An empirical economic model to reveal behaviour characteristics driving the evolution of agriculture in Belgium

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Abstract—**Effective design of agricultural policies requires an understanding of the drivers behind the evolution of the agricultural sector. This project builds an evolutionary economic model of the Belgian agricultural sector, as a testing ground for new policies. This agent-based model simulates the dairy, cow and pig sector. The model is calibrated to historical data of production and farm diversity during the period 2003 – 2013.**

Profit maximising agents cannot replicate the historical trends. When assuming heterogeneous behaviours, the actual evolution can be reproduced much more closely. The calibration reveals key behaviour variables. The evolution in the agricultural sector can only be explained when accounting for a resistance to change at farm level or at market level. However, this approach cannot determine the exact location of this resistance. The resistance to change can result from personal convictions of the farmer or from market rigidities and learning effects.

I. INTRODUCTION

Multiple agricultural policies and instruments are created to direct farmers towards more innovation, higher sustainability and efficiency. This requires in practice a far-reaching transition in the sector. Currently, the European Common Agriculture Policy (CAP) focuses on three objectives. First, enhanced competitiveness of agricultural markets is promoted by reducing production constraints and encouraging modernisation. Secondly, the CAP pursues a more sustainable agriculture with intense rural development. And finally in order to achieve this, the CAP wants a more effective and equitable framework of support policies for agriculture. Unfortunately, the creation of effective policies is challenging, given the complexity of agriculture and its relations with the environment and society. New policies influence an on-going evolution of the sector, though these policies are not always designed taking their evolutionary effects into account. Historically, policies are often designed based on a neo-classical understanding of the farmer's situation. There are concerns that this approach, founded on static equilibriums or general optimisation principles is too constrained [1]. It is not equipped to deal with uncertainty, lack of knowledge on diversity or complexity effects between markets. Evolutionary economics

offers a more appropriate starting point to analyse economic transitions and to design policies [2]. Evolutionary models can also incorporate different behaviours. This can be an additional step in agricultural research to bring models closer to reality, given the complexity and diversity in behaviour of farmers [3, 4]. This project builds an empirical evolutionary model of the Belgian agricultural sector. We compare two types of modelled behaviour with the evolution of the sector between 2003-2011. The results indicate that rational profit-optimising behaviour cannot always explain the past evolutions.

Evolutionary economics have seen a growing interest since the second half of the last century. The evolutionary approach engages in the study of a phenomenon over time. The models include imperfections, non-equilibrium and selection mechanisms over time. There is a large focus on group effects, complexity and learning [5]. A specialised strand of evolutionary economics focuses on the development of agent-based modelling of economic evolutions. This approach models economies as decentralised, complex and adaptive systems. The models are founded on groups of autonomous agents, that have individual behaviours, technical characteristics and communication possibilities [6]. Such agent-based models (ABM) directly provide possibilities to investigate interactions and relations in detail. An ABM model is built from the bottom up: the individual agents being each represented with their decision process and historical pathways. This leads to research on co-evolution of markets, dynamics in consumer demand, emergence of innovations, historical path-dependence, environmental impacts and effects or co-evolution with institutions and policies [7-9]. Especially the translation of this approach to empirical research unlocked new methods to investigate economic and social phenomena [10].

This approach has also been applied to study evolutions in agriculture on multiple occasions. The first models have been created by Balmann [11], studying structural change in an abstract landscape. Further developments have elaborated this model to study impacts of new policies and CAP changes in different regions in Europe [12-14]. Berger [15] continued this approach and integrated detailed submodels for farm-level innovations, water management and irrigation. Other models included the effect of forest clearing by farmers to model regional land use changes in Indiana [16].

There are even initiatives to standardise farm models in this context [17].

A particular strength of this approach is the openness to interdisciplinary models. Several applications combine for instance technical, geological, and behavioural submodels. In the context of evolutions of the agricultural sector, the inclusion of behaviour is very important. Farms are often modelled at household level. The behaviour is related to the household directly and this implies influences from personal risk adversity, off-farm labour, work preferences, resistance to change or limited information availability. The behaviour, the bounded knowledge and the adaptation capacity of the agents confronted with new developments are all hidden drivers of agricultural transitions. Many models incorporate particular behavioural rules such as heuristics or constrained maximisation [18]. These decision rules are already more developed than the standard profit-maximising procedure from neo-classical models. However, most models exert the same decision procedure for every agent. Decisions ultimately vary due to differences in technical and historical characteristics. But the heuristic process remains the same. Empirical applications demand a method that also relaxes this requirement for a similar behaviour for all agents. Other research projects include an intrinsic diversity of behaviour rules in the construction of ABM.

The increased application of evolutionary modelling has also nurtured the debate on the robustness of ABM-modelling. There are several reasons to control carefully an ABM-based analysis. First of all, this is a new development. Neoclassical models can present a long historical range of applications and scrutiny, as well as regular modes of operation. These new evolutionary models are being developed in a new and burgeoning discipline. Agreed standards of construction and application have not yet been developed and the knowledge on the limitations of this approach is restricted. Secondly, compared to standard neoclassical economic models, an ABM can display several times the number of degrees of freedom. This implies that validation and calibration of empirical models is a crucial step to demonstrate the robustness and credibility of the results [20-22].

This paper reports advances in a project focussed on the Belgian dairy, cow and pig production sector. This sector is confronted with multiple problems such as low profitability of animal farms, high environmental impacts and high price volatility. The model needs to provide a testing ground for new policies and future scenarios. One particular focus of the model is the integration of new sustainable innovations for manure treatment in the current economic structure. Excess of manure constitutes an important economic and environmental problem in Belgium. The excess of manure leads to water pollution, high costs for disposal and important changes in local ecosystems. This urgency has led to the creation of new innovative methods to treat manure in a more sustainable way. These innovations are intensively researched and provide new production methods for fertilisers, algae-based products, feedstock or water purification. The potential influence on the overall sustainability of agriculture is large. However, the integration of these new technologies encounters multiple structural barriers. The current project builds an ABM model to test different scenarios of support policies for agriculture and for related sustainable technologies.

This paper develops the calibration of the ABM model according to the Werker-Brenner approach [23]. The calibration is aligned to the historical evolutions in dairy, pig and cattle production during the years 2003 – 2013. We compare two different models of farm agent behaviour. A first model follows uniform behavioural rules for all agents, based on profit maximisation. A second model implements a structured behavioural diversity. The calibration method allows the determination of several behavioural variables.

This paper is structured as follows. In the second section, the structure of the ABM model is described. This comprises the architecture and the behaviour submodels. The third section reports the calibration results for the initial benchmark situation and for the historical evolution. The fourth section discusses and interprets these results. Section five concludes.

II. CHOICES IN THE MODEL CONSTRUCTION

The main research orientation looks at the evolution of the agricultural sector in Belgium, and the influence of new manure-treatment methods on this evolution. More particularly, the focus is directed towards the investigation of structural change in agriculture. Structural change has been investigated as shifts between different types of producers (Baumol et al., 1985) or shifts in labour allocation per sector (Ngai and Pissarides, 2007). Generally, structural change can be regarded as shifts in productive assets at the level of an economic sector. The definition of the farm agent should thus include different types of productive assets, and allow to see modifications in asset compositions over time. The main answer to this requirement is the inclusion of different types of animal stocks, investments and land types for each individual farm agent. The farm agent can therefore specialise on one type of production, or he can choose to combine multiple stocks and create a mixed farm.

Mixed farms are an important part of the Belgian agriculture. Multiple economic studies focus on specialised farms (Berentsen, 2003; Meul et al., 2007; Nevens et al., 2006; Van Passel et al., 2007; Van Passel et al., 2009). But the Belgian agriculture contains different forms of mixed farming. This combination of different animal products and crops can be historical, but can also be strategic in response to economic adversity or low productivity (Meert et al., 2005). Mixed farms keep different production options open, allowing for more evolutionary pathways than specialised farms. So co-production and mixed farming should in principle remain possible for the farm agent. The chosen farm model allows for a simultaneous production of crops and animals. However, the categories of production do not detail specific crops or products. The different types of crops are divided in four groups (i) Forage : cultivation of plants destined for animal nutrition, (ii) Pastures and grasslands, (iii) Horticulture and (iv) Crops : all other types of crops. The animal products are grouped in three broad

categories : (i) Pig products : The output of this category consists mainly of live pigs, (ii) Dairy products : This output does contain raw milk, but also live reform cows for sale, (iii) Cattle products : All other live cattle are grouped in this category.

Pastures and grasslands constitute a particular category, as in this model the farmer cannot directly draw profit from the grassland. The available grassland is integrated in the production for dairy products and cattle. The production of the other categories can be used internally or can be sold, leading to six potential types of revenue for each farm. Specialised farms will focus on one category only. Mixed farms can combine different revenue streams.

A second field of detailed investigations is the agricultural land. The level of detail in the description of the agricultural land is highly dependent on the objectives of the study. For instance, many projects incorporate geographical data of land parcels to study local characteristics and geographical proximity as determinants of land transactions. This can be spatially explicit in a theoretical land framework (Epstein and Axtell, 1996; Happe et al., 2004), or based on real geographical information (Smajgl and Bohensky, 2013). This has been used to study water management options, regional farm structure, or management of common resources (Matthews et al., 2007; Parker et al., 2003).

In this case however, the focus is not on the geographical characteristics of the farm. The main objective is to study the emergence on the market of new technological solutions for manure treatment. Given the small size of the region under consideration – Belgium – differences in regional characteristics can play a role in reality, but are not preponderant. The emergence of these technologies is studied as a results of technology evolution, learning, acceptance by farmers and related policy measures. Other studies also investigate agent-based dynamics without geographical specification (Möhring et al., 2010).

If geographical information is not included in the land market, then this requires specific assumptions for the land market model. Because in reality geographical limitations impose specific dynamics on the exchanges of land between farmers, the implemented market model ensures that these are preserved.

III. THE MODEL ARCHITECTURE

Figure 1 present a schematic overview of the model. It illustrates the group of farmers in relation with different markets. The exogenous markets are capital, labour, fertilisers, investments and output markets for different products. Their prices are fixed and given by external data. The endogenous markets react to the quantities and prices requested by the farmers: for land, for manure, and for live animals. The market for live animals considers the exchange with slaughterhouses. The price determination is based on an econometric model of market power in the slaughterhouse market. The other two markets, for land, manure and feedstock, are implemented as double auction markets [24]. In these markets, any party has the possibility to enter bids for either the purchase or the sale of a good, combined with a requested price. The double auction mechanism combines sales bids with purchase bids and establishes a negotiated price for the transaction. For the purpose of the calibration, the manure treatment sector is fixed. Existing technologies are present and unchanging, new technologies are not yet introduced.

Other external evolutions are set according to the historical prices in terms of market prices. Hence, the current application focuses on the dynamics within the agricultural sector itself. No external shocks are applied during the calibration.

The evolution of a farm agent during the course of one year is illustrated in Figure 2. The annual process in divided in four steps : (i) After the initialisation of the

Figure 1: Schematic overview of the agent-based model
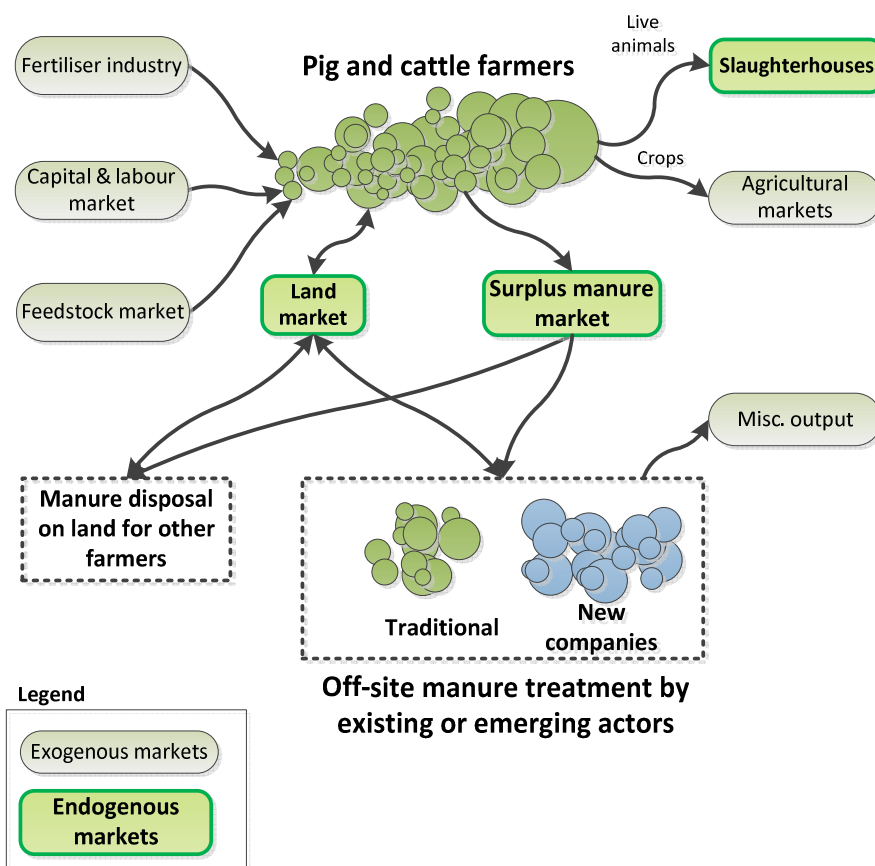
model for the first year, the agent starts producing. Whenever possible, the manure is first spread on the fields of the farm itself. The remaining manure has to be sold in the manure market. (ii) The second step is the sales of output products and manure. After the sales, the total annual turnover can be calculated and farm agents decide whether they want to continue farming or not. Reasons to cease activity are bankruptcy, passing of the farmer or a decision to leave animal farming and to focus on crops only. (iii) If the farm agent continues, he optimises assets for next year. This step contains most of the behavioural decisions. (iv) Finally the farmer updates his financial liabilities and new starting farmers enter the group for the next year.

The third quadrant of the annual cycle combines all steps to decide on the future lay-out of the Farm Agent. The decisions concern a number of variables that cover assets and efficiency investments. This part of the annual cycle also gathers all aspects related to adaptation and learning of the farm agent. The decisions are split between three steps, each changing several production variables. The first step of the decision process is the overall strategic decision, allowing the farmer to review the types of animals on his farm. This means that the agent can decide whether or not to continue raising a certain type of animal. The agent can also decide to invest in an innovation to improve production efficiency.

Figure 2: The different steps for every farm agent in the evolution of one year.
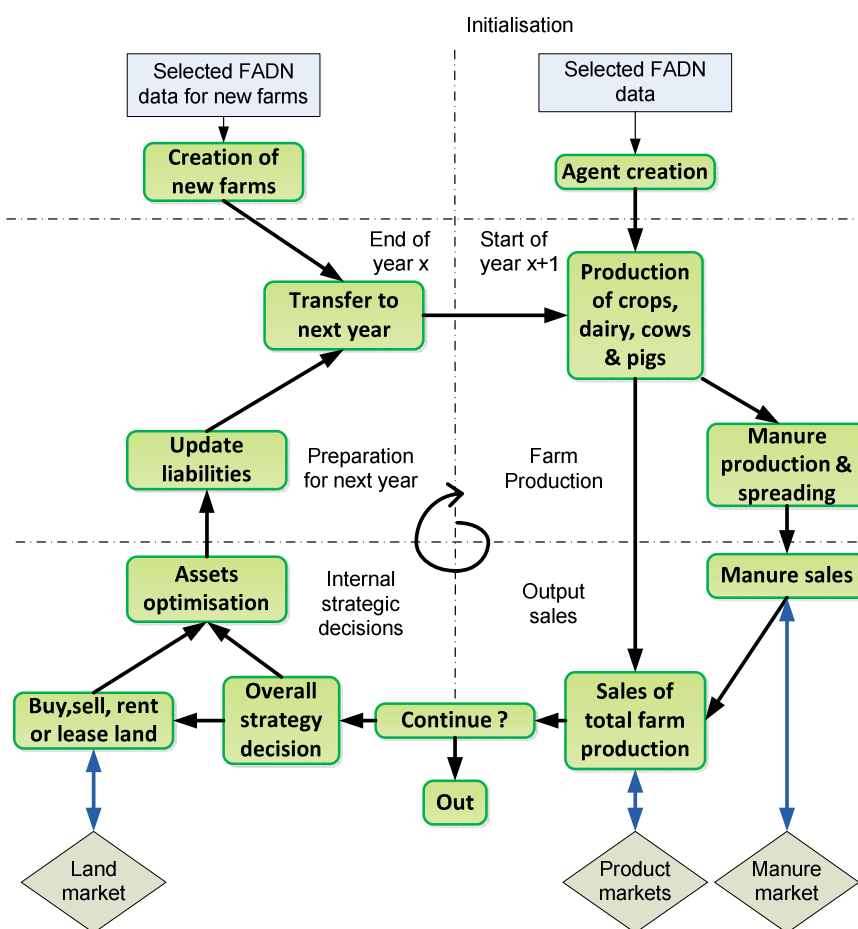
In the second step, the farm agent can change land surfaces, and interacts on the land market. Consistent with the choices of the land market rules, this second step is not entirely available to all Farm Agents every year. On an annual basis, only a small percentage of the Farm Agents (according to the 'Land Access Factor'), can carry out this second step to buy land. Finally in the third step, the farm agent optimises the production assets by minor de- or investments and allocates different crops to the remaining available land surfaces. Based on the type of animals and the land surfaces available, the farm agent can adjust the amount of livestock with a maximum of ± 20%. Increases in animal stock are accompanied by investments for additional stables and machinery, and the farmer has to respect a minimum surface of grassland per cow at all times.

The third quadrant of the annual cycle assembles the different parts of the decision framework of the farmer. In this paper, we compare the results of two different behaviour submodels each applying a different set of decisions for the agents : a profit-maximising model and a diversified behaviour model. As all other input data remain equal, the results show the impact of the decision heuristics on the simulated evolution.

The evolution of the farmer's community is subject to the following variables in each case :

- Transaction costs : Changes at farm level do not immediately yield their optimal return. The farm agent has to adapt to the new specialisation or investment. This learning period is implemented as a transaction cost, proportionate to the investment cost of the change, separately for each of the three animal productions.

- Adaptability: The general framework provides the option for the farmer to change his overall strategy every year. In reality there are several reasons that induce a farmer not to change his strategy every year. First of all, large strategic changes require willingness to change and a learning capacity. Secondly, large changes are disruptive at farm level. They reduce the options for future production and render some past investments obsolete. Finally, there can also be a form of persistence or stubbornness that explains why farmers continue production with an existing configuration rather than 'giving up' one type of animal or crop. The model integrates this lack of adaptability. The overall adaptability of the farmers' community is defined as the percentage of the farmers that review their strategy in one year.

IV. ADAPTATION AND LEARNING

Three aspects that determine the adaptation and learning capabilities of the Farm Agent, are historical path-dependence, the ability to forecast and the individual objective function. Adaptation of an agent requires the maintained link with the historical evolution of the agent. The agent follows a path during its development, and the effects of learning are determined by the past experiences of the agent. The second obliged concept in relation with adaptation is the ability to forecast. Even in situations where high uncertainty is prevalent over future trends, agents are obliged to determine forecasts for future productions and prices [33, 35]. Finally, adaptation obliges the definition of an objective function or fitness measurement. The agent will then adapt his situation in order to maximise his fitness [36]. These three aspects are reflected and implemented at different instants during the decisions taken in the third quadrant of the annual cycle.

First, historical path-dependence is present in the decisions taken in the third quadrant of the annual cycle. As such, path-dependence is a standard characteristic in agent-based models. Each agent starts an evolutionary cycle with an individual situation as a result of choices and experiences in the past. The starting situation determines to a large extent the possibilities that the agent has for the future. This is also the case in this model. At the start of the cycle, the Farm Agent begins with the results of the past cycle. The choices of productive assets indicate the present productions. Also, the past expenditures determine the present production efficiency and characteristics. Finally, the starting situation also limits his future choices for coming cycles. Farm Agents can choose to reduce the types of animals they raise, but they cannot choose to increase them. This means in practise for instance that a specialised dairy farmer cannot decide strategically to discard all dairy production and to turn to specialised pig farming instead.

Secondly, the farm agents display an ability to forecast. Each farm agent individually optimises his annual income based on personal price predictions. These price predictions are formed by averaging the prices the farmer received for this output during the last three years. External trends that could influence future prices are not taken into account by the farm agent. This is narrow foresight, similar foresight methods used in other projects [12].

V. OBJECTIVE FUNCTIONS AND OPTIMISATION CONSTRAINTS

The final aspect of adaptation is the objective function and the related optimisation constraints. Multiple models use an objective function based on various forms of profit-optimisation. In these models, every farmer decides on his strategy and assets while optimising his annual profit. Profit-optimisation has been applied before in agricultural agent-based models, but rarely in the strict neoclassical sense. Several adaptations to this basic decision model have been applied to bring the behaviour closer to reality. The Agripolis model [12, 13] utilise a farm income maximisation decision module. This maximisation is based on limited

information and personal prediction of future output prices. Similar constrained and bounded rational optimisation of annual farm income is found in agricultural models such as MP-MAS [18, 25] or CATCHSCAPE [26, 27], the latter combining optimisation with linear programming.

In this model, the objective maximisation of the farm agent is constrained by the availability of loans and by the level of financial risk the farm agent is willing to take. New investments in land, animals, farms or installations require loans. Banks will not base the restrict the maximum amount of the loan on the future business plan, but to the value of the land of the farm that the farmer can give as a guarantee. The financial risk of the farm agent is defined as the ratio of liabilities over owned assets. Every farmer disposes of a unique maximum level of risk he is willing to take. This maximum financial risk level RF is age-dependant. The fixed level RF_0 is normally distributed among the agents with parameters N(0.32; 0.224), corresponding to risk levels in 2003. With growing age, the risk preference of farmers decreases and falls to zero at the age of 65 :

$$RF = RF_0 \left(1 - e^{\frac{x-65}{10}} \right).$$

Because two different behaviour submodels, of which one with behavioural diversity are used, as explained in the next section, three different objective functions are integrated. A first objective function is based on profit. This is similar to the projects mentioned above. Constrained by limited choices and loan availability, the farm agent decides on the optimal quantity of land, animals and animal types for a maximum profit next year. A second objective function expands this to farm value. Annual profit maximisation is a very short-term planning horizon for the farm agent. In order to incorporate a focus with a longer time-frame, farm agents maximise the entire value of the farm rather than solely their profit. This entire value includes liquid and fixed assets and agricultural land. This type of farmers does not pursue the largest profit for next year, but they pursue the creation of a large and rich farm, yielding important annual profits each year.

The third objective function is not based on a value, but on an ideal farm structure. Maximisation implies that the agent disposes of a range of choices. For instance, the choice of a mixed farmer to stop raising pigs and to specialise on dairy farming instead, can be part of the decision process. But this is not a valid choice for one type of farms called 'stable family farms'. The 'stable family farm' is based on characteristic behaviour of Belgian small-scale farmers. This type of farmers are active in agriculture and are passionate about their specific farm type or about the animals they raise. Entirely driven by personal preferences and conviction, this type of farm can for instance prefer pigs. Despite the fact that crop farming presents larger marginal benefits, this farm will continue to raise pigs. There are no alternatives considered during a maximisation process. Their objective is the creation of an 'ideal' farm configuration and size, based on personal preferences of animals and crops. The 'ideal'

farm contains a certain land surface, and a specific stock of animals. This ideal also consists of a full ownership of all the land under cultivation. Every affordable step that can bring the farm closer to the ideal, is implemented. When achieved, the farmer stops the farm growth and invests only in efficiency.

VI. BEHAVIOUR DIVERSITY

The first behaviour model uses behaviour uniformity and assumes a constrained profit maximisation for all agents.

The second behaviour model implements behavioural diversity, constructed according to the procedure of Smajgl et al. [19]. Diversity is a key feature in evolutionary analyses. Following the variety of farmers in Belgium, the implementation of technical diversity leads to a large range of technical variables, combinations and characteristics in the model. The additional implementation of behavioural diversity adds another level of differentiation between the agents, leading to a multiplication of variable combinations. This large combinatorial freedom could signify in practice that the model is very hard to build empirically. But the application of diversity in both technical and behavioural characteristics is feasible because one can rely on the coherence between the two aspects. Farm agents are classified in different groups based on their technical characteristics, including farm size, type of activity, location, profitability, or age. This defines the attribute data, and attribute-based classes. The behavioural diversity is also explicitly integrated by forming classes of farmer behaviour. When one considers certain behaviour to be continuous, it will influence the lay-out and structure of the farm over the long term. Mixed farms will not be held by farmers pursuing a maximum production efficiency, or large farms require a certain willingness to take risks from the farmer. Through recursive optimisation of the classes, groups of farmers are constructed that combine each a technical type and a behaviour class. In each case, the method integrates empirical datasets and qualitative information to build the full model [28].

Figure 3 : The links between the different farm agent behaviour types
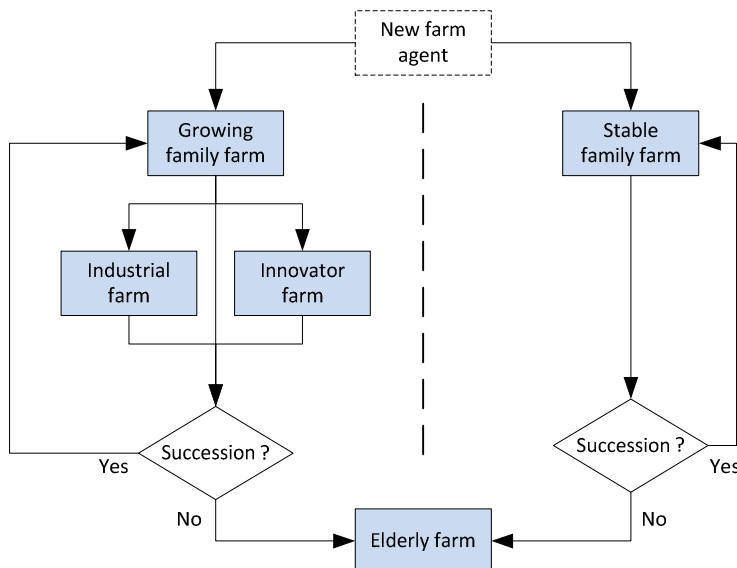
In this case, different types of farmer behaviour have been distinguished through discussion with experts. For this application, five different types of farms have been determined: (i) growing family farms, (ii) stable family farms, (iii) innovator farms, (iv) elderly farmers and (v) industrial farms. Every behaviour type is related to technical farm characteristics, as described in Table 4.

At the start the farm agent can be defined as a growing family farm, or as a stable family farm. The two types have very different behaviours. Stable family farms are based on one family pursuing a stable surface of land and stock of animals. The main objective of these farmers is to obtain a stable farm configuration, while increasing ownership of the land under cultivation and achieving a growing income and farm value. The farmer does not optimise the value nor the income of the farm. The farmer defines an ideal farm and pursues this structure. Investments to increase efficiency are implemented when affordable. The farm size is limited, the total amount of external labour does not exceed 1 FTE. Growing family farms on the other hand, have a very different behaviour. These farms are also created from one family with a growing surface of land and stock of animals. But the main objective of these farmers is to grow steadily. Growth of production can be achieved both by acquisition of production assets as by implementing innovative technologies for increased production efficiency. Through multiple adaptations, the growing family farm can become an innovator farm or an industrial farm.

The innovator farm adopts a long-term strategy based on high specialisation and innovation. The farm aims for high specialisation and innovation. Growth is pursued, but it is not the primary objective. Investments in efficiency increase and in niche production are preferred. The farmers of innovator farms are over 45 years old, allowing them to achieve sufficient experience and background to invest in multiple innovations. These farms achieve the highest production efficiencies. The type is most commonly associated with specialised pig and dairy farms, less with cattle farmers. The industrial farms on the other hand, are less specialised, but larger than innovator farms. Industrial farms are managed as industrial plants. The farms maximises the total value of the farm in the long run. The strategy is based on economies of scale, and leads to intensive growth of the farm. These are the largest farms but do not require specialisation.

Finally, at the end of the lifetime of the farmer, the farm has to find a successor, or he is to evolve into an elderly farm. Succession is a crucial step in the history of family farms. This is increasingly the case, as farms grow larger in size, to a point where it is difficult to start a new farm without any capital or assets available from a predecessor [37]. However, the current rate of farms that find a successor on time is low. Farms without a successor can present zero growth or decrease in total farm assets [38]. On the other hand, elderly farmers stay active after their pension age, and continue farming without further adapting their farm structure.

The typology of elderly farms consists of farmers that gradually retire, and don't find a successor. The elderly farmers live up the farm's assets, maintain the land in ownership and do not invest in higher efficiency or new innovations. The activity only stops when the owner passes away. Besides the high age of the farmer, these farms also present low efficiencies and high stability of activities or even decreasing activities. Currently, a succession rate of 41% is implemented in the model. Any farm that fails to have a successor on time (growing family farm, innovator, industrial or stable family farm), becomes an elderly farm when the farmer's age reaches 65 years.

So the behaviour typology can be divided in two very different evolutions, one based on stable family farms, the other on growing family farms that can potentially evolve towards industrial or innovator farms. Both types turn to elderly farms at the end of their life. The difference between the two evolutions is especially a difference of adaptability & learning capacity. The growing family farm is responding to market prices by adapting his production assets. This is characteristic shared with the innovator and industrial farms. On the other hand, the stable family farms remain focused on their ideal farm structure. Stable family farms do not adjust their production according to market prices. At most they delay investments because of insufficient liquid assets. The stable family farms represent a very stubborn and fixed behaviour. The other farm types represent a very flexible and adaptive behaviour. The percentage stable family farms in the total farm population is therefore an important factor for the overall adaptability of the agricultural sector. This percentage also has to be determined through calibration.

VII. CALIBRATION METHOD AND RESULTS

Empirical calibration of evolutionary models has been gaining attention lately [39], and several approaches are available [40]. Still, calibration has been noted as a critical problem in applications of empirical ABM's and solid calibration methods are required to guarantee the credibility of the results [41]. Standard calibration takes two steps. The first step calibrates the input data of the model on realistic data sets and benchmarks. The second step compares the output with empirical data for the output and determines the validity of the model. A specific and pragmatic calibration method, the Werker-Brenner method, adds a third step [23]. The method uses specificities of evolutionary models, exhibiting often numerous degrees of freedom. The Werker-Brenner approach labels itself as 'critical pragmatist' in the sense that the model is not required to deliver one correct solution. The more pragmatic approach is to allow for several realistic solutions that are able to explain the same phenomenon. Several acceptable sets of input data are determined that return solutions in line with the calibration constraints. The third step is thus to investigate the underlying dynamics, similarities and differences between the inputs sets. These patterns show underlying principles common to all acceptable data sets. This approach narrows the sets of possible entry data down to more realistic figures, and this improves robustness of the model [42]. This paper applies this calibration method. First the initial situation is fixed. This initial situation is calibrated to technical and production characteristics of the Belgian agricultural sector in the period 2001-2003. A limited number of immeasurable parameters, especially those related to behaviours, are selected at random. The model is executed separately with profit maximising and with the heterogeneous behaviour rules. After hundreds of model runs with random parameters, the results are chosen that correspond best with the historical evolutions in the period 2003-2013.

Table 1 : Comparison of the calibrated farm agent set with quantities in reality

General data		
# of reference farms selected		49
Total number of agents at initialisation		40583

Comparison according to farmer's age		
Age	Number of farmers in reality	Represented at initialisation
18-34	5 002	99%
35-44	12 059	97%
45-54	11 154	96%
55-64	9 989	97%
>65	9 016	96%

Comparison according to land size		
Land size	Number of farmers in reality	Represented at initialisation
<5	8 780	84%
5-10	5 180	88%
10-20	7 010	102%
20-30	5 850	102%
30-50	7 840	103%
>50	7 240	103%

Weights			
Avg	SDv	Min	Max
828	299	86	1 000

Comparison with macroeconomic benchmarks			
	2001	2002	2003
Cow production	104%	96%	103%
Pig production	104%	103%	101%
Dairy production	100%	101%	101%

Comparison according to the size of the animal stock on the farm			
	Total LSU on farm	Number of animals in reality	Represented at initialisation
Cows	< 20	109 440	100%
Cows	20-50	1 082 940	98%
Cows	>50	1 585 710	97%
	Total LSU on farm	Number of animals in reality	Represented at initialisation
Pigs	< 20	3 480	100%
Pigs	20-50	85 380	102%
Pigs	>50	1 872 723	108%

A. Calibration of the initial reference farm agents

The start of the model is calibrated on production benchmarks and on benchmarks of farmer diversity during the years 2001-2003. The model is populated with a heterogeneous group of farm agents. This group consists of reference farm agents, each attributed a specific weight that determines their multiplication at the initialisation of the model. The model selects farms from the Farm Accountancy Data Network (FADN) database to shape the reference situation of the farm agent on a realistic basis. In this case, the farm selection is not based on expert knowledge, as this would imply a manual selection. This is not feasible given the high number of agents and several simultaneous conditions. Therefore, we adopted a method, based on the solution of Happe et al. [12] and Sahrbacher et al. [14]. This enables to automate the selection as an optimisation solved with quadratic programming. There have been 26 criteria fixed for the selection of the reference farms. Nine criteria are related to the total macroeconomic production of the Belgian agriculture during the years 2001-2003.

It is the objective that the selected farms should replicate the annual national production of cows, dairy and pigs. The reason to decide on three consecutive years rather than on one single year, is to avoid selection of farms with irregular production output, or farms for which data was not available for a longer period. Seventeen additional criteria relate to the age diversity and size distribution of farms in the year 2003. The selected group of reference farms should represent the same age pyramid, and size distribution, both in land surface as in livestock size, as the Belgian agricultural sector in reality. The quadratic optimisation yielded a total of 49 different reference agents, representing 40 583 farms. The comparison of this selection for each criterion is illustrated in Table 1.
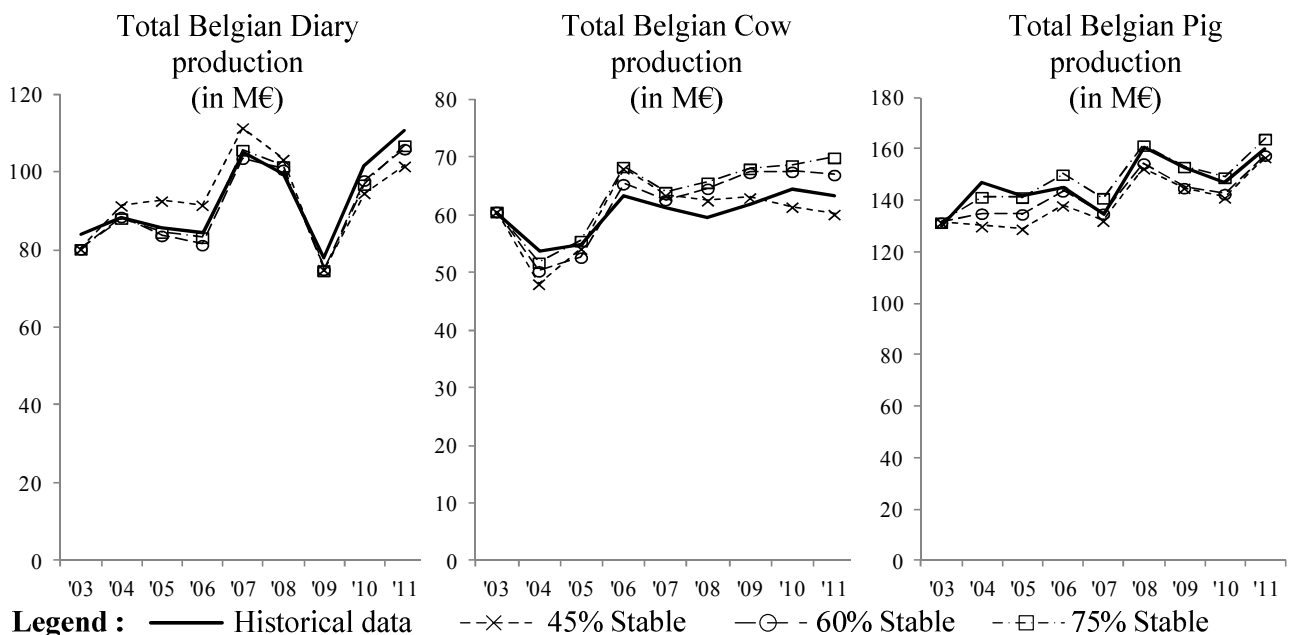
B. Calibration runs compared with historical evolutions

The simulation results are compared to the actual productions of dairy, cows and pigs during the period 2003-2011. The calibration is used to determine behavioural uncertainties.

When the first submodel is used, all agents are focused on profit maximisation. Profit-maximisation is a more determined behaviour, but it still disposes of some variables that have to be chosen randomly for the calibration runs. These are the size of transaction costs, the annual land availability for farmers and the price of efficiency investments. In this case however, no sufficient approximation has been found for the profit-maximising model. The results are illustrated in Figure 4. When the model assumes profit-maximising behaviour for all farms, the simulated productions cannot be brought closer to the quantities in reality.

In the second submodel, assuming heterogeneity, several scenarios can be determined that bring the simulated evolutions closer to the real annual productions. The variables that need to be determined through calibration are : the adaptation capacity of the farmers' community, the annual availability of land, the transaction costs, the efficiency increase/innovation cost for efficiency improving investments, the proportion of growing family farms compared to the number of stable family farms.
Not all of these variables exert a similar influence on the evolution of the model. An essential role remains for the proportion of growing family farms compared to the proportion of stable family farms. This can be clarified by highlighting the large differences between the two.

Figure 4 : The model assuming profit-maximising behaviour cannot replicate the real evolutions.

Total Belgian Diary production (in M€)

Total Belgian Cow production (in M€)

Total Belgian Pig production (in M€)

Legend : ——— Historical data   --✕-- 45% Stable   —⊖- - 60% Stable   - ⊟- ·· 75% Stable

| | Total Belgian Diary production (in M€) | Total Belgian Cow production (in M€) | Total Belgian Pig production (in M€) |

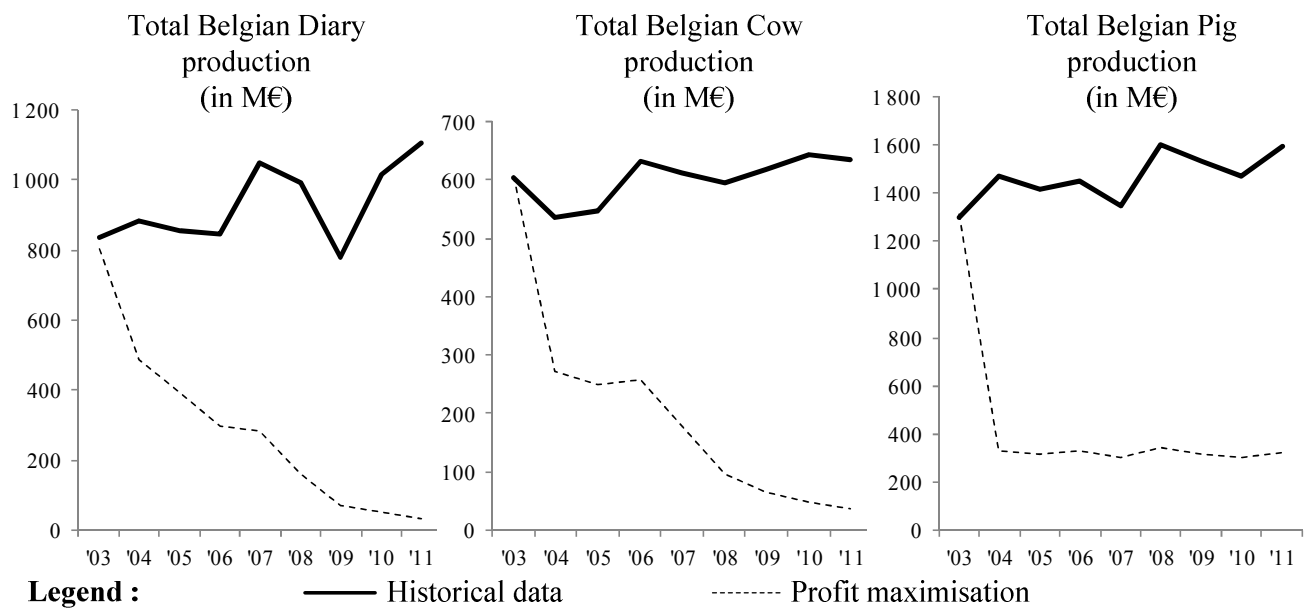**Legend :** —— Historical data ------ Profit maximisation

Figure 5 : Comparison of annual turnover for simulations and historical data

The growing family farms are very reactive to their environment and to the price signals they receive. They are also the basis for the emergence of larger and more innovative farms.

The stable family farms however, are mostly driven by internal motivations and constrained by personal limits on size and labour. A high proportion of growing family farms yields a model that is highly reactive to price evolutions. Consequently, a high proportion of stable family farms yields a model driven by changes in land surfaces and age pyramids of the farmers.

The calibration has been done for a varying proportion of growing versus stable family farms. The optimal values for the corresponding parameters are reported in Table 2. The three best approximations (with 45%, 60% and 75% of stable family farms) are illustrated in Figure 4.

Table 2 : Optimal parameter sets to simulate the actual production

Proportion of stable family farms	0%	15%	30%	45%	60%	75%	90%
Adaptation capacity[1]	1%	10%	10%	15%	20%	30%	10%
Land availability[2]	5%	10%	20%	30%	40%	40%	50%
Transaction costs[3]							
Dairy	5	-	-	-	-	-	-
Other cattle	15	10	-	-	-	-	-
Pigs	5	5	5	5	5	5	-
Efficiency / cost ratio[4]							
Dairy	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Other cattle	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Pigs	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Approximation quality[5]	22.1%	11.1%	7.0%	3.8%	2.8%	4.1%	7.2%

[1] : The adaptation capacity is the proportion of farm agents that execute the strategic decision process per year.
[2] : The Land availability is the proportion of farm agents that has land available for purchase or for rent in his neighbourhood per year.
[3] : The transaction costs are defined as an additional cost when change is undertaken, of x times the price of the livestock quantity change.
[4] : The cost of an efficiency improving investment is the e/c ratio times the size of the livestock, per percentage efficiency improvement.
[5] : The average relative differences with the real macroeconomic productions is used as a measure of approximation quality for the scenario.

Table 3 : Translation of the behaviour in modelled rules

Name	Evolutionary traits	Technical characteristics	Optimisation objectives	Optimisation constraints
Industrial farms	These farms set out from the start to behave strategically as industrial firms and have a relatively high chance to find a successor.	Farm owner is older than 45 years. Farm size exceeds 350 LSU. Farm is not specialised in one animal type.	The farm maximises the profit of the firm.	Growth is constrained by a maximal financial risk of 60%.
Innovators	These farms start as family farms. When the farm achieves sufficient experience, efficiency and specialisation, it can become an innovator. These farms also have a relatively high chance to find a successor.	Farm owner is older than 45 years. Farm is specialised in one animal type. The farm production efficiency exceeds 110% for dairy farms, 135% for cattle farms, 150% for pig farms.	The farm maximises a double objective, maximum farm value and maximum production efficiency.	Growth is constrained by a maximal financial risk dependant of the owner's preference. And the total labour burden should remain smaller than 20 times the farm household size.
Growing family farms	Farms start as growing or as stable family farms. Only growing farms are interested in an evolution towards industrial or innovator configurations.	The farm owner is younger than 65 years, or has a successor. There is no other technical restriction for this type of farms. Farm types are randomly designed growing or stable family farms at the creation of the farm agent.	The farm maximises the total value of the farm, composed of liquid assets, and fixed assets including land.	Growth is constrained by a maximal financial risk dependant of the owner's preference. And the total labour burden should remain smaller than the farm household size plus one.
Stable family farms	Farms start as growing or as stable family farms. These farm remain in this category unless they fail to find a successor in time.		The farm pursues a size of land and livestock, determined on beforehand as ideal. Whenever land is available or financial reserves allow it, these farmers grow their assets until they reach their ideal size.	Purchase of new assets is constrained by a maximal financial risk dependant of the owner's preference. And the total labour burden should remain smaller than the farm household size plus one.
Elderly farmers	All farms that do not find a successor in time become elderly farms.	The farm owner is older than 65 years, and has no successor.	The farm doesn't change investments any more, nor does it invest in efficiency improvements. The same activity is maintained with slowly declining efficiency.	
Remarks: - Farms that are facing bankruptcy due to negative cash flows, revert to cash maximisation as a short term survival strategy. When the danger of bankruptcy is averted, they return to their standard optimisation procedure.				

VIII. DISCUSSION

Profit-optimisation in this approach induces a lot of effects that do not represent realistic behaviour. A first effect is that farmers tend to sell land, and increase their rented area under cultivation. Secondly, the agents are not inclined to invest in longer-term solutions or in innovations to improve production efficiency. Finally, production forecasts are set on prices. The real prices have been relatively low in this period; so many farm agents decide to focus on crops or to leave farming altogether. A decrease in sales prices for one year has the immediate effect that the least productive farmers leave this segment of production. One year of bottom prices thus has a very strong effect on the number of active farmers. The assumption of profit-maximisation is related to several other suppositions. It implicitly assumes that farmers have multiple alternatives to choose from and that they also consider these choices annually. This is not supported by the actual evolutions of animal production. As discussed above, because of lack of skills or knowledge, several alternatives can be unattainable for the farmer. The farmers prefer a longer time-frame, and present a certain persistence. They avoid making disruptive changes to their farm. Finally it has to be stressed that the considered decade 2003-2013 has not been very profitable for Belgian farmers. The prices for their production were and are still relatively low. Several segments of the market contain active farmers that have a very hard time to cope with these negative market developments. Still bankruptcy remains very low in agriculture. This is again a sign of strong persistence, showing why classic economic behaviour models cannot replicate the actual historical evolutions adequately.

The results from the model applying diversified behaviour are more realistic. The evolutions for pigs and dairy can be approximated closely. The closest predications can be made assuming a proportion of stable family farms between 45% and 75%. Both below and above this range the simulations remain further from the real historical productions. However, there are general tendencies over the entire range. With a low proportion of stable farmers, higher transaction costs , low adaptability and rigid land markets are required to match the real evolutions. Transaction costs serve as a barrier for change. When considering a change, the farm agent calculates the benefit. Large transaction costs indicate that the additional benefit from the change has to be substantial, before the change is considered. With an increasing proportion of stable family farms, the transaction costs diminish, the adaptability has a tendency to increase, as well as the land availability. However, these increases are non-linear, indicating intricate dynamic relations between the different parameters. The best approximation, with 60% stable family farms, stays each year within a range of 5% of the historical dairy production, and within a 10% range of the cow and pig production.

The common patterns between these parameter sets are the resistance to change in the agricultural sector. With low proportions of stable farms, there is rigidity in the market

and in the learning processes. With growing proportions of stable family farms, the rigidity in the market and in learning can be reduced significantly. In these last cases, the rigidity resides in the behaviour of the farm agents themselves. Stable family farms are modelled to remain on an evolutionary track that they determine themselves at the start of their activity. Adverse price conditions or market pressure do not change their strategy. This rigidity is required if one is to explain the reasons behind the evolution of Belgian agriculture during the last decade. Whenever a modelled farm agent gets a chance to review his own situation and to consider alternatives, he chooses in most cases to leave animal farming and to do something else. An extreme illustration of this rational decision making is in the profit maximising model. But these large exits from animal farming did not happen in reality. Farmers rather continue to produce and invest despite low output prices. It is mostly because of this behaviour that the Belgian agriculture is capable of presenting a stable and growing annual production.

This application of diversified behaviour modelling yields promising results, given the fact that it flows from a first tentative construction of such a model for the Belgian agriculture. The model results are capable as such to indicate the existence of important rigidities in the evolution of farms. But it cannot pinpoint the exact location of this rigidity in this first application. The current application can only present the first step in an iterative refinement of the model through questionnaires, participatory techniques or mediated modelling. The present shortcomings include the difficulty to adequately predict the production of live cows, and the simplicity of behaviour rules for certain farm agent types.

IX. CONCLUSIONS

A better understanding of the drivers and dynamics behind of the evolution of the agricultural sector is crucial to increase the effectiveness of new policies in the long run. To this effect, an agent-based model of the dairy, cow and pig production sector in Belgium is constructed, to benchmark new policy scenarios. This model is calibrated on historical data, with two different behaviour submodels, all other inputs remaining equal. A first submodel assumes constrained profit-maximisation with limited information availability. The second submodel assumes behaviour heterogeneity, linked with technical characteristics of the farm agents. The results from the profit-maximising submodel indicate that this type of optimisation behaviour is not appropriate for most farms in Belgium. We show that a combination of diverse types of behaviour should be preferred to model farm evolutions. Hence, using a more diversified range of optimisation objectives and constraints can mimic closer the past evolutions of production.

The results of the calibration show an important resistance to change. This resistance can be caused by difficulties in the learning process, by market rigidities or by farmers unwilling to give up their ideal farming configuration. The exact cause of the evolutionary rigidity can be the subject of further research. Still, these results show that farmers very often

continue producing the same animals and crops, despite adverse economic situations. And it is mostly because of this behaviour that the Belgian agriculture is capable of presenting a stable and growing annual production. Both behaviour and technical characteristics influence heavily the evolution of the agricultural sector. Currently, there is a lot of data available to describe the technical characteristics and the micro-economic situations of farms. Unfortunately, data on behaviour and decision frameworks is less available. More research on the actual behaviour of farmers is required to produce more realistic models. Aspect such as household characteristics and risk balancing behaviour can improve actual behaviour models.

X. ACKNOWLEDGMENTS

XI. REFERENCES

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