computing and its application to social simulation. In addition, it reviews existing models of trade and crises. Chapter 3 presents the design of the model we developed, the empirical data it uses for its initialization, the analysis of the model and the specifics of its implementation. Chapter 4 features the results of the analysis of the model and our main findings. These findings and their consequences for preventing food crises and for economic modeling are discussed in chapter 5.

Chapter 2

Literature review

In this chapter, we first review the main literature on agent-based computing and its applications to social simulation. We distinguish between agent-based modeling and multi-agent systems and draw upon both to define the main elements of the architecture that will be used in our model, and to justify our design choices. We then review the main existing approaches and applications to trade and the economy. Finally, we briefly present its application to the modeling of crises.

2.1 Agent-based computing and social simulation

2.1.1 Agent-based models and multi-agent systems

The field of agent-based computing consists in three sub-domains (Niazi and Hussain, 2011):

- agent-based, multi-agent based or individual-based models,
- agent-oriented software engineering,
- multi-agent systems (MAS) in artificial intelligence (AI).

Agent-oriented software engineering aims at applying the best-practices of MAS for software engineer (Jennings, 1999). Thus, it falls outside of the scope of this research. MAS stems from the field of distributed artificial intelligence (Weiss, 2000). MAS are *"systems in which several interacting, intelligent agents pursue some set of goals or perform some set of tasks"*(Weiss, 2000). In AI, MAS are used to design rational agents which act to achieve the best outcome or, under uncertainty, the best expected outcome of a task (Russell and Norvig, 2016). In this frameworks, the agents are expected to be adaptive, autonomous and to pursue and achieve goals which require to define a success measure to quantify their performance (Niazi and Hussain, 2011). Therefore, their design focuses on the concepts of intelligence and rationality.

On the other hand, agent-based modeling uses MAS for the representation and simulation of social, economic, ecological and other similar systems in a software environment to gain understanding of their fundamental processes (Axelrod, 1997; Šalamon, 2011). ABM have been developed to investigate systems whose behaviour results from the interplay of dynamics at two different scales of a system (its macro-level and its micro-level) (Leombruni and Richiardi, 2005). Thus, even simple ABM can show complex behaviours and provide information about the real-world system that it simulates (Bonabeau, 2002). Since the goal of our research is to emulate real-life price dynamics to understand the role of information transmission in the price dynamics of the ITN, our approach fits within the framework of ABM. However, since ABM stems from MAS, we build upon its methodology to structure the design of our model. MAS's building blocks are the agents and their environment. Thus, we dedicate the two next subsections to define and reviewing the existing types of agents and environment.

Finally, ABM is often seen as an alternative to traditional differential equation modeling (Bonabeau, 2002). However, it has been argued that systems in which the constituent units are described by a set of differential equations already constitute ABM (Bonabeau, 2002). Thus, it has been argued that ABM allow to computationally simulate the solution of the interactions between these individual units without having to solve it analytically (Leombruni and Richiardi, 2005). The counterpart of this approach is that the simulation provides a more limited knowledge about the solution of the mathematical problem than for an analytically solved set of equations. Yet, it remains that ABM can be described using mathematical or computer science syntax. In addition, they can built upon existing results from these two fields. Therefore, in this thesis, we consider the two approaches in the design and interpretation of the model.

Therefore, the goal of our research motivates our choice of an ABM rather than a MAS. However, we build upon MAS methodology to structure the design of our model. In addition, since ABM can be seen as the computational simulation of systems of equations, we also consider this mathematical approach in the design and interpretation of our model. In the next two subsection, we review the definitions and existing types of agents and environment, the two building blocks of MAS.

2.1.2 The environment

In MAS, the environment is characterized by a set of possible states which depends on the history of the system (Wooldridge, 2009). The environment is characterized by the following properties (Wooldridge, 2009; Russell and Norvig, 2016):

1. single agent or multiagent,
2. fully and partially observable (also called accessible), depending on whether or not the agents have perfect knowledge and access to the state of the environment at each point in time,
3. deterministic or stochastic, depending on whether the next state of the environment is completely determined by the current state of the environment and the actions of the agents,
4. dynamic or static, depending on whether the state of the world can change while the agent is deliberating,
5. episodic or sequential, depending on whether the current experience of the agent depends on its actions taken in the past,
6. discrete or continuous, depending on whether there is only a finite number of possible percepts and actions in the environment,
7. known or unknown, whether the outcome of all actions are given, either to the agents or to the designer.

The hardest type of environment is multiagent,inaccessible (or partially observable), stochastic, dynamic, sequential, continuous and unknown. In addition, the MAS approach defined a task environment which correspond to a performance measure, an environment, actuators and sensors which corresponds to the problem to which the agents are the solution (Russell and Norvig, 2016). The sensors are what the agents view and perceive their environment through, while the actuators are what they act upon it through. The performance measure evaluate the desirability of any given sequence of environment states for its agents. If an agent has performed well, then the sequence of states is highly desirable for it.

Since the goal of our simulation is not to optimize the performance of the agents but to simulate the real-life process of price formation in the ITN of rice, we choose to leave out the performance measure of the agents in the description of the environment. Instead, we consider the ABM concept of empirical validity of the model which correspond to the extent to which the model, view as a data-generation-process, is a good representation of the real world data-generation-process (Windrum et al., 2007). Axtell and Epstein (1994) identify four levels of agent-based model performance and analysis that have been more recently proposed as a measure of the validity of an ABM (Barde and Van Der Hoog, 2017; Fagiolo et al., 2019), presented in Table 2.1. We will follow this approach in the definition of a validity measure for our model.

Level 0	The model is a caricature of reality, as established through the use of simple graphical devices (e.g., allowing visualization of agent motion)
Level 1	The model is in qualitative agreement with empirical macro- structures,as established by plotting, say, distributional properties of the agent population
Level 2	The model produces quantitative agreement with empirical macro-structures, as established through on-board statistical estimation routines
Level 3	The model exhibits quantitative agreement with empirical micro-structures, as determined from cross-sectional and longitudinal analysis of the agent population

Table 2.1: Axtell and Epstein's four levels of ABM performance and analysis

2.1.3 The agents

Within the field of MAS and ABM, several definitions of agents coexist. Thus an agent can be described as:

- "anything that can be viewed as perceiving its environment through sensors and acting upon that environment through actuators." (Russell and Norvig, 2016),
- "a computer system that is situated in some environment and that is capable of autonomous action in this environment in order to meet its design objectives" (Wooldridge, 2009),
- mathematically speaking, a "function that maps any given percept sequence to an action", implemented concretely in a computer program running within some physical system. (Frankish and Ramsey, 2014)

Since our research aims at simulating realistic price dynamics of the ITN rather than optimizing the behaviour of the economic agent to achieve a certain task, we rather focus on the first and last one. In addition, more work define an agent percepts' as its perceptual inputs at any given instant (Frankish and Ramsey, 2014; Russell and Norvig, 2016). Based on their percepts, the agents output actions which, in turn, modify the environment. This mapping from a sequence of previous environment states to new actions can be either explicitly or implicitly specified.

Classical methods from the field of agent-based modeling (ABM) designed single isolated software systems based on rigid pre-defined rules (Frankish and Ramsey, 2014). Agents were pure functional computer systems explicitly implementing this mapping. They provided a predictable output from a predictable input based on some predefined goals. However, most realistic environments happen to be nondeterministic, dynamic and partially observable which does not allow for an explicit mapping. In addition, simulating social activities requires the agents not only to interact with their environment but also to understand the goals of their fellow agents and exchange information with them. Thus, ensuring the interactions of several of those systems required the agents to acquire additional abilities such as cooperation, coordination, and negotiation. Consequently, autonomy, situatedness, and sociability characterize agents in MAS. The agents should be able to make their own decisions, extract specific information, realize action in their environment, and interact with one another (Wooldridge, 2009; Frankish and Ramsey, 2014).

Deductive reasoning agents, practical reasoning agents, and reactive and hybrid agents stem from this attempt (Wooldridge, 2009). Their main characteristics are summarized in table 2.2. Our working hypothesis does not emphasize the role of complex adaptive behaviour of the countries in triggering a global price crisis, but rather define two simplified strategies that national governments can choose from, protectionism or free-trade, together with corresponding environment conditions for governments' choice. In addition, since the environment of the model is unknown, since we did not identify a simple mechanism for price formation, we argue that a simpler agent design allows to better understand the complex environment dynamics that we aim at reproducing. Therefore, we choose to focus on the design of reactive agents.

Deductive reasoning agents	**Practical reasoning agents**	**Reactive and hybrid agents**
Purely logical reasoning and rationality based on theorem proving	Bounded rationality (limited computational power, time, resources) using mean-end reasoning and deliberation to generate plans	behavioural and situated approach of ABM. No explicit representations or reasoning, rational behaviours emerge from agent-environment interactions

Table 2.2: Classification or intelligent agents and their corresponding type of reasoning and decision making

In addition, (Russell and Norvig, 2016) identify four basic types of agent programs that embody the underlying principles of most of intelligent systems:

1. simple reflex agents which select an action based on the current percept, ignoring the rest of the percept history, using condition-action rule, also called situation-action rules, productions or "If-then" rules,
2. model-based reflex agents, in which the agents keep track of the states of the world that are not currently accessible,
3. goal-based agents, in which, in addition to the current state description, the agents use a goal as a description of desirable situations,
4. utility based agents, which make use of an internal performance measure as a description of desirable situations.

All these agents can be converted into learning agents, which can improve their performances. The goal of our research sets our focus on simple non-learning reflex agents.

Examples of reactive approaches in the literature encompass the use of simple rules of the form of a situation implies a specific action (Brooks, 1999), the use of several simple rules with an explicit ordering (Steels, 1990)), situated automata based on declarative specifications (Rosenschein and Kaelbling, 1986) and agent network architectures in which agents feature several sets of competence networked together (Maes, 1991). MAS models also require to define the society design for the multiagent interactions. The first models of societies were simulated based on differential equations models(Squazzoni, 2012). From the 90s, when the field increased its focus on micro behaviours, it adopted the traditional modeling framework in AI: game theory (Wooldridge, 2009).

2.1.4 Social simulation

By increasing the delegation and intelligence capacities of computer systems, the development of MAS represents a turning point in the theory of artificial intelligence (AI) and its application to social science (Wooldridge, 2009; Squazzoni, 2012). MAS for social simulation combines two overlapping lines of research: one from computer science, presented in the last subsections, and one from sociology. The use of computational methods in sociology is known as computational sociology and can be traced back to the 60s when the influence of systems theory and structural functionalism led to model feedback mechanisms in organizations, cities or global populations (Squazzoni, 2012). These first models only considered the macro level of description of the systems they studied, and it is only in the 90s that computational sociology moved to the study of local micro-interactions between agents and their environment. This research was fueled by the work of Axelrod and Hamilton (1981) on the emergence of cooperation in a population of rational self-interested agents. More recently, Squazzoni (2012) defined computational sociology as *"the study of social patterns by computer models of social interaction between heterogeneous agents embedded in social structures"*. In computational sociology, MAS is an experimental tool to the social science (Wooldridge, 2009). MAS can simulate the interactions of individuals and collective actors, such as governments, institutions or companies. They allow to observe both individual and collective behaviour in several potential alternatives to situations occurring in nature, in social environments or resulting from a governmental policy (Wooldridge, 2009). Therefore, they are used to study and understand the social processes from which emerge certain social phenomena and structures (Conte et al., 2001). MAS as models of human societies typically investigates the emergence of cooperation in societies of self-interested agents, the languages that agents can use to communicate with people and other agents, the abilities of the agents to reach agreements without resorting to conflict and coordinate their activities to cooperatively achieve goals (Wooldridge, 2009). For this research, we aim at simulating the micro-interactions between trading countries and PMI, and observe the resulting patterns of the domestic (micro-level) and global price (macro-level) of the commodity traded depending on the price information shared between the different economic agents. Thus, we investigate the emergence of global price dynamics from local information interactions.

2.2 Models of trade and the economy

2.2.1 Rationality

Russell and Norvig (2016) defines AI as the study of rational action and follow the rational agent approach according to which for each possible percept sequence, a rational agent should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and its built-in knowledge. This approach is also the one that has been followed in the field of economics which treats economies as consisting in individual agents maximizing their own economic well-being (Russell and Norvig, 2016). This approach led the field of economics to defined the preferred outcome of an agent's actions mathematically by optimizing a utility functions (for large economies) or the payoff of games (for small economies). Following this approach would favor the use of goal-based or utility based agents.

However, this approach has been strongly questioned by its inability to account for price formation and the development of crises (Headey and Fan, 2010; Sornette, 2003; Kirman, 2010). On the other hand, the framework of bounded rationality draws on insights brought out by the field of cognitive science and acknowledges that humans are not able of pure rational reasoning. Instead, it is concerned with building models of human decision making which account for perception and action under uncertainty and limited resources (computational power and time) (Gershman et al., 2015). Similar stream of work have recently spread to the economics under the name of behavioural economics (Laibson and List, 2015; Bellemare and Lee, 2016). They claim that economic observations, such as market volatility or security price, may not only depend on purely economic factors but also psychological or biological factors determining the formation of expectations and risk aversion to name but a few (Tom et al., 2007; De Bondt et al., 2008; Murphy et al., 2012). Therefore, a more realistic model of economic behaviours may rather feature reactive agents which are not fully goal or utility-based but rather account for these biases.

2.2.2 Structure of the agents' interactions

Since the 90s, the application of MAS to the economy explored different directions. As a consequence, review papers such as those of Tesfatsion (2002) and more recently Chen (2012) reports a significant variety of methods which define corresponding structures for the interactions of the agents. Even though some models are tailored to specific applications, bodies of work stemming from similar origins inherited from common methods. Consequently, we review four types of models that relate to our topic of interest: network-based models, game-theory-based models, equation-based models.

Network-based approaches of economic ABM are rooted in graph-theory and optimization problems in networks (Kirman, 1997; Sharkey, 1995). Even though their first applications can be traced back to the 90s (Epstein and Axtell, 1996), it only gained importance among the economists from the mid-00s (Kirman, 2010). Research in this domain stems from economics, sociology, and complex systems research in physics and computer science (Schweitzer et al., 2009). It favors analyses in terms of relational structures rather than the agents attributes (Wellman and Berkowitz, 1988; Kim and Shin, 2002). Individuals are characterized by their position in the network, their connectivity to other individuals or their membership in a subpart or substructure of the network. Most ABM already implicitly assume and require a network structure to represent the interactions between the different agents (Kirman, 1997; Helbing, 2012; Tesfatsion, 2002; Klos and Nooteboom, 2001). When combined, network- and agent-based models encompass the trade system main characteristics - heterogeneity, interdependencies, asymmetry, complexity of the dynamics. Network-based models of the socio-economical systems are often social networks in which individual economic agents are nodes and edges represent their social interactions, or transaction in the specific case of trade. Network-based approach of ABM of the economy investigate the emergence of dynamic and evolving economic networks from the cooperation and competition between adaptive agents trying to optimize their profit on the basis of their trustworthiness and past experiences (Tesfatsion, 2002; Albin and Foley, 1992; Klos and Nooteboom, 2001).

Game theoretical models of the economy have mostly been used to simulate the dynamic and formation of markets, the evolution of norms, and have been quickly complemented with genetic algorithms (Axelrod, 1997; Epstein and Axtell, 1996). Thus, the first simple strategies chosen and implemented by the researchers have been superseded by computationally generated ones based on evolutionary learning and reinforcement learning. These methods allow the agents to learn actual decision-making behaviours, sometimes at the level of a neighbourhood or of a single individual. They have been used in automated markets and to simulate real-world economy and they have been proven able to account for complex phenomena such as innovation and social mimicry (Tesfatsion, 2002). They demonstrated that the long-behaviour of a simulation is strongly influenced by the type of strategies followed by the agents, their distribution in a population of agents, and the number of agents which can interact together within a society (Dawid, 2011; Marks, 1992). When it comes to international trade more specifically, games have been used to analyze imperfect markets of importers and exporters (Karp and McCalla, 1983), to study the role of trade agreement (Jusufovic, 2018) and also the implementation of protectionist policy during the 2008 crisis (Boffa and Olarreaga, 2012), to name but a few applications. Such simulations provided evidence that countries tend to impose protectionism measures on countries that have similar size, with whom they share a border, from where they import more and which did not introduce liberalizing measures on their home exports. They showed no evidence of retaliation consequently to the implementation of anti-trade policies but rather the opposite.

Equation-based models are used in mainstream economics to formulate the General Equilibirum theory and corresponding models such as gravity equations, transaction-cost analysis based on the optimization of utility-functions and statistical regression analysis fitted on empirical data (Bergstand, 1985, Farmer et al., 2009, Kirman, 2010). This set of equation-based methods has been acknowledged for its relative simplicity compared to the complexity of the economics (Arthur, 2006). However, this simplicity comes at a price and their assumption of equilibrium, homogeneity and rational behaviours of the economic agents which are all represented by the same utility function, and predictive power had been questioned for already several decades (Sharkey, 1995). Consequently, in these models, agents behaviours are equation-based and the models' parameters are calibrated on macroeconomic and financial data. For instance, Klos and Nooteboom (2001) use transaction costs economics and network structure to investigate how agents choose their trading partners and the efficiency of the resulting markets. They link the efficiency of transaction networks to market transition and trust. It has also been argued that using mathematical formalism is a way to bring more generality to ABM and thus overcome one of their main limitation (Leombruni and Richiardi, 2005).

2.3 Multi-agent models of crises

Agent-based models have more recently been used to model and investigate the spread of systemic risks within certain systems, crises and bubbles. On the economic side, such models built upon simple computer simulations of spin-like models or cellular automata proving that very simple models of money and economic markets can already undergo sudden change of behaviour or phase transitions even in the absence of exogenous shocks (Sánchez et al., 2002; Bornholdt and Wagner, 2002; Bouchaud, 2013, 2009). Such basic example are to keep in mind when trying to understand more complex behaviours produced by ABM simulations. More complex models have been developed in the study of financial crises but can benefit to the modeling of economic crises as well. For instance, Harras and Sornette (2011) propose an adaptive multi-agent model of bubble and financial crash based on adaptation, imitation, information transmission and expectations. After the crisis of 2008, agent-based models have been increasingly used to model the rise and spread of systemic risk, mostly in financial networks (May and Arinaminpathy, 2009; Nier et al., 2007). Agent-based models have been used to explore the relationship between interconnectedness of agents and systemic risk, demonstrating that increased connectivity and risk sharing is beneficial to an interconnected banking system only when agents' ability to absorb shock is high (Namatame and Tran, 2013). In such models, a very small change in the parameters is able to generate a sudden switch in the aggregate behaviour of the agents of the type that we described in the triggering of the economic crisis of 2008 which show the importance of model's calibration.

Chapter 3

Methods

In this chapter, we present the methods used for the design of the model, the initialization of the model, and the analysis of the model. The specifics of the implementation can be found in appendix C.

3.1 Design of the model

In this section, we first provide an overview of the model before specifying the details of the environment and agents' design. The list of all the assumptions made in the design of the model are listed in appendix A lists. We refer to them when required, using their corresponding code in bold and between brackets (e.g. (**A1**)).

3.1.1 Overview of the model

We developed a highly simplified model the ITN of rice (see Figure 3.1). It simulates the evolution of the price on the domestic and global trade markets of rice based on the transmission of information between the different markets players.

The model features 79 country agents and one institution agent which are the nodes of a network of information transmission. Based on our working hypothesis, the edges between the country agents are weighted based on their trade relationships (orange edges on Figure 3.1). The edges between the country agents and the institution agents are weighted based on the integration of the countries in the ITN in 2006 measured by their centrality (red edges on Figure 3.1).

Each country agent is characterized by the price of rice on its domestic market of rice and its trade policy. The domestic price of rice of all country changes at each time-step depending on information that the domestic market of a country received from three different sources: its past variations, the domestic markets of its trading partners and the global market monitored by the institution agent. It defines three information feedback loops: a domestic feedback loop (the domestic price reacts to its own variations), a local feedback loop (the domestic prices of trading partners react to each others' variations) and a global feedback loop (the domestic prices of country agents reacts to the global price, itself computed from the aggregation of domestic prices), as shown in Figure 3.2. In order to investigate our research question on the relative role of each feedback loop in the triggering of global price crises, three parameters allow to explore different values of the sensitivity of the country agents to the three sources of information (x_1 for the domestic feedback loop, x_2 for the local feedback loop, x_3 for the global feedback loop).

In addition, a country can implement two types of trade policies: free-trade or protectionism. Country agents are purely reactive agents and change strategy based on the value of rice on their domestic markets. When prices are too far from their target value, they implement a protectionist policy. Implementing a protectionist policy can partially isolate them from the price variations of their trading partners, but it amplifies the price variations of their trading partners proportionally to the value of a last parameter (λ_l). Otherwise, they cooperate with the rest of the ITN and stick to free-trade.

The institution agent monitors the network of country agents and computes the price of rice on the global market as an aggregate of the domestic prices of certain countries. We define a benchmark aggregation method, but other will be explored during the analysis of the model in order to answer our research question. At every time step this price is shared with all the country agents and influence the evolution of the price of rice on their domestic market. The goal of our research is to generate a realistic evolution of this global price.

We give an overview of the structure of our proposed model as defined in Richiardi et al. (2006):

- **goal of the model**: emulating the dynamics of the global price and the domestic prices of the countries of the ITN of rice, as well as the changes in trade policies of the countries of the ITN of rice observed in the wake of the rice price crisis of 2008.
- **population of agents**: the agents' population is static and features 79 country agents, which represents the trading countries which are part of the ITN, and one institutional agents which represents the PMI.
- **topological space**: network-based. Each agent is a node in the network environment which represents the ITN of rice (see Figure 3.1). The edges between country nodes stand for trading relationships (orange solid lines in Figure 3.1). In addition, the institutional agent is connected to all countries (red dashed lines in Figure 3.1).
- **treatment of time**: the model runs in discrete time. One simulation lasts 200 time steps and correspond to the period January 2006 - December 2008.
- **treatment of fate**: the model is purely deterministic.
- **agent behaviour**: reactive simple-reflex agent, competitive.
- **interactive structure**: non-localized, the agents do not evolve in a spatial environment.
- **learning**: no learning mechanism.

3.1.2 Environment design

Table 3.1 presents the description of the environment of the two type of agents that the simulation features.

Agent type	Environment	Actuators	Sensors
Country agent	Domestic market, markets of trading partners and global markets	Changing trading policy	Private, local and global market information
Institution agent	Domestic markets of all country agents	Transmission of global price information	Attention to countries' domestic market

Table 3.1: Description of the environment of the model

Architecture of the environment

A specification of the environment's architecture in terms of network naturally arises from the object of our modeling exercise. In addition, our literature shed light on the role of network effects related to their structure in emerging properties such as the resilience of the trade network or its ability to foster cooperation between the agents. Together with assumption (**C1**), it justifies to preserve the underlying network's structure that defines the possible agent interactions. Thus, we chose to allow each country agent to interact with other country agent if they are first neighbours in the ITN. The edges of the ITN are weighted based on trade relationships of the countries according to assumption (**C1**), and their integration within the ITN following assumption (**C4**).

Because of the simplified reasoning that we proposed to model countries and institutions decision making, we ruled out more complex agent architecture that we reviewed earlier, that is, situated automata, layered architectures and agent network architectures. In addition, we chose to follow the methodology defined by bottom-up approaches of the economy and calibrate the parameters of our ABM on existing macroeconomic data. Social-network analysis of the trade network encouraged us to make us of network measures to deduce the value of some of them from the network structure of the international trade.

In accordance with assumption (**B2**) and our working hypothesis, we opted for the implementation of a global cross-scale feedback loop in the form of an institution agent, fully connected to the rest of the ITN and responsible for information transmission and potential amplification from countries to the institution agent and back to the countries themselves. This alteration of the structure of the ITN is motivated by the importance of institution agents in spreading information through the network.

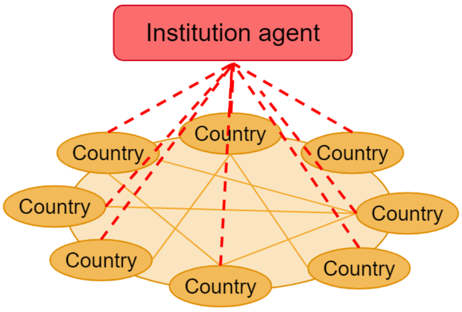


Figure 3.1: Network structure of the model

Properties of the environment

The properties of the environment are the following:

- **Multiagent**: The environment features 79 country agents, accounting for 95.6% of all the rice trade flows in 2006, and one institution agent. In addition, it is competitive from the perspective of the country agents since they implement strategies which are detrimental to the other agents and beneficial for themselves. It is also competitive for the institution agent since these same strategies may increase the value or the volatility of the global price.
- **Partially observable**: Even though PMI such as the FAO and the International Monetary Fund (IMF) monitor and alert about the trend of international prices, they do not systematically report information coming from all markets but from a rather limited of major markets. Thus, based upon the summary statistic used by PMI (see introduction), the institution agent only have access to the market information of the main exporters.Since it seems unrealistic for each country to be able to obtain and analyze the information relative to all domestic markets in the world, we chose to make the assumption that countries only share domestic market and trade policy information with their trading partners and the PMI (**D2**). Thus, we chose the environment of our simulation to be only partially accessible to the simulated agents. Then, even though the main characteristics and structure of the trade network are stable over time, it remains a highly uncertain environment. Consequently, the country agents can only observe the domestic markets of their trading partners.
- **Deterministic**: In the baseline version of the model, the environment is deterministic since the next state of the environment is fully determined by the current state together with the choice of strategy of the country agent and the communication of the institution agent. However, the analysis of the model will explore its sensitivity to noise, thus, the description of our model includes a variable dedicated to introducing noise into the model.

[0]see section 3.2 on data and initialization of the model.

- **Sequential**: Each state of the world depends on the actions taken by the agents during the previous time steps.
- **Static**: The environment does not change while the agent is deliberating. It only changes when all agents have taken their decision.
- **Discrete/continuous**: In the model, time takes discrete steps and prices can take any continuous value.
- **Unknown**: Our research question consists in exploring the effect of the sensitivity of the domestic prices of the country agents to each source of information. Thus, we cannot assume the type of price dynamics that our model will generate. Thus, the environment of the model is unknown.

3.1.3 Country agents

Agent type

Assumptions (**B3**) and (**B4**) ground our approach in behaviourism and bounded rationality. Thus, we chose not to consider implementing deductive or practical reasoning agents on the basis that they are purely rational or utility maximizing which is incompatible with our hypotheses. Thus, we chose to rather develop a reactive agent based on a simple decision rule that we derived from the assumptions (**B5**), (**B6**) and (**B7**).

As for collaboration, the fact that the implementation of protectionist policies for the sake of a country domestic interest is seen as detrimental to its trading partners and potentially to the global market motivates our choice of a model of cooperation among competitive agents. We consider that countries can decide whether or not to cooperate with each other. Because our additional review of the economic mechanisms of trade did not emphasize the role of discussions and negotiations between national governments, but rather described a process of unilateral decision making by single countries, we ruled out deliberative and negotiative agents. Still, because of the crucial role of information transmission between countries and institutions, we chose to make our country agents communicative and to allow them to transmit price and policy information to one another. Because assumptions (**B5**) and (**B6**) define a simplified mechanism for decision making which is assumed to be common to all country agents, we rejected the possibility of implementing social learning and imitation mechanisms. One could argue that the price transmission mechanism defined by the set of corresponding economic assumptions implicitly assume such dynamics.

Our literature review identify the contribution of game theoretical approaches to the modeling of trading agents, and even specifically in the case of protectionism during the crisis. Even though we acknowledged the advantages of building-up upon existing game theoretic approaches of the cooperation between country agents, we argue that we cannot easily determine the exact payoff of such a game. Due to the assumption (**A2**), the same action of changing trading policy may have very different result based on the economic context in which it is implemented. Thus, we would have had to consider an iterated game with changing payoffs based on the state of the environment, an option that we declined due too its complexity.

Finally, we drew upon the agent decision making rule developed by Harras and Sornette (2011). We chose to implement a similar type of rule based on the weighting of three different sources of information and a threshold for decision making. The three sources we retained are the domestic market of one agent, information coming from their trading partners and information delivered by PMI. However, because we chose our baseline model not to be adaptive, we decided not to adapt the learning mechanism described in this publication to our model.

Sensors, actuators and functional mapping

Each country agent i has one sensor and one actuator:

- **Sensor**: domestic price $p_i(t)$
  The domestic price at time step t of the country i expressed in US$
- **Actuator**: strategy $s_i(t)$
  The trading policy implemented by the country i at time step t. The strategy can take two possible values: 0 if the country stays open to free-trade and 1 if it implements a protectionist policy.

The reasoning implemented by each country agent is the following. If the current domestic price moves too far from a target price, the country implements a protectionist policy, otherwise, it stays open to free-trade. The distance to the target price which justifies a change of policy depends on the robustness of each country, defined as the ratio of its relative GDP per capita and its relative trade dependence. At each time step, country i updates its trading strategy, which is its only possible action on the environment, based on the simple following rule.

function COUNTRY−AGENT(*domesticprice*)
persistent: *strategy rule, target price, robustness*

state ⟵ domesticprice

$$\textit{strategy rule} \longleftarrow \begin{cases} \textbf{If } |domesticprice - targetprice| > targetprice \times robustness, \\ \ \textbf{then } strategy \longleftarrow protectionism \\ \textbf{Else,} \\ \ \textbf{then } strategy \longleftarrow freetrade \end{cases}$$

returns strategy

In mathematical terms, it is equivalent to the following equation:

$$\begin{cases} s(t+1) = 0 & \text{if } |p_i(t) - p_i| < r_i.p_i \\ s(t+1) = 1 & \text{otherwise.} \end{cases} \tag{3.1}$$

In words, these formulations mean that if the domestic price of a country agent gets too far from its target price (by a margin which is determined by its robustness), then the country agent changes strategy and moves from free trade to protectionism. It is justified by research suggesting that policy-makers adjust their rates of distortion to domestic food prices to partially offset deviations of international prices from their trend value (Anderson and Nelgen, 2012b).

In addition, each country agent i is characterized by six additional parameters:

- Market integration α_i: The weight of the edge between country i and the institution agent.
- Strength of the trading relationship with country j, $t_{i,j}$: The weight of the edge between country i and country j
- Target price p_i: The value is US$ of the domestic price that each country aims at maintaining.
- Relative GDP per capita GDP_i: Country i relative GDP compared to the other countries, takes its value between 0 and 1.
- Dependency on rice as a food supply d_i: The relative importance of rice for the food supply of each country, takes its value between 0 and 1.
- Robustness r_i: Quantifies the distance of the domestic price to the target price which justifies a change of policy, takes its value between 0 and 1.

Together, they allow to introduce heterogeneity between the different country agent. There are use to adapt the relative importance and sensitivity to these three sources of information by market player.

3.1.4 Institution agent

The institution agent sense the domestic prices and trade policies of all country agents. It acts by computing the global price of rice.

- **Sensors:** domestic prices of all country agents $p_i(t)$ for $i \in [1, 79]$
- **Actuator:** global price $p(t)$

At every time step, it processes all the domestic price and strategy coming from the different agents in order to generate an estimation of the global market price. We chose to implement ,as a baseline, a simple weighted average of the most important market players to account for the limited processing ability of the institutions and the fact that most of them report only information from a few major markets. One of our experiment will investigate the effect of varying the calculation rule of the institution agent.

function INSTITUTION-AGENT($\{p_i(t)\}_i$)
persistent: *aggregation rule*

state $\longleftarrow p_i(t)$
aggregation rule $\longleftarrow p(t) = \sum_{i=1}^{4} p_i(t)$
action $\longleftarrow p(t+1)$

returns $p(t+1)$

In mathematical term, it is equivalent to the following equation:

$$p(t) = \sum_{i=1}^{4} p_i(t) \tag{3.2}$$

with i corresponding to the 4 main importers of the global rice markets (see section 3.2.2)[1]. This rule does not explore the full potential of our model since it does not use the price information of all countries and it does not use any strategy information. These are possibilities that we will explore during the analysis of the model.

3.1.5 Information transmission

In our model, the country agents, which represent national government, only have a limited control over the evolution of the price on their domestic market, that they can influence by changing their trading policy. Apart from this mechanism, the domestic market of each country evolves independently of the country agent by processing information comming from three different sources. This way, the working hypothesis of our research is embedded in the process of information transmission implemented in the model. The working hypothesis assumes the existence of three information feedback loops in the ITN:

1. **domestic feedback loop**: the evolution of the domestic price of a country is influenced by its past variations,
2. **local feedback loop**: the evolution of the domestic price of a country is influenced by the domestic price of its trading partners for the same commodity,
3. **global feedback loop**: the evolution of the domestic price of a country is influenced by the variations of the global price.

[1]In fact, they correspond to the four main export markets in 2006 that is Thailand, Viet Nam, India and the United Stated of America (FAO, 2007d)

The strength of these three feedback loops correspond to the sensitivity of the domestic market to each of this three information sources. They are quantified by the variables x_1, x_2 and x_3, respectively, as shown on Figure 3.2. In addition, assuming that countries are aware of the amplifier effect, the adoption of anti-trade policy by a country agent is assumed to further increase the attention given to the evolution of the domestic price of the country which implemented this policy. The sensitivity of the domestic market of each country to the change in the policy of their trading partners is quantified by the variable λ_l.

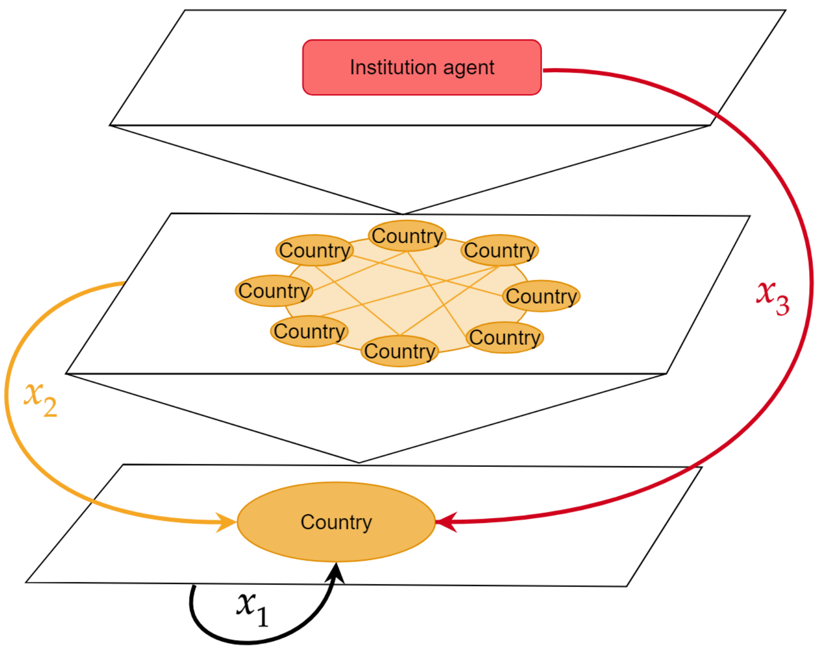


Figure 3.2: Information feedback loops and corresponding parameter

As a consequence, at every time step the domestic market of a country processes information from its past states, its trading partners, and the institution agent, in a fully deterministic-fashion. Let's denote n the number of neighbours of a country agent i. These pieces of information are represented by the following variables:

- Domestic price $p_i(t)$: The domestic price at time step t of the country i expressed in US$
- Domestic price of country j $p_j(t)$ for $j \in [1, N]$,
- Trading strategy of country j $s_j(t)$ for $j \in [1, N]$,
- Global price $p(t)$ computed by the institution agent,

In addition, we define the variable $\epsilon_i(t)$ which correspond to external shocks to the domestic market of country i at the time step t, in order to be able to assess the sensitivity of the model to noise during its analysis.

Price update rule

At each time step, the price of rice on the domestic market of each country is updated according to a predefined rule. This price update rule consists in computing the rate of price change due to all three sources of information.

$$p_i(t+1, s_i(t+1)) = \Big(1 + \sum_{k=1}^{3} x_k.rate_{k,i}\big(t+1, s_i(t+1)\big)\Big)p_i(t) \tag{3.3}$$

At each time step, the domestic price of each country changes by a rate of change which is computed based on the three information loops. Thus, the new price $p_i(t+1)$ is equal to the former price $p_i(t)$ multiplied by $(1 + rate_{k,i})$, with $rate_{k,i}$ being the weighted sum of the rates of change from the three sources of information (domestic, local and global) quantified by the three rates $rate_{k,i}$. The parameters x_k control the sensitivity of the domestic price to each of the three information source. By changing their value, we can investigate the influence of each information feedback loop on the evolution of the prices. In addition, because the evolution of the domestic price also depends on the policy implemented by the country agent, the value of the domestic price is a function of the current strategy of country i $s_i(t+1)$.

Domestic feedback loop (x_1)

The domestic feedback loop quantifies the rate of change of the domestic price caused by its own past variations.

$$rate_{1,i}(t+1, s_i(t+1)) = \epsilon_i(t) + d_i\big(1 - GDP_i s_i(t+1)\big)\frac{p_i(t) - p_i(t-1)}{p_i(t-1)} \tag{3.4}$$

Assuming that large price movements heighten attention to the information they carry (**A3**), the rate of change is proportional to the difference in price observed between the last time step $p_i(t)$ and the second to last time step $p_i(t-1)$. In addition, we divide this difference by $p_i(t-1)$ to obtain a rate of change of the price during the last time step. Thus, if the domestic price of country i increased during the last time step, due to this feedback loop it will further increase in the future. Conversely, if it decreased, it will keep decreasing. The rationale is the following: the economic agents of the domestic markets use the price as a proxi for supply and demand information. Thus, if the price increase, the corresponding information interpreted by the economic agents is that the supply decreased or the demand decreased. In order to anticipate a further price rise, economic agents engage in panic buying or hoarding behaviours which accentuates the trend in the eye of the other economic agents. The variations are only anticipated regarded the last time step assuming a present bias preference of the economic agents of the domestic markets (**B4**). Country agents believe that implementing trade policy will shield their economy from the movements of the domestic price of their neighbours and from the movements of the global price. However, because the actual price transmission is based on information transmission, the actual screening depends on the quality of the institutions of each country, that we correlate with its GDP. Thus, even though countries implement protectionist policies, for most of them they end up being only partially protected from the actual price change of the different markets. Therefore, the factor $1 - GDP_i s_i(t+1)$ correspond to the ability of a country to reassure its domestic market and isolate it from its own price movements which we assume to depend on a country's quality of institutions and thus GDP per capita (**D1**). When the country i implements a protectionist policy $s_i(t) = 1$. For $GDP_i = 1$, the country would have a rate of change of 0 and thus its domestic price would stay constant. In this model, most countries are only partially isolated when they implement a protectionist policy. The factor d_i accounts for the fact that the self-reinforcement of a price trend on the domestic market is assumed to be proportional to the dependence of the country on the commodity for its food security. The more dependent a country, the more it will reinforce an existing trend. The more a country depends on rice for its food security, the more its domestic market will be sensitive to price variations. Finally, the variable ϵ_i is used to introduce noise in the model by generating random shocks to the domestic rate of change.

Local feedback loop (x_2)

The local feedback loop quantifies the rate of change of the domestic price caused by the domestic price of its trading partners.

$$rate_{2,i}(t+1, s_i(t+1)) = \big(1 - GDP_i.s_i(t+1)\big)(1-\alpha_i)\sum_{j=1}^{n_i} t_{i,j}\Big(1 + \lambda_l.\sum_{n=0}^{t-1}\frac{\Delta s_j(t-n)}{r^{t-n}}\Big)\frac{p_i(t) - p_j(t-1)}{p_i(t)} \tag{3.5}$$

with $\Delta s_j(t) = |s_j(t) - s_j(t-1)|$ and $r = 2^{\frac{1}{10}}$ Equation 3.5 is similar to equation 3.4.The factor $1-GDP_i s_i(t+1)$ plays the exact same role. It partially isolates the domestic market from the variations of the domestic price of its trading partners when implementing a protectionist policy. The rate of change is proportional to the difference between the domestic price of the country and the domestic price of its trading partners at the last time step $p_j(t-1)$, assuming a lag in the spread of the price information about its trading partners. Assuming no tariffs, it means that information about the price on the domestic markets of a country trading partners' influences the price on the domestic markets unless the two prices are equal. Thus, if the price is lower on a market and higher on the other, traders on each market will modify their price proportionally to compensate for it. Then, the factor $(1 + \lambda_l.\sum_{n=0}^{t}\frac{\Delta s_j(t)}{r^{t-n}})$ correspond to the impact of a sudden change of trade policy from one of the country trading partners. Based on assumption **A3** that large price movement heighten attention to the information and increase information flow, we consider that a change of policy will also heighten the attention on the corresponding domestic market and will increase price transmission. Thus, if the country partner applies a protectionist policy because of a price rise, its neighbours will suffer from an even higher price rice and conversely, if a country partner switches to free trade because of the decrease of the price, its neighbours will also undergo a price decrease because of the increase of the impact of the announcement. The effect is weighted by the parameter λ_i that we calibrated following the procedure described in section 3.3.3. It is also weighted by the parameter $t_{i,j}$ on the basis that the effects of export bans were more pronounced in countries that import higher share of a commodity from the restricting country than in countries with lower import dependencies (Fackler and Goodwin, 2002), but also because More generally, volatility transmission has been shown to occur more among countries with higher trade dependence (Ceballos et al., 2017). The weighted sum $\sum_{n=0}^{t}\frac{\Delta s_j(t)}{r^{t-n}})$ implements a memory effect corresponding once again to the present bias preference of the agents. It has been chosen so that an information loses half of its impact factor after two weeks, that is 10 times steps in the setting of our simulation. Finally, the factor α_i quantifies the screening effect of a country being very well integrated in the global market described in assumption **C5**. The more integrated in the global market, the less it will pay attention to local information compared to global information.

Global feedback loop (x_3)

The domestic feedback loop quantifies the rate of change of the domestic price caused by the variations of the global price.

$$rate_{3,i}(t+1, s_i(t+1)) = \alpha_i\big(1 - GDP_i.s_i(t+1)\big)\frac{p(t) - p(t-1)}{p(t-1)} \tag{3.6}$$

It is computed based on the same assumption (**A3**) as the two other feedback loops that large price movements heighten attention to the information they carry, thereby increasing price information. Thus, the stronger the variation of the global price, measured by its rate of change $\frac{p(t)-p(t-1)}{p(t-1)}$, the stronger the variation of the domestic market of country i. This variation is computed between the current price and the price at the last time step (and no more back in the past) on the basis of the present bias preference of the agents (see assumption **B4**).

Thus, these four rules define a simplified mechanism for price transmission within the ITN of rice based on information transmission and behavioural assumptions.

3.1.6 Sequence of actions

During the simulation, the variables are updated according to the following stages:

1. **Domestic prices update**
   (a) The domestic price of each country agents is updated,
   (b) domestic price information flows through the network from each country to the institution agent and its neighbours.
2. **Strategy update**
   (a) The trade policy of each country is updated,
   (b) country policy information flows through the network from each country to the institution agent and its neighbours.
3. **Global price update**
   (a) The institution agent computes a global price,
   (b) global price information flows through the network from the institution agent to each country agent.

3.2 Data and initialization

3.2.1 Data

To inform the initialization of our model's parameters, we collected data from several publicly available FAOSTAT and GIEWS - FAO databases which gather food and agricultural data, as well as macroeconomic data for over 245 countries and territories from 1961 (Food and of the United Nations, 2012; GIEWS, 2019).

Network adjacency matrix
We collected import and export quantity for rice (expressed in tonnes of rice milled equivalent) for all available areas and years from the FAOSTAT Detailed trade matrix gathering all food and agricultural products imported and exported for each available reference year by country from 1986 to 2016. We chose to quantify import and export flows by their quantity (in tonnes) rather than their value to minimize the impact of exchange rate in our model. The dataset gathers the trade flows reported by both the importer and the exporter side. However, it has been acknowledge that importer data underestimates the total trade volume compared to data reported by exporters (Fagiolo et al., 2008). Consequently, we chose to average each reported import and export matrices per available year to define a symmetric weighted adjacency matrix of the rice trade network for each available year. Even though this method leads to a slight underestimation of the total traded quantity, it preserves the structural features of the network.

Producer price
We collect the annual producer prices in US$ of all 80 available countries for the year 2006 from the FAOSTAT Procuder Prices database. The list of corresponding countries and prices can be found in appendix. Producer prices are prices received by farmers for rice collected at the point on initial sale but countries vary from this concept in their collection and some of them rather collect the wholesale, local market or retail price of rice.

International and domestic price time-series
From the GIEWS - FAO datasets, we collected 138 domestic price monthly time-series for 27 different countries. The corresponding list can be found in appendix A. We also collect 15 international weekly time-series for

National macro-indicators
We collect the Gross Domestic Product per capita in US$ in 2006 of all 211 available countries and territories from the FAOSTAT Macro Indicators database. From the FAOSTAT Food Balance Sheets database, we collect the domestic supply quantity of rice (milled equivalent) expressed in kg, as well as the import quantity of rice (milled equivalent) for 2004, 2005 and 2006 in all 177 countries and territories available.

National trade policies
Demeke et al. (2009) reports the trade policies of 81 developing countries from Asia, Africa and Latin America and Caribbean during the food security crisis of 2008, among which 35 developing countries who implemented a protectionist policy. We use this information as data to design the empirical validation of our model.

3.2.2 Initialization of the model's parameters

Our model features 79 country agents whose account for 95.6% of all the rice trade flows in 2006. The export market is dominate by four major player (Thailand, Pakistan,the United States of America and Viet Nam), while the import market appears more balanced (see appendix B.2). A summary table gathering the parameters' value of all country agents can be found in appendix B.2.

Network architecture

The network architecture is computed using the yearly adjacency matrices of the ITN from 1986 to 2006 from the FAOSTAT database. Based on assumption (**C1**) and (**C3**), we computed a weighted average of these adjacency matrices (see equation 3.7) accounting for an increase of the market integration in time which also embeds the present bias preference of countries of assumption (**B4**).

For all pair of countries $(i, j) \in [1, 79]^2$, let's $t_{i,j,y}$ be the elements of the adjacency matrix of the ITN for the year $y \in [1986, 2006]$. The weights $M_{i,j}$ of the adjacency matrix M of the trade network of year 2006 are defined as follows:

$$M_{i,j} = t_{i,j} = \sum_{y=1986}^{2006} \frac{t_{i,j,y}}{2^{2006-(y-1)}} \tag{3.7}$$

The $t_{i,j}$ for a specific i define the market share of country i's trading partners in term of the total volume of rice traded by country i. This measure sanctions quite harshly a no-trade year in the short-term but allows for a quick recovery of the trading relationships (in 3 years of uninterrupted trade, it can be restored by more than 90% of its maximal level, by 75% in two-years and by 50% in one year)

In addition, the edges between the institution agent and all other country agents are weighted by their market integration. According to assumption (C4), we associate the value of the market integration of a country to its centrality, based on research showing the importance of the position occupied in the trade network in reducing the price difference between different markets (Bakucs et al., 2015). For a node u, the computational of its closeness centrality based on the Wasserman and Faust improved formula (Wasserman and Faust, 1994) is computed according to the following formula:

$$\alpha_i = \frac{n-1}{N-1} \frac{n-1}{\sum_{j=1}^{n-1} d(i,j)} \tag{3.8}$$

with N the number of nodes, n the number of nodes that can reach u in the network, and $d(v, u)$ the average shortest path distance to u over all $n-1$ reachable nodes.

Domestic price and target price

We initialized the domestic price of countries with the FAOSTAT producer price data presented in the above data section. Because this data was missing for 31 of all chosen countries, we fitted the distribution of available prices to a Pareto distribution of probability density function described in equation 3.9, with $b = 1.23$ as a shape parameter of the distribution and by scaling and shifting the distribution by a factor 124. The corresponding prices can be found in appendix B.2 identified by an asterix. The target price of each country is initiated at the same value than its domestic price.

$$f(x, b) = \frac{b}{x^{b+1}} \tag{3.9}$$

Strategy

The strategy of all countries is initiated with value 1 unless indicated otherwise in the experiment design.

Relative GDP per capita

We computed the relative GDP per capita of each country according to the following formula:

$$GDP_i = \frac{real\ GDP_i - real\ GDP_{min}}{real\ GDP_{max} - real\ GDP_{min}} \tag{3.10}$$

with $real\ GDP_i$ the GDP per capita of country i extracted from data (see section 3.2), and $real\ GDP_{max}$ and $real\ GDP_{min}$ the highest and lowest real GDP per capita among all the country agents.

Relative dependence on rice

We computed the relative dependency on rice as a food supply of each country according to the following formula:

$$GDP_i = \frac{domestic\ supply_i - domestic\ supply_{min}}{domestic\ supply_{max} - domestic\ supply_{min}} \tag{3.11}$$

with $rdomestic\ supply_i$ the domestic supply quantity of rice of country i extracted from data (see section 3.2 on national macro-indicators), and $real\ GDP_{max}$ and $real\ GDP_{min}$ the highest and lowest domestic supply quantity of rice among all the country agents.

Because the FAOSTAT dataset were missing the value of domestic supply quantity of rice for Qatar, Somalia, Singapore and Syria, we initiated their values based on the literature (see appendix B.2).

Robustness

Based on assumption (**B8**), we initialized the robustness of a country to price change using its relative GDP compared to world's distribution and its relative dependence on rice according to equation 3.12.

$$r_i = \frac{GDP_i}{d_i} \tag{3.12}$$

3.3 Analysis of the model

A model $M_{(P,I_0)}$ is characterized by a set of four parameters $P = x_1, x_1, x_3, \lambda_l$ and initial conditions I_0 which are detailed in section 3.2.2.

This section presents the methodology of the analysis of the model's behaviour. Since ABM generally do not have an analytical solution, the analysis aims at identifying general propositions about the dynamic of the model based on the outcome of a finite number of simulations (Richiardi et al., 2006). This goal motivates the design of the simulations to be conducted, the choice of the variables to investigate and the scope of the analysis to conduct over these variables. Following Richiardi et al. (2006)'s framework for agent-based social simulations, the following subsections define the analysis of the model as follows:

1. Scope of the analysis
2. Investigation of the model
3. Calibration of the model
4. Sensitivity analysis
5. Validation of the model

Subsection 3.3.1 specifies the type of analysis being performed and motivates the choice of the variables used to characterize the model regarding the hypothesis and goal of the research. The subsequent sections all correspond to one step of the analysis. Subsection 3.3.2 corresponds to the exploration of the behaviour of the model in the parameter space. Its goal is to determine whether information feedback loops can cause price inflation and lead to global food crises, as we hypothesized. By exploring ranges of values for the parameters which control the strength of each feedback loop, the corresponding results should provide a first answer to our research question on whether it is possible to prevent or reduce the severity of food crises by modifying the strength of the three feedback loops. Subsection 3.3.3 defines a measure to choose the values of the model's parameters for the simulation to best fit the real-life data on the food crisis. Defining this measure is a crucial step to reach the goal of the research to design an ABM capable of generating the price dynamics and changes in trade policies observed during the crisis. Subsection 3.3.4 consists in designing additional experiments to reveal potential variations in the behaviour of the models by altering the value of its inputs. Thereby, it tests the robustness of the observations made in subsection 3.3.2 as well as the validity of the design choices we made earlier. It also aims at investigating the role of the structure of the institutional information feedback loop in the unfolding of price crises through the study of alternative information aggregation processes at the institution level. Finally, subsection 3.3.5 defines a validity measure of the models used during the analysis in order to assess their degree of similarity with the real-world process of formation of the rice prices. This last subsection is also of critical importance in quantifying to which extend the goal of the research has been reached and to quantify the extend of the validity of the results it presents.

3.3.1 Scope of the analysis

The analysis of the model is designed to test the hypothesis that the price spike in the global price of rice observed in 2008 can be generated by information feedback loops within the ITN of rice. Therefore, it requires to identify the type of behaviours of the global price of rice that the model is able to generate. To do so, we define a measure of the convergence of our model, together with four aggregate variables that we considered relevant to explore the simulated.

Convergence measure

Thus, the first step of our analysis consists in a coarse characterization of these behaviours by identifying for each simulation whether the global price of rice convergences toward an equilibrium value, takes unrealistically high or low values or stays bounded within a reasonable interval of values. Subsequently, we define the convergence condition of the model as follows:

Convergence condition

For a given set of parameters P and a given set of initial conditions I_0, the model $M_{(P,I_0)}$ converges if the standard deviation of the global price during the last 50 steps is smaller than 2US$, that is, if equation 3.13 holds.

$$\sigma(M_{(P,I_0)}) < 2US\$ \tag{3.13}$$

with $\sigma(M_{(P,I_0)}) = \sqrt{\frac{\sum_{i=150}^{200}(p(i)-\overline{p})}{50}}$ the standard deviation of the global price computed for the last 50 time steps of the simulation and $\overline{p} = \sum_{i=150}^{200} \frac{p(i)}{50}$ the average global price during the last 50 time steps of the simulation.

This definition is relative to the time of the simulation. It defines a convergent model has a model which converged within the time of the simulation, that is, within 200 time steps. It is thus tailored to our application rather than to the assessment of asymptotic behaviour in the mathematical sense. We recall that our time scale has been chosen so that 200 time steps correspond to two years, which only covers the time scale of the food crisis. Thus, the last 50 steps used in this definition correspond to 6 months in real time scale. Therefore, it correspond to a short-term definition of convergence. Considering that food prices reported in the FAOSTAT reports and in the literature before the crisis (FAO, 2004a) undergo variations of the scale of several tenth of US dollars per tonne per month, our definition of convergence based on a range of only 2US$ is a hard condition compared to real-life conditions. It aims at identifying the most extreme possible behaviours of the model. Based on this definition of convergence, we classified the main behaviours exhibited by the model in three categories defined as follows. For a given set of initial values I_0 and model's parameters P:

- **Bounded**
  A model $M_{(P,I_0)}$ is said to be bounded if the global price computed by the institution $p(t)$ stays within the $[0, 10.p_{max}]$ interval defined in the validation section (3.3.5),
- **Convergent**
  A model $M_{(P,I_0)}$ is said to be convergent if it is bounded and if it respects the convergence condition, that is, if the standard deviation of the global price during the last 50 steps is smaller than 2. In addition, we further distinguish between "convergent high" type of models for which the global price converges to a higher value than its starting value at the beginning of the simulation, and "convergent low" for which the global price converges to a lower value than its starting value.
- **Divergent**
  A model $M_{(P,I_0)}$ is said to be divergent if it is not bounded.

Figure 3.3 shows a visual interpretation of the definition. In divergent models the global price diverges outside of the 0-10700US$ price interval (orange area on the Figure) and takes unrealistic values (red areas on the Figure). In bounded models, the global price does not converge but stays positive and below the critical value of 10700US$ (orange area). In convergent models the global price computed by the institution agent stays bounded and converges towards a fixed value within the 200 time steps of the simulation (see green area in the model). According to this definition, a realistic model of the price crisis has to be a bounded model. Therefore, it will restrict our search of an appropriate model to bounded models only rather than all models explored during the investigation step.

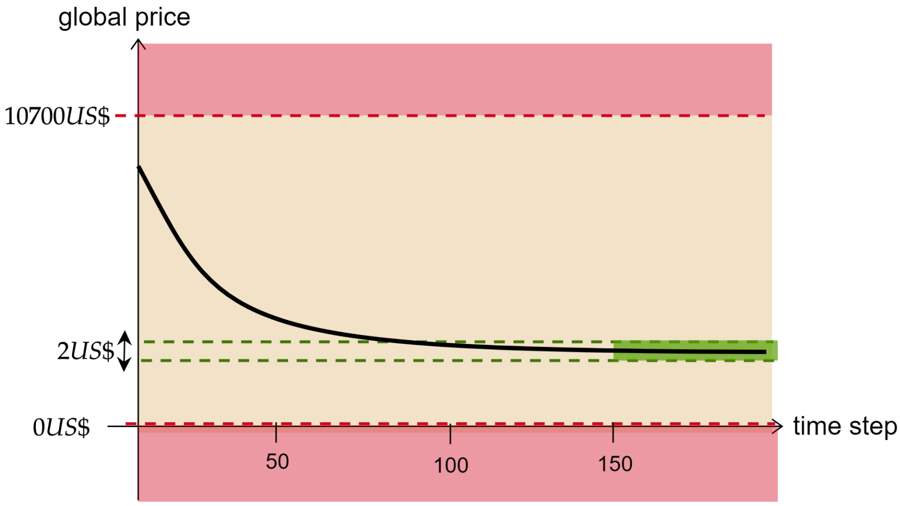


Figure 3.3: Convergence type define for the analysis of the model on an example time-serie (black curve). If a simulated global price time-series reaches the red areas than the corresponding model is divergent. If it stays within the orange area then it is bounding. If it stays within a 2US$ range of its final value during the last 50 steps of the simulation, corresponding to the green area on this figure, than it is convergent.

Aggregate variables

Since we aim at understanding the role of each feedback loop on the dynamics of the global price, we further characterize their influence on it thanks to three variables. In addition, one variable is used to assess the hypothesis that change in trade policies can generate price crisis by increasing the variations caused by information flow within the ITN. We focus our investigation on convergent models even though they are not realistic because they are stable and thus allow to quantify the relationship between each variable of the model and the simulated global price more easily than in bounded models. Thus, the first three variables that we introduce are mostly designed for the investigation of convergent models even though they also apply to bounded ones. They are used to characterized the three main variables of the model: the global price, the domestic prices and the trading strategy of each country agent. The global price is characterized by its value at the last time of the simulation which allows to compare convergent models with one another on the basis of different values of their parameters. The domestic prices are characterized by the spread of their distribution at the last time step of the simulation. Once again it allows to compare convergent models with one another and see how each feedback loop may lead the domestic prices to converge to a same value. This way it allows to compare the outcome of our model with the LOP which predicts that under certain conditions the prices in all markets align to a common equilibrium value. Finally, this measure allows to aggregate the potential diversity of prices between countries in a single variable. Finally, the trading strategy of each country agent is characterized by its value at the end of the simulation. Since the number of defections only depends on the global price, its value stays constant if the price stays constant as well. Therefore, even though this variable is not telling as for the influence on the change in trading strategy on the dynamic of the global price, it allows us to identify the effect of each parameter on the number of defecting countries in convergent models. Finally, the last variable that we introduce is the volatility of the global price measured by the standard deviation of the generated time-serie. It is the only measure that can be interpreted easily regardless of the type of model under study. Since we assumed that the change of trading strategies generate more price instability, testing this hypothesis requires to use a measure which can account for changes in the dynamic of the model. Thus, the study of the volatility of the global price aims at characterizing the influence of the change of trading strategy on the dynamic of the global price all along the simulation.

Aggregate variables explored

For a given set of parameters P and a given set of initial conditions I_0, we explore the behaviour of the model $M_{(P,I_0)}$ using the following aggregate variables:

- The final value of the global price computed by the institution agent:

$$p_{final}(M_{(P,I_0)}) = p(t = 200) \tag{3.14}$$

with $p(t = 200)$ the value of the global price computed by the institution agent at the time step 200 of the simulation.

- The final value of the spread of the distribution of the domestic price for the N=79 country agents measured by its standard deviation:

$$\sigma_{domestic}(M_{(P,I_0)}) = \sum_{i=1}^{N} \sqrt{\frac{p_i(t = 200) - \overline{p_i(t = 200)}}{N}} \tag{3.15}$$

with $\overline{p_i(t = 200)} = \sum_{i=1}^{N} p_i(t = 200)$ the average of the domestic price of all countries at the end of the simulation.

- The final number of defections, that is, the number of country agents implementing a protectionist policy at the end of the simulation:

$$s_{final}(M_{(P,I_0)}) = \sum_{i=1}^{79} s_i(t = 200) \tag{3.16}$$

with $s_i(t = 200)$ the strategy of the country agent number i at the time step 200 of the simulation

- The volatility of a price time-serie generated by the model is its average standard deviation:

$$\sigma_{global}(M_{(P,I_0)}) = \sum_{t=0}^{200} \sqrt{\frac{p(t) - \overline{p}}{200}} \tag{3.17}$$

with $\overline{p} = \sum_{t=1}^{200} p(t)$ the average of the global price over the simulation.

Scope of the analysis

From these measures and their motivations, we can define the scope of the analysis that is conducted. Following Richiardi et al. (2006), the exploration of an ABM can be done in two ways:

- **Full exploration**: the behaviour of all meaningful individual and aggregate variables is explored, with reference to the results currently available in the literature.
- **Partial exploration**: the model is investigated only with respect to a subset of all defined variables.

In addition to the time-serie of global price simulated, for each simulation, at each time step our model generates the domestic price and the strategy or all 79 agents. Therefore, each simulation generates 200 values for 159 different variables (2 for each country agent and 1 for the institution agent). This large number of variable makes it challenging to conduct a full exploration of each model. It justifies the use of the four aggregate variables previously introduced to characterize the behaviour of all simulation. Consequently, the analysis conducted consists in a *partial exploration* of each model. In addition to it, we chose to display a few additional figures in appendix to show more disaggregated behaviours when we judged it relevant for the discussion.

We further define our analysis regarding Richiardi et al. (2006)'s definition of equilibrium. The analysis of a model can be performed in equilibrium, out-of-equilibrium or both. Two definitions of equilibrium are to be considered:

- **Micro-level equilibrium:** a state where individual strategies are constant.
- **Macro-level equilibrium:** a state where some relevant (aggregate) statistics of the system are stationary.

Since food crises are characterized by important price variations over time, most of our models are not stationnary. In the case of the convergent models, one could consider them as stationnary at the level of the global price over the last 50 time-steps of the simulation. To this regard, the three first variables that we introduced allow to conduct an analysis of the model at a macro-level equilibrium. However, in all other cases, the analysis is conducted *out-of-equilibrium* at both the micro and macro-level.

3.3.2 Investigation of the model

The investigation of the model consists in trying to determine its behaviour in the parameter space. The parameters of the model consists in two sets of variables. First, the three x_k which control the strength of each feedback loop by altering the rate of change of the domestic price caused by price information from the three sources of information (domestic for x_1, local for x_2 and global for x_3). They are used to investigate the hypothesis according to which these three information feedback loops can cause price inflation and lead to global food crises. Second, λ_l quantifies the amplification of the local rate of change of the domestic price caused by a trading partner announcing a change of trade policy. Therefore, it is used to investigate the hypothesis according to which the change of trading policy during the crisis further increased its severity. Following Richiardi et al. (2006)'s methodology, these parameters can be investigated in either a local or a global fashion:

- **Global investigation**: analysis of the behaviour of the model in a broad region of the parameters' space
- **Local investigation**: analysis of the behaviour of the model only in restricted regions of the parameters' space.

A local investigation requires to have an estimated value of the model's parameters so to explore the parameters space in a restricted region located around these values of the parameters. In this model, that requires to have either empirical data or expert knowledge as for the strength of the three feedback loops to properly set the values of the x_k. However, since the information feedback loops were designed from the top-down, that is informed by the theory rather than based on empirical data, it is not possible to estimate the precise numerical value of these parameters.

In the global and local investigation of the x_k simulations, we chose not to account for the additional information effect of the change of trading strategy of each country. Thus, all countries are fully cooperative and there is no external shock. In order to understand the qualitative effect of each x_k on the global price computed by the institution agent in each of the simulated model, we classified its behaviour in the parameter space.

Therefore, we first conduct a *global investigation* for the x_k as well as local investigations for one or two parameters being fixed, that is for slices and along straight lines in the 3D-parameter space. Once the calibration done, the sensitivity analysis and the validation of the model are done locally. In practice, they are only conducted for the most realistic models identified in the calibration step. Since the x_k correspond to a rate of change in the domestic price of each country, we assumed that this rate should remain close to 1 and consequently that the x_k should take values between zero and one. Therefore, we chose to investigate the following values of the x_k:

Global investigation of the x_k

For $\lambda_l = 0$, we explored the following parameters' space:

$$x_1 \in [0.01, 1],\ x_2 \in [0.02, 2],\ x_3 \in [0.02, 2] \tag{3.18}$$

for 20 points in each interval $[x_k(0), x_k(n)]$ picked according to the following log-scale. For $i \in [0, 19]$ and $n = 20$:

$$x_k(0)\Big(\frac{x_k(n)}{x_k(0)}\Big)^{(\frac{i}{n-1})}$$

Since we investigate values of the parameters between zero and one and we aim at exploring relatively small values of the x_k since they represent rates of change, we chose to explore a log-range of values between 0 and 1. Thus, we studied the behaviour of 8000 different models within this parameter space. To better understand the effect of each of the three feedback loops (private, local and global) and their interactions, we then conducted a local exploration of the x_k by either varying one of them, or two of them at a time.

Local investigation of the x_k

For the three x_k, we conduct a local investigation in restricted parts of the parameters' space:

1. for one varying parameter:
   - for $x_1 \in [0.01, 1]$, $x_2 = 0.02$ and $x_3 = 0.02$,
   - for $x_1 = 0.01$, $x_2 \in [0.02, 2]$ and $x_3 = 0.02$,
   - for $x_1 = 0.01$, $x_2 = 0.02$ and $x_3 \in [0.02, 2]$
2. for two varying parameters:
   - for $x_1 \in [0.01, 1]$, $x_2 \in [0.02, 2]$ and $x_3 = 0.467$,
   - for $x_1 \in [0.01, 1]$, $x_2 = 0.109$ and $x_3 \in [0.02, 2]$,
   - for $x_1 = 0.112$, $x_2 \in [0.02, 2]$ and $x_3 \in [0.02, 2]$.

Due to the computational costs of running thousands of models, we chose to perform a partial investigation of the λ_l's parameter space. Taking a global approach, we explored the full x_k parameters' space for 3 different values of λ_l that we chose based on prior knowledge. λ_l quantifies the increase in the variation rate of the domestic price of a country due to the change of policy of one of its trading partner.

Global investigation of the λ_l

We explored the following values of λ_l:

$$\lambda_k \in \{0.1, 0.5, 2\} \tag{3.19}$$

within the intervals of x_k defined previously but for 10 points rather than 20, that is, for $i \in [0, 9]$ and $n = 10$:

$$x_k(0)\big(\frac{x_k(n)}{x_k(0)}\big)^{(\frac{i}{n-1})}$$

By setting $\lambda_l = 0.1$, we increase the variation of the domestic price of all countries due to local information coming from a trading partner by 10% at each time step when this partner changes its trading policy. For $\lambda_l = 2$, we double the price variation. Since we explored 10 values for each x_k, we ran 1000 different models for each value of λ_l, that is 3000 models in total.

3.3.3 Calibration of the model

The calibration of the parameters consists in choosing the values of the parameters that maximise the accordance of the model's behaviour with the real-world system (Richiardi et al., 2006; Leombruni and Richiardi, 2005). It consisted in adjusting the weighting of the price update rule (corresponding to the x_k equation 3.3)as well as the scaling factor λ_l of the impact of the implementation of a protectionist policy by one country one the domestic market of its neighbors (see equation 3.5). We chose to calibrate our model such as 200 times account for the two years of the food crisis, that is one time step corresponds to 3-4 days, as a reasonable trade-off between the resolution of the model and its computation time. To identify the most realistic model, for all models explored, we computed the Pearson correlation between the time-serie of the global price for bounded and convergent models and a time-serie of reference for the international price of rice between January 2007 and January 2009.

Correlation measure

The correlation between the reference time-serie between January 2007 and May 2008 scaled-up to 40 time-points and 160 different time-windows of the global price time-serie of the model of length 40 time-points:

$$corr(M_{(P,I_0)}) = max_{j\in[0,160]}\ corr\big(ref, p(j, 40+j)\big) \tag{3.20}$$

with $corr\big(ref, p(j, 40+j)\big) = \begin{cases} corr\Big(\big(ref, p(j, 40+j)\big)\Big) \text{ if } \sigma(p(j, 40+j) > 100\text{US\$}, \\ 0 \text{ if } \sigma p(j, 40+j) \leq 100\text{US\$}. \end{cases}$
and ref the time-serie of reference for the period January 2007 and May 2008 up-scaled to 40 time points[2].

Thereby, we identified 64 most correlated models among the 3000 models investigated for the three values of λ_l. Because the two time series to compare are of different sized, we averaged our time series of length 200 to length 40 and removed the 3 first terms to correlate them with the time series of real data of length 37. Because we do not want to reject models which may be well correlated but with a time delay, we use a sliding window and computed the correlation for the corresponding 8 possible time

[2]The procedure used to scale-up the time-serie can be found in appendix C.

windows. We then define the correlation of the global price in a model as the correlation coefficient of the highest correlated time window.

3.3.4 Sensitivity analysis

The sensitivity analysis consists in altering the input values of the model to corroborate the main results of the simulation and reveal possible variations in the results (Richiardi et al., 2006). For our model it has a threefold purpose. First, these sensitivity analyses aim at testing the robustness of the observations made in subsection 3.3.2. The results of these earlier simulations can be said to be significant if they occur when the output values are robustness to this alteration of the input values. Thus, we design two sensitivity analyses to investigate the sensibility of our model to parameter variations for the parameters that were not fully calibrated on empirical data (initial domestic price and initial strategy of the country agents). In addition, we test its robustness to noise of different amplitudes. We then define a robustness measure which encompasses these three first sensitivity analyses. Second, the purpose of the sensitivity analyses we conduct is also to explore our research question on the role of the three information feedback loops in the genesis of price crises and the effect of alternative information aggregation processes at the institution level. Consequently, we conduct a sensitivity analysis to the level of data aggregation done by the institution agent. Finally, these analyses also fulfill the purpose to quantify the level of validity of the design choices made for the initialisation of the model, its structure and the type of aggregation done by the institution agent. Eventually, we conducted the following sensitivity analysis on the most correlated models identified in the calibration:

- sensitivity to initial domestic price distribution,
- sensitivity to initial strategies of the country agents,
- robustness to noise in the domestic prices of the country agents,
- sensitivity to variation in the level of data aggregation.

Sensitivity to initial price distribution

We investigated the sensitivity to parameter variations of our model to quantify the impact of potential errors and uncertainty in the initial value of the domestic price. For all most correlated models, we initiate the model with 10 different initial domestic price distributions. For each most correlated model, the 10 domestic price distributions are randomly drawn from the following Pareto distribution:

$$f(x, b) = \frac{ab}{(a + x)^{b+1}}$$

with $b = 1.23$ and by scaling and shifting the distribution by a factor $a = 124$.

Sensitivity to initial strategies

We tested the impact of the assumption of initial full cooperation of the country agents. We initialized our model with 3 different percentage of defectors: 0.2, 0.5 and 0.7. For each ratio, we tested 10 different initial distributions of defectors among the population of country agents. In other word, for each proportion $p \in [0.2, 0.5, 0.7]$, we ran 10 simulations where the value of the initial strategy of each country was randomly drawn from a binomial distribution or parameter p. Thereby, each simulation was initiated with approximately p percent of defectors in the population of country agents.

Sensitivity to domestic price shocks

So far, the model's design as been done in a purely deterministic fashion in order to evaluate the impact of the x_k and λ_l independently of any other factor. However, by adding noise in our model, we aim at evaluating the resilience of our model to external shocks and identify the relative role of internal and external dynamics in the development of crises. We used the variable $\epsilon_i t$ to generate random shocks to the domestic markets of each country. At each time step, a random realization was drawn from a logistic distribution centered in 0. We explored 10 values of λ taken in the following interval in log-scale:

$$\lambda \in [0.01, 1]$$

Robustness measure

We aim at identifying whether the global price's behaviour of the calibrated models is robust or arises from a specific combination of initial conditions and parameters. Thus, for all models, we quantify the general results of the sensitivity analysis using the following measures:

Robustness measures

The robustness of a run of a model is equal to one if the model did not change convergence type during the run, that is, if it is still bounded.

- **Global**
  For each model tested, its global robustness is the average of the 3 following robustness.
- **Initial Price**
  For each model tested, its robustness to initial price is the average of its robustness for each of the 10 run, that is, the 10 different distribution of initial price randomly generated.
- **Initial Strategy**
  For each model tested, its robustness was first computed separately for each of the 3 values of p tested and than averaged. For each value of p tested, the robustness of a model is the average of its robustness for each of the 10 run, that is, the 10 different distribution of initial defectors in the population randomly generated.
- **Shocks**
  For each model tested, its robustness to shocks is the average of its robustness for each of its 10 runs, that is, for the 10 different amplitude of shocks tested.

Sensitivity to variation in the level of data aggregation

This sensitivity analysis is designed to investigate the effect of alternative information aggregation processes at the institution level. Thereby, it tests the role of the structure of the institutional feedback loop in the unfolding of price crises. The current measure of global food crises is the international price of rice, which is communicated by PMI such as the IMF, the FAO, the AMIS and the USDA. As discussed earlier, most of them only use quotations on a very limited number of export markets to compute the global price of rice. We modelled this effect through the aggregation rule of the global price computed by the institution agent which, in the benchmark model, is the weighted sum of the domestic price of the four largest rice exporters in 2006 (Thailand, Vietnam, the United States and India). In this sensitivity analysis, we test alternative rules for the computation of the global price by the institution agents. This way, we explore the influence of the cross-scale feedback loop between the institution agent and the country agents in shaping the price dynamics. We replaced the computation of the global price (see equation 3.4) done by the institution agent by the four following alternatives:

1. **Average over all countries (Avg):**
   $global\ price(t) = \sum_{i=1}^{N} \frac{1}{N} p_i(y)$.
   Rather than averaging the domestic price of the four main exporters, the institution agent now average the price of all country agents to compute the global price.

2. **Weighted average over all countries (Avg trade)** based on their market share in the ITN of rice:
   $global\ price(t) = \sum_{i=1}^{N} t_{i,1} p_i(y)$ with t_i the share of country i in the ITN of rice.
   Rather than averaging the domestic price of the four main exporters, the institution agent now average the price of all country agents proportionally to their weight in the ITN of rice to compute the global price. Therefore, this measure gives more weight to the four main exporters again but does not completely disregard the effect of price variations on the domestic markets of other countries.

3. **Weighted average over all countries and perception bias (Avg strat)**:
   $global\ price(t) = \sum_{i=1}^{N} (1 + 0.5|strat_i(t) - strat_i(t-1)|) t_i p_i(t)$ with t_i the share of country i in the ITN of rice. In addition to what is described in the previous rule, the institution agent amplifies the trend of all countries which changed their trading strategy by 50%. For instance, if the price of rice decreased by 20US$ in Thailand and Thailand just switched from protectionism to free-trade, the perceived price change will be a decrease of 30US$.

4. **No global information (None)**:
   $rate_{3,i}(t+1, s_i(t+1)) = 0$ for all $t \in [0, 200]$ and $\alpha_i = 0$ for all country agents i.
   The institution agent is excluded from the simulation.

For all 64 most realistic models of the food crisis identified during the calibration, we run the same simulation than used for for the investigation of the benchmark model, using the same initial conditions (full cooperation of the agents, no shocks to the domestic prices during the time of the simulation, same initial value of the domestic prices). Thus, we ran a total of 256 additional simulations.

3.3.5 Validation of the model

Once we identified the most correlated model, we quantified their validity. Thus, in this section we propose a validity measure of our ABM of price dynamics for the international trade of rice. Windrum et al. (2007) define the empirical validation of an ABM as "the process by which a modeller tries to evaluate the extent to which his/her model data-generation-process is a good representation of the real world data-generation-process.". We follow Axtell and Epstein (1994)'s approach, presented in the literature review, to design a measure of the validity of an ABM of the 2008 food security crisis. We recall the empirical macro and micro-structures that our model aims at generating and for each of them we propose a qualitative and a quantitative measure of the model performance based on available empirical data. Our model uses one macro- and two micro-variables upon which we build a validation measure.

Global price (macro structure)
The international price of rice of the four largest rice exporters is the macro-indicator of the price dynamics international trade of rice that we defined in this model. Level 0 of validity only requires the model to produce a caricature of reality. To qualitatively and quantitatively characterize the empirical behaviour of the global price, we compute the characteristics of an ensemble of international prices of rice during the 2008 price crisis using the monthly price (US$/tonne) time series from January 2006 to

December 2009 for 4 international export markets in Thailand (4 different export markets), Vietnam (2 different export markets), India and the United States. In order to give the same weight to each country, we averaged the 4 time-series from Thailand together, as well as the 2 time-series from Vietnam, thus define 4 time-series of reference, one per country. Figure 3.4 shows the mean, the median as well as the maximum and minimum values taken by these 4 time-series for each point in time. The highest observed price during the chosen time range is $pmax = 1070US\$$. From this data, we characterize level 0 validity of the global price by a graphically shown spike-like behaviour within the reasonable price range $[0, 10pmax]$[3] and with a similar change in the slope of the global price. This choice is justified by the fact that a crisis has been characterized in the literature by a sharp increase in price in a short period of time (Headey and Fan, 2010; Timmer, 2009). We further consider the simulated global price valid at the level 1 if for each corresponding time step, that is between January 2007 and May 2008, it falls between the maximum and minimum value taken by the 4 price time series. Visually, this requirement holds if the simulated price for each time step stays within the grey area on Figure 3.4 for the time period highlighted in red on the x-axis.

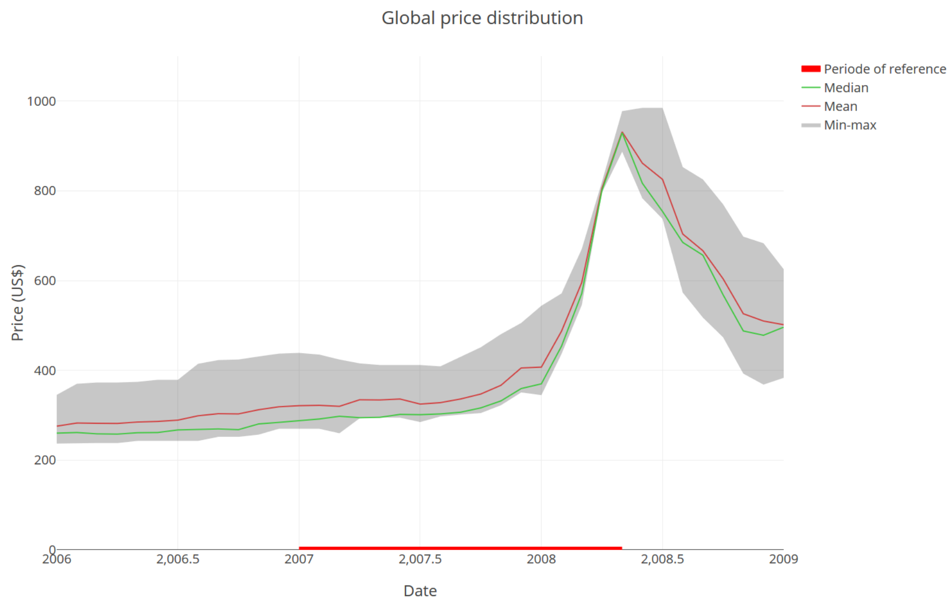


Figure 3.4: Main characteristics of export price of rice from 10 international export market price time-series

To quantitatively characterize the global price, we compute the Pearson correlation matrix between the 4 time-series and their average (see Figure 3.5). All 4 time series are significantly correlated with each other with correlation coefficients all higher than 0.94 except for India (25% broken) and US (Long Grain 2.4%). In addition, the mean of the 4 time series is significantly correlated with all the 4 time series with a correlation coefficient of at least 0.98 for each time series. Therefore, we choose to use this computed average of the 10 time series as a benchmark for the simulated prices. A simulated time-series of global price is considered quantitatively valid at the level 2 and 3 if it is significantly correlated with the mean time-series (p-value lower than 0.001) with a correlation coefficient of at least 0.9 for the time-period of the simulation corresponding to January 2007 to May 2008.

[3]Even if the price rise started immediately from the beginning of the simulation and increased by a factor equals to the average slope of the global price shown in Figure 3.4 between January 2008 and May 2008, the final value of the price would still stay within this $[0, 10pmax]$ interval.

	Thailand	US	India	Viet Nam	Mean
Thailand	1	0.98	0.95	0.97	1
US	0.98	1	0.85	0.94	0.98
India	0.95	0.85	1	0.95	0.97
Viet Nam	0.97	0.94	0.95	1	0.98
Mean	1	0.98	0.97	0.98	1

Figure 3.5: Correlation matrix between price time series and their average (p-value$< 10^{-15}$ for all values)

Domestic price (micro structure)

The first indicator of the micro-structure of the rice price crisis is the variation of domestic prices in the simulated countries. Since our literature review did not identify specific domestic price trends which would be characteristic from the crisis, the level 0 of validity that we propose only requires all domestic prices to stay within the $[0, 10pmax]$ price range defined earlier. We consider 139 available monthly price time series of 27 countries among our simulated countries (see table B.1). The highest and lowest price values encountered in all 139 time series are $p_{minseries} = 137.8 US\$$and $p_{maxseries} = 990 US\$$. However, because we only found time series for 27 countries of the 79 countries that we simulate, the lowest (respectively highest) initial agent price happens to be lower (respectively higher) than $p_{minseries}$ (respectively $p_{maxseries}$ series). Therefore, we cannot use these 139 time series to design a validation measure for the domestic prices of all agents but we have to limit ourselves to the corresponding 27 country agents. Therefore, level 1 and 2 of validity requires to all domestic prices to stay within the [0,p_{max}]interval and [$p_{minseries}$,$p_{maxseries}$] for the 27 countries for which we have time serie information. For level 3, we require for the 27 country agents with available time-series a significant correlation between the mean of the available time series and the generated time-serie of domestic prices for the time period of the simulation corresponding to January 2007 to May 2008, with a correlation coefficient of at least 0.75.

Countries with available monthly time series (27)	Others (52)
Africa Ghana (4), Madagascar (2), Mali (4), Mozambique(8), Niger (10), Senegal (9), Somalia (9), South Africa (1), Togo (6), United republic of Tanzania (1)	**Africa** Benin, Cameroon, Côte d'Ivoire, Egypt, Guinea, Guyana, Jordan, Kenya, Nigeria, Yemen
Asia Bangladesh (1), India (8), Israel (1), Nepal (1), Pakistan (10), Philippines (26), Thailand (2)	**Asia** Afghanistan, China, Hong Kong, Taiwan, Indonesia, Iran, Iraq, Japan, Kuwait, Malaysia, Oman, Qatar, Republic of Korea, Saudi Arabia, Singapore, Syrian Arab Republic, United Arab Emirates,Viet Nam
Europe Italy (1)	**Europe** Belgium, Czechia, France, Germany, Greece, Netherlands, Poland, Portugal, Russian Federation, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom
Latin America & Caribbean Brazil (3), Colombia (7),Costa Rica (2), Ecuador (3), El Salvador (1), Guatemala (2), Haiti (10), Mexico (4), Nicaragua (3)	**Latin America & Caribbean** Argentina, Cuba, Honduras, Uruguay
	North America and others Australia, Canada, United States of America

Table 3.2: List of countries with available time serie for the period January 2006 - December 2009. The number of time serie per country is specified into brackets.

Strategy (micro structure)

The second indicator of the micro-structure of the rice price crisis that our model encompasses is the distribution of the strategy chosen by the agents at each time step. At each time step, an agent can choose whether to keep trading normally or to apply a protectionist policy. Our literature review pointed out the simultaneity of the increase in the number of countries implementing protectionist policies in the wake of the price surge. Therefore, level 0 of validity requires for the distribution of strategy among countries to reflect this trend of having an increase in protectionist behaviours as the price increase. Demeke et al. (2009) reports the trade policies of 81 developing countries from Asia, Africa and Latin America and Caribbean during the food security crisis of 2008, among which 35 developing countries who implemented a protectionist policy. However, this publication does not explicitly report the full list of the 81 countries surveyed but only the one who changed their domestic or trade policy during the crisis. Therefore, among the 79 countries modelled in our simulation, only 33 of them have been identified as protectionist in Demeke et al. Based on our literature review, we chose to make the assumption that all European and North American countries modelled as well as Australia did not implement a protectionist policy during the crisis. Still, 28 countries remain out of the scope of both Demeke et al.'s survey and our assumption.

Simulated countries reported as having implemented a protectionist policy (33)	Countries assumed not to have implemented a protectionist policy (18)	Others (28)
Africa (12) Benin, Cameroon, Guinea, Jordan, Kenya, Liberia, Madagascar, Niger, Nigeria, Senegal, United Republic of Tanzania, Yemen	**Europe (15)** Belgium, Czechia, France, Germany, Greece, Italy, Netherlands, Poland, Portugal, Russian Federation, Spain, Sweden, Switzerland, Ukraine, United Kingdom	**Africa (7)** Côte d'Ivoire, Ghana, Mali, Mozambique, Somalia, South Africa, Togo
Asia(14) Bangladesh, China, Egypt, India, Indonesia, Iran (Islamic Republic of), Nepal, Pakistan, Philippines, Republic of Korea, Saudi Arabia, Thailand, Turkey, Viet Nam	**North America and others (3)** Australia, Canada, United States of America	**Asia (13)** Afghanistan, Hong Kong, Iraq, Israel, Japan, Kuwait, Malaysia, Oman, Qatar, Singapore, Syrian Arab Republic, Taiwan province of China, United Arab Emirates
Latin America & Caribbean Argentina, Brazil, Ecuador, El Salvador, Guatemala, Mexico, Nicaragua		**Latin America & Caribbean (8)** Chile, Colombia, Costa Rica , Cuba, Guyana, Haiti, Honduras, Uruguay

Table 3.3: Empirical evidence and assumptions of countries' strategy during the crisis

According to table 3.3, among all simulated countries the empirical share of countries which allegedly implemented a protectionist policy is 0.41. Since there is an uncertainty about the actual policy implemented by Asian, African, Latin American and Caribbean countries falling into the category "others", we define a corresponding upper error range of 35% for the relative number of countries having implemented a protectionist policy. We consider the distribution of agent strategies to be qualitatively valid at the levels 1 and 2 if the maximum proportion of agents having implemented a protectionist policy during the price spike, that is during the time period of the simulation corresponding to January 2007 to May 2008 falls within the [0.41;0.76] interval and is lower than 0.41 before. For the distribution of strategies to be valid at level 3, we expect that the agents who changed policy are the same countries as the one reported in the literature and that the timing of their policy change correspond to what is reported in the literature. However, we still lack the data to propose a quantitative measure of the agents' strategy distribution which would satisfy the requirements we just stated, therefore we do not specify a more precise measure and consider to tackle this question in the case our model would already reach level 2 of validity.

Summary of the four validity levels Table 3.4 contains a summary of the 4 levels of validity that our model can achieve based on the quantitative and qualitative validity measures that we defined for the simulated global price, domestic prices and strategy distributions. We consider the criteria as cumulative meaning that for a model to be valid at a certain level it should also meet the criteria of the lower levels.

	Global Price Macro structure	**Domestic Price** Micro structure	**Strategy** Micro structure
Level 0 (Caricature of reality)	Spike-like behaviour with change in the slope of the global price similar to the average time-serie, stays within the $[0, 10p_{max}]$ interval	All domestic prices stay within the $[0, 10p_{max}]$interval	Increase of protectionist behaviour during price rise
Level 1 (Qualitative macro-structure)	Stays within the min-max area defined by the 10 price time-series for the period of the simulation corresponding to January 2007 to May 2008	Stay within $[0, 10p_{max}]$ for all country agents and stay within $[p_{minseries}, p_{maxseries}]$ the 27 corresponding country agents for the time period of the simulation corresponding to January 2007 to May 2008	Proportion of protectionist agents within [0.41,0.76] during price spike, lower than 0.41 before
Level 2 (Quantitative macro-structure)	Significant correlation with average time-serie, correlation coefficient $>$ 0.90 for the time period of the simulation corresponding to January 2007 to May 2008	Stay within $[0, 10p_{max}]$for all country agents at each time step, stay within [pmax series,pmax series] for the 27 corresponding country agents for the time period of the simulation corresponding to January 2007 to May 2008	Proportion of protectionist agents within [0.41,0.76] during price spike, lower than 0.41 before
Level 3 (Quantitative micro-structure)	Significant correlation with average time-serie for the time period of the simulation corresponding to January 2007 to May 2008, correlation coefficient $>$ 0.90	For the 27 countries with time series, significant correlation with average time-serie for the time period of the simulation corresponding to January 2007 to May 2008, correlation coefficient $>$ 0.75	The countries who changed policy are the same than in the literature and they change policy during the correct time step.

Table 3.4: Summary of the proposed validation levels for a model of 2008 rice food crisis

Based on the validation measure, we classified the level of validity of the model once calibrated and chose the best model on which to perform our experiments.

Chapter 4

Results

In this section, we present the results of the analysis of the model. Our results revealed that the model was able to reproduce the main stylized-facts of the food crisis : a spike-like increase of the global price of rice within a realistic range of values and an increase of the number of countries implementing a protectionist policy during this price spike. Its calibration allowed to identify 64 combinations of its four main parameters (controling the three price information feedback loops between the different markets and the sensitivity of trade policy information) that were able to generate a global price highly correlated with the time-serie of reference. The validation of the model showed that the 64 calibrated models were of similar validity level regarding the validity measure we defined. The 64 models were all valid at least at the minimum level of validity for two out of the three indicators of validity defined, and close to the minimum validity level for the third one. In addition, 2 models reached a global robustness score of at least 0.60 (one reaching 0.63 and the other 0.70), meaning that the behaviour of the global price remained realistic and highly correlated with empirical data in at least 60% of all sensitivity analyses that were conducted. None of the parameter of the model was found to be correlated with any of the robustness measure defined. Therefore, each parameter taken alone was not enough to explain the observed variability in robustness between the 64 models investigates. Even though no fully valid model of the crisis was found among the 3000 points of the parameter space sampled, the 64 calibrated models still provide the evidence that our model is able to generate spike-like behaviour of global prices. The global price simulated by all 64 models can be found in appendix in Figure D.5.

The combinations of parameters that led to a realistic simulation of the dynamics of the global price during the crisis were the following: a high strength of the domestic feedback loop combined with a low strength of the two other feedback loops, a high strength of the global feedback loop combined with a low strength of the two other feedback loops, and finally, combinations of intermediate strengths of all three feedback loops. In other words, the most realistic models of the crisis featured either:

- a high sensitivity of countries' domestic price to their own price variations,
- a high sensitivity of countries' domestic price to the variations of the global price,
- an intermediate sensitivity of countries' domestic price to their own past price variations, the variations of the global price and the value of the price of their trading partners.

These three configurations indicate conditions that were required for food crises to arise in the model. In addition, the most realistic models of the crisis featured various values for the sensitivity of the domestic price to trade policy information. Therefore, no specific value of this last parameter seems required for the model to generate global price-spike. In other words, the model generated food price crises regardless of the sensitivity of domestic prices to changes in trade policies. However, it remained that the higher the sensitivity of countries' domestic prices to changes in the trading policy of their neighbours, the more volatile the global price.

In addition, changing the type of aggregation method used by the institution agent to compute the global price from the domestic prices of the country agents prevented a spike of the global price in about a third of the most realistic models (depending on the type of aggregation measure used) causing it to converge to a lower value than its initial value at the beginning of the simulation. Removing the institution agent from the simulation while increasing the sensitivity of the countries to the prices of their trading partners accordingly[1] prevented the price crisis in 75% of the most realistic models. These results provide evidence for the ability of sharing information on the variations of the global price within the ITN to generate spikes in the global price later on. However, for a few models, changing the type of aggregation or removing the institution agent from the network had the opposite effect causing the global price to diverge when it was originally bounded. Thus, in the models studied, the global price information shared by the institution agents within the ITN can either stabilize or destabilize the global price depending on the parameters of the model. Changing the aggregation method or removing the institution agent from the simulation was stabilizing for models with a high sensitivity to the variations of the global price, and was destabilizing for models with a low sensitivity to the variations of the global price. Finally, when having changed the aggregation method used by the institution agents, we compared two different ways to measure the value of the global price in these simulations: as the value computed by the institution agents and using the initial aggregation method (see Figure D.5). For a few models, the two types of measures used led to contradicting conclusions as for the presence or absence of a global price crisis for the same simulation. This result highlights the importance of the type of indicator used to define a global price crisis since different indicators can give contradictory descriptions of the same reality.

The sensitivity analysis conducted on the 64 most realistic models shed light on additional drivers of a global price spike in the model: the initial distribution of domestic prices, the initial share of defectors and noise in the domestic prices of the countries. In about 11% of the simulations, changing the initial distribution of the domestic price prevented a spike in the global price. For some of them, the global price converged to a lower value than its initial value at the beginning of the simulation. However, in almost 41% of them, it led the global price to diverge when it was originally bounded. Increasing the initial share of defectors in the population of the country agents also prevented a global price spike in a bit less than 4% of the cases. However, it led the global price to diverge in 13 to 22% percents of the simulations, increasing with higher numbers of initial defectors. In general, it only had a limited impact on the dynamics of the global price, with 70 to 80% of the models remaining highly correlated with the empirical data of the rice crisis. Finally, the model happened to be extremely sensitive to noise in the domestic prices of the country agents. For shocks with an average amplitude of 2% of the domestic price of the country agents, the global price only 18% of the most correlated models stayed bounded. For all other models, the global price diverged. Thus, for the amplitude explored, noise was highly destabilizing for most of the most realistic models of the crisis. Therefore, even though the most correlated models we identified were capable of generating global price spikes in the absence of noise, we conjecture that adding noise would generate price spikes or the divergence of the global price for a larger number of models. However, having proven that a purely deterministic model could simulate the main stylized facts of the crisis shed light on the validity of considering purely endogenous phenomena as legitimate potential drivers of price crises.

Moving away from the models that were calibrated to simulate the rice crisis of 2008, the more general results of the analysis of the model pointed out more behaviours of interest that it was able to generate under certain circumstances. First, the model simulated a variety of global price dynamics: the convergence of the global price towards an equilibrium value either higher or lower than its initial value, its divergence towards infinitely high or low values, oscillations of increasing amplitude, or other various bounded dynamics (these behaviours can be seen on Figures D.1 and D.5).
In general, higher values of the strength of the three feedback loops led the simulated global price to diverge outside of a realistic range of values. This behaviour could have been expected from the definition of the feedback loops. The more sensitive the domestic price to price changes, the more these observed price changes are amplified potentially leading to overshooting effects and the divergence of the global price. In addition, the global price started to diverge for comparably high values of the strength of each of the feedback loops, meaning that the sensitivity of the domestic prices to each source of information was of similar importance for the stability of the global price. For models in which the global price converged within the time of the simulation towards a fix value, the sensitivity

[1] See assumption (**C5**) about the screening effect

to the variations of the global price was identified as the strongest determinant of the convergence value of the global price. The more sensitive the domestic prices to variations in the value of the global price, the higher the convergence value of the global price.
In addition, the higher the sensitivity to differences between the domestic price of a country and the domestic prices of its trading partners, the smaller the spread of the distribution of the domestic prices of convergent and bounded models. Thus, for high enough values of this sensitivity, the domestic prices of most countries synchronize and take the exact same value, provided that the strength of the local feedback loop remains under a certain threshold (the value of this threshold value happened to depend on the strength of the other feedback loops, as can be seen on Figure D.5). However, for too high sensitivities to this difference in price, the spread of the distribution of domestic prices increases which may be due to overshooting effects. Too large movements of the domestic prices of all countries make them miss any potential equilibrium value. In addition, we conjectured that, under this certain threshold and for reasonable strength of the two other feedback loops, the more sensitive the domestic prices to this difference in price, the faster the convergence of the model. We further conjecture from the results of the analysis that there exists an optimal value of the parameters of the model, that is, an optimal combination of the sensitivities of the domestic markets to other price and policy information, that allows for the fastest convergence of all domestic prices and the smallest spread of their final distribution. However, because of this threshold effect, it may be that this optimal value is very close in the parameter space to much more divergent configurations of the model, and that a small change in the value of the parameters may lead to an significant synchronization of the domestic prices.

Finally, the analysis of our model assessed the validity of certain design choices that were made. We saw that the behaviour of the global price in the model is highly influenced by the type of aggregation of the domestic prices conducted by the institution agent, the initial distribution of domestic price, and to an even larger extent, by the introduction of noise in the domestic price of the country agents. Thus, the random generation of the domestic price of a few country agents for which data were missing may have had an impact on the type of behaviour that the model was able to generate. On the other hand, the low sensitivity of the model to changes of its initial share of defectors shows that the assumption of full cooperation of the agents was probably not a strong assumption to make. However, the high sensitivity to noise shown by our model questioned the validity of the calibrated models. Yet, in spite of the perturbations introduced in the various sensitivity analyses, the simulated global price of almost all models which stayed bounded remained very highly correlated with the time-serie of reference. Thus, these models demonstrate the relative strength of the choices and assumption made in the design of the model.

The remainder of this section presents the detailed results of each part of this analysis:

1. Investigation of the model
2. Calibration of the model
3. Sensitivity analysis
4. Validation of the model.

4.1 Investigation of the model

The investigation of the model showed that the three information feedback loops defined in the model are able to generate a wide range of global price dynamics, from its convergence (sometimes with the convergence of all domestic prices towards the exact same value) to its divergence towards infinitely high or low values, even in the absence of external shocks. For the range of parameters' values explored, the convergence value of the global price was always higher than its initial value in all convergent models. Even though an increase in the value of any of the four parameters led to an increase in the convergence value of the global price, the final value of the global price in the convergent models happened to mainly depend on the sensitivity of the of domestic markets to global price information. Similarly, even though the spread of the distribution of the domestic prices in the end of the simulation happened to depend on all parameters, it was mostly determined by the sensitivity of domestic markets to local information. The investigation of the model also showed that a higher sensitivity of the domestic markets to changes of trading policies of their trading partners drove the global price to diverge and take unrealistically high or low values in more models, especially when the sensitivity of the domestic markets to the price on the domestic markets of their trading partners was already high. An increase in the sensitivity of the domestic markets to changes in trading policies seemed to drive the global price higher, to increase its volatility and to increase the spread of the distribution of domestic prices. In the remainder of this section, we further detail these results in the parameters' space of the model as follows:

1. convergence of the model,
2. value of the global price at the end of the simulation,
3. spread of the distribution of domestic prices at the end of the distribution,
4. defection of the country agents (only for λ_l),
5. volatility of global and domestic prices (only for λ_l).

4.1.1 Convergence

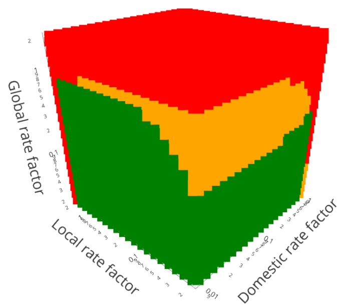
In this subsection, we investigated the behaviour of the model in the parameter space in order to test the hypothesis according to which the price inflation observed during the crisis could be caused by information transmission dynamics as defined in our model. We also investigate the impact of the sensitivity of the domestic markets to changes in the trade policy of the countries' trading partners, controlled by the parameter λ_l. We explored the effect of varying the strength of each information feedback loop: the domestic feedback loop, controlled by the parameter x_1 (the domestic rate factor, corresponding to the sensitivity of the domestic markets to their own past variations), the local feedback loop between trading partners, controlled by the parameter x_2 (the local rate factor, corresponding to the sensitivity of the domestic markets to the domestic price of their trading partners), and the global feedback loop between the country agents and the institution agent, controlled by x_3 (the global rate factor, corresponding to the sensitivity of the domestic markets to the variations of the global price). We investigated their effect on the convergence of the global price in the model, the spread of the distribution of the domestic prices, the final value of the global price (for convergent and bounded models), the final number of defectors, and the volatility of the global price.

Global investigation of the x_k

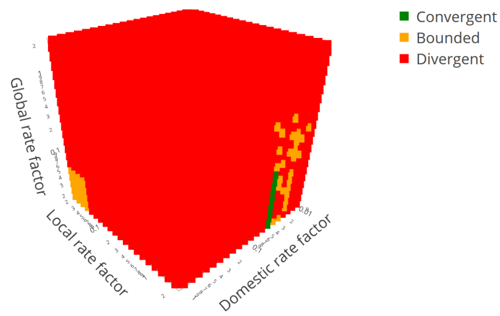
Figure 4.1 shows two views of the parameter space of the price update rule corresponding to the three possible macro-behaviours shown by the model within the range of values explored (convergent, bounded and divergent). Figure 4.1(a) and (c) are two views of the parameter space from the side corresponding to low values of x_1 and x_2, and Figures 4.1(b) and (d) show the side corresponding to high values of these two parameters. Figures 4.1(a) and (b) show the full parameter space whereas Figures 4.1(c) and (d) leave the divergent model out (red regions of the parameter space) and only display the location of the convergent and bounded models (green and orange regions). We observed that the behaviour of the model depended on the strength of each feedback loop. For low values of the three parameters, that is, $x_1 \leq 0.78$, $x_2 \leq 1.56$ and $x_3 \leq 0.18$, the global price computed by the institution agent always converged, which corresponds to most of the green region in Figure 4.1(a). For high enough values of the three parameters, that is for $x_1 \geq 1$, x_2 at least greater than 2 but maybe higher[2], and $x_3 \geq 1.23$, the global price of all models diverged within the 200 time steps of the simulation. The area between theses two extreme boundaries contains models of all three types with more convergent and bounded models for lower values of the parameters. When excluding the divergent models from the parameter space, it revealed non-trivial relationships between the three parameters and the evolution of the global price for higher values of them (see Figure 4.1(c) and (d)). It also showed that for high values of the

[2]The limit in x_2 of the convergent area is not reached in all direction by the range of values we chose, as shows the green stripe on the bottom right corner of the parameter space on Figure 4.1(b)

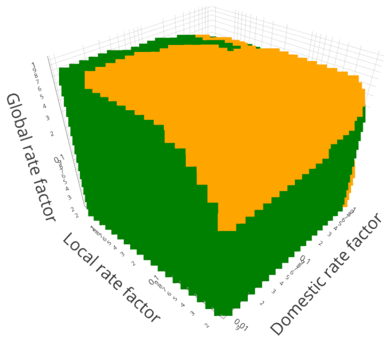
local rate and global rate (that is for a high sensitivity of the domestic markets to information local and global price information), increasing the domestic rate (that is the sensitivity of domestic markets to their own past price variations) led the global price to diverge.



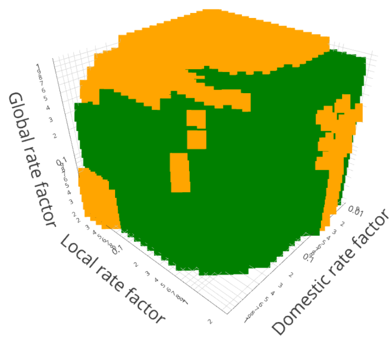
(a) View of the parameter space from the side corresponding to low values of x_1 and x_2.



(b) View of the parameter space from the side corresponding to high values of x_1 and x_2.



(c) View of the parameter space from the side corresponding to low values of x_1 and x_2. Only convergent (green) and bounded (orange) models are displayed, divergent (red) models are left out.



(d) View of the parameter space from the side corresponding to high values of x_1 and x_2. Only convergent (green) and bounded (orange) models are displayed, divergent (red) models are left out.

Figure 4.1: Parameter space of the price update rule and behaviour of the corresponding models. The value of the x_k is shown in logarithmic scale. The parameter space is divided in three main regions: in green, the global price of all corresponding models converges within 200 time steps, in orange, the global price of all corresponding models does not converge but stays positive and below 10700US$, in red, the global price diverges. Most models are divergent for high values of the three rates. When both global and local rates are low enough, or when both domestic and local rates are low enough, models are bounded or even convergent for some specific values of domestic rate factors, that is x_1. Subfigures (c) and (d) show only the convergent and bounded models of the parameter space

Local investigation of the x_k

The interaction between these effects can be better understood by considering only two parameters at a time. Consequently, Figure 4.2 shows three slices of the 3D parameter space for x_1, x_2 or x_3 kept constant across models. Figure 4.2(a) shows the influence of x_1 and x_2 on the macro-behaviour of the model for $x_3 = 0.467$. In addition to the our first observations, it reveals that low values of the local rate factor prevent the global price from converging for low and intermediate values of the domestic rate factor. This effect can be seen in appendix for the model 4 of Figure D.1.
The curved boundaries that can be seen on Figure 4.1(a), as well as on all three subplots of Figure 4.2, show that, for certain regions of the parameter space, the effect of two parameters can either reinforce

or compensate for each other. The curved boundary between the convergent (green) and divergent (red) areas for high values of the domestic and local rate factor (see the right side of the parameter space on figure 4.1(a) or see 4.2(a)) is an example of one of these reinforcing effects. The same effect can be found in the top-right-corner of all three subplots of Figure 4.2. However, the shorter ranges of values for which this effect happens on 4.2(c), compared to the two other subplots, and on 4.2(a) compared to Figure 4.2(b), indicates a stronger reinforcement between the effect of x_2 and x_1, than between the effect of x_1 and x_2, and even less for x_1 and x_3. One compensating effect of two parameters appears for low values of the local rate factor and for intermediate values of the global rate factor. That corresponds to the curved boundary on the left side of the parameter space on Figure 4.1(a) or on the left-hand side of Figure 4.2(c). It shows that, for this specific region of the parameter space, models leave the convergent area for the bounded area, for lower values of x_2 and higher values of x_3.

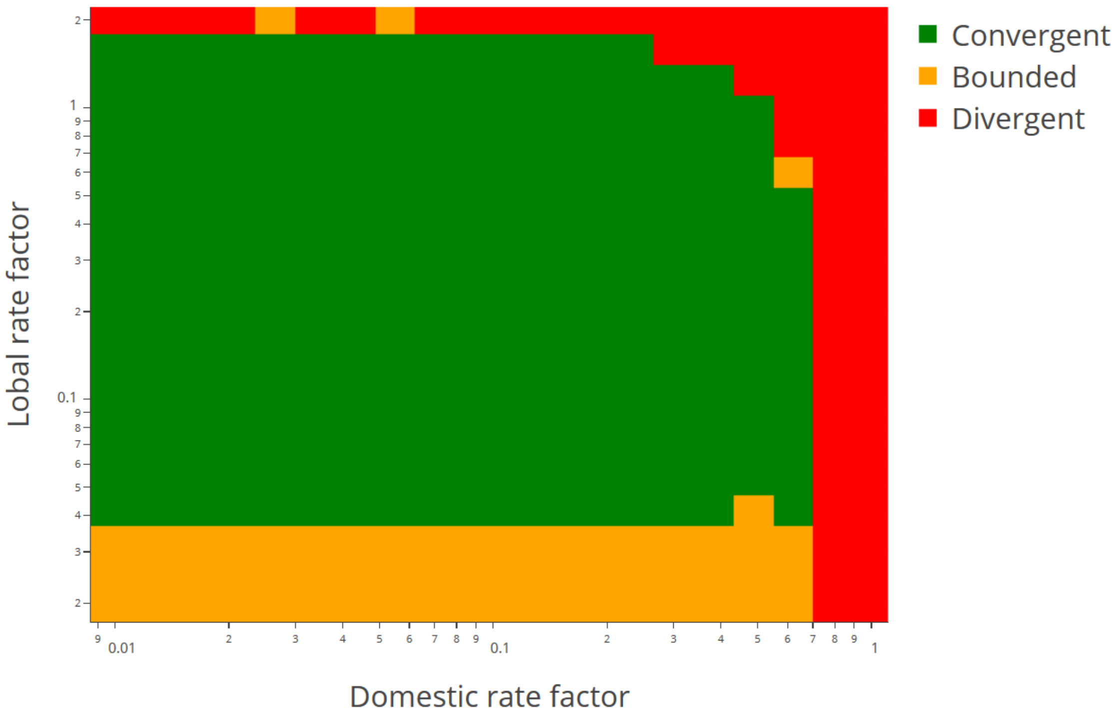
For a fixed value of the global rate factor x_3 (see Figure 4.2(a)), the red area for high values of x_1 and x_2 shows that too high values of x_1 or x_2 at the same time led the model to diverge. The orange area for $x_2 < 0.02$ corresponds to models which did not reach their convergence price yet at the end of the simulation but which would eventually converge given a long enough simulation time (for an example see model 4 of Figure D.1).

For a fixed value of the global rate factor x_2 (see Figure 4.2(b)), the situation is similar to the last case. For high values of x_1 and x_3, lower values of x_1 prevent the model from diverging. For this chosen value of x_2, all models with low enough values of x_1 and x_3 on the chosen interval converge before the end of the simulation.

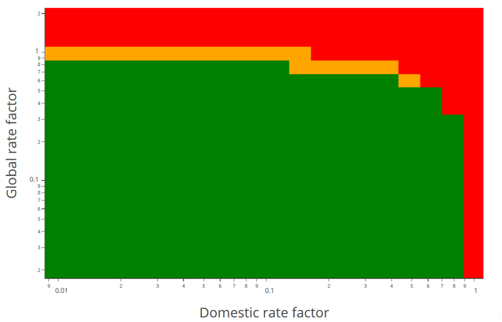
For a fixed value of the global rate factor x_1 (see Figure 4.2(c)), the effect of x_2 and x_3 slightly differ. Even though it still holds that too high values of either of the two parameter drove the models to diverge, for $0.2 < x_3 < 0.8$ lower values of x_2 prevented the convergence of the model, whether for $0.8 < x_3 < 1.1$, lower values of x_2 prevented the model from diverging.

The influence of the x_k on the global price's time-serie can be seen in appendix in Figure D.1. It shows that for a same value of x_1 and x_3, increasing x_2 seemed to fasten the convergence of the global price to its equilibrium value, but higher values of x_2 may have led to overshooting effects (see model 3). For x_1 and x_2 kept constant, it seems that increasing x_3 mostly increases the value of the global price but not its convergence speed. Finally, for x_2 and x_3 kept constant, increasing x_1 seems to destabilize the model and lead to what looks like an oscillating behaviour.

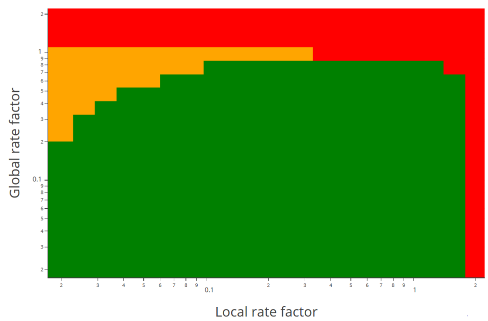
The three feedback loops seem to have a comparable effect on the convergence of the model since their threshold value from which all models start diverging are of the same order of magnitude.



(a) Models' macro-behaviour depending on x_1 and x_2 for x_3=0.467. For higher values of x_1 and x_2, most models became divergent which corresponds to the red area on the top and right part of the figure. The orange area at the bottom probably corresponds to models that low local rate value slew the convergence down too much to reach a stable price before the end of the simulation.



(b) Models' macro-behaviour depending on x_1 and x_3 for x_2=0.109. For higher values of x_1 and x_3, most models became divergent, which corresponds to the red area on the top and right part of the figure. The orange area shows the impact of the global rate factor which increased the value of the global price for a fixed value of the domestic rate factor, driving the value of the global price outside of the convergence interval.



(c) Models' macro-behaviour depending on x_2 and x_3 for x_1=0.112. For higher values of x_2 and x_3, most models became divergent, which corresponds to the red area on the top and right part of the figure. In the orange area, for a fixed value of the global rate factor, smaller values of the local rate factor probably slew down the convergence of the models, thus they did not converge within the time of the simulation.

Figure 4.2: Convergence of the global price of each model in the parameter space

Global investigation of the λ_l

Figure 4.3 shows the macro-behaviour of the models in the parameter space for the three values of λ_l explored in our simulation: $\lambda_l = 0.1$, $\lambda_l = 0.5$ and $\lambda_l = 2$. When increasing λ_l, the position and shape of the convergence area (in green on Figure 4.3) of the models in the parameter space changed. For higher values of λ_l, the range of x_2's values in which the model converge was smaller whereas the range of x_3's values in which the models converge increased. Certain models happened to be convergent for low values of λ_l, divergent for an intermediate value, and divergent again for a high value of λ_l. The value taken by λ_l had no influence on the range of x_3's values in which the models converged. Visually, that corresponds to the boundary between bounded and divergent models which did not seem to change with different values of λ_l. Thus, λ_l may both have a stabilizing or a destabilizing effect on the global price, depending on the model.

In addition, Table 4.1 shows the number of models for each type of convergence depending on λ_l. It shows an increase in the number of divergent models and a corresponding decrease in both the number of convergent and bounded models with increasing values of λ_l. In total, 1000 models were run for each value of λ_l.

λ_l	Number of convergent models	Number of bounded models	Number of divergent models
0.1	574	81	345
0.5	535	76	389
2	469	41	490

Table 4.1: Convergence of the models depending on the value of λ_l

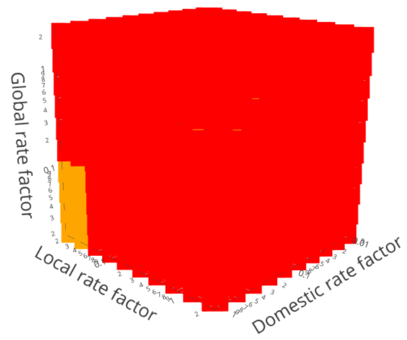
In addition, we investigated the evolution of the global price for a model whose macro-behaviour changes depending on the value of λ_l[3]. Its parameters are $x_1 = 0.01$, $x_2 = 1.19$, and $x_3 = 0.02$. It shows that the influence of λ_l is not trivial. Even though a high value of λ_l destabilized the global price, an intermediate value of λ_l seems to decrease the final value of the global price.

Finally, Figure D.2 shows the influence of λ_l for a model for which changing the value of λ_l changes the behaviour of its global price. It shows that for both low and high value of λ_l, the model stays bounded but shows an important price spike. For the highest of the two values of λ_l, the global price showed a much higher volatility, in the absence of external price shocks, as an internal property of the model. Interestingly, for an intermediate value of λ_l, the model only produced an oscillation of the global price of low amplitude. However, for the model shown in Figure D.1, increasing the value of λ_l from 0.5 to 2 led it to switch from a convergent to a divergent behaviour. Thus, even though Table 4.1 indicates a clear tendency of λ_l to drive more models towards divergence, understanding its effect seems to require a per-case analysis. Thus, the impact of λ_l on the convergence type of the model remained unclear.

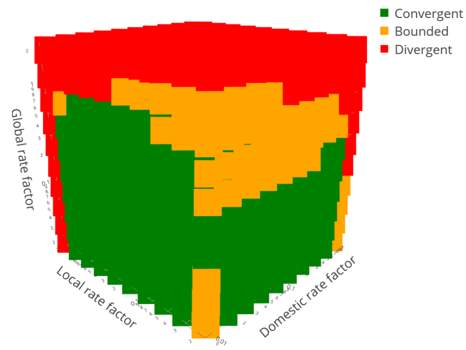
Summary

The results of the investigation of the model showed that it is able to generate important price variations in the absence of external shocks and under full cooperation of the country agents when initialized as defined in the method section. It showed that changing the strength of each of the three feedback loops (that is modifying the values of the parameters x_k) dramatically changed the behaviour of the model. For the values of the parameters explored, the model showed three types of convergence: divergent, bounded and convergent high. Thus, by modifying the strength of the feedback loops, it was also possible to generate stable and convergent dynamics of the global price, as well as fully divergent ones, with the global price taking infinitely high and low values, sometimes preceded by oscillations of increasing amplitude. Higher sensitivity to changes of trade policy of a country's trading partners, controlled by the parameter λ_l, increased the number of divergent models and decreased the number of convergent and bounded models. In general, it led the model to diverge for weaker strength of the local feedback loop. In addition, the comparison of the global price time-serie of a few models allowed to make the following conjectures. First, in convergent models, the stronger the local feedback loop, the faster the convergence, but too high values lead to overshooting effects. Second, the strength of the global feedback loop has no effect on the convergence speed of the global price. Finally, increasing the strength of the domestic feedback loop prevents the convergence of the model and may generate oscillations in the value of the global price.

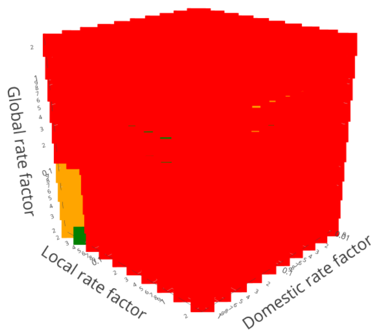
[3]The corresponding plots can be found in Figure D.1 in appendix



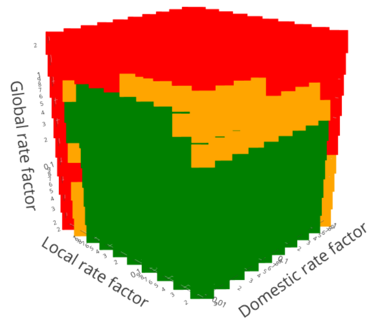
(a) For $\lambda_l = 0.1$, region of the parameter space with high values of x_1 and x_2.



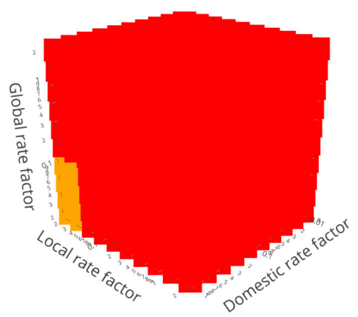
(b) For $\lambda_l = 0.1$, region of the parameter space with low values of x_1 and x_2.



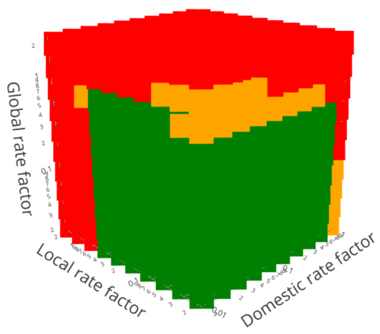
(c) For $\lambda_l = 0.5$, region of the parameter space with high values of x_1 and x_2.



(d) For $\lambda_l = 0.5$, region of the parameter space with low values of x_1 and x_2.



(e) For $\lambda_l = 2$, region of the parameter space with high values of x_1 and x_2.



(f) For $\lambda_l = 2$, region of the parameter space with low values of x_1 and x_2.

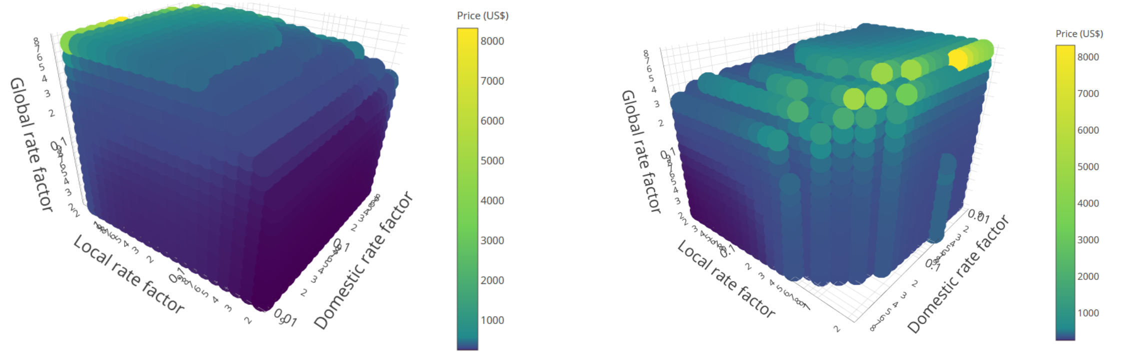
Figure 4.3: behaviour of the model in the parameter space for three value of λ_l. The shape of the convergence area changes depending on the value of λ_l. For lower values of λ_l, the models converge for higher values of x_1 and x_2, however, for higher values of λ_l, models stay convergent for higher values of x_3. In the specific case of $\lambda_l = 0.1$, the models with the lowest values of the three parameters do not converge which corresponds to the orange stripe in the bottom corner of the parameter space in subplot (b).

4.1.2 Final value of the global price

In this subsection, we investigated the final value of the global price at the end of the simulation for different combinations of the parameters. We first investigated the effect of the sensitivity of the domestic markets to the three price information sources through the global and local investigation of the parameters x_k, for fully cooperative agent and for $\lambda_l = 0$. Then, we investigated the effect of λ_l, the sensitivity of the domestic markets to changes in the trade policy of the trading partners of each country agents. We summarized our main findings at the end of the subsection.

Global investigation of the x_k

Figure 4.4 shows the value of the global price as computed by the institution agent at the end of the simulation for t=200 time-steps. The final value of the global price of most models stayed below 1000US$. However the higher the three parameters, the higher the final value of the global price. The highest values were reached for high values of x_3, but all three parameters seemed to play a role.



(a) View of the parameter space from the side corresponding to low values of x_1 and x_2.

(b) View of the parameter space from the side corresponding to high values of x_1 and x_2.

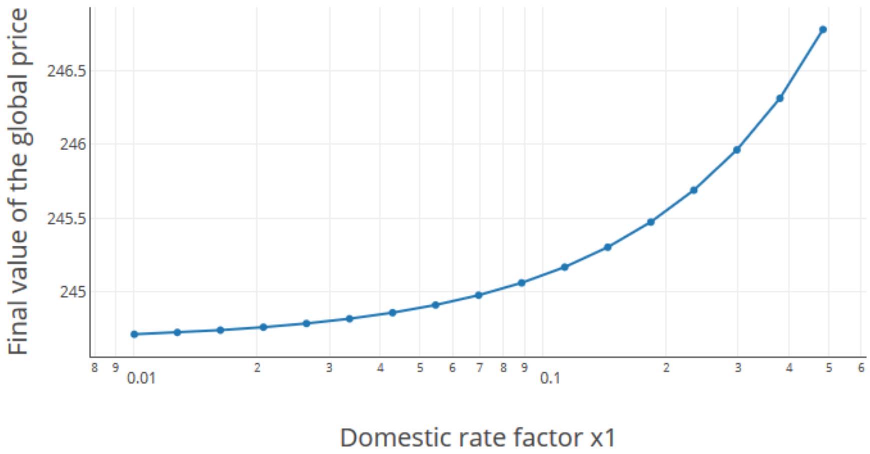
Figure 4.4: Final value of the global price in the parameter space. For most models, its value stayed lower than 500US$, which corresponds to most of the blue area. However, certain bounded models showed very high values of the global reaching 8000US$. Models whose global price took values high than 10700US$ were classified as divergent and excluded from this analysis.

Local investigation of the x_k

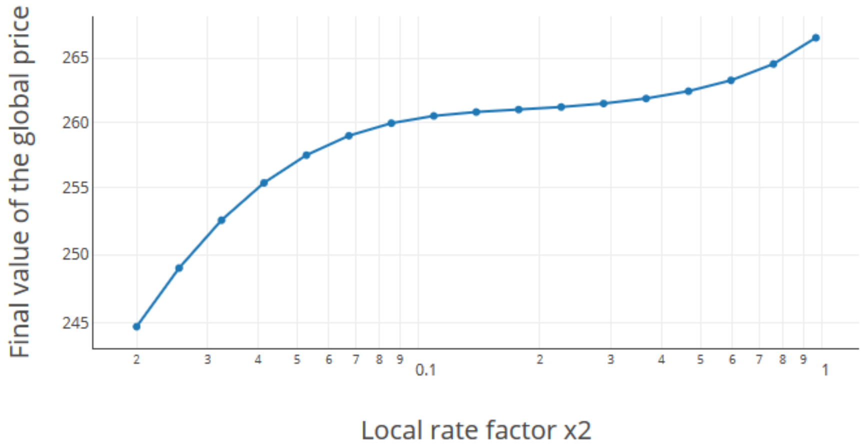
Figure 4.5 shows the behaviour of the global price in three different areas of the parameter space, for only one varying parameter among the three x_k. It shows that the value of the global price increased with all the three x_k. It increased faster with higher x_1 and x_3. Its relationship with x_2 was less clear since the increase in the final value of the global price seemed less strong for intermediate value of x_2. It is worth noting that the influence of x_1 and x_2 was less strong than the effect of x_3 on the global price, as shows the varying ranges of values covered by the graphs of Figure 4.5. The very different relationship between the final value of the global price and x_2 compared the the two other parameters x_1 and x_3 was to be expected from the difference in the definition of the local feedback loop compared to the domestic and global information feedback loop.

In addition, Figure D.3, that can be found in appendix, shows the evolution of the global price depending on two of the x_k for the last one kept constant. In general, increasing the value of one x_k either increased the value taken by the global price or increased the rate of variation of the global price[4].

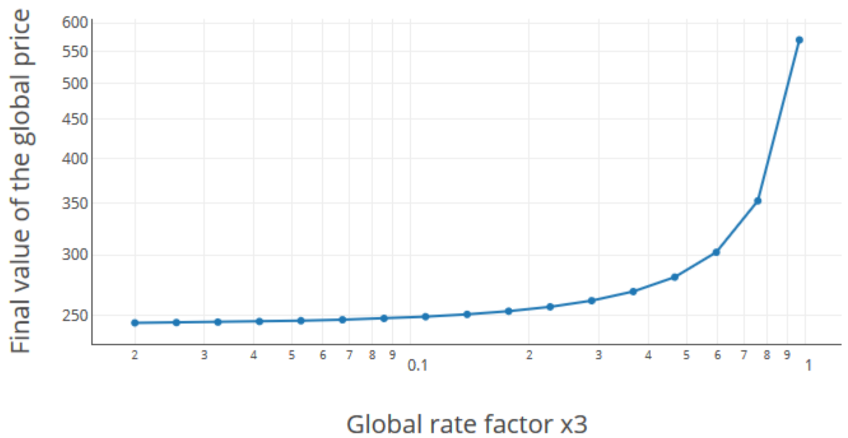
[4]In normal scale (rather than log scale) for x_1, taking the logarithm of the price several times still gave a power-law function. It may indicate that the final value of the global price varied as a power of powers of x_1.



(a) Final value of the global price depending on x_1



(b) Final value of the global price depending on x_2

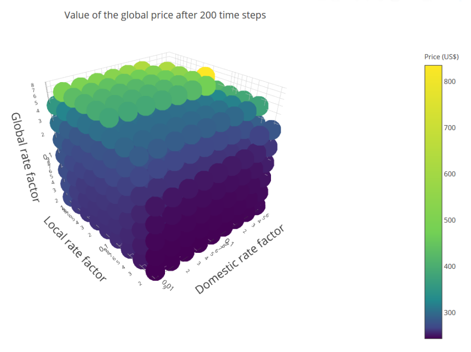


(c) Final value of the global price depending on x_3

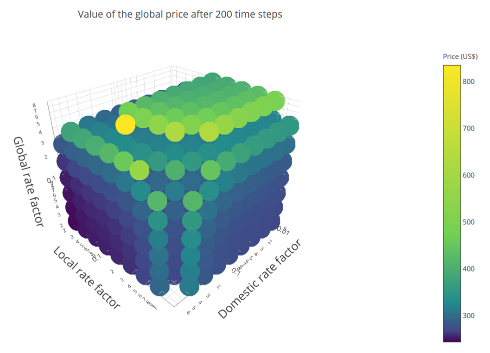
Figure 4.5: Final value of the global price in the parameter space. The range of values taken by the global price at the end of the simulation depended on the parameter explored. It was the largest for x_3.

Global investigation of the λ_l

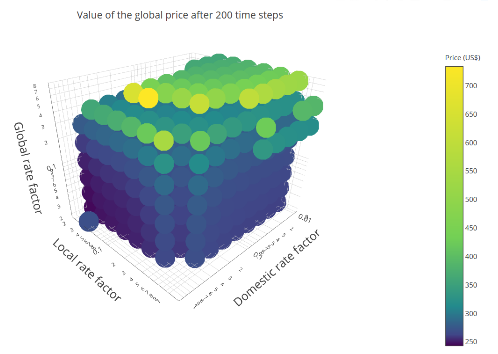
We investigated the influence of λ_l on the final value of the global price. Figure 4.6 shows its value in the parameter space for the models whose global price convergent or stayed bounded. We do not display the divergent models since, for most of them, the global price at the end of the simulation took infinitely high or low values. The shape of the convergence domain changes from subfigure to subfigure due to the influence of λ_l on the convergence type of the model. Figures 4.6(a) and (b) correspond to $\lambda_l = 0.1$, while 4.6 (c) and (d) correspond to $\lambda_l = 0.5$ and $\lambda_l = 2$, respectively. Because of the very small differences in the results for low values of x_1 and x_2 across the three values of λ_l, we only show the corresponding view of the parameter space for $\lambda_l = 0.1$, in Figure 4.6(a). The three other subfigures correspond to the other view of the parameter space for high values of x_1 and x_2. The final value of the global price increased with x_3, and to a fewer extend with x_2 as well although not systematically. The value of x_1 seemed to influence the final value of the global price only for very high values. The main effect of λ_l on the final value of the global price was to modify the range of value that the global of convergent models reached. For $\lambda_l = 0.1$, the global price of convergent models took values within the range $[250, 850]$US\$, whether for $\lambda_l = 0.5$, its value stayed within $[250, 750]$US\$, and for $\lambda_l = 1$, it was restricted to the range $[250, 600]$US\$. As a comparison, the initial value taken by the global price was about 203US\$.



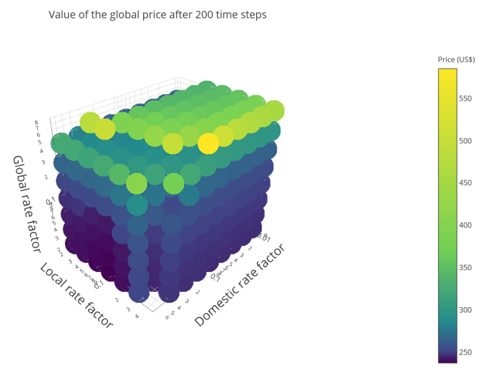
(a) $\lambda_l = 0.1$ - Region of the parameter space with low values of the x_1 and x_2



(b) $\lambda_l = 0.1$ - Region of the parameter space with high values of the x_1 and x_2



(c) $\lambda_l = 0.5$ - Region of the parameter space with high values of the x_1 and x_2



(d) $\lambda_l = 02$ - Region of the parameter space with high values of the x_1 and x_2

Figure 4.6: Value of the global price at time step $t = 200$ for three values of λ_l. Two views of the parameter space are shown, one in subfigure (a) corresponding to the region with low values of x_1 and x_2 for $\lambda_l = 0.1$, and three in subfigures (b), (c) and (d) corresponding to the region with high values of x_1 and x_2.

Summary

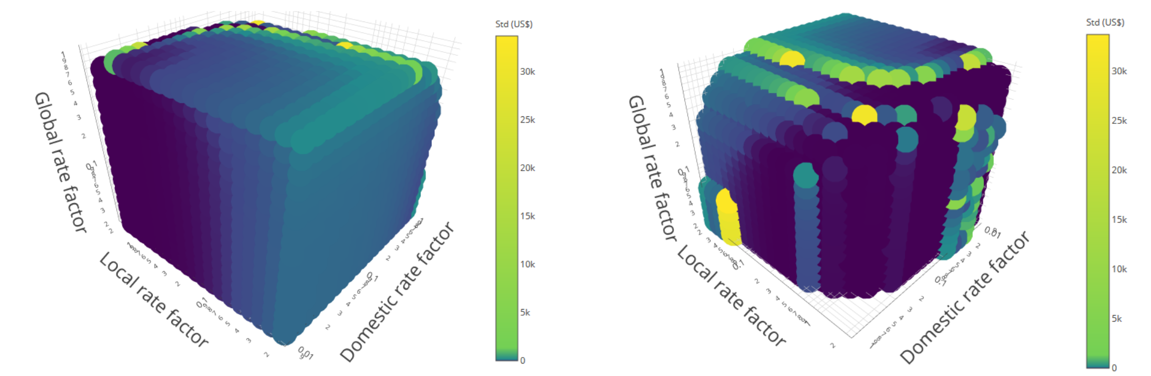
Among convergent models, no model converged towards lower values than the initial value taken by the global price. Finer analyses of the influence of each feedback loop on the value of the global price for convergent and bounded models showed that all three feedback loops had an influence on it. However, when the domestic and local rates x_1 and x_2 only changed its value by a few US dollars for the first one, and a few tens of US dollars for the second, a change in the global rate x_3 led the final value of the global price to span a range of several hundred of dollars. In addition, increasing the sensitivity of domestic markets to changes of the policy of their trading partners, as quantified by λ_l, drove the simulated global price of the convergent models higher.

4.1.3 Final value of the spread of the distribution of domestic prices

In this subsection, we investigated the final value of the spread of the distribution of the domestic price for different combinations of the parameters. We first investigated the effect of the sensitivity of the domestic markets to the three price information sources through the global and local investigation of the parameters x_k, for fully cooperative agent and for $\lambda_l = 0$. Then, we investigated the effect of λ_l, the sensitivity of the domestic markets to changes in the trade policy of the trading partners of each country agents. We summarized our main findings at the end of the subsection.

Global investigation of the x_k

Figure 4.7 shows the standard deviation of the distribution of domestic prices at the end of the simulation for $t = 200$ time steps for all convergent and bounded models. It shows that low values of x_1 and x_3, its value seems to mostly depend on x_2. For increasing values of x_2, the spread of the distribution of domestic prices at the end of the simulation gets smaller. However, higher values of x_3 drives it towards higher values. Its highest values are found for high values of x_1 only, or high values of the three x_k simultaneously. In general, higher values of the x_k show more complex patterns between this standard deviation and the x_k. The smallest values of the standard deviation was 8.17e-7 whereas the highest value was 5.6e+146 (infinite otherwise).

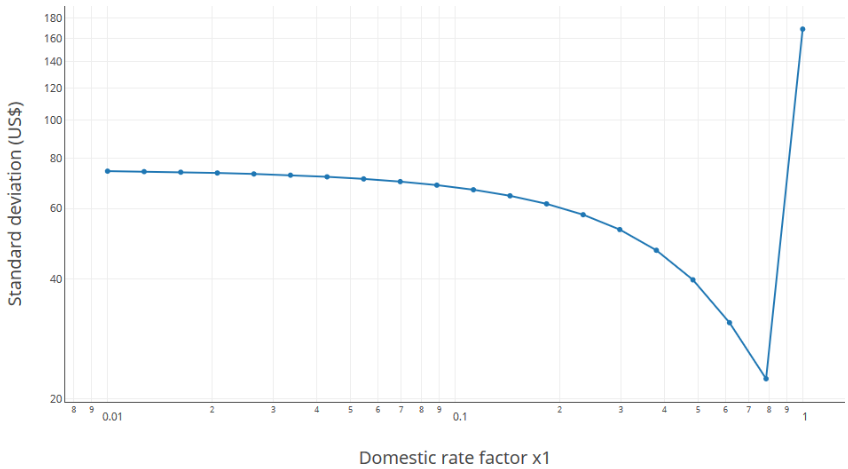


(a) View of the parameter space from the side corresponding to low values of x_1 and x_2.

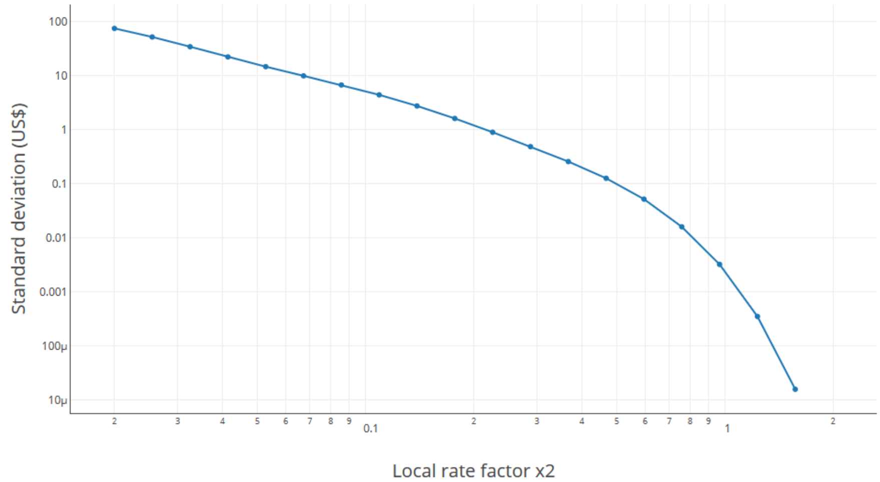
(b) View of the parameter space from the side corresponding to high values of x_1 and x_2.

Figure 4.7: Final value of the standard deviation of the distribution of domestic prices in the parameter space.

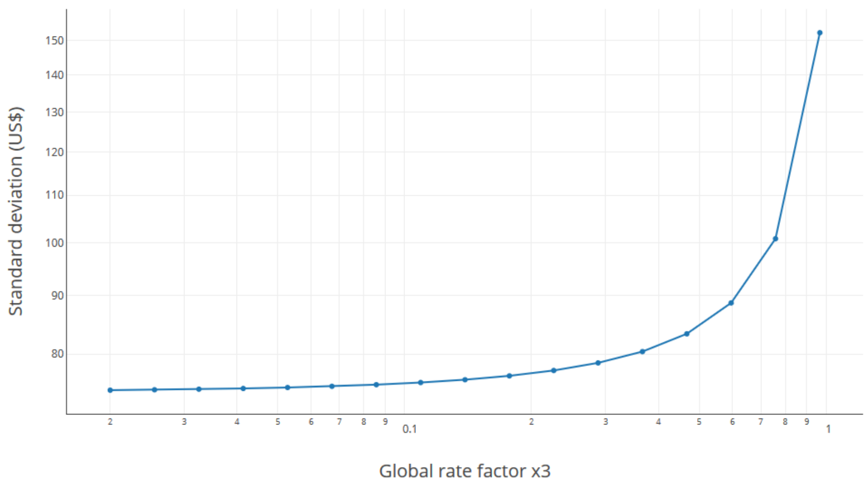
Local investigation of the x_k



(a) Final value of the spread of the distribution of the domestic prices depending on x_1



(b) Final value of the spread of the distribution of the domestic prices depending on x_2



(c) Final value of the spread of the distribution of the domestic prices depending on x_3

Figure 4.8: Final value of the spread of the distribution of the domestic prices in the parameter space.

Figure 4.8 shows the evolution of the spread of the distribution of the domestic prices depending on the value taken by each of the x_k. As a comparison, at the beginning of the simulation, the standard deviation of the distribution of domestic prices is 349US\$ for all models. Its value clearly decreased with higher values of x_2, and increases with higher values of x_3. This result reflects the fact that higher values of x_2 lead the domestic prices of two country partners to experience larger variations, until they reach close enough values, but that when the domestic markets follow the variations of the global price, it hindered this effect. The evolution of the spread of the distribution depending on x_1 shows that it may first amplify the effect of x_2, but that for too high values it also hindered the convergence of the two domestic prices towards a similar value. In addition, it shows what could be a threshold effect. From a certain value of x_1, the spread of the distribution of the domestic prices ceased to decrease with x_1 and started to diverge. This is probably due to the large variations of the global price caused by the high sensitivity of the domestic markets to their own past variations. Finally, the ranges of values taken by the spread of the distribution on Figure 4.8 shows that the spread of the distribution of the domestic prices happened to be more sensitive to x_2 than to x_1 and x_3. This result is in accordance with the fact that only the local feedback loop can ensure the convergence of the domestic price of two country partners towards a similar value.

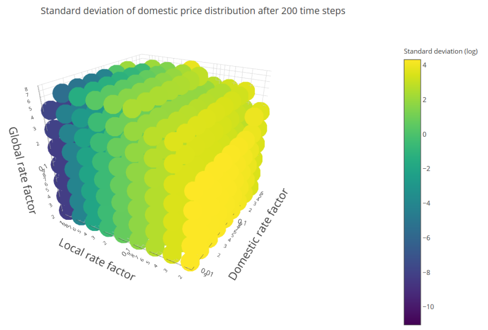
In addition, Figure D.4, that can be found in appendix demonstrates that the spread of the domestic prices' distribution also showed a threshold effect in x_2 for high enough values of x_1 or x_2. In general, it shows that for low enough values of x_1 and x_3, a higher value of x_2 decreased the spread of the distribution. However, for higher values of x_1 (resp. x_3), the threshold value of x_3 (resp. x_1) from which the spread of the distribution started taking higher values was smaller.

Global investigation of the λ_l

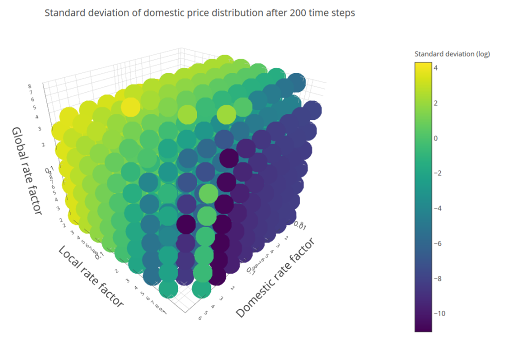
Figure 4.9 shows the standard deviation of the domestic price distribution at time step 200 for all convergent and bounded models. We do not display the standard deviation of the final distribution of the domestic price for divergent models since some of them took infinitely high or low values. The shape of the convergence domain changes from subfigure to subfigure due to the influence of λ_l on the convergence of the models, mentioned earlier. The spread of the distribution of domestic price at the end of the simulation was the smallest for $\lambda_l = 0.5$, with values smaller than 10^{-12}US\$. For $\lambda_l = 0.1$ and $\lambda_l = 2$, the smallest value of the spread of the distribution were not lower than 10^{-11}US\$ and 10^{-9}US\$, respectively. For all values of λ_l, the standard deviation of the domestic price distribution decreased exponentially with x_2, as can be seen on Figures 4.9(a), (b) and (c). For all values of λ_l, x_1 and x_2 only influenced the final spread of the domestic price distribution for high enough values (see Figures 4.9(b), (d) and (f)). For high values of x_2, the spread of the distribution of domestic prices increased with x_1. For reasonable values of x_2, this observation also holds for x_3, but on the frontier of the converge domain, it does not hold any more. For these specifics points, the smallest spread of the distribution is not found for the lowest values of x_3, but rather for intermediate ones. For $\lambda_l = 2$, the relationship between the spread of the final distribution of domestic prices and x_3 was actually reversed compared to $\lambda_l = 0.1$ for high enough values of x_1 and x_2 (see the foreground angle of Figure 4.9 (f)).

Summary

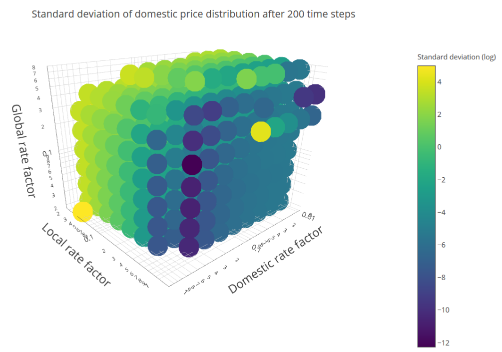
The value of the three sensitivities to the three information feedback loops impacted the spread of the distribution of the domestic prices in the end of the simulation. However, the local feedback loop plays a predominant role compared to the two other feedback loops, with price variations spanning 9 or 10 orders of magnitude for the value of x_2 explored. In comparison, variations in the strength of the domestic and local feedback loops only lead to variations of a tens of dollars. As for the sensitivity of the domestic markets to changes of trading policies, higher values seemed to prevent the convergence of the domestic prices of all country agent towards a single value. However, for higher values of the three other sensitivities, the relationship between this parameter and the spread of the distribution of domestic prices was less trivial and requires further investigation of the micro-behaviours of the model.



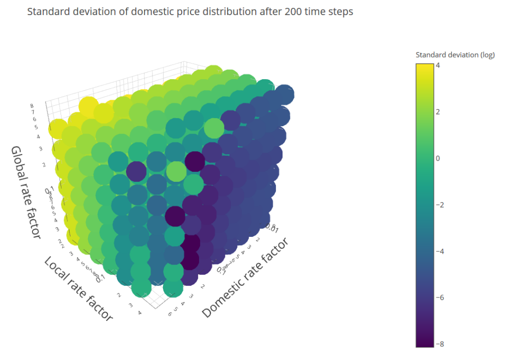
(a) $\lambda_l = 0.1$ - Region of the parameter space with low values of the $x_1 and x_2$



(b) $\lambda_l = 0.1$ - Region of the parameter space with high values of the $x_1 and x_2$



(c) $\lambda_l = 0.5$ - Region of the parameter space with high values of the $x_1 and x_2$



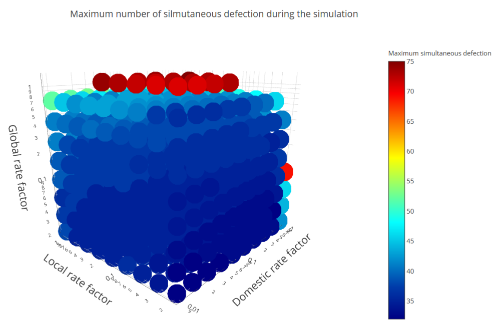
(d) $\lambda_l = 2$ - Region of the parameter space with high values of the $x_1 and x_2$

Figure 4.9: Standard deviation of the domestic price distribution at time step $t = 200$

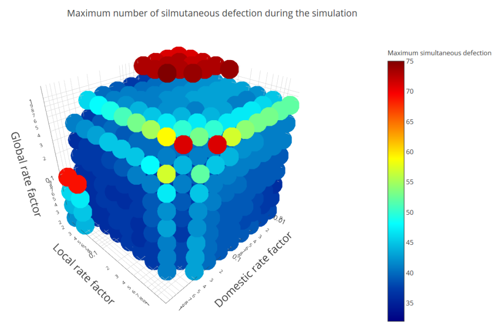
4.1.4 Number of countries having defected during the time of the simulation

Global investigation of the λ_l

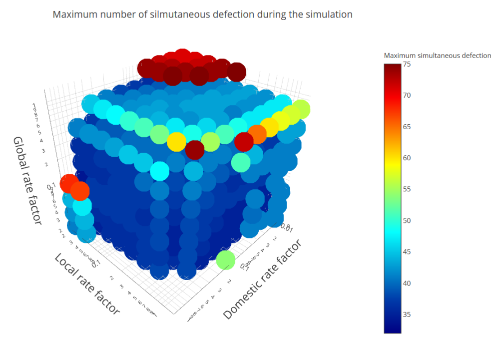
Figure 4.10 shows the value of the maximum number of simultaneous defections of country agents during the simulation. For low values of the x_k, a maximum of about 35 to 40 countries defect. For all three values of λ_l that were tested the same regions of the parameter space reveal high values of the maximum number of simultaneous defection during the simulation. They correspond to high values of x_3, high values of x_1, and a combination of both intermediate values of x_1 and x_2. No more than 75 countries defected simultaneously during the simulation, for all values of λ_l. In general, the maximum value of the simultaneous number of defection seemed to roughly follow the final value of the global price, which is coherent with the definition of the behaviour of the country agents. The higher the global price, the higher the domestic prices and thus the further from the target price of the country agents. However, a better understanding of the influence of the parameters of the simulation on the dynamics of defection would require to define better micro-level methods of analyzing the results from the model.



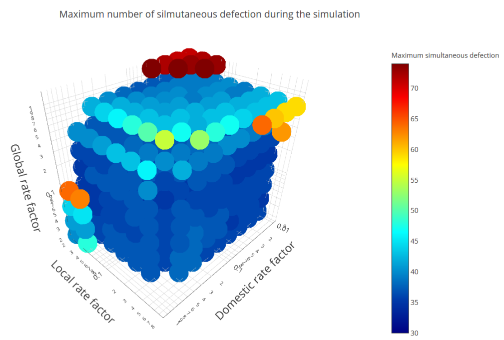
(a) $\lambda_l = 0.1$ - Region of the parameter space with low values of the x_1 and x_2



(b) $\lambda_l = 0.1$ - Region of the parameter space with high values of the x_1 and x_2



(c) $\lambda_l = 0.5$ - Region of the parameter space with high values of the x_1 and x_2



(d) [$\lambda_l = 1$ - Region of the parameter space with high values of the x_1 and x_2

Figure 4.10: Maximum number of simultaneous defections during the simulation

4.1.5 Price volatility

Global investigation of the λ_l

Table 4.2 shows the evolution of both the global price computed by the institution agent, and domestic prices' volatility for all convergent models. It shows that both the volatility of the global price of a model increased by 1.29US$ on average when increasing λ_l from 0.1 to 0.5, and by 4.20US$ when increasing λ_l from 0.1 to 2. In addition, it shows that this increase in volatility concerned all convergent models when changing λ_l from 0.1 to 0.5, and 98% of them when moving to $\lambda_l = 2$. The same trend is shown at the level of the domestic prices whose price volatility increased almost systematically with λ_l. This is coherent with the definition of λ_l. Since the change of trading policy of the country agents are discrete events, they induce sudden shocks to the domestic prices of the trading partners of these country agents, which increases the volatility of the domestic prices, and thus, of the global price. The more sensitive the domestic markets, the more larger the price variations in their domestic markets.

λ_l compared	Average change in global price volatility	Percentage of models with increased global price volatility	Average change in median domestic price volatility	Percentage of models with increased median domestic price volatility
0.1 and 0.5	1.29US$	100%	1.14US$	97.1%
0.5 and 2	2.91US$	98%	2.74US$	98.4%
0.1 and 2	4.20US$	98%	3.89 US$	98.4%

Table 4.2: Evolution of price volatility between the different values of λ_l for convergent models

4.2 Calibration of the model

In this section, we identified 64 combinations of parameters for which the simulated global price was highly correlated with the time-serie of reference (correlation coefficient of the Pearson correlation higher than 0.90, p-value lower than 10e-3). Figure 4.11 shows the value of the correlation between the reference time-serie and the model for each of these 64 models in the three parameter spaces corresponding to the three different values of λ_l investigated. The value of the correlation for all other convergent and bounded models was set to zero. We identified four areas of the parameter space where the most correlated and most valid models are:

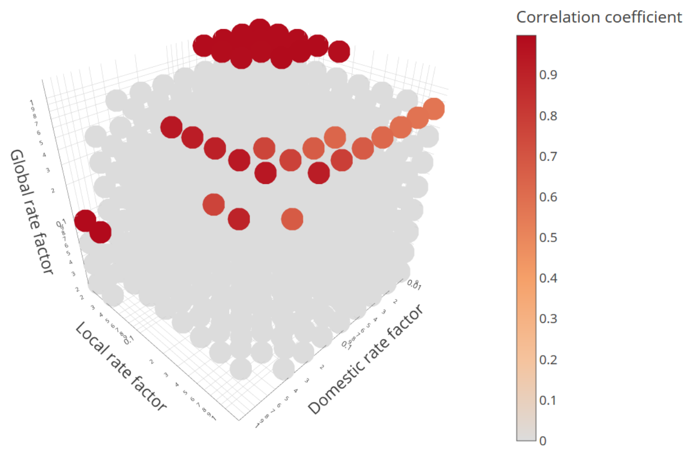
- Region 1: models with high values of x_1
- Region 2: models with high values of x_3
- Region 3: models with intermediate value of x_3 and either high value of x_1 or x_2, or intermediate value of x_1 and x_2,
- Region 4: in the case of $\lambda_l = 0.5$ only, one model with a low value of x_3, but intermediate value of x_1 and high value of x_2.

In addition, Table D.1, that can be found in appendix, shows the parameters of the each of the 64 model. The correlation of a model with the time-serie of reference decreased for higher values of the local rate factor. The most correlated models seemed to be at the boundary of the regions of the space corresponding to bounded models, that is, towards more divergent models. That is coherent since our time-serie of reference itself shows an increasing trend of relatively high slope, a type of behaviour that was also found in divergent models. One can wonder whether a different sampling of the parameter space may not have identified more highly correlated models. An hypothesis that could be tested by a better sampling is whether the most correlated models can be found at a similar distance from the origin of the parameter space, defining a quarter of a sphere of highly correlated models. In this case, the drivers of the price spikes would not be specific values of the parameters but rather the sufficiently high value of a certain combination of them.

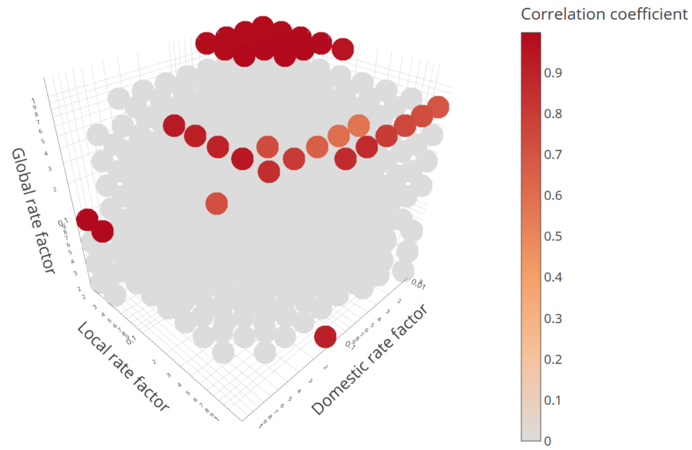
As a summary, the calibration showed that the model achieved high levels of correlation between the generated global price and time-serie of reference for 67 different combinations of the four parameters in four different locations of the parameter space. For all values of the sensitivity of the domestic markets to changes of trading policies, these most correlated models were found for:

- high values of the strength of the domestic feedback loop while low values for the two others,
- high values of the strength of the global feedback loop while low values for the two others,
- high values of the strength of both the domestic and local feedback loop combined with a high value of the strength of the global feedback loop.

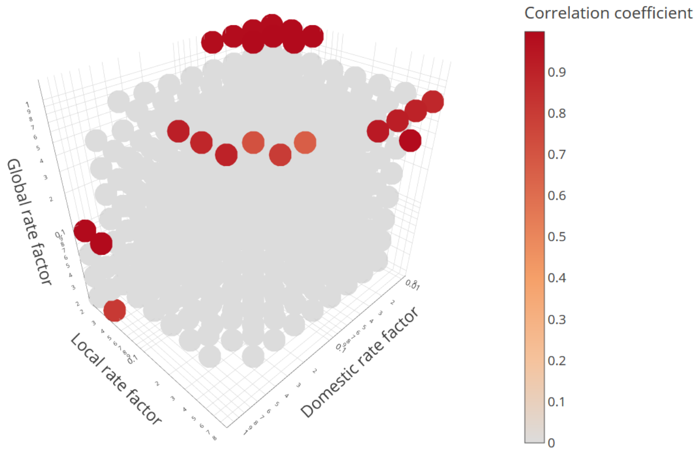
In addition, for an the intermediate value of λ_l only, one model with a low value of the global rate and intermediate values for both the local and domestic rate was highly correlated with the time-serie of reference. Thus, price inflation can be caused by all corresponding settings starting from full cooperation of the country agents and with no external shocks to the simulated system. Thus, several corresponding explanations can be given for price spikes. It seems that it can stem from a high sensitivity of the domestic markets to their own variations, a high sensitivity of the domestic markets to the variations of the global price or a combination of intermediate sensitivity to domestic, local price and global prices. However, these results may just result from the sampling of the parameter space that was investigated. Highly correlated models were found for all values of the sensitivity of the change in trading partners' trading policies tested, therefore, in this model, it did not appear as a strong driver of the price spike.



(a) $\lambda_l = 0.1$



(b) $\lambda_l = 0.5$



(c) $\lambda_l = 2$

Figure 4.11: Maximum correlation between the reference time-serie between January 2007 and May 2008 and the global price time-serie of each model in the parameter space for all three values of λ_l. Only convergent and bounded models are shown. The models with a standard deviation lower than 100US$ in the time window corresponding to their highest correlation with the reference time-serie have been set to the value 0 and appear in grey.

4.3 Sensitivity analysis

In this section, we investigated the sensitivity of the 64 calibrated models to changes of the initial distribution of the domestic price of the country agents, to changes of the initial share of defectors in the population of country agents and to the introduction of noise in the domestic prices of country agents. Thus, we quantified their robustness to changes in each of these factors, and their average robustness. We also investigated the impact of implementing alternative aggregation methods in the computation of the global price by the institution agent, as well as the consequences of removing the institution agent from the simulation. This way, we tested the validity of our modeling assumptions, and we investigated the question of whether it is possible to prevent food crises or reduce their severity by modifying the aggregation of information done by the institution agent and the structure of the network.

4.3.1 Sensitivity to initial domestic price distribution

Table 4.3 shows the change in convergence type for all the simulations that were performed (64 most correlated models of bounded type, 10 different initial distributions of domestic price for each model). Changing the initial distribution of the domestic prices changed the convergence of the model in 52% of the simulations. In 40.8% of the cases, changing the initial price of domestic prices led the global price to converge. In 7.0% of the cases, changing the initial distribution of domestic prices led the global price to converge to a lower value than the initial value of the global price of all the 64 benchmark models, which did not happen in the simulations ran for the previous parts of the analysis of the model.

	Convergent (low value)	Convergent (high value)	Bounded	Divergent
Number of models	45	27	307	261
Percentage of models	7.0%	4.2%	48.0%	40.8%

Table 4.3: Convergence type of all models on which the sensitivity analysis was performed.

Among the models which remained bounded, we investigated whether the evolution of the global price was still correlated with the time-serie of reference (see Table 4.4). More than 66% of them still showed a correlation of more than 0.90 with the global price time-serie of reference. The global price of most of the remaining models showed variations whose amplitude was smaller than 100US$. This range of global price variations does not correspond to the amplitude of the price variations observed in the time-serie of reference.

	Bounded models	Highly correlated models (corr>0.90)	Small variations' amplitude models
Number of models	307	204	83
Percentage of models	100%	66.4%	27.0%

Table 4.4: Price dynamics of all models which stayed bounded in spite of the change of initial domestic price distribution.

Table 4.5 shows the influence of λ_l on the sensitivity to the initial distribution of domestic price. It shows that for different values of λ_l, the repartition of the type of convergence of the models stayed similar.

Value of λ_l	Total number of models	Percentage of convergent models	Percentage of bounded models	Percentage of divergent models
$\lambda_l = 0.1$	240	10.0%	46.7%	43.3%
$\lambda_l = 0.5$	230	11.7%	50.0%	38.3%
$\lambda_l = 2$	170	12.3%	47.1%	40.6%

Table 4.5: Repartition of the models per type of convergence depending on the value of λ_l.

We further investigated the influence of the initial value of the global price on the convergence type of the model (see Figure 4.12). It seems that the type of convergence of a model did not depend on the initial value of the global price.

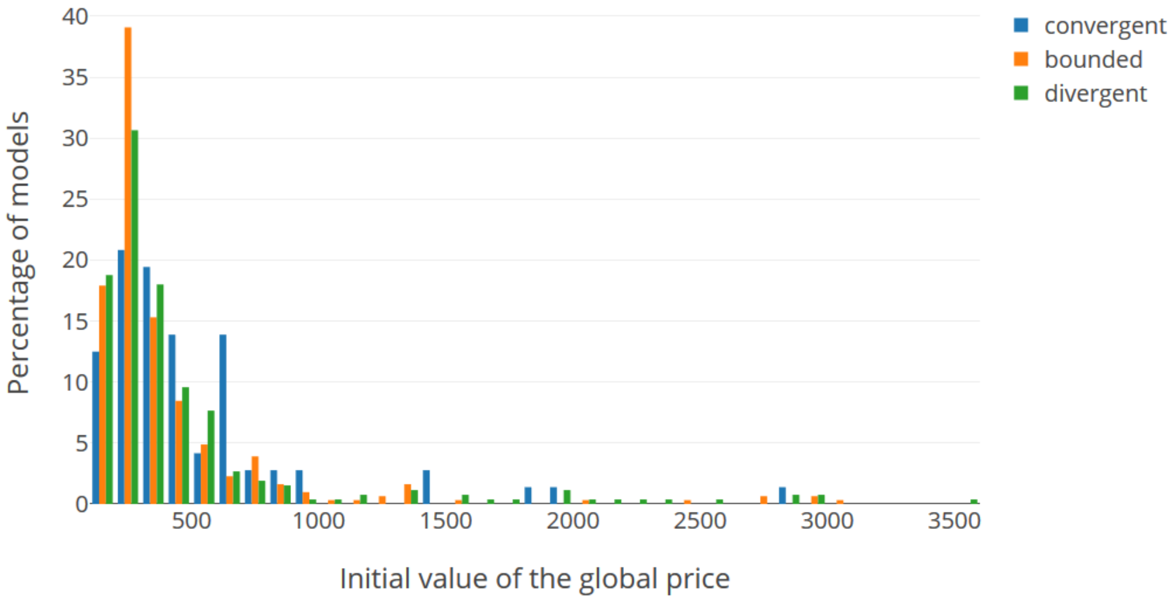


Figure 4.12: Convergence of the model depending on the initial value of the global price

In addition, we looked at the repartition of convergence type based on the spread of the initial distribution of the domestic price distribution (see Figure 4.13). The type of convergence of a model does not seem to depend on the initial value of the spread of the distribution of domestic prices.

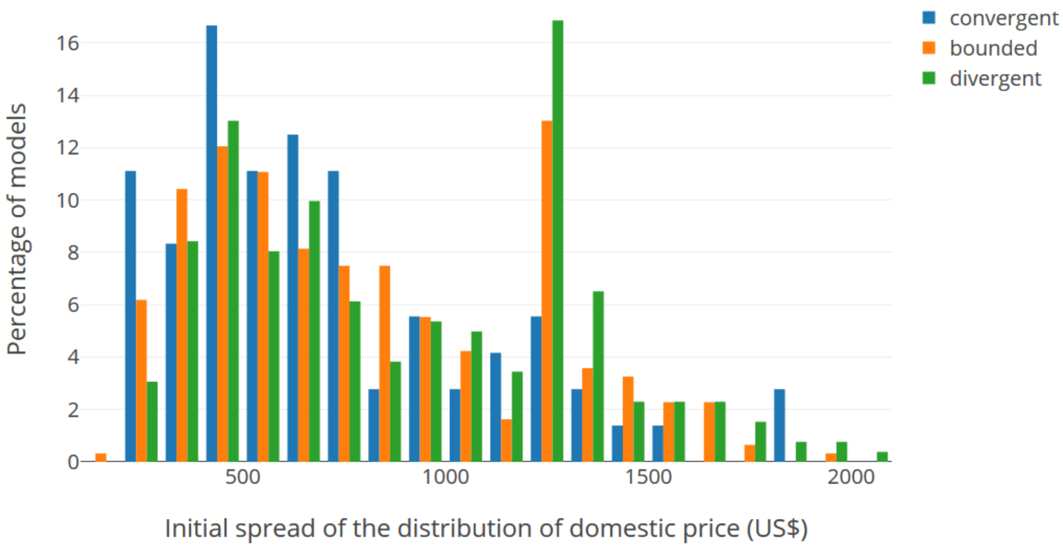


Figure 4.13: Convergence of the model depending on the spread of the initial distribution of domestic prices

Summary

Among the 640 simulations ran on the 64 most correlated models for different values of the initial domestic price distributions, barely half of them stayed bounded, among which about two-thirds were still highly correlated with the time-serie of reference. In the second half of the simulations, the global price of most models diverged, but it also converged for a few of them. In addition, for certain initial distribution of the domestic prices, the global price in these models converged towards a lower value than its initial value. In general, the observed type of convergence did not depend on the sensitivity to changes in the trading policy of trading partners (controlled by the parameter λ_l), nor on the initial value of the global price or the initial spread of the distribution of domestic prices. To this regard, it is impossible to rule out the possibility that the domestic prices that were randomly generated may have significantly impacted the price dynamics of the model. It also shows that the observation made during the investigation of the model that the model only generated convergent high models has to be revised. A limitation of the analysis was that the 10 domestic price distributions used to initiate all 64 models were randomly generated for each models, which may not allow to finely compare the performance of the 64 models.

Sensitivity to initial strategies of the country agents

Table 4.6 shows the characteristics of the distributions of initial strategies of the country agents randomly generated for the analysis. It shows that for each of the value of the binomial distribution used to randomly initialize the strategy of each agent, the average number of defection varied around this value by about 5%.

p	mean of the initial strategy distribution	standard deviation
0.2	0.196	0.0476
0.5	0.500	0.0548
0.7	0.700	0.0513

Table 4.6: Characteristics of the initial strategy distribution generated for the sensitivity analysis

Table 4.7 shows the repartition of the type of models depending on the initial proportion of defectors. Although more than half of the models stayed bounded, it shows that the initial number of defectors did change the convergence type of a significant number of models, most of which became divergent. In addition, it shows that the higher the initial proportion of defectors, the more models became divergent.

p	Convergent (low value)	Convergent (high value)	Bounded	Divergent
0.2	0	23	533	84
0.5	0	25	500	115
0.7	0	26	468	146

Table 4.7: Convergence type of all models on which the sensitivity analysis was performed.

Table 4.8 shows the correlation of the simulated global price with the time-serie of reference for all models which did not change convergence type despite the change in initial share of defectors. For all initial proportion of defectors, more than 97% of them show a high correlation (correlation coefficient high than 0.90, p-value lower than 10^5) with the time-serie of reference.

p	Bounded models	Highly correlated models (corr>0.90)	Small variations' amplitude models
0.2	533	524 (98.3%)	0
0.5	500	488 (97.8%)	0
0.7	468	458(97.9%)	0

Table 4.8: Price dynamics of all models which stayed bounded in spite of the change of initial domestic price distribution.

Summary

For all 1920 simulations ran for the three different initial shares of defectors among the country agents, it affected the convergence type of the models in only a fifth of the cases. Among this fifth, 80% of the models were driven towards divergence, whether the remaining one converged to a higher value of the global price than its initial value. The higher the initial share of defectors, the higher the number of models whose divergence type changed. Among the models which stayed bounded, the simulated global price of almost all of them remained highly correlated with the time-serie of reference. Thus, the calibrated models appear relatively robust to changes in the initial share of defectors among the country agents. Therefore, the assumption of initial full cooperation between the country agents is not a very strong assumption. A limitation of the analysis is that the method used to randomly generate the distribution of defectors led to a variation of about 5% of the initial number of defectors around its mean expected value.

Robustness to domestic price shocks

Table 4.9 shows the convergence type of all the models on which the sensitivity analysis was performed (64 models, 10 different value of the amplitude of the random shocks per model). Regardless of the amplitude of the shocks, almost 90% of the models diverged, which means that the behaviour of the model is very sensitive to noise in the value of the domestic prices.

	Convergent (low value)	Convergent (high value)	Bounded	Divergent
Number of models	0	0	84	556
Percentage of models	0 %	0 %	13.1%	86.9%

Table 4.9: Convergence of the models on which the sensitivity analysis was performed, regardless of the amplitude of shocks

Table 4.10 shows the correlation between the global price and the time-serie of reference for all the models which stayed bounded. It shows that among the 84 models which stayed bounded, 94% of them were still highly correlated with the time-serie of reference, and that all others showed variations in the global price of amplitude higher than 100US$.

	Bounded models	Highly correlated models (corr>0.90)	Small variations' amplitude models
Number of models	84	79	0
Percentage of models	100%	94%	0%

Table 4.10: Price dynamics of all models which stayed bounded in spite of the change of initial domestic price distribution

Higher values of λ_l seem to have increased the number of models which stayed bounded, but this effect was not proven significant (see Table 4.11).

Value of λ_l	Total number of models	Percentage of bounded models	Percentage of divergent models
$\lambda_l = 0.1$	240	10.9%	89.1%
$\lambda_l = 0.5$	230	13.9%	86.1%
$\lambda_l = 2$	170	15.3%	84.7%

Table 4.11: Convergence type of the models depending on λ_l

Finally, Figure 4.14 shows the share of the amplitude of the shocks for both bounded and divergent models. It shows that more models stayed bounded for lower amplitude of the shocks, and that the divergent models are almost uniformly distributed between the different amplitude of shocks tested. In total, 53% of the models stayed bounded for the lowest amplitude of domestic price

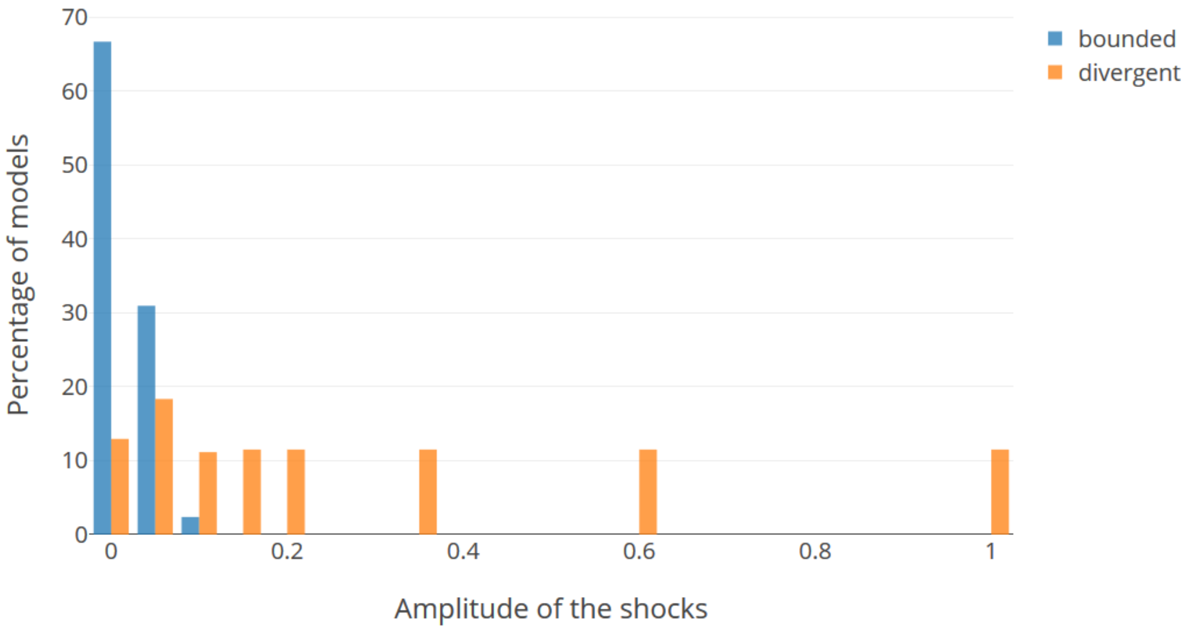


Figure 4.14: Convergence of the model depending on the amplitude of the shocks

Summary

The introduction of random external shocks to the domestic prices of the country agents led the most correlated models to diverge in almost 90% of the 640 simulations. Among them, all models were driven towards divergence. In the 10% of the models which stayed bounded, the simulated global price of almost all of them remained highly correlated with the time-serie of reference. In addition, it seems that higher sensitivity to the change in the trading policies of the trading partners' correlates with a higher number of models which stayed bounded. However, the small number of values tested does not allow to prove this effect significant. As expected, the higher the amplitude of the shocks, the smaller the number of models that stayed bounded. For an amplitude of 0.1, no model stayed bounded anymore. Thus, the calibrated models are very sensitive to noise, especially for higher amplitude of the noise. From random shocks with an amplitude of about 20% of the domestic price, all models diverged. For random shocks with an amplitude of about 2% of the domestic price (that is of about 1 to 10 US dollars depending on the country agent), only about 18% of the models stayed bounded. These are realistic variations of the price during stable periods, thus the dynamic of our model can be considered very sensitive to noise. Considering that the calibration of the model has been done in the absence of noise, it seems crucial that a realistic model of the crisis should be chosen among the models which are the most robust to noise.

4.3.2 Robustness of the different models

The value of the global robustness measure of all 64 calibrated model is shown in appendix D.3. Table 4.12 summarizes the mean and standard deviation of the robustness measure for all 64 models. It shows that the calibrated models were more sensitive to the change of the initial distribution of the domestic prices and the introduction of shocks to domestic prices than to the change in the initial strategies of the country agents.

Global		Initial Price		Initial Strategy		Shocks	
Mean	Std	Mean	Std	Mean	Std	Mean	Std
0.464	0.074	0.480	0.159	0.782	0.105	0.131	0.136

Table 4.12: Robustness measures of the 64 calibrated models

Table 4.13 shows the correlation between the parameters of the model and the robustness to the different sensitivity tests. It shows no significant correlation between the sensitivity of the 64 models studied and their parameters. However, the highest correlation and the lowest p-value are found for x_2 which seem to indicate that this parameter has the most explanatory power. None of the parameter of the simulation was significantly correlated with any of the robustness measure.

	x_1		x_2		x_3		λ_l	
Robustness measure	Corr	p-value	Corr	p-value	Corr	p-value	Corr	p-value
Global	-0.201	0.11	-0.225	0.074	0.24	0.05	-0.109	0.39
Initial price	-0.123	0.33	-0.267	0.03	0.191	0.131	-0.014	0.91
Initial strategy	0.008	0.95	-0.184	0.146	0.025	0.84	0.215	0.087
Shocks	0.021	0.87	0.0638	0.61	0.002	0.98	-0.235	0.06

Table 4.13: Correlation between the robustness tested and the parameters of the models

4.3.3 Sensitivity to variation in the level of data aggregation

Table 4.14 shows the variation in convergence type of all models for the different type of global price aggregation conducted by the institution agent. The global price used to determine the convergence type of the model was computed using the same method as the benchmark model rather than using the global price computed by the institution agent during the simulation. For the three first aggregation methods (avg, avg trade and avg strat), changing the type of aggregation led to a change of the convergence type of more than 40% of the models, most of which became convergent with their global price converging to a lower value than its initial value at the beginning of the simulation. When the institution agent was completely removed from the simulation, almost 97% of the models changed convergence type, most of which became convergent, with the global price converging to an higher value than its initial value at the beginning of the simulation.

	Convergent (low)		Convergent (high)		Bounded		Divergent	
Aggregation type	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Benchmark	0	0	0	0	64	100	0	0
Avg	24	37.5	0	0	34	53.1	6	9.4
Avg trade	20	31.2	1	1.6	38	59.4	5	7.8
Avg strat	21	32.8	2	3.1	36	56.3	5	7.8
None	0	0	48	75.0	2	3.1	14	21.9

Table 4.14: Convergence type of the models depending on the aggregation method based on the default computation of the global price

Table 4.15 shows the Pearson correlation between the convergence type of the models for which the simulations in which the institution agent was removed. It shows that convergent models were significantly negatively correlated with the strength of the domestic and local feedback loops, that is, models with weak domestic and local feedback loops were more likely to be convergent once the institution agent was removed. Models for which removing the institution agent led to more instability of the global price ere characterized by a low strength of the global feedback loop and a higher strength of the two other feedback loops.

	x_1		x_2		x_3		λ_l	
Convergence type	Corr	p-value	Corr	p-value	Corr	p-value	Corr	p-value
Convergent	-0.622	4.1e-8	-0.631	2.27e-8	**0.821**	**9.7e-17**	-0.211	0.09
Bounded	0.308	0.013	0.0422	0.74	-0.263	0.035	-0.151	0.23
Divergent	0.522	9.7e-6	0.643	9.92e-9	**-0.749**	**1.1e-12**	0.285	0.022

Table 4.15: Pearson correlation between the convergence type of a model when the institution agent was left out of the model, and its main parameters. The convergence type was represented by the variable 1 for all models of a certain convergence type and 0 otherwise.

Table 4.16 shows the convergence type of all models as determined using the global price computed by the institution agent during the simulation, except for the aggregation type 'None' in which the institution agent was removed from the simulation. It shows similar results than in Table 4.14.

	Convergent (low)		Convergent (high)		Bounded		Divergent	
Aggregation type	Number	Percent	Number	Percent	Number	Percent	Number	Percent
Benchmark	0	0	0	0	64	100	0	0
Avg	22	34.3	0	0	36	56.2	6	9.4
Avg trade	19	29.7	0	0	40	62.5	5	7.8
Avg strat	23	35.9	0	0	36	56.2	5	7.8
None	-	-	-	-	-	-	-	-

Table 4.16: Convergence type of the models computed based on the global price announced by the institutional agent

Among all bounded models, the global price of only 2 of them (computed as in the benchmark model) showed variations of more than 100US$, one of which remained highly correlated with the time-serie of reference (corr=0.998). The other showed a correlation with the time serie of reference of 0.61 (p-value = 3.10^{-5}). The model which stayed correlated had the following parameters: $\lambda_l = 0.1$, $x_1 = 1$, $x_2 = 0.02$ and $x_3 = 0.093$, and the aggregation method used by the institution agent was avg strat. This model was also the only one which stayed bounded for all aggregation methods. On the contrary, five models diverged systematically when changing the aggregation method.

In addition, Figure D.5, that can be found in appendix, shows the effect of the aggregation method on the behaviour of the global price (computed as in the benchmark model) for 4 models which changed behaviour for almost all aggregation method. It appears that the dynamic of the average price of the main exporters dramatically depends on the type of aggregation done by the institution agent. Figure D.5 also presents two ways of measuring the value of the global price for these four models across experiments. For each model, for each of the four aggregation method used, it first shows the global price computed as the average of the domestic prices of the four main exporters, and then the global price as computed by the institution agent during the actually simulation. For the first two models, only the value of the global price differs from the first to the second way of measuring it, but not its overall behaviour. However, for the fourth model, the first measure of the global price (the average of domestic price of the fourth main exporters) showed a price bubble for the avg trade and avg strat aggregation methods. However, the second measure (the global price as computed by the institution agent) only shows a general decreasing trend of the global price. Thus, changing the way the global price is measured dramatically changes the analysis of its dynamics. Introducing the possibility of changing the aggregation method used by the institution agent to compute and measure the value of the global price questions the definition of the global price and global food crises.

Summary

The analysis of the sensitivity of the calibrated models to the level of data aggregation reveals that for all three alternative data aggregations method investigation, about 45% of the models changed convergence type (when measured by the value of the global price computed as in the benchmark model)[5]. Among the models that changed convergence type, almost 80% of them were driven to convergence. Thus, for about a third of the models, changing aggregation method had a stabilizing effect. When leaving the institution agents out of the simulation, the stabilizing effect was even more important. The convergence type of the global price changed in 97% of all simulation. It converged in 77% of the models (to higher value than the initial value of the global price). This last analysis indicates that spikes in the global price may be caused by the global information feedback loop and the type of information aggregation done at the institutional level. In addition, it questions the way the global price is defined and measured by the institution agent but also by the analyst itself. Thus, this analysis also revealed the importance of the choice of the empirical measure of the global price used by the institutions for two reasons. First, because of its influence on the behaviour of the trade system itself. Second, because of the importance of the choice of the definition of the global price within the analysis of the model itself which can lead to draw different conclusions from the same model.

4.4 Validation of the model

In this section, we assessed the validity of the 64 most correlated models that we identified in the calibration section based on the validity measure defined earlier. We recall that level 0 of validity corresponds to the following requirements:

1. **Global price criteria:** The global price should have a bubble-like behaviour which stays within the interval of price $[0, 10p_{max}]$ defined in section 3.3.5,
2. **Domestic price criteria:** All domestic price should stay within the $[0, 10p_{max}]$ interval,
3. **Strategy criteria:** There should be an increase of the number of agents who implement a protectionist policy during the global price rise and a decrease during the price fall.

The validity level of all 64 calibrated models can be found in appendix D.3. Eventually, none of the 64 calibrated model was valid at level 0 for the three validity criteria. 36 of them were valid at level 1 for the global price criteria, valid at level 0 for the strategy criteria, but invalid for the domestic price criteria due to the domestic price of a few country agents (from 1 agent, for 13 of the 36 models, to 10 agents, for 2 of the 36 models). 14 of the 36 models were valid at level 0 for the domestic price criteria, valid at level 0 or 1 for the strategy criteria but invalid for the global price criteria because the simulated global price of these models did not show a stable period of slowly increasing price before the start of the price spike (the corresponding simulated global price can be found in appendix in Figure D.5). The remaining models were only valid for one of the three criteria.
When it comes to the robustness of the models, only 2 models reached a global robustness score of at least 0.60, one reaching a robustness of 0.63 and the other 0.70. The first one corresponded to a low strength of the domestic and local feedback loop, a low strength of the impact of a change in trading policies, and a high strength of the global feedback loop. It was of level 1 validity for the global price, level 0 for the strategy criteria and not valid for the domestic price since two domestic prices took higher values than 10700US$. As for the second model, it corresponded to intermediate values of the strength of all four parameters. It was of level 1 for the strategy criteria, of level 0 for the domestic prices, but not valid for the global price since it only showed a price spike but no preceding period of slow and stable increase of the price. Thus, the two models had a similar validity level, but none of them was fully valid according to the validity measure defined.
Even though none of the 64 calibrated models happened to be valid for all three criteria, they illustrate several parameters combinations that led the model to generate price spikes.

[5]Similar results are found when using the global price computed by the institution agent during the time of the simulation

Chapter 5

Discussion

In this chapter, we first present the drivers of a food price crisis identified in the analysis of the model and propose corresponding strategies to prevent price spikes. Then, we discuss more general price dynamics that our model is able to generate in light of the existing economic theories of price formation, transmission and crises. Finally, the main limitations of the model are discussed in the last section.

5.1 Consequences for global food crises

Our results showed that the model is able to generate spike-like behaviours which were highly correlated with the time-serie of reference. It also featured a realistic evolution of the number of countries having applied a protectionist policy during the price spike. Thus, our model achieved the main goals of the research. Thus, we claim that even though no combination of parameters explored allowed to reach a fully valid model for all the validity criteria, our model constitutes a proof of concept of the ability of information mechanisms to generate crisis-like behaviours of the global price of rice in the ITN. To the best of our knowledge, no other model in the literature focused on generating the behaviour of the global price of rice during the crisis based on information transmission mechanisms in an ABM. Although the relevance of considering information transmission mechanism has already been proven in the context of financial markets in at least one ABM, the corresponding model featured a different mechanism for price formation (Harras and Sornette, 2011). Even though it was able to generate price bubbles in a financial market, it featured adaptive agents that were able to adjust the weight they dedicate to different streams of news on the basis of their performances. On the other hand, because our model features purely reactive agents using constant weights for each source of information, it proves that price spikes and bubbles do not require complex agent behaviours to arise. The ability of the model to generate divergent price behaviour even in the absence of change in agents' strategies suggests that crisis may arise from the properties of the system itself regardless of agent behaviours. Therefore, it raises the question of whether it is possible to design intelligent agents whose behaviour could adapt and compensate for these properties.

Thus, our model confirms the ability of two-ways micro and macro-level feedback resulting from the interactions of the economic agents to explain the price dynamics of economic markets, already identified as a crucial economic mechanism and a major motivation for applying ABM to economic modeling (Tesfatsion, 2002). It confirms that the diffusion of price information within the different scale of trade network is a realistic determinant of price formation that can lead to endogenous price spikes even in a purely deterministic model. Thus, our model provides computational evidence for mechanisms that has been proposed from a posteriori data analyses of the price dynamics during the crisis (Tadasse et al., 2016). While this existing work identified speculation on future price dynamics as the main driver of these dynamics, our model also includes the effect of the communication of price information between trading partners as an additional, and potentially complementary, mechanism driving endogenous price spikes. Regardless of the exact mechanism used, the ability of the model to simulate the main stylized facts of the crisis without any external shocks strengthens and legitimates its analysis in term of endogenous dynamics. Thus, it confirms that the focus of mainstream analyses of the crisis on identifying the external shocks that could have caused the observed change in price could gain to be complemented by an investigation of the endogenous mechanisms of the ITN that could have lead the price to spike (Tadasse et al., 2016; Rutten et al., 2013). In this section, we identify several factors that could have caused the global price crisis of 2008, three of them being endogenous to the model, the last one confirming the importance of considering exogenous drivers of the crisis as well:

- an endogenous shock caused by information feedback loops,
- an endogenous shock caused by the process of aggregation of market information used by the PMI,
- an increased in global price variability caused by changes in trade policies,
- an increased in global price variability caused by price shocks in the domestic markets.

The first and last points allow to answer positively to our research question: it appears possible to prevent food price crises or reduce their severity by modifying the strength of the three information feedback loops or the processing of market information done by the PMI. the model showed that it is possible to prevent food price crises or reduce their severity by modifying the strength of these three feedback loops or the aggregation of information done by the international institution. In addition, the analysis of the model identified two other potential drivers of food crises and corresponding strategies that could prevent the development of food crisis: limiting the change of trade policies of the countries involved in the ITN of rice and limiting the external shocks to the domestic markets of rice of the trading countries. Thus, our results on the role of the aggregation measure used by the institution agents identified a potential role of the institutional communication in the spread and absorption of price shocks and corresponding strategies to mitigate price crisis, which was also a goal of the research. The following subsections present each of the drivers we identified and, for each or them, a corresponding strategy that could prevent or mitigate spikes in the global price of rice. In addition, we discuss the importance of the indicator used to monitor global price crises.

5.1.1 Information feedback loops

Our work aimed at identifying the importance of each information feedback loop in triggering a global price crisis. In other words, it aimed at identifying whether the sensitivity of countries' domestic price to its own variations, or to the variations of the global price, or to its difference with the domestic price of the country's trading partners could have been internal driver of the price crisis. Our results found that the 64 most realistic models featured either:

- a high sensitivity of countries' domestic price to its own past variations,
- a high sensitivity of countries' domestic price to the variations of the global price,
- an intermediate sensitivity of countries' domestic price to their own past price variations, the variations of the global price and the value of the price of their trading partners.

However, these combinations of parameters may be caused by the specifics of the sampling of the parameter space. This hypothesis is supported by the rest of the analysis of the model which did not identify a single parameter as being a stronger determinant of price crises, and identified high variations of the global price for high enough values of the sensitivity of the domestic markets of at least one of the information source. In addition, the robustness of the models did not correlate with any of the parameter taken in isolation. Thus, it is more likely that food crises stem from the interaction and reinforcement effects between the three information feedback loops. This effect is confirmed by the reinforcing effects of the three parameters observed when studying the final value of the global price and the final spread of the domestic price distribution in the simulations. In addition, it is in line with the current literature on systemic risk which identifies networks properties such as interconnectedness, modularity and structure, together with individual nodes properties[1], as the main determinants of the resilience of the global food system to crises (Battiston et al., 2012; Helbing, 2012; Lee et al., 2011; Torreggiani et al., 2017; Gao et al., 2016; Distefano et al., 2018; Dolfing et al., 2019). Therefore, gaining a better understanding of the emergence of price spikes in our model would require to understand the effect of each feedback loop on the structure of the information network within the model. We can argue that this information network differs from the trade network itself by its weighting. Rather than being weighted based on the volume traded between each country, which is assumed constant during the simulation, its edges could be weighted by the rate of domestic price change caused by the information shared between each pair of agents. Since this rate depends on the variation of the domestic price of each agents, it changes at each step of the simulation [2]. Yet, the current results of the analysis of the model allow to identify a first coarse strategy to prevent the development of food crises in the ITN.

Strategy 1: monitoring and reducing the sensitivity of domestic markets to one or several of the three sources of price information accordingly.

Assuming that it is possible to map the current state of the ITN unambiguously to a certain point or at least region of the parameter space of the model, it would be theoretically possible to determine how to modify the value of the model's parameters to achieve a better convergence and stability of the global price of rice, and thus prevent a price surge. This modification of the parameters could then be translated into real life policies. However, translating these parameters into a corresponding measurable real-life indicator seems challenging, and is made even more difficult by the simplifying assumptions used in the model. In reality, the ITN is not made up of tens of trading countries, but of million of individuals interacting together. Therefore, while our model simulated the emergence of a global price from the prices in national markets, the global trade network and the national markets both emergence from the aggregation of the interactions of these individuals, at the national and global scale respectively. Thus, the aggregation mechanism simulated by our model at the level of the global price, also happen at the level of the domestic price. Thus, reducing the sensitivity of the domestic market to information requires to reduce the sensitivity of each, or at least several, of these individual economic agents to price information which seems hardly implementable in a real life policy.

Yet, strategy 1 can be related to existing dynamics and policy in the ITN. For instance, a reduced sensitivity of domestic markets to the price variations of a country's trading partners or to the variations of the global price could have a similar effect as imperfect market information, a mechanism that has been shown to impede price transmission between several markets, and thus prevent the transmission of price shocks within the ITN (Brooks and Matthews, 2015). On the other hand, increased market transparency is the main institutional recommendation to national government (IMF and UNCTAD, 2011). It aims at reducing price volatility by limiting panic-driven price-movements. We argue that imperfect market information limits the price variations perceived by the economic agents (which could correspond to replacing the real rate of change of the price of the trading partners in equation 3.5 by a perceived rate of change), whereas improving market transparency corresponds to lowering the sensitivity of the domestic markets to the price variations (which could correspond to lowering the value of any of the multiplicative factor of equation 3.5). As for the sensitivity of the domestic price to its own past variations, one could interpret certain existing governments' policies as attempts to reduce its value and thus stabilize the domestic markets. For instance, that could be the case of carry-over stocks which are used by national governments as a crucial buffer to balance the supply and demand throughout the year to limit the variability of domestic price (Headey, 2011). However, when these policies are thought to decrease the domestic price by increasing the supply available on the domestic market, our model identifies the information effect of the policy as an additional factor to account to explain the policies' impact on prices.

[1]This last factor can be seen in the sensitivity of our model to changes in the initial distribution of domestic prices and strategies of the country agents.

[2]The structure of this network could be easily investigated in a follow-up project since the three components of the rate of change of the domestic price of each country caused by each of the three information sources has been saved for all the simulations that have been ran.

5.1.2 Information processing of the PMI

Our results showed that changing the type of aggregation method used by the institution agent to compute the global price had a significant impact on the dynamic of the global price of the most realistic models of the crisis. For a third of the most realistic model, it prevented the development of a global price spike. In addition, modifying the topology of the network by removing the institution agent successfully prevented a global price spike in 75% of the cases. It questions the current ability of trade-related international institutions to prevent price instabilities and increase the predictability of the system by promoting relevant communication as they are supposed to (Headey, 2011). Because highly trusted sources of information have the ability to both attenuate, but also increase amplification effects when they release risk information(Frewer, 2003), they may facilitate the rise of panic movements and the transmission of price shocks within the ITN. Therefore, we propose the following strategy as a way to prevent food crises:

Strategy 2: changing the aggregation method used by the institutions to compute the global price or changing the topology of the information network of trade.

The observed role of the aggregation process used by the institution agents relates to the initial motivations of the development of modern macroeconomics methods such as the General Equilibrium theory. This set of method as being developed to solve the problem of deriving relevant macroeconomics property from individual behaviour in an analytically tractable way which led to assimilate the economy's behaviour to that of one average rational individual (Kirman, 2010). The market analyses, and therefore the indicators, provided by the PMI are grounded on these macroeconomic indicators. However, our model reveals that the choice of the indicator may change the dynamic of the price system itself. Even though certain PMI put significant efforts in improving the monitoring of the markets and improving the complexity of their indicators (GIEWS, 2019; FAO, 2002), they set up an additional information feedback loop which amplifies the price variations of the domestic markets. However, it is crucial to keep in mind that, for a few of the most realistic models, changing the indicator used to define the global price or leaving the institution agent out of the simulation actually increased the instability of the global price. Therefore, it is necessary to identify the conditions to ensure the stabilizing effect of this strategy. This problematic relates to the questions of using feedback loops in distributed systems as a control mechanism for the behaviour of their individual units and finds its current application in more engineering-related fields (Lu et al., 2006; Guan et al., 2010).

5.1.3 Changes in trade policies

The model generated food price crises regardless of the sensitivity of domestic prices to changes in trade policy. However, a higher sensitivity of countries' domestic prices to changes in the trading policy of their neighbours increased the volatility of the global price. This effect is consistent with the observed ability of foreign market news to cause volatility spillovers from one market to the next (Gotz et al., 2012; Ito et al., 1992; Durevall and van der Weide, 2014). It confirms the analyses of Headey and Fan (2010); Demeke et al. (2009); Anderson and Nelgen (2012b); Ivanic and Martin (2014) on the importance of trade shocks for the stability of the food prices. Thus, even though changes of trading policy did not have a strong influence on the ability of the model to generate spike-like behaviour, it may have increased the chance of a model to develop a price crisis. Since existing recommendations for food security claim that limiting instabilities in food prices is necessary to ensure the economic access of all households to sufficient food supplies (Timmer, 2012), we propose the following strategy as a way to prevent food crises:

Strategy 3: ensuring the stability of trade policies and reducing the sensitivity of domestic markets to changes in the trade policy of their international partners.

This strategy corresponds to the existing recommendations of the main trade insitutions which identify protectionism as a major drivers of price instability. Increasing the trust between trading partners and in the international trade institutions may ensure this stability but also potentially increase the sensitivity of changes in the trade policies of certain players. However, our results do not identify the multiplier effect caused by the changes in the trade policy of certain countries as a major driver of price crises unlike a number of publications (Giordani et al., 2016, 2014; Gotz et al., 2012; Abeysinghe and Forbes, 2005; Fair et al., 2017). This may be caused by several of our design choices which limited the impact of changes in trade policies. Rather than generating an additional shock to the domestic markets a its trading partners, a change in the trading policy of a country amplifies the impact of the current price variation of the country on the domestic markets of its trading partners. If the country which changed policy did not undergo a significant change in its domestic price, this mechanism won't generate a significant shock on the domestic markets of its trading partners. In addition, as currently implemented in the model, this effect is proportional to the share of the country in the total volume traded by its partners. However, if a country only represents a little share in its partners' trade but is one of the main players of the ITN, the expectation of a negative effect at the level of the whole economy may amplify the effect of the news on the domestic markets of its trading partners.

5.1.4 Price shocks in the domestic markets

Our results showed that the model is very sensitive to noise and that even moderate levels of noise in the domestic prices of the countries led the global price of the most realistic models to quickly diverge outside of a realistic range of values. It may be that the nature of the noise used during the sensitivity analysis was not realistic, either by its too large amplitude or its too high frequency. In the simulation, the smallest average amplitude of noise was of 1 to 10US$ (depending on the domestic price of the country agent) and the frequency of the shocks was every 3-4 days. Since the empirical domestic and global time-series do not directly give access to the level of noise caused by non information-related markets process such as changes in supply, demand, elasticities (for instance weather conditions, diet changes, an increase in demand for non-food usage, changes in the level of stocks (Trostle, 2008; Headey and Fan, 2008; Headey, 2011; Headey and Fan, 2010; Hochman et al., 2014)), additional data analyses would be required to properly calibrate the noise level that our model should contain. Yet, the destabilizing effect of noise on the most calibrated models points out an additional strategy to prevent important variations in the global prices:

Strategy 4: limiting external shocks to the domestic prices of the trading countries.

This strategy is in line with work in traditional economic analyses according to which crises are caused by external shocks to the economy (Kirman, 2010). However, our analysis does not identify external shocks as the main drivers of the crisis but rather as aggravating factors which trigger internal amplifying dynamics caused by information feedback loops. Eventually, it leads to the same recommendation of stabilizing the domestic prices as one of the basic approach to coping with high food prices and food crises which is domestic price stabilization (Headey and Fan, 2010; Timmer, 2010). Public price stabilization is one of the three main axis of recommended best practice by the World Bank (Timmer, 2010). This strategy has been proven to promote economic growth, poverty reduction, social and political stability, and thus successfully to improve food security in Asian countries (Dawe and Timmer, 2012). We mentioned that the will to stabilize their domestic prices is what motivated more countries to implement protectionist policies during the crisis (Demeke et al., 2009; Timmer, 2012). However, the subsection on the increased volatility caused by changes in trade policies shows that limiting external shocks has to be done through alternative policies.

5.1.5 Indicator of global food crises

Finally, the results highlighted the importance of the choice of the indicator used to define a global price crisis since using different indicators gave contradictory descriptions of the same reality. Our choice to compute the global price as the average of the domestic prices of the four main exporters may be an oversimplification of the reality. However, our results still allow to question the current choice of indicators, especially for the institutions which currently monitor the variations of a single price-serie. It echoes the analysis of Lang (2010) on the definition of food crises and : "Crisis is an over-used word covering a spectrum from, at one end, expression of irritation with petty difficulties to, at the other end, meltdown and reconfiguration. It can mean different things to different people. What matters is the frame of reference and indicators. Hunger and food availability have been central to twentieth century food policy discourse. " It also relates to existing concerns in the literature on the food crisis of 2008 which claims that because the price trends were followed using the US-dollar as a base currency, the perception of the severity of the food price rise of 2008 may have been amplified by the simultaneous depreciation of this currency (Headey, 2011). Thus, the fact that all PMI that we identified in our introduction do use this currency, together with General Equilibrium models, to infer an analysis and thus send information through the trade network may have undesirable consequences.

5.2 Price dynamics of the model

The analysis of the model showed that it was able to generate 3 types of convergence behaviour depending on the value of the parameters: the convergence of the global price towards an equilibrium value (higher or lower than its initial value), various bounded variations of the global price, and its divergence outside of a range of realistic value and towards infinitely high or low values. In addition, the model was able to generate the synchronization of the domestic prices and cross-scale aggregation effects that we already mentioned in the last section. Some of these behaviours relate to traditional economic theories. However, our model proposes alternative underlying mechanisms for these behaviours that we will further detail in the following subsections. In addition, the last subsection will propose a last driver of large price changes in the ITN in term of self-organized criticality.

5.2.1 Convergence and the General Equilibrium Theory

According to our results, it appears that the convergence and equilibrium of the model depends on its parameters (the strength of the three information feedback loop and the sensitivity to change in trade policies), structure, initial values and on the rules of the agents. Under certain conditions, the global price converges to an equilibrium value. This behaviour relates to the main principle of the General Equilibrium Theory according to which the behaviour of supply, demand and price results in an equilibrium state of the whole economy that can be deduced from the aggregate contribution of each of its actors (Walras, 1954; Farmer and Foley, 2009). Since our model is purely deterministic, its final state could theoretically be deduce from the initial state and thus from the parameters of all the economic agents. Thus, the equilibrium state appears in the model as a special case that can manifest itself under certain conditions on the value of its parameters and its initial conditions.

However, this equilibrium results from a different mechanism than in the General Equilibrium theory. Considering the perspective of parallel distributed processing, the economic agents of the model are simple processing elements that allow for information processing within the whole network. The final value of the global price and its convergence result from the computation done by the ITN itself and could theoretically be deduce from the initial state of the economy, its network structure and the rules of the agents (McClelland et al., 1987; Mitchell, 2009), rather than from the equilibrium of supply and demand and trade policy information. Thus, the underlying mechanism of the equilibrium in our model is the transfer and processing of price information within the ITN rather than the transfer of excess demand from one market to another through the physical flows of commodities (Barrett and Li, 2002).

5.2.2 Synchronization and the LOP

The extremely low values of the spread of the distribution of the domestic prices found for certain parameters of the model attests of the ability of the model to generate the synchronization of the domestic prices (see Figure D.4). This synchronization has been shown to depend on the local feedback loop. When isolating the local feedback loop from the rest of the model by setting the parameters x_1 and x_3 to zero, our model defines a system of coupled differential equations with delay (CDED). The literature CDED and their application to multi-agent dynamical systems (MADS) attests of their to lead to synchronization effects on networks and provides analytical results on the conditions of the synchronization for some simpler cases (Yu et al., 2010; Lu et al., 2006). Most of them points to the necessity of time-delay to generate such synchronization (Lu and Chen, 2005; Yu et al., 2013).

The ability of the prices to synchronize under certain conditions relate to the LOP according to which a commodity gas a single price in a common currency unit throughout the world (Isard, 1977; Barrett and Li, 2002). Thus, the LOP appears as a special case of our model. However, rather than relying on trade to adjust the price, our model proposes an alternative mechanism for price synchronization based on information transmission between trading partners. In addition, the LOP explains remaining differences in price by the costs of trade and trade restrictions (Listorti and Esposti, 2012). Instead, in our simulation, the synchronization is prevented by a low strength of the local information feedback loop, or a high strength of the three information feedback loops. In other words, national markets which are too sensitive to their own variations or to variations in the global price won't synchronize locally with their neighbours. This observation is in line with empirical results on market integration and price transmission(Listorti and Esposti, 2012; Barrett and Li, 2002). Thus, in our model, the LOP arises from a decentralized and local information transmission mechanisms. It is in line with the hypothesis that information carries price changes and anxiety from the world to the domestic market more efficiently than physical trade flows an outweighs the dampening spatial price equilibrium effect predicted by the LOP (Gotz et al., 2012). Because the model is very sensitive to the initial distribution of the domestic prices, it may be that certain configurations of the value of the domestic prices in the world lead more easily to price crises than others. For instance, more homogeneous distributions may stabilize by diminishing the effect of the strength of the local feedback loop.

5.2.3 Self-organized criticality and crises

The threshold type of behaviour shown by the strength of the local information feedback loops indicates that for certain combinations of the strength of the three information feedback loops the convergence of all the domestic prices is maximal. Figure D.4 indicates that they may be a combination of these parameters for which the spread of the distribution of the domestic prices is minimal. However, it also suggests that the position of this minimum in the parameters' space could correspond to a state in which a very small increase of any of the parameter may induce a large desynchronization of the domestic prices. Research from complex systems theory describes how positive feedback loops can drive a system towards self-organized criticality, a state in which it becomes particularly vulnerable to small external or internal shocks and phase transition, that is, a sudden change in the aggregate state or macro-behaviour of a system. Several authors provide an account of financial and economic crises in term of self-organized criticality leading to a phase transition (Sornette and Cuypers, 2004; Kirman, 2010). Such cross-scales positive feedbacks in complex systems have been shown to lead to dynamic instability, amplification effects and to prevent equilibrium and stationary states from being maintained. They have been linked with cascading failures, bubbles ans crashes dynamics as well as cooperation break down Helbing (2012). Our results suggests that the strongest synchronization of the model may correspond to such a state.

Several authors provide an account of financial and economic crises in term of self-organized criticality leading to a phase transition (Sornette and Cuypers, 2004; Kirman, 2010). Such cross-scales positive feedbacks in complex systems have been shown to lead to dynamic instability, amplification effects and to prevent equilibrium and stationary states from being maintained. They have been linked with cascading failures, bubbles ans crashes dynamics as well as cooperation break down Helbing (2012). On the economic side, simple models based on spin-like models or cellular automata proving that very simple models of money and economic markets can already undergo sudden change of behaviour or phase transitions even in the absence of exogenous shocks (Sánchez et al., 2002; Bornholdt and Wagner, 2002; Bouchaud, 2013, 2009). In addition, Sornette (2003) also concluded that major changes in the aggregate state of the economy may result from long-term endogenous dynamics leading to self-organized criticality rather than short-term exogenous shocks. Therefore, we propose the hypothesis that certain large variations of the global price may be caused by the self-organization of the ITN towards a state of greater stability, but that in this state the ITN may be more sensitive and vulnerable to small price variations.

5.3 Limitations

The limitations of this work are of two types. First, they concern the design of the model that has been developed. Second, they correspond to the weaknesses of the analysis of the model that has been conducted.

Even though this research tried to build upon and include results and mechanisms from existing economic theories, it finds its main limitations in its over-simplification of the mechanisms underlying price formation. The implementation of our model reduced trade and chances in tariffs to price and information dynamics, and only included the effect of short term changes in supply and demand as short-term noise. Defining a single domestic price for each country required to disregard the differences between the price of the commodity in the domestic market and in the international market caused by tariffs and transaction costs. It disregarded the more local process of domestic price formation at the level of the economic agents which make up the domestic markets and their interactions within the ITN.
Although considering a static and deterministic model allowed to better understand the major dynamics of the model and demonstrate their ability to generate price spikes from internal dynamics only, it hinders the generality and the realism of the model. The trade system constantly undergoes supply, demand, price and trade shocks, and several researchers even argue that the frequency and amplitude of these shocks is likely to increase in the future (Fair et al., 2017; Dolfing et al., 2019; Headey, 2011; Distefano et al., 2018). In addition, assuming a constant value of the four parameters of the model during the entire simulation is very questionable. In practice, it is more likely that the sensivitity of the domestic markets to the different sources of information depends itself on the information shared by these different sources, as it has been implemented in the case of financial markets in Harras and Sornette (2011).
Finally, our model implemented simple reactive agents whose behaviour was overly simplified compared to the complexity of the decision making under certainty that lead to political decision making.

As for the analysis, its main shortcoming can be found in its focus on the description of the macro-dynamics of the models, rather than the underlying micro-dynamics and interactions that led to the aggregate price dynamics observed. In addition, even though we mentioned the importance of network properties and dynamics in the spread, amplification and absorption of shocks in dynamical systems (Battiston et al., 2012; Torreggiani et al., 2017; Dolfing et al., 2019), we did not provide an analysis of the behaviour of the model in term of these network properties, and did not test its sensitivity to its network structure. Considering that positive feedback loops can generate interdependent or cascading failures within networks from a single local shock (Helbing, 2012), a more complete analysis of the model would gain from testing the diffusion and amplification of a single local shock within the system. Besides, choices that have been made to limit the computational efforts to investigate the model can be questioned, such as the ranges and number of points chosen to sample the parameter space of the model. It is especially true for the sensitivity analysis and the corresponding measures of the robustness of the models, which were computed from a rather limited number of runs. In the words of Leombruni and Richiardi (2005), "the artificial data may not be representative of all outcomes the model can produce. In other words, it is possible that as soon as we move to different values of the parameters, the behaviour of the function computed by the model will change dramatically.". In addition, the fact that our analysis encountered difficulties in distinguishing between the 64 most correlated models on the basis of their validity proves that it is not because a model implements a reasonably realistic data-generation process that it identifies the data-generation process that corresponds to the system under study.

Chapter 6

Conclusion

In this research, we developed an ABM of the rice price crisis of 2008 capable of reproducing the main price and trading strategy behaviours than observed during the unfolding of the crisis. To our knowledge, this is the first ABM of the crisis that implemented a mechanism of price formation based on the transmission and processing of price information between trading countries and the PMI. Although our model confirmed the ability of external price shocks in triggering large price variations, it also revealed the importance of considering the internal mechanisms of the price dynamics of the trade system. More specifically, it proved that realistic price dynamics can be caused by internal drivers of the trade system, even in the absence of external shock. The model showed that a price crisis can be caused by the excessive sensitivity of a country domestic market to its own price variations, to the variations of the global price, and to its difference with the domestic price of its trading partners. It showed that the development of a price crisis or its mitigation depends on the type of aggregation processed used by the PMI to compute the global price, and that, depending on the relative strength of each sensitivity to price and price variations, removing the PMI from the ITN could either improve or hinder the stability of the ITN. Finally, it confirmed the importance of preventing changes in trade policies of trading countries to reduce the volatility of the global price, or to reduce the sensitivity of the domestic markets to these policy changes. These results are in line with several existing policy recommendations for price stabilization on the ITN. However, it sheds light on the importance of designing strategies to limit the sensitivity of markets to price and trade information in order to further ensure price stability in the ITN.

The analysis of the model focused on the aggregate macro-level dynamics of the model. Yet, investigating finer micro-level dynamics is of great importance for the understanding of the system. Thus, future work could focus on testing whether the local and network properties of the country agents determine their robustness to food crisis. It could consist of testing several existing results of research on the topic of network resilience such as the role of a core-periphery structure of the trade network, its skewed distribution of degree and node centrality and the presence of hub nodes in the propagation of shocks (Kim and Shin, 2002; Gai et al., 2011; Sartori and Schiavo, 2015; Puma et al., 2015). In addition, conducting a more mathematically analysis of the model in term of CDED could allow to identify additional conditions for the convergence of the global price, the synchronization of the domestic prices and potentially the diffusion of random shocks to domestic prices. Therefore, it could identify the condition for higher or lower levels of systemic risks. In addition, we mentioned the over-simplification of economic mechanisms as being the biggest limitation faced by our current model. Overcoming this shortfall may require to implement a simulation of the actual trade interactions between the country agents and the economic effect of changes in tariffs, transaction costs and trade exchanges on price and trade beyond information dynamics. It could further require to implement a dynamical adaptation of the sensitivity of each domestic market to the three sources of information and to add an additional spatial scale to the model corresponding to the individual agents of the domestic markets. Finally, in AI, MAS are used to design rational agents which act to achieve the best outcome or, under uncertainty, the best expected outcome of a task (Russell and Norvig, 2016). Thus, following an engineering approach of modeling could allow to develop optimal agent strategies to better ensure the stability of the global price.

Appendix A

Model's assumptions

In this subsection, we present the approach, assumptions and motivations that support the choice of our model. We recall the goal of our research which is to develop and validate an ABM of the rice price crisis of 2008 in order to investigate the role of PMI in triggering the crisis and identify corresponding ways to prevent the development of global price crises. Thus, the time-scale of our simulation spans approximately 2 years, from beginning 2007 to end 2008. The geographic scale corresponds to all countries which are involved in the ITN of rice.

Economic assumptions on price transmission

Our approach is grounded in behavioural economics and aims at providing a test bed for its findings and hypothesis concerning price formation and transmission mechanisms which stand in contradiction with the mainstream theories of price formation and transmission. Among them, we chose to use the following as assumptions for our model:

(A1): price volatility transmission and trade are weakly correlated, thus volatility transmission can happen even when trade is minimal or in the absence of trade,

(A2): information carries price expectation and volatility between the world and the domestic market more efficiently than physical trade flows and outweighs the dampening spatial price equilibrium effect predicted by traditional theories, thus imperfect market information can impede price transmission,

(A3): large price movements heighten attention to the information and increase price information flows,

(A4): new price information coming from domestic markets and institutional analyses are immediately processed by the market players and new information screens older information.

Assumptions (**A1**) and (**A2**) motivate our choice for a model in which global and domestic prices are updated based on information receive by the different agents rather than based on the actual trade flows. Assumption (**A3**) justifies to update the value of the prices proportionally to the price change compared to the last time step of the simulation. Finally, with the assumption (**A4**), we seek to implement a simple version of the present bias preference in the information processing process of the markets reported in the literature (O'Donoghue and Rabin, 1999). Finally, the two last assumptions are necessary to quantify the relative impact of news coming from different countries.

Economic assumptions on governments and institutions analyses

From our study of the countries' rationale during the food crisis of 2008, we derive a simplified account of decision makers reasoning grounded in price and trade policy analysis in terms of mainstream economics. Correspondingly, we take as hypothesis for the design of our model the following statements:

(B1): National governments and institutions ground their decision making in mainstream economics analysis of the traditional determinants of price formation (variation of supply, demand, costs and trade),

(B2): the world rice market operates under highly incomplete and imperfect information about short-run supply and demand factors as well as price expectations, countries and institutions use price themselves and trade policy information as proxies for the traditional determinants of price, setting-up a clear positive feedback loop between prices (Timmer, 2012),

(B3): countries and PMI are ruled by individuals with bounded time, memory, and resources, therefore they only have access to a limited amount of information to inform their analysis and decision making,

(B4): national governments and institutions are not purely rational agents and suffer from a present bias preference,

(B5): because mainstream economics assume trade to be the main vector of price transmission, national governments make use of protectionist policies[1] to try and shield their domestic markets from global price movements and off-setting domestic price deviations from its trend value,

(B6): because mainstream economics assume that protectionist policies further tighten the market by diminishing the supply available for trade and increasing the global demand, institutions and countries expect prices to rise if they know that some countries are implementing protectionist policies, proportionally to the volume share of these countries in the global market,

(B7): national governments balance domestic, trade and global interests based on their reliance on trade to ensure their food security and their share in the global markets,

(B8): the sensibility of national governments to price change is correlated with both its GDP and its depend on rice for its food security[2].

Assumption (**B2**), (**B3**) and (**B4**) states the imperfect knowledge, behavioural bias and bounded rationality of the countries and institutions that our model features. (**B5**) and (**B6**) follow from assumption (**B1**) and correspond to the core of our simplified account for the reasoning process of countries and institutions. Even though we implicitly assume a unique reasoning process for all the market agents, assumptions (**B7**) and (**B8**) introduce some heterogeneity between countries, which we will account for in our model through country agents' attributes.

Behavioural assumptions on countries and their relations with institutions

Research in the field of behavioural economics claims that economic observations, such as market volatility or security price, may not only depend on purely economic factors but also psychological or biological factors determining the formation of expectations and risk aversion (Tom et al., 2007; De Bondt et al., 2008; Murphy et al., 2012; Laibson and List, 2015; Bellemare and Lee, 2016). We chose to ground our model on corresponding assumptions. Because we aim at investigating different scenarios and hypotheses, we propose two version of the second assumption, the first being use for the design of the model, the second one being only used in the first experiment we propose.

(C1): Information transmission correlates with trade, thus the structure of the ITN of rice embodies the price information flows between the different trading partners,

(C2):
a Due to the relative stability in time of the ITN and the existence of trade agreements, relationships between countries can be assumed stable over time and do not change during a crisis,

b When they choose for their domestic interest to prevail over the one of their trading partners, for instance by implementing protectionist policies, countries break the trade relationship with their trading partners,

[1] By protectionist policies, we designate both exporters anti-trade policies (trade restrictions or ban and increase of export tariffs.) and importers over-trading policies (decrease in tariffs on imports, panic buying and hoarding)

[2] see Demeke et al. (2009)

(C3): Because of trust mechanism which are self-reinforcing, the longer two countries traded together, the stronger their present trade relationship and their information transmission,

(C4): The more central a country in the international trade network, the higher its market integration,

(C5): Global market integration prevails compared to local market integration, screening countries from the local functioning of the trade network.

The first four assumptions allow to infer the structure and characteristics of the information flows between the members of the ITN from empirical data on the ITN. Assumption (**C5**) will be used in subsection 3.1.3 and 3.1.2 to introduce heterogeneity between the relative attention given by the different countries to information coming from their trading partners compared to information coming from PMI.

Simplifying assumptions from the model design

In addition, the building of our model required to make the following simplyfing assumptions:

(D1): the informational impact of the change of trade policy of a country on its domestic market depends on the quality of its institutions which correlates with its gross domestic product (GDP) per capita,

(D2): countries only share domestic market and trade policy information with their trading partners and the PMI,

(D3): countries follow their own agenda and do not explicitly cooperate with one another.

Appendix B

Data

B.1 Price time series

In this appendix, we list the references of the price time-series gathered for the validation of the model. The first table corresponds to the domestic prices of 27 countries from the GIEWS - FAO dataset. The second table gathers the references of the time series used for the computation of the global price.

Country	**Number of time series**	**Reference**
Bangladesh	1	Wholesale, Dhaka, Rice (coarse- BR-8/ 11/ Guti/ Sharna)
Brazil	2	Retail, São Paulo, Rice Wholesale, National Average, Rice (paddy)
Colombia	6	Wholesale, Bogotá, Rice (first quality) Retail, National Average, Rice (first quality) Retail, National Average, Rice (second quality) Wholesale, Barranquilla, Rice (first quality) Wholesale, Barranquilla, Rice (second quality) Wholesale, Bogotá, Rice (second quality) Wholesale, Medellín, Rice (first quality)
Costa Rica	2	Retail, National Average, Rice (first quality) Retail, National Average, Rice (second quality)
Ecuador	3	Wholesale, Cuenca, Rice (long grain) Wholesale, Guayaquil, Rice (long grain) Wholesale, Quito, Rice (long grain)
El Salvador	1	Wholesale, San Salvador, Rice
Ghana	4	Wholesale, Bolgatanga, Rice (local) Wholesale, Accra, Rice (local) Wholesale, Kumasi, Rice (local) Wholesale, Techiman, Rice (local)
Guatemala	2	Wholesale, Guatemala City, Rice (first quality) Wholesale, Guatemala City, Rice (second quality)
Haiti	10	Retail, Cap Haitien, Rice (local) Retail, Hinche, Rice (imported) Retail, Hinche, Rice (local) Retail, Jacmel, Rice (imported) Retail, Jacmel, Rice (local) Retail, Jeremie, Rice (imported) Retail, Jeremie, Rice (local) Retail, Les Cayes, Rice (local) Retail, Port-au-Prince, Rice (imported)

		Retail, Port-au-Prince, Rice (local)
India	8	Retail, Chennai, Rice Wholesale, Chennai, Rice Wholesale, Mumbai, Rice Retail, Mumbai, Rice Wholesale, New Delhi, Rice Retail, New Delhi, Rice Wholesale, Patna, Rice Retail, Patna, Rice
Israel	1	Retail, National Average, Rice
Italy	1	Wholesale, National Average, Rice (paddy, Arborio Volano)
Madagascar	2	Retail, National Average, Rice Retail, National Average, Rice (local)
Mali	4	Wholesale, Bamako, Rice (imported) Wholesale, Bamako, Rice (local) Wholesale, Kayes, Rice (imported) Wholesale, Kayes, Rice (local)
Mexico	4	Wholesale, Guadalajara, Rice (Sinaloa) Wholesale, Mexico City, Rice (Morelos) Wholesale, Mexico City, Rice (Sinaloa) Wholesale, Puebla, Rice (Morelos)
Mozambique	8	Retail, Angonia, Rice Retail, Chokwe, Rice Retail, Gorongosa, Rice Retail, Maputo, Rice Retail, Manica, Rice Retail, Montepuez, Rice Retail, Nampula, Rice Retail, Ribaue, Rice
Nepal	1	Retail, Kathmandu, Rice (coarse)
Nicaragua	3	Wholesale, Managua (oriental), Rice (third quality) Wholesale, Managua (oriental), Rice (second quality) Wholesale, Managua (oriental), Rice (first quality)
Niger	10	Retail, Agadez, Rice (imported) Wholesale, Agadez, Rice (imported) Retail, Dosso, Rice (imported) Retail, Maradi, Rice (imported) Wholesale, Maradi, Rice (imported) Retail, Niamey, Rice (imported) Wholesale, Niamey, Rice (imported) Retail, Tillaberi, Rice (imported) Wholesale, Tillaberi, Rice (imported) Retail, Zinder, Rice (imported)
Pakistan	10	Pakistan, Retail, Karachi, Rice (basmati) Retail, Karachi, Rice (irri) Retail, Lahore, Rice (basmati) Retail, Lahore, Rice (irri) Retail, Multan, Rice (basmati) Retail, Multan, Rice (irri) Retail, Peshawar, Rice (basmati) Retail, Peshawar, Rice (irri) Retail, Quetta, Rice (basmati) Retail, Quetta, Rice (irri)
Philippines	26	Retail, Cebu, Rice (regular milled) Wholesale, Cebu, Rice (regular milled)

		Wholesale, Cebu, Rice (well milled) Retail, Cebu, Rice (well milled) Retail, Davao City, Rice (regular milled) Wholesale, Davao City, Rice (regular milled) Wholesale, Davao City, Rice (well milled) Retail, Davao City, Rice (well milled) Retail, Iloilo, Rice (regular milled) Wholesale, Iloilo, Rice (regular milled) Wholesale, MetroManila, Rice (regular milled) Retail, Iloilo, Rice (well milled) Retail, MetroManila, Rice (regular milled) Wholesale, MetroManila, Rice (well milled) Retail, MetroManila, Rice (well milled) Retail, National Average, Rice (regular milled) Wholesale, National Average, Rice (regular milled) Wholesale, National Average, Rice (well milled) Retail, National Average, Rice (well milled) Retail, Nueva Ecija, Rice (regular milled) Wholesale, South Cotabato, Rice (well milled) Retail, South Cotabato, Rice (well milled) Wholesale, South Cotabato, Rice (regular milled) Retail, South Cotabato, Rice (regular milled) Retail, Nueva Ecija, Rice (well milled) Wholesale, Nueva Ecija, Rice (well milled)5
Senegal	9	Retail, Dakar, Rice (imported) Retail, Diourbel, Rice (imported) Retail, Kaolack, Rice (imported) Retail, Kolda, Rice (imported) Retail, Louga, Rice (imported) Retail, Matam, Rice (imported) Retail, SaintLouis, Rice (imported) Retail, Tambacounda, Rice (imported) Retail, Thies, Rice (imported)
Somalia	9	Retail, Baidoa, Rice (imported) Retail, Bossaso, Rice (imported) Retail, Buale, Rice (imported) Retail, Galkayo, Rice (imported) Retail, Hudur, Rice (imported) Retail, Kismayo, Rice (imported) Retail, Lasanod, Rice (imported) Retail, Marka, Rice (imported) Retail, Belet Weyne, Rice (imported)
South Africa	1	Retail, National Average, Rice
Thailand	2	Wholesale, Bangkok, Rice (25% broken) Wholesale, Bangkok, Rice (5% broken)
Togo	6	Retail, Amegnran, Rice (imported) Togo, Retail, Anie, Rice (imported) Togo, Retail, Cinkassé, Rice (imported) Togo, Retail, Kara, Rice (imported) Togo, Retail, Korbongou, Rice (imported) Togo, Retail, Lomé, Rice (imported)
United Republic of Tanzania	1	Wholesale, Dar es Salaam, Rice

Table B.1: Domestic price monthly time-series retrieved from the GIEWS - FAO database

Country	Number of time series	Reference
India	1	25% broken
Thailand (Bangkok)	7	Rice (5% broken) Thai 100% B Thai A1 Super 25% broken Fragrant 100% Glutinous 10% Parboiled 100%
US	2	US Long Grain 2.4% US California Medium Grain
Viet Nam	1	25% broken 5% broken

Table B.2: International price weekly time-series retrieved from the GIEWS - FAO database

B.2 Value of the parameters

Country	Market integration	Domestic price	Dependence	GDP
Afghanistan	0.527027	134.379894*	0.101610	0.001120
Argentina	0.600000	146.100000	0.030732	0.094983
Australia	0.644628	205.600000	0.049050	0.657885
Bangladesh	0.600000	139.000000	1.000000	0.004304
Belgium	0.644628	146.874306*	0.038655	0.639068
Benin	0.530612	151.737211*	0.238816	0.006710
Brazil	0.619048	208.800000	0.210634	0.093899
Cameroon	0.557143	395.700000	0.104925	0.014298
Canada	0.684211	678.474281*	0.041127	0.667500
Chile	0.553191	161.700000	0.039911	0.154276
China, Hong Kong SAR	0.565217	1678.903150*	0.276883	0.466201
China, Taiwan Province of*	0.577778	152.834143	0.266548	0.279461
China, mainland	0.804124	331.100000	0.439683	0.030775
Colombia	0.516556	263.700000	0.158250	0.058069
Costa Rica	0.513158	303.000000	0.295966	0.083657
Cuba	0.513158	299.396359*	0.378846	0.074060
Czechia	0.561151	250.685026*	0.017965	0.247747
Côte d'Ivoire	0.573529	283.000000	0.355312	0.012143
Ecuador	0.523490	165.400000	0.249877	0.052101
Egypt	0.764706	188.000000	0.220185	0.019248
El Salvador	0.520000	249.000000	0.049599	0.040291
France	0.661017	259.600000	0.020416	0.603248
Germany	0.650000	126.016254*	0.005570	0.609606
Ghana	0.541667	600.400000	0.129283	0.016636
Greece	0.573529	203.700000	0.027457	0.397787
Guatemala	0.530612	221.800497*	0.029967	0.033874
Guinea	0.527027	131.600000	0.501206	0.003399
Guyana	0.553191	143.147930*	0.457491	0.028695
Haiti	0.527027	212.447303*	0.232991	0.004922
Honduras	0.527027	286.400000	0.076742	0.020400

India	0.866667	258.900000	0.407009	0.009748
Indonesia	0.569343	231.700000	0.728137	0.024418
Iran (Islamic Republic of)	0.527027	982.400000	0.166781	0.058563
Iraq	0.541667	508.500000	0.188531	0.029091
Israel	0.553191	209.549771	0.051972	0.375984
Italy	0.829787	451.200000*	0.021554	0.543978
Japan	0.655462	1864.400000	0.322913	0.583863
Jordan	0.565217	155.437810*	0.136500	0.038992
Kenya	0.569343	415.300000	0.035027	0.007896
Kuwait	0.545455	215.098061*	0.313401	0.707907
Liberia	0.530612	959.105128*	0.336720	0.000309
Madagascar	0.545455	225.000000	0.585460	0.002024
Malaysia	0.565217	177.200000	0.451999	0.099945
Mali	0.561151	262.000000	0.299516	0.004975
Mexico	0.541667	174.900000	0.022868	0.143865
Mozambique	0.513158	157.500000	0.086666	0.002711
Nepal	0.484472	150.100000	0.505050	0.002059
Netherlands	0.702703*	125.411733	0.008100	0.739276
Nicaragua	0.513158	248.800000	0.273333	0.016957
Niger	0.577778	476.700000	0.098335	0.000584
Nigeria	0.549296	511.900000	0.113966	0.023601
Oman	0.541667	128.181573*	0.288533	0.236286
Pakistan	0.857143	217.100000	0.062621	0.010740
Philippines	0.565217	203.800000	0.691934	0.019469
Poland	0.577778	191.358994*	0.000000	0.146065
Portugal	0.573529	279.500000	0.081586	0.324023
Qatar	0.569343	156.179284*	0.397713*	1.000000
Republic of Korea	0.569343	1813.900000	0.444017	0.340976
Russian Federation	0.590909	149.700000	0.020377	0.112465
Saudi Arabia	0.661017	126.155290*	0.184942	0.251721
Senegal	0.582090	208.500000	0.397007	0.013739
Singapore	0.604651	992.546317*	0.272922*	0.530093
Somalia	0.523490	586.480118*	0.002275*	0.000000
South Africa	0.624000	241.842068*	0.082626	0.087946
Spain	0.690265	273.700000	0.030811	0.467226
Sweden	0.582090	987.343321*	0.023338	0.766390
Switzerland	0.604651	131.682396*	0.021985	0.955701
Syrian Arab Republic	0.569343	309.243193*	0.043460*	0.025443
Thailand	0.886364	180.300000	0.679853	0.052404
Togo	0.523490	250.500000	0.123399	0.002990
Turkey	0.590909	518.000000	0.042558	0.130126
Ukraine	0.569343	195.000000	0.011297	0.036265
United Arab Emirates	0.609375	497.811878*	0.285415	0.711320
United Kingdom	0.715596	273.970059*	0.021985	0.735209
United Republic of Tanzania	0.586466	272.600597*	0.110357	0.004002
United States of America	0.951220	220.000000	0.030242	0.768933
Uruguay	0.619048	155.200000	0.055679	0.094196
Viet Nam	0.684211	155.300000	0.866991	0.009278
Yemen	0.534247	196.722404*	0.079390	0.014243

Table B.3: Value of the parameters used to initialize the model

The domestic price values followed by an asterix correspond to prices randomly generated from a Pareto distribution fitted to the rest of the domestic price distribution. The dependence values followed by an asterix correspond to data computed using value reported in the literature rather than the FAOSTAT dataset. The corresponding articles are Al-Thani et al. (2017); Omwega (2002); Maldonado (2011). We accordingly initiated our model using the following values of domestic supply of rice for Qatar, Somalia and Syria: 69.12 kilo/capita/year, 48 kilo/capita/year and 9 kilo/capita/year. As for Singapore, our difficulty to find a reliable figure motivated us to set the value of its domestic supply of rice per capita per year at an intermediary value between China and Japan (48 kilo/capita/year).

Appendix C

Additional methods

C.1 Scaling-up of the time-serie of reference

The time serie of reference for the global price between January 2007 and August 2008 is made of 20 time-points with a time-scale of a month. However, in the simulation, the time-scale used correspond to about 166 time-steps. In order to compare the time-serie of reference with the time-series generated by the simulation, it was necessary to scale it up. To do so, we applied the following procedure:

- From the time-serie of reference we extracted the 8 points corresponding to the price rise (reference[11:]),
- we converted the 20 time-points of the time-serie of reference to the 200-points time scale of the simulation assuming that the beginning of the simulation, t=0, corresponds to January 2007 and the end of the simulation, t=200, corresponds to January 2009. Using this scale, the 6 time-points of the time-serie of reference correspond to time-step [88, 96, 104, 112, 120, 128].
- the points defined by the list of price values and the list of corresponding time points were interpolated in a cubic-fashion[1],
- the resulting polynomial function was used to generate a new time-serie of global price by taking its value in the 40 following time points corresponding to the expected time of the price rise in the simulation in the interval [40,128].

C.2 Implementation

The model was programmed in Python 3.6.4. It used the following packages and corresponding versions:

1. numpy 1.12.1
2. pandas 0.19.2
3. plotly 3.4.2
4. pickleshare 0.7.4
5. scipy 1.0.0

[1] using the scipy 1d interpolation function as described in the software subsection

Appendix D

Additional figures and tables

D.1 Investigation of the model

D.1.1 Convergence of the model

Figure D.1 shows the effect of each parameters and their combination for a few selected models. It reveals that a high value of x_1 seems to amplify the variations of the global price and destabilizes it due to what seems to be overshooting or oscillations, while lower values seem to dampen it (compare models 0 and 6). The local rate factor x_2 seems to fasten the convergence of the global around its final value. As for the global rate factor, it seems to increase the value of the global price, whether the models converges or not. For instance, model 7 shows how a higher value of x_1 and x_3 amplifies the increase and variation of the global price compare to a higher value in x_1 or x_3 only, as in model 6 and model 4.

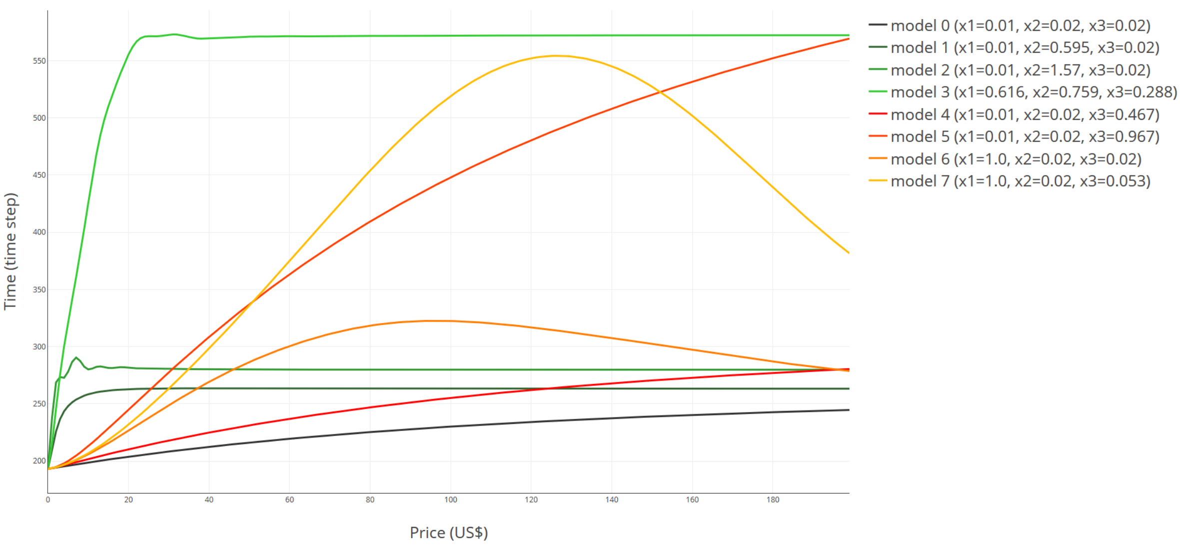
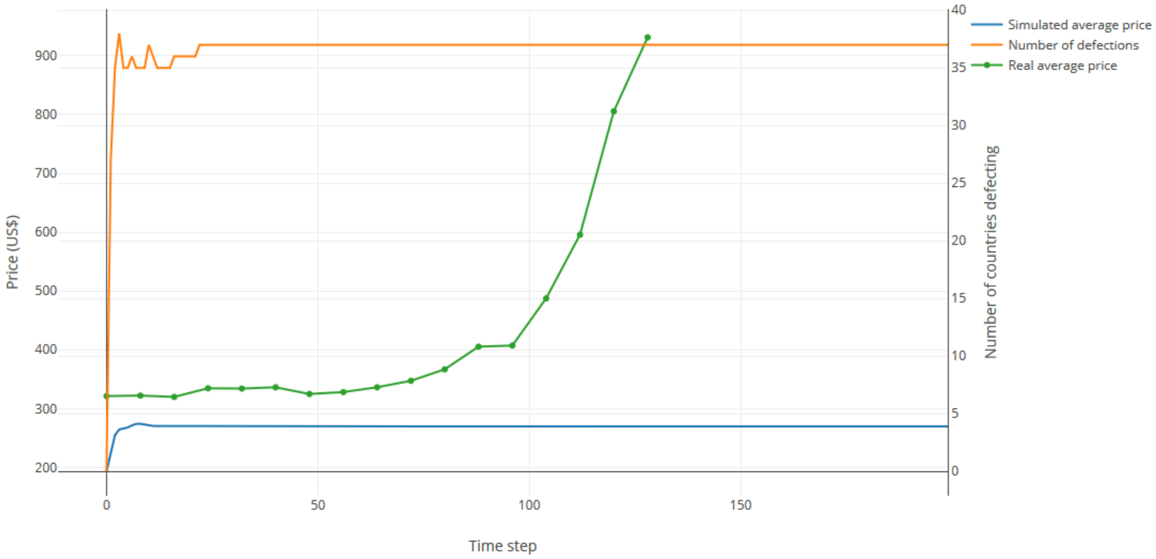
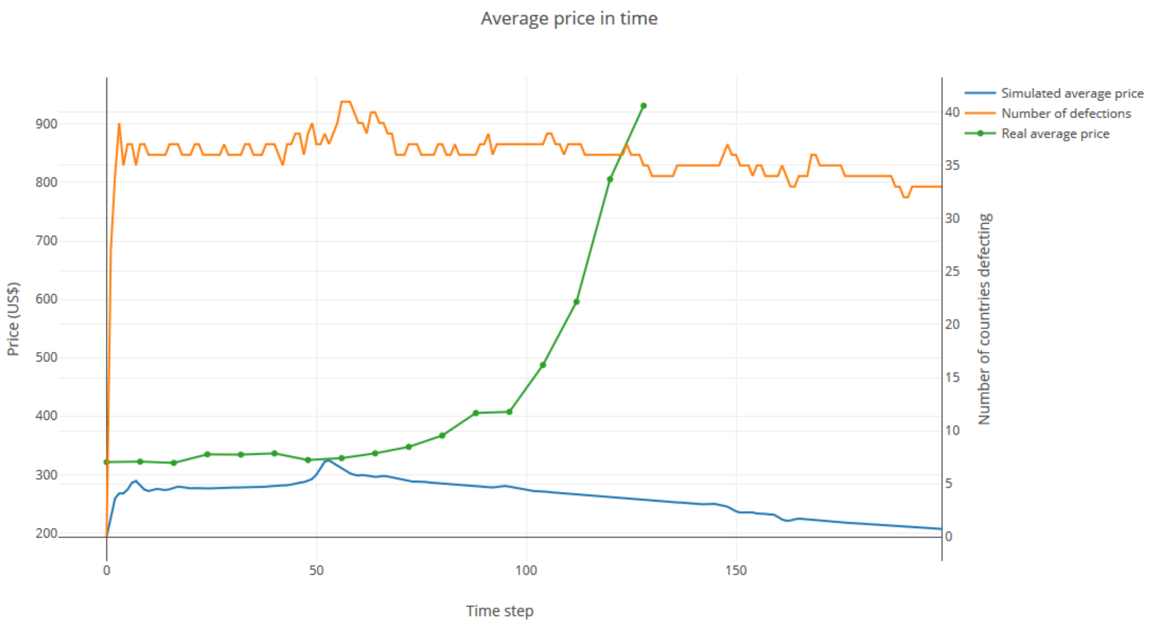


Figure D.1: Examples of the behaviour of the global price for convergent and bounded models. Models 0 to 3 are convergent models. Models 4 to 7 are bounded models. An increase in the local rate fastens the convergence and increases the value reached at the end of the simulation (compare models 0, 1 and 2). The higher the global rate factor, the higher the value of the global price (compare models 0, 4 and 5, or models 6 and 7). An increased domestic rate factor seems to destabilize the price dynamics (compare models 0 and 6)

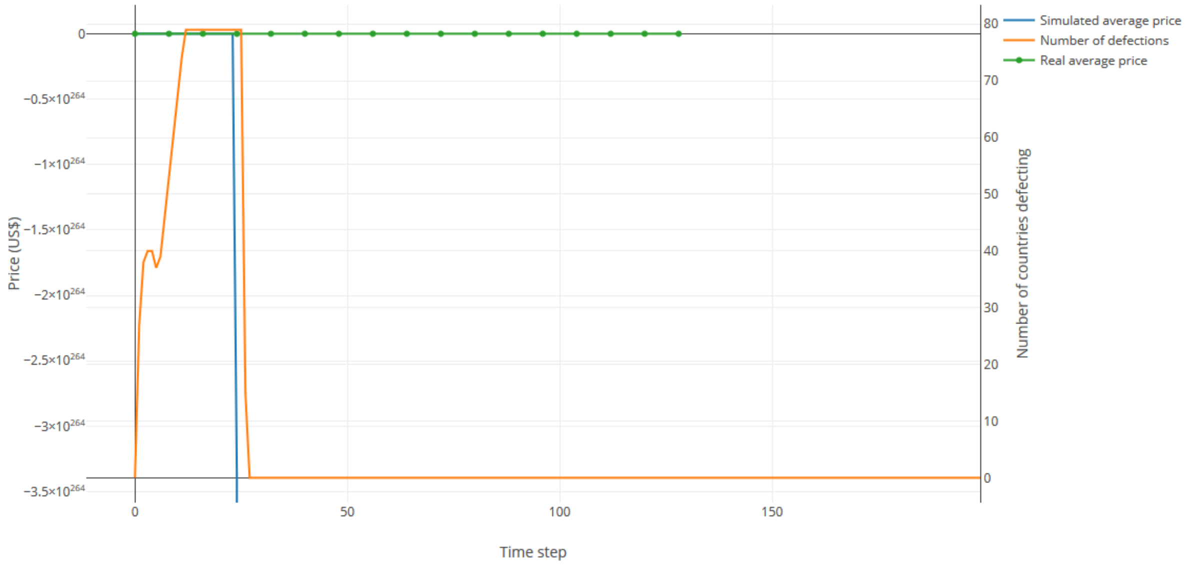
Figure D.1 shows the evolution of the global price for a model whose macro-behaviour changes depending on the value of λ_l. Its parameters are $x_1 = 0.01$, $x_2 = 1.19$, and $x_3 = 0.02$.



(a) Evolution of the global price of model ($x_1 = 0.01$, $x_2 = 1.19$, $x_3 = 0.02$) for $\lambda_l = 0.1$



(b) Evolution of the global price of model ($x_1 = 0.01$, $x_2 = 1.19$, $x_3 = 0.02$) for $\lambda_l = 0.5$

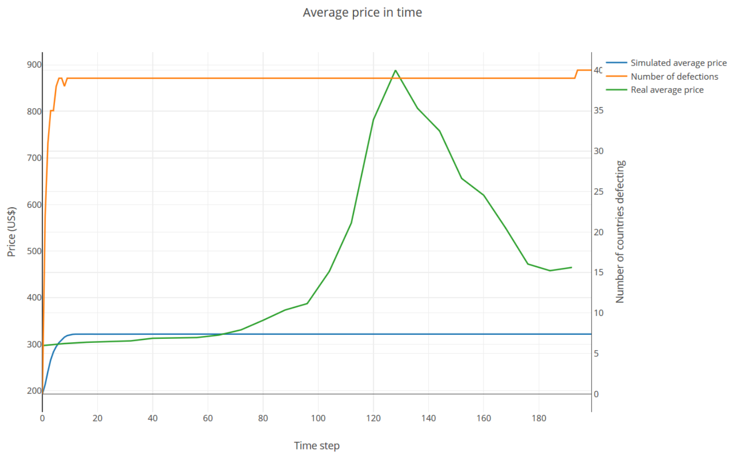


(c) Evolution of the global price of model ($x_1 = 0.01$, $x_2 = 1.19$, $x_3 = 0.02$) for $\lambda_l = 2$

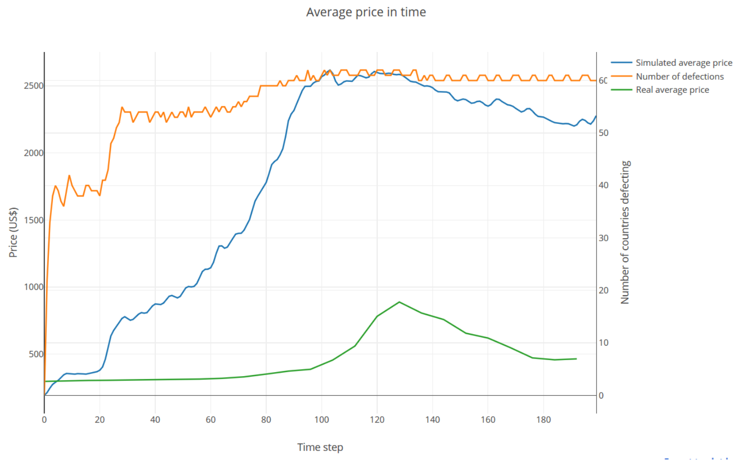
Figure D.1: Effect of λ_l on the price dynamic of a specific model. The green curve correspond to the reference time-serie for the global price between January 2007 and May 2008. The blue curve is the time-serie output by the simulation and the orange line corresponds to the number of country agents being defecting, that is who switched strategy from free-trade to a protectionist policy. For a tow high value of λ_l the global price quickly diverges to negative values. For the lowest value of λ_l, the price quickly converges. However, for an intermediate value of λ_l the price dynamic stays bounded but tends to decrease.

Figure D.1 shows the evolution of the global price for another model whose macro-behaviour changes depending on the value of λ_l. Its parameters are $x_1 = 0.016$, $x_2 = 0.72$ and $x_3 = 0.43$.

(d) $\lambda_l = 0.1$



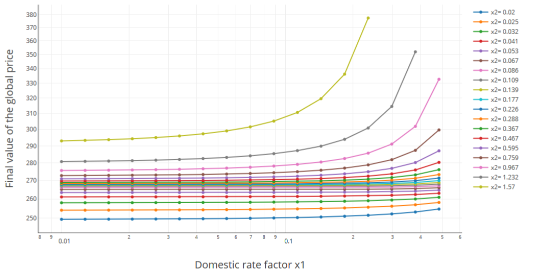
(e) $\lambda_l = 0.5$



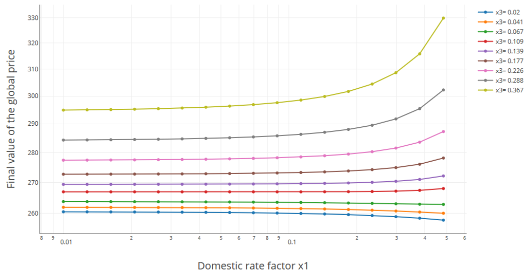
(f) $\lambda_l = 2$

Figure D.2: Evolution of the global price and number of defections for the three λ_l $x_1 = 0.016$, $x_2 = 0.72$ and $x_3 = 0.43$

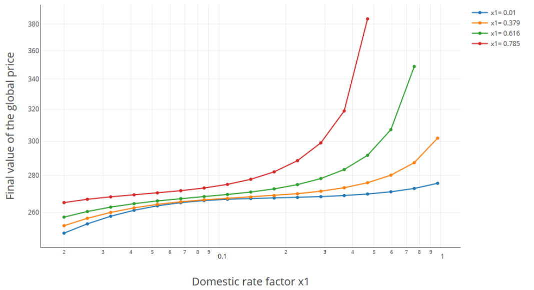
D.1.2 Final value of the global price



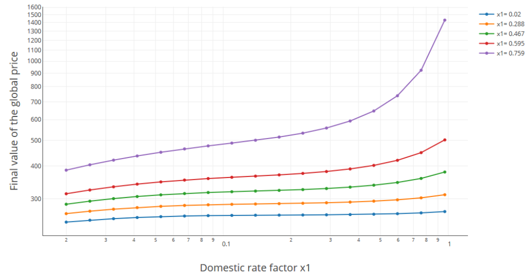
(a) Final value of the global price depending on x_1 for different values of x_2



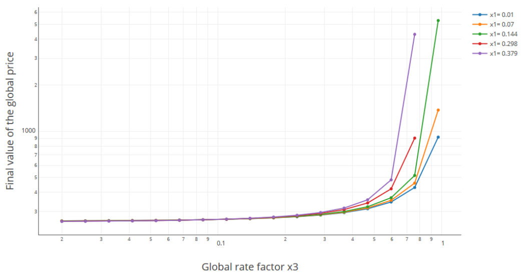
(b) Final value of the global price depending on x_1 for different values of x_3



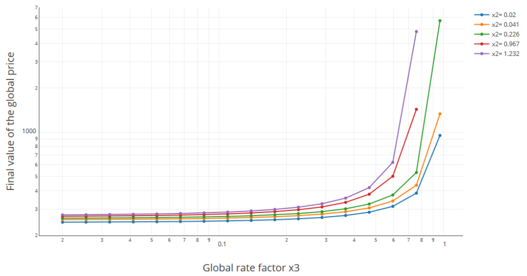
(c) Final value of the global price depending on x_2 for different values of x_1



(d) Final value of the global price depending on x_2 for different values of x_3



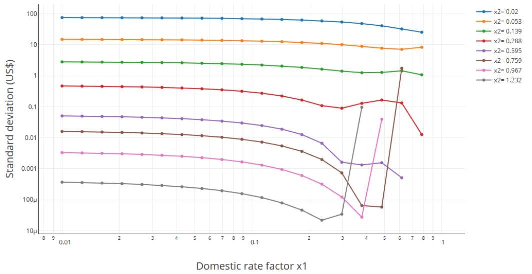
(e) Final value of the global price depending on x_3 for different values of x_1



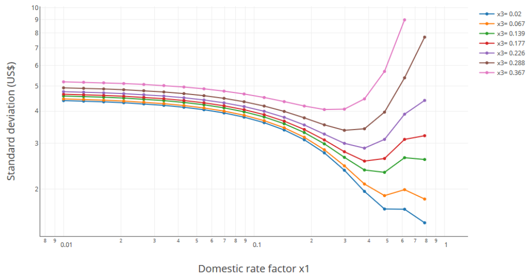
(f) Final value of the global price depending on x_2 for different values of x_2

Figure D.3: Final value of the global price in local regions of the parameter space for $\lambda_l = 0$

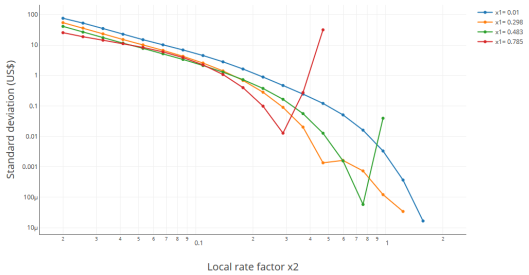
D.1.3 Final value of the spread of the distribution of domestic prices prices



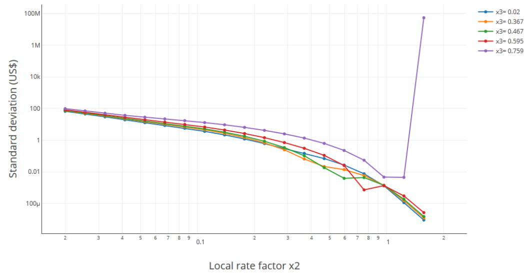
(a) Final value of the spread of the distribution of the domestic prices on x_1 for different values of x_2



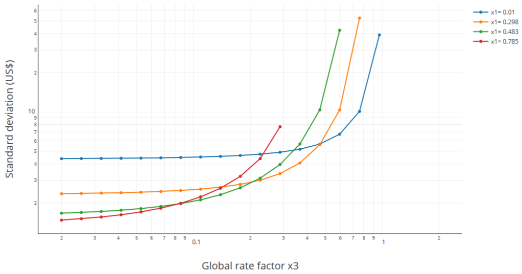
(b) Final value of the spread of the distribution of the domestic prices depending on x_1 for different values of x_3

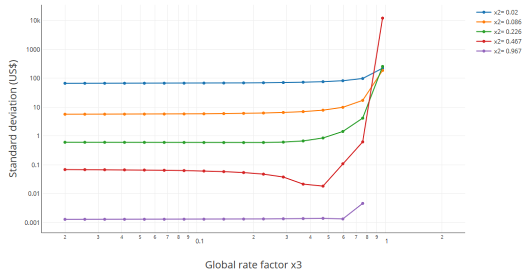


(c) Final value of the spread of the distribution of the domestic prices depending on x_2 for different values of x_1



(d) Final value of the spread of the distribution of the domestic prices depending on x_2 for different values of x_3



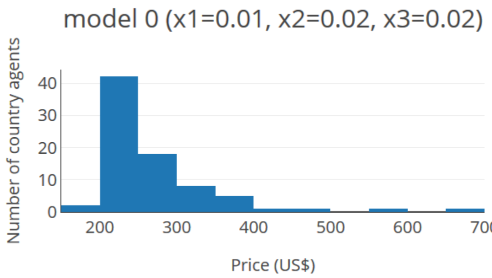


(e) Final value of the spread of the distribution of the domestic prices depending on x_3 for different values of x_1

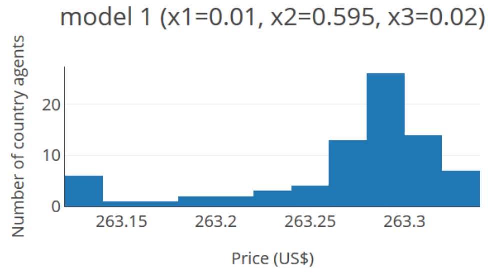
(f) Final value of the spread of the distribution of the domestic prices depending on x_2 for different values of x_2

Figure D.4: Final value of the spread of the distribution of domestic prices in local regions of the parameter space for $\lambda_l = 0$

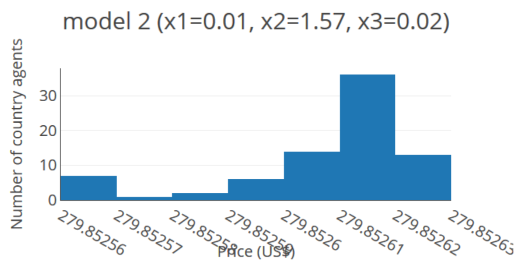
In addition, we investigate the effect of the three parameters on the distribution of the domestic prices at the end of the simulation. Figure D.5 shows the histogram of the domestic price distributions corresponding to all 8 models whose global price dynamic was shown in Figure D.1. The spread of the final distribution of the domestic price varies from more than a thousand dollars to less than 0.01US$. For the same value of x_1 and x_3, an increase in x_2 considerably diminish the spread of the distribution (see models 0, 1 and 2 of Figure D.5). For the same value of x_2 and x_3, an increase in x_1 increases the spread of the distribution (see models 0 and 6 of Figure D.5). For the same value of x_1 and x_2, an increase in x_3 also increases the spread of the final distribution of domestic price (see models 0 and 5 of Figure D.5).



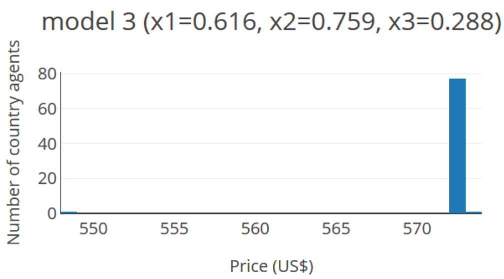
(a) Final price distribution of model 0



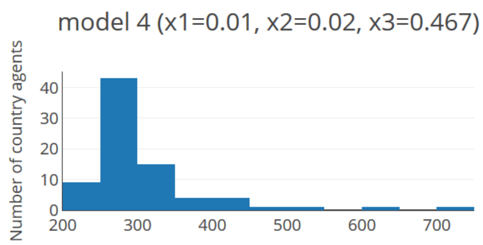
(b) Final price distribution of model 1



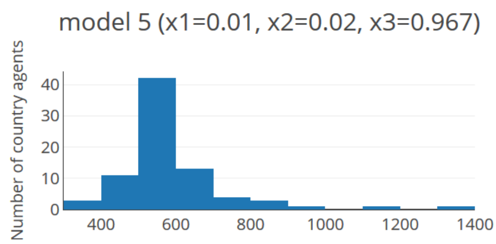
(c) Final price distribution of model 2



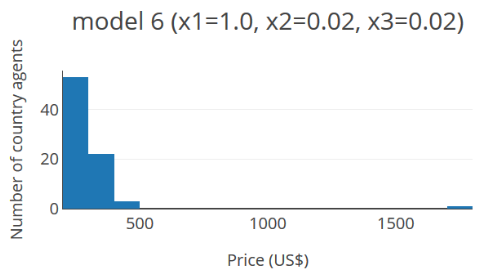
(d) Final price distribution of model 3



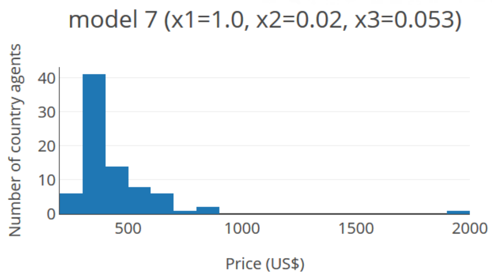
(e) Final price distribution of model 4



(f) Final price distribution of model 5



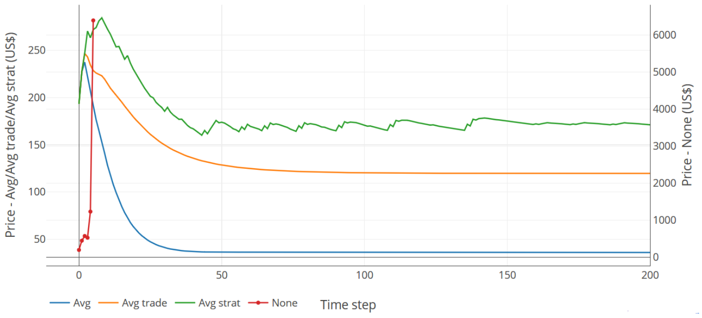
(g) Final price distribution of model 6



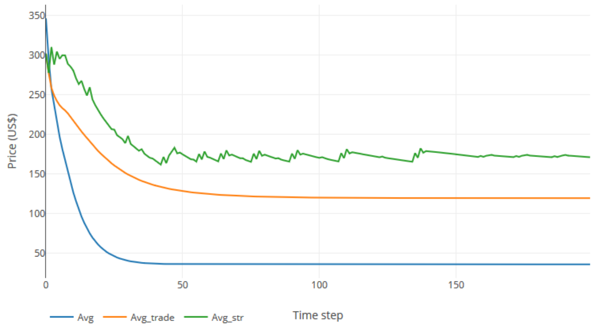
(h) Final price distribution of model 7

Figure D.5: Distribution of the domestic price at the end of the simulation. The spread of the distribution varies from less than 1US$, for models 1 and 2, to several hundred of US$ for models 0,4,5,6 and 7. In the case of model 3, all final domestic prices differ by less than 1US$ except for one country (The Netherlands) which is about 25US$ off from the others. Model 6 shows a similar situation with the domestic price of the same country being more than a thousand dollars further from all other agents.

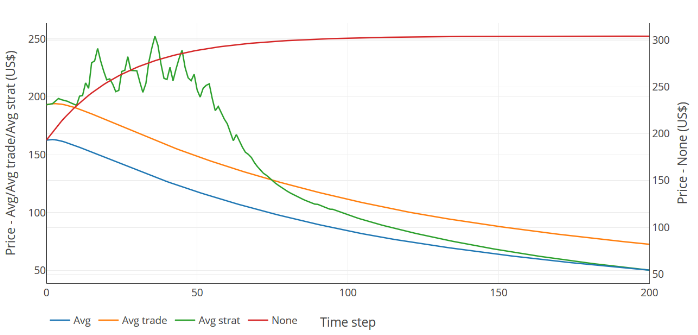
D.2 Sensitivity to the aggregation method



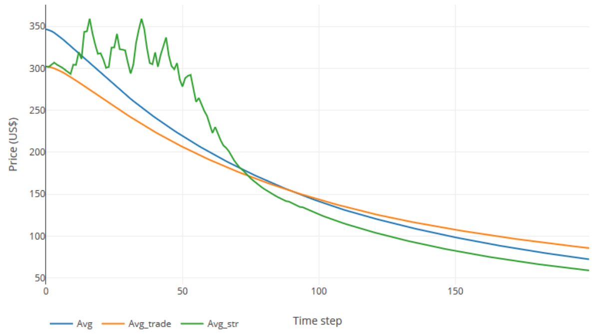
(a) $\lambda_l = 0.1$,$x_1 = 0.21$, $x_2 = 1.19$ and $x_3 = 0.72$ average of four main exporters



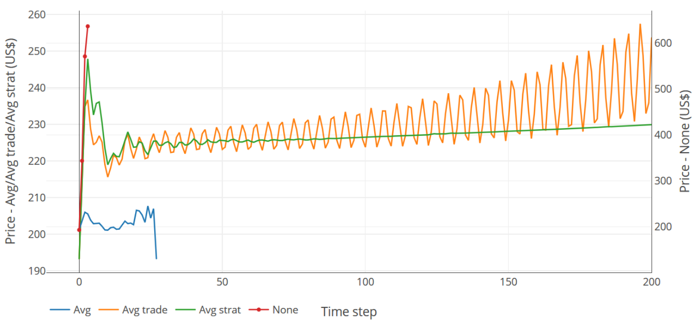
(b) $\lambda_l = 0.1$,$x_1 = 0.21$, $x_2 = 1.19$ and $x_3 = 0.72$ global price computed by the institution agent



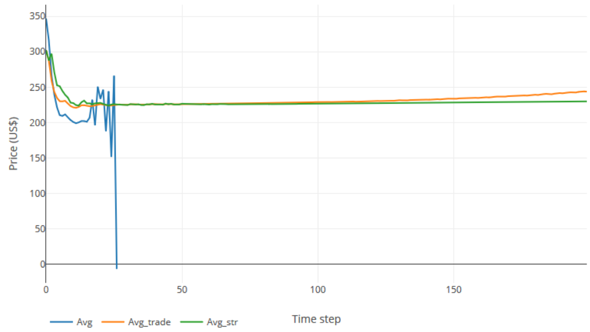
(c) $\lambda_l = 0.5$, ,$x_1 = 0.027$, $x_2 = 0.02$ and $x_3 = 1.19$ average of four main exporters



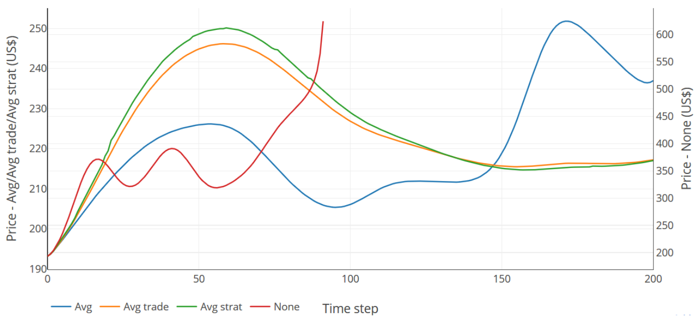
(d) $\lambda_l = 0.5$, ,$x_1 = 0.027$, $x_2 = 0.02$ and $x_3 = 1.19$ global price computed by the institution agent



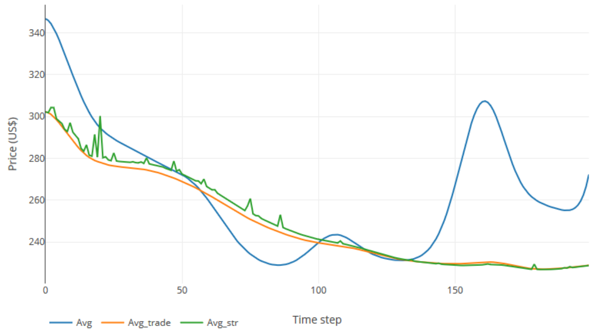
(e) $\lambda_l = 2$,$x_1 = 0.01$, $x_2 = 0.71$ and $x_3 = 0.43$ average of four main exporters



(f) $\lambda_l = 2$,$x_1 = 0.01$, $x_2 = 0.71$ and $x_3 = 0.43$ global computed by the institution agent



(g) $\lambda_l = 2$,$x_1 = 1$, $x_2 = 0..02$ and $x_3 = 0.092$ average of four main exporters



(h) $\lambda_l = 2$,$x_1 = 1$, $x_2 = 0..02$ and $x_3 = 0.092$ global price computed by the institution agent

Figure D.5: Price dynamics as measured either by the average of the four main exporters (subfigures a, c, e and g) or as computed by the institution agent during the simulation (subfigures b, d, f and h) depending on the type of aggregate

D.3 Calibration of the model

Table D.1 shows the value of the parameters, the validity level for each criteria and the robustness measure of the 64 models whose global price was the most correlated with the time-serie of reference. The p-values of all the Pearson correlation whose correlation coefficient is reported in the table were smaller than 10^{-15}.

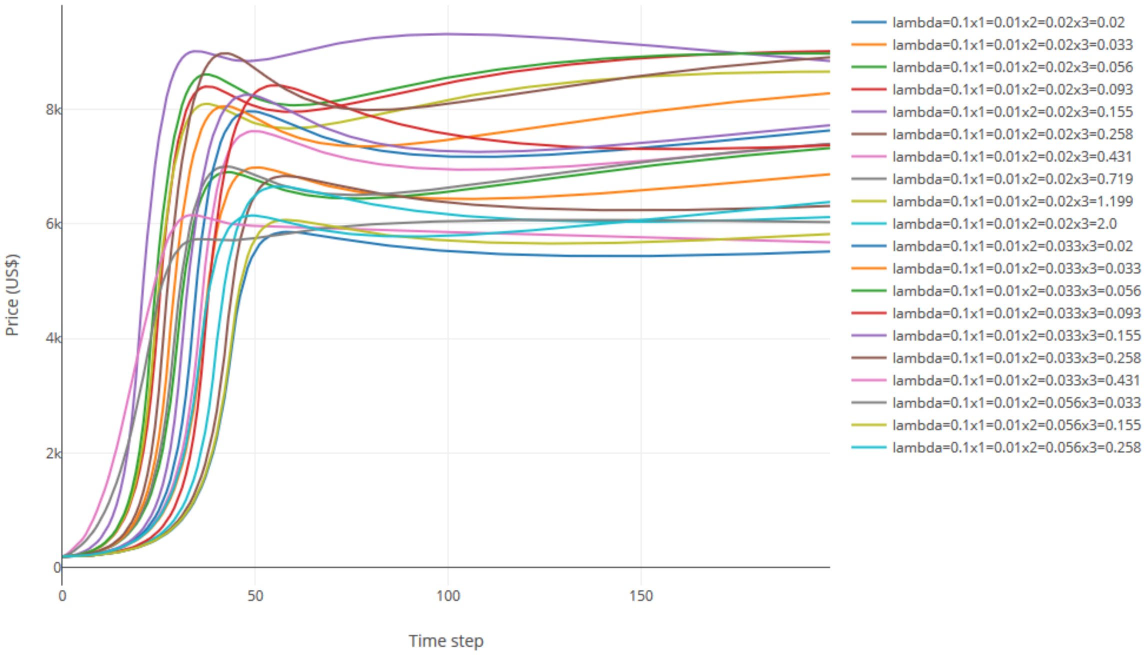
Parameters of the model				Validity for each criteria			Robustness measure	
λ_l	x_1	x_2	x_3	Global price	Domestic price	Strategy	Global	Shock
0.1	0.01	0.02	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.556	0.1
0.1	0.01	0.033	1.20	Level 1 (corr>0.98)	Not bounded (2)	Level 0	0.533	0.2
0.1	0.01	0.056	1.20	Only increasing slope (corr>0.98)	Not bounded (1)	Level 0	0.522	0.1
0.1*	0.01	0.093	1.20	Only increasing slope (corr>0.99)	Not bounded (4)	Level 0	0.478	0
0.1*	0.01	0.15	1.20	Only increasing slope (corr>0.98)	Not bounded (10)	Level 0	0.422	0
0.1	0.017	0.02	1.20	Level 1 (corr>0.99)	Not bounded (2)	Level 0	**0.633**	0.3
0.1	0.017	0.033	1.20	Level 1 (corr>0.98)	Not bounded (4)	Level 0	0.478	0.1
0.1	0.017	0.056	1.20	Level 1 (corr>0.98)	Not bounded (1)	Level 0	0.511	0.1
0.1*	0.017	0.093	1.20	Only increasing slope (corr>0.99)	Not bounded (4)	Level 0	0.522	0
0.1	0.028	0.02	1.20	Level 1 (corr>0.98)	Not bounded (2)	Level 0	0.411	0.1
0.1	0.028	0.033	1.20	Level 1 (corr>0.98)	Not bounded (5)	Level 0	0.444	0.1
0.1*	0.028	0.056	1.20	Level 1 (corr>0.98)	Not bounded (4)	Level 0	0.422	0
0.1*	0.028	0.093	1.20	Only increasing slope (corr>0.99)	Not bounded (6)	Level 0	0.511	0.1
0.1	0.046	0.02	1.20	Level 1 (corr>0.98)	Not bounded (8)	Level 0	0.556	0.1
0.1*	0.046	0.033	1.20	Level 1 (corr>0.98)	Not bounded (7)	Level 0	0.400	0.1
0.1*	0.046	0.056	1.20	Level 1 (corr>0.98)	Not bounded (10)	Level 0	0.344	0.1
0.1**	0.22	1.20	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.311	0.2
0.1*	0.36	0.093	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.489	0.5
0.1**	0.36	0.15	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.456	0.4

0.1*	0.36	0.26	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.478	0.3
0.1**	0.36	0.43	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.489	0.4
0.1**	0.36	0.72	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.422	0.3
0.1	1.0	0.02	0.093	Level 1 (corr>0.99)	Not bounded (9)	Level 0 (close to 1)	0.389	0
0.1	1.0	0.033	0.093	Level 1 (corr>0.99)	Not bounded (8)	Level 0 (close to 1)	0.356	0
0.5	0.01	0.02	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.478	0.3
0.5	0.01	0.033	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.444	0.1
0.5	0.01	0.056	1.20	Only increasing slope (corr>0.99)	Not bounded (1)	Level 0	0.456	0.3
0.5*	0.01	0.093	1.20	Only increasing slope (corr>0.99)	Not bounded (7)	Level 0	0.467	0.2
0.5*	0.01	0.15	1.20	Only increasing slope (corr>0.95)	Not bounded (36)	Level 0	0.400	0
0.5	0.017	0.02	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.422	0.1
0.5	0.017	0.033	1.20	Level 1 (corr>0.98)	Not bounded (1)	Level 0	0.411	0.2
0.5	0.017	0.056	1.20	Only increasing slope (corr>0.99)	Not bounded (2)	Level 0	0.456	0
0.5*	0.017	0.093	1.20	Only increasing slope (corr>0.99)	Not bounded (5)	Level 0	0.344	0
0.5	0.028	0.02	1.20	Level 1 (corr>0.98)	Not bounded (3)	Level 0	0.411	0.1
0.5	0.028	0.033	1.20	Level 1 (corr>0.98)	Not bounded (7)	Level 0	0.400	0
0.5*	0.028	0.056	1.20	Only increasing slope (corr>0.99)	Not bounded (6)	Level 0	0.522	0.1
0.5*	0.028	0.093	1.20	Only increasing slope (corr>0.99)	Not bounded (14)	Level 0	0.478	0.1
0.5	0.046	0.02	1.20	Level 1 (corr>0.98)	Not bounded (9)	Level 0	0.567	0.1
0.5*	0.046	0.033	1.20	Only increasing slope (corr>0.98)	Not bounded (10)	Level 0	0.489	0.2
0.5*	0.046	0.056	1.20	Only increasing slope (corr>0.99)	Not bounded (25)	Level 0	0.611	0.1
0.5**	0.13	1.20	0.02	Level 1 (corr>0.91)	Not bounded (1)	Level 0	0.456	0
0.5**	0.36	0.093	0.74	Only increasing slope (0.90<corr<0.95)	Level 0	Level 1	0.589	0.4
0.5**	0.36	0.15	0.74	Only increasing slope (0.90<corr<0.95)	Level 0	Level 1	0.467	0.5
0.5**	0.36	0.26	0.74	Only increasing slope (0.90<corr<0.95)	Level 0	Level 1	**0.700**	0.4
0.5**	0.36	0.43	0.74	Only increasing slope (0.90<corr<0.95)	Level 0	Level 1	0.500	0.3
0.5	1.0	0.02	0.093	Level 1 (corr>0.99)	Not bounded (9)	Level 1	0.378	0
0.5	1.0	0.033	0.093	Level 1 (corr>0.99)	Not bounded (7)	Level 0	0.511	0
2	0.01	0.02	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.589	0.2
2	0.01	0.034	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.544	0.1
2	0.01	0.056	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.433	0
2	0.017	0.02	1.20	Level 1 (corr>0.99)	Not bounded (1)	Level 0	0.522	0.1
2	0.017	0.034	1.20	Level 1 (corr>0.99)	Not bounded (2)	Level 0	0.511	0
2	0.017	0.056	1.20	Level 1 (corr>0.99)	Not bounded (3)	Level 0	0.444	0

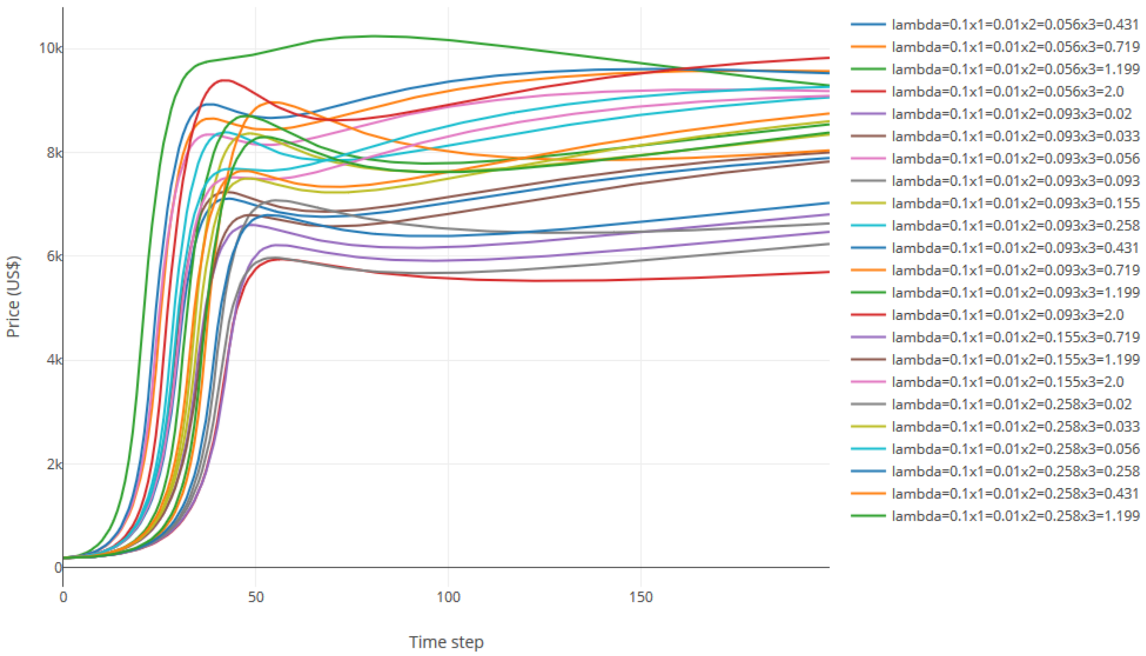
2**	0.017	0.72	0.43	Level 1 (corr>0.99)	Not bounded (1)	Level 0 (close to 1)	0.433	0
2**	0.017	0.72	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.444	0.1
2	0.028	0.02	1.20	Level 1 (corr>0.98)	Not bounded (2)	Level 0	0.467	0.2
2	0.028	0.034	1.20	Level 1 (corr>0.99)	Not bounded (4)	Level 0	0.489	0.1
2**	0.028	0.72	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.433	0
2	0.046	0.02	1.20	Level 1 (corr>0.98)	Not bounded (8)	Level 0	0.367	0
2**	0.046	0.72	0.72	Level 1 (corr>0.93)	Not bounded (1)	Level 0	0.378	0.1
2*	0.36	0.093	0.72	Only increasing slope (0.90<corr<0.95)	Level 0	Level 0	0.389	0.3
2*	0.36	0.26	0.72	Only increasing slope (corr>0.90)	Level 0	Level 0	0.356	0.1
2	1.0	0.02	0.093	Level 1 (corr>0.99)	Not bounded (6)	Level 1	0.378	0
2	1.0	0.034	0.093	Level 1 (corr>0.99)	Not bounded (6)	Level 1	0.444	0

Table D.1: Validity level of most correlated models for each criteria. In the models with the mention "only increasing slope", the global price increases directly from the beginning of the simulation. For the models with the mention "Not bounded", the number of country agents whom domestic price does not stay bounded is stated into brackets. One asterisk (*) stands for models which appear for only 2 values of λ and two asterisks (**) stand for models which appear for only one value of λ.

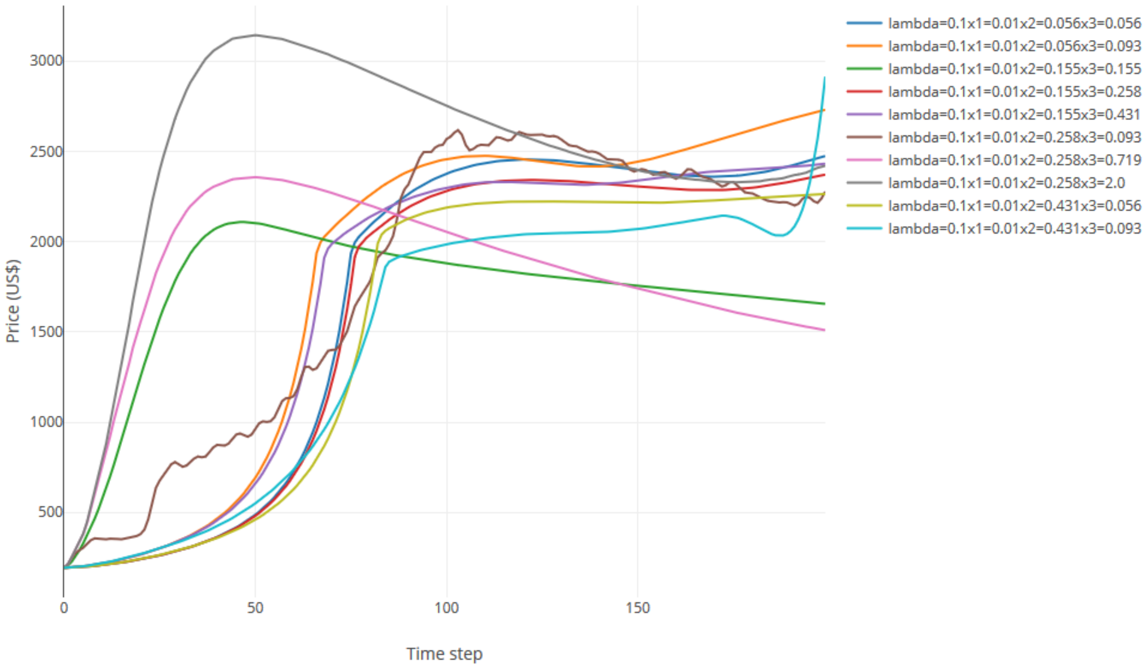
Figure D.5 show the simulated global price of all 64 models.



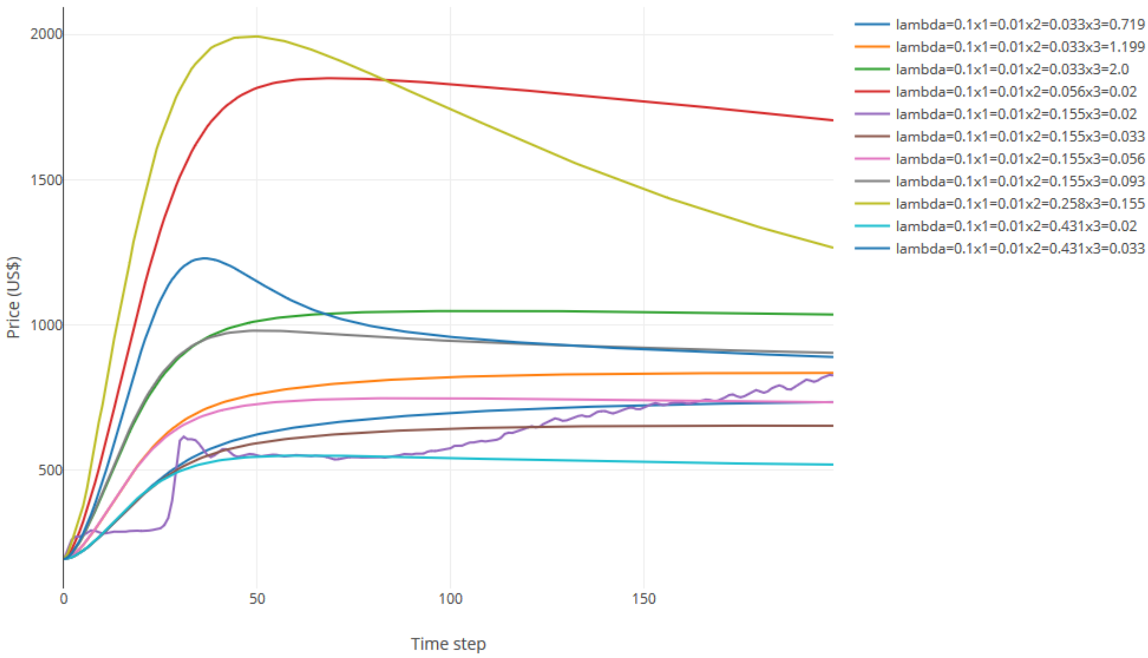
(i) First part of the models whose global price reached values higher than 4000US$



(j) Second part of the models whose global price reached values higher than 4000US$



(k) Models whose global price reached values higher than 2000US$ but lower than 4000US$



(l) Models whose global price remained lower than 2000US$

Figure D.5: Simulated global price in the 64 most correlated models

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