An agent-based model of the market penetration of a new product

Author: Thandulwazi Magadla
Supervisor: Dr Ian Durbach
Co-Supervisor: Dr Leanne Scott

Dissertation presented for the degree of Master of Science

in the department of statistical sciences

university of cape town

February 17, 2014

Publication

I hereby grant the University free licence to publish this dissertation in whole or part in any format that the University deems fit.

Plagiarism Declaration

1. I know that plagiarism is wrong. Plagiarism is to use another's work and pretend that it is my own.
2. I have used the APA referencing guide for citation and referencing. Each contribution to, and quotation in this dissertation from the work(s) of other people has been contributed, and has been cited and referenced.
3. I know the meaning of plagiarism and declare that all of the work in the dissertation, save for that which is properly acknowledged, is my own.

Signature: Signed by candidate

Date:

Acknowledgements

I'd like to express my gratitude to the CSIR and The Institute of Applied Statistics for granting me funding without which this research would not have been possible.

To my supervisors, Dr Ian Durbach and Dr Leanne Scott, thank you for your patience and helping me see the forest for the trees. I didn't think I ever would.

I'd like to thank the CSIR High Performance Computing Centre for the use of their facilities although the simulation results were eventually not used. I'd like to thank the Statistical Sciences department for making computers available for me to run my simulations.

A very big and heartfelt thank you to my colleagues at the CSIR especially Nontembeko Dudeni-Tlhone (you saved me from the brink of insanity on several occasions) and Reneé Koen. Thank you for all your patience and all your help and words of encouragement when I just couldn't make out left from right.

Thank you to my parents for your unwavering support and belief in me. I hope that milestones such as these make you feel that it was all worth it in the end. Thank you Darryn Williams for being my sounding board even when you had no idea what I was on about. Thank you to Sandisile Khanyile and Sandile Malinga for being there for me through rain or shine. Thank you very much to my friends and family for believing when I didn't and for all the support (even when it was not what I wanted to hear).

Abstract

This dissertation presents an agent-based model that is used to investigate the market penetration of a new product within a competitive market. The market consists of consumers that belong to social network that serves as a substrate over which consumers exchange positive and negative word-of-mouth communication about the products that they use. Market dynamics are influenced by factors such as product quality; the level of satisfaction that consumers derive from using the products in the market; switching constraints that make it difficult for consumers to switch between products; the word-of-mouth that consumers exchange and the structure of the social network that consumers belong to. Various scenarios are simulated in order to investigate the effect of these factors on the market penetration of a new product. The simulation results suggest that:

- A new product reaches fewer new consumers and acquires a lower market share when consumers switch less frequently between products.
- A new product reaches more new consumers and acquires a higher market share when it is of a better quality to that of the existing products because more positive word-of-mouth is disseminated about it.
- When there are products that have switching constraints in the market, launching a new product with switching constraints results in a higher market share compared to when it is launched without switching constraints. However, it reaches fewer new consumers because switching constraints result in negative word-of-mouth being disseminated about it which deters other consumers from using it.

Some factors such as the fussiness of consumers; the shape and size of consumers' social networks; the type of messages that consumers transmit and with whom and how often they communicate about a product, may be beyond the control of marketing managers. However, these factors can potentially be influenced through a marketing strategy that encourages consumers to exchange positive word-of-mouth both with consumers that are familiar with a product and those who are not.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Markets in which firms offer similar products or services that consumers consider to be substitutes for each other often exhibit strong competition among firms (Jager, 2007) as they each vie for a share of the market. New products and services are often launched into the market in an effort to address consumers' ever changing needs and preferences (Goldenberg and Efroni, 2001) and as a means of creating the competitive advantage necessary for long-term success within a competitive environment. However, many products and services that are launched into the market often end in failure (Rogers, 2010). Firms thus have a vested interest in finding launch strategies that lead to the successful diffusion (or uptake) of new product or service offerings (Rogers, 2010).

In a competitive context, churn or the switching behaviour of consumers influences the diffusion and the market share of a new product (Libai et al., 2009a) and thus its success or failure. Churn refers to the situation where an individual discontinues using a particular product or service in favour of a competing one (Libai et al., 2009a). Churn is affected by a complex interaction between factors such as consumer satisfaction (Libai et al., 2009a); the information that consumers have about alternative products in the market (Libai et al., 2009a) that they gather through word-of-mouth (WoM) communication and the switching constraints (Libai et al., 2009a) that consumers may be faced with when switching from one alternative to another.

The effects that churn has on the market penetration of a new product is a topic that has received little attention in innovation diffusion research (Libai et al., 2009a). Innovation diffusion research is primarily concerned with understanding how innovations (which, according to Rogers (2010), can be ideas, practices, products or services that are perceived as being new) are adopted by a society over time (Kiesling et al., 2012). According to

Libai et al., "There is a need for an approach that explicitly incorporates both customer switching and competitive growth" (Libai et al., 2009a). This dissertation is a step towards filling this gap. The purpose of this dissertation is to provide a simulation model that can be used to examine how various factors affect the market penetration of a new product within a market that has several similar products that compete for market share from a common pool of consumers.

Markets often exhibit complex non-linear dynamics, observable at the level of the system as a whole (i.e. at the macro-level), which are the result of the actions of the individual decision-makers that make up the system (i.e. processes at the micro-level). These dynamics are often difficult to anticipate and thus model using traditional analytical tools. Agent-based modelling (ABM) provides a framework that can be used to describe a system at the micro-level and analyse the emergent patterns at the macro-level. It has gained popularity in the simulation of markets as it can be used to develop useful tools that facilitate the understanding of the dynamics within certain markets (Jager, 2007); assist with planning, developing, testing and improving new product launch strategies (Jager, 2007; Kiesling et al., 2012) and enable model-based decision support (Kiesling et al., 2012).

1.1 Aims

The interest in this dissertation is to investigate:

- The effect of consumer satisfaction, WoM and switching constraints on the rate of churn in the market.
- The extent to which the structure of the network affects the propagation of information and thus market dynamics.
- How the market penetration of a new product is affected by its quality and the rate of churn in the market.
- How launching the new product with switching constraints given that there are products that have switching constraints in the market affects its market penetration.

In essence, the aim is to determine how the interaction between product performance, consumer satisfaction, switching constraints, WoM and the network structure affects market dynamics and in turn the market penetration of a new product. An agent-based model is used for this purpose where the agents in the model are consumers.

1.2 Scope and limitations

An experience-goods (Farrell and Klemperer, 2007) market is modelled. In experience-goods markets the quality of a product is only ascertained after use and so consumers prefer to repurchase a brand they have tried and liked rather than try a brand the quality of which they do not know (Farrell and Klemperer, 2007). The model presented in this dissertation is based on the model presented by Durbach and Hofmeyr (2007).

In the model, a new product is introduced into a market that consists of a set of products that have similar attributes that compete for market share from a common pool of consumers. Consumers search for satisfying products using information gathered from personal product trials as well as information gathered from word of mouth (WoM). Consumers belong to a social network and use their contacts to exchange information about their product experiences. A satisficing decision-making strategy is used rather than a utility maximisation decision-making strategy. That is, consumers aspire to attain a level of satisfaction that meets or exceeds a threshold rather than aspiring to maximise it (Candale and Sen, 2005). In each time period consumers choose a product, evaluate its performance and compare this performance evaluation to their satisfaction threshold. Consumers may continue (discontinue) using a product that they find satisfying (dissatisfying). Consumers may disseminate positive WoM about a product they found satisfying and may disseminate negative WoM about a product they found dissatisfying. Once a consumer has used a product, he/she has his/her own knowledge about its performance and thus relies more on their own assessment of the product than on new information obtained about the product (Buttle, 1998; Libai et al., 2009b). As such, consumers only accept information about products they have not used before and ignore information about a product that they are currently using or have used in the past. Because consumers can hold different opinions about the performance of a product, they will not necessarily find the same products satisfying or dissatisfying. Thus, even though consumers may be influenced to use (or avoid using) a product because of WoM that they may have received, they may not necessarily have a satisfying experience (or a dissatisfying experience if they do eventually use the product). Products can have switching constraints which make it difficult for consumers to switch in the event that they find it dissatisfying. That is, consumers get locked-in and are forced to continue using a dissatisfying product. The level of satisfaction that a product provides in each time period is dynamic due to random fluctuations in consumers' product evaluations and consumers becoming habituated (or bored) with a product that they use for several periods and thus discounting its performance. Jager (2007) asserts that a high level of satisfaction with a product results in repeat purchases which become habitual. This habitual decision-making reduces the frequency with which consumers scan the market for alternative products that may result in a higher level of satisfaction. A decrease in the level of satisfaction that they derive from a product ensures that the market is scanned more frequently thus leading to a change in consumption.

While a wide range of simulations can be conducted with this model – some of which could facilitate in answering the research questions – only a limited set was conducted because of time and resource constraints. This model is based on theoretical assumptions about how consumers would behave in a real-world market which would have to be validated empirically. Thus, the results of the simulations are intended to serve as a tool that guides intuition rather than a predictor of what would happen in a real-world setting.

This dissertation is organised as follows: In chapter 2 agent-based modelling is discussed. In Chapter 3 a brief literature review is given. The model which forms the basis of this dissertation is presented in chapter 4. The hypotheses, experimental design and methods of analysis are presented in chapter 5. In chapter 6, the simulation results are analysed. Finally, the dissertation is concluded in chapter 7.

Chapter 2

Agent-Based Modelling

ABM is a new modelling paradigm that has found widespread use in the modelling of complex dynamic systems (Macal and North, 2008) as shown in Table 2.1.

Table 2.1: Applications of agent-based modelling (source: Macal and North, 2008)

Field	Application
Business and organisations	Manufacturing operations, supply chains, consumer markets, insurance industry
Economics	Artificial financial markets, trade networks
Infrastructure	Electric power markets, transportation, hydrogen infrastructure
Crowds	Pedestrian movement, evacuation modelling
Society and culture	Ancient civilizations, civil disobedience, social determinants of terrorism, organizational networks
Military	Command & control, force-on-force
Biology	Population dynamics, ecological networks, animal group behavior, cell behavior and sub-cellular processes

Unlike traditional analytical modelling or other simulation techniques, ABM is a bottom-up, disaggregate, individual-based approach (Kiesling et al., 2012). In ABM, a system is modelled as a collection of autonomous, heterogeneous decision-making entities, often referred to as agents, that interact with each other or with their environment based on a set of behavioural rules (Kiesling et al., 2012).

ABM provides a methodology to model behavioural patterns that are not easy to represent analytically (Garcia, 2005). In an agent-based model, the interactions between agents are specified through a set of behavioural rules and the consequences of these interactions are then observed at the level of the whole system. The interactions between agents may have non-linear effects which can often be too difficult to represent as a mathematical solution (Axelrod, 1997).

ABM allows for the interactions between agents to be modelled at a micro-, meso- and macro-level (Kiesling et al., 2012) as illustrated in figure 2.1.

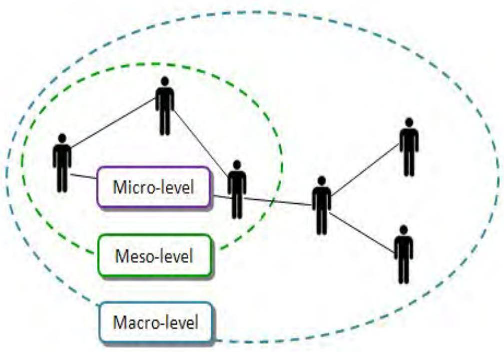


Figure 2.1: Social interactions that can be modelled with ABM (source: Kiesling et al., 2012)

Micro-level interactions pertain to the pairwise interactions that occur between agents at a local level (Kiesling et al., 2012). An example of this would be the word of mouth that consumers exchange about products and services.

Meso-level interactions pertain to the interactions that occur between agents at a group level (Kiesling et al., 2012). Examples of these sorts of interactions include concepts such as group conformism, herd behaviour and social comparison which posit that the social value of a product is more important than its intrinsic value (Kiesling et al., 2012).

Macro-level interactions pertain to interactions that occur at a global level (Kiesling et al., 2012). Examples of these sorts of interactions include technological, economic, demographic, institutional and cultural developments (Janssen and Jager, 2001) which determine the norms or the collective behaviour of agents and thus describe the society in which agents reside (Janssen and Jager, 2001).

Emergence and co-evolution are of particular interest in ABM. System dynamics stemming from the dynamic behaviour of agents can result in emergent phenomena or co-evolving systems (Garcia, 2005). Emergence can be defined as macro-level patterns that are not explicitly modelled but which result from the repetitive interactions of agents at the micro-level (Garcia, 2005). Co-evolving systems result from agents directly influencing each other's behaviour.

Agent-based models provide insight into and facilitate the understanding of fundamental processes that give rise to complex social systems. The focus of the ABM approach is on how processes evolve over time (Garcia, 2005). The objective is to build theory and aid intuition rather than to construct a descriptively accurate or predictive model (Garcia, 2005). While ABM adds an element of reality to a model, its role is not to create an exact facsimile of a particular system or environment but rather to assist in the exploration and the understanding of the consequences of various scenarios that emulate real-world systems (Garcia, 2005).

In ABM there is a trade-off between realism and complexity. Realistic and accurate representation of many details of a particular setting is not as important as keeping the assumptions underlying the fundamental processes of a model simple (Axelrod, 1997). "The complexity of agent-based modelling should be in the simulated results, not in the assumptions of the model" (Axelrod, 1997).

2.1 Developing an agent based model

According to Rand and Rust (2011), developing an agent-based model involves the following steps: (1) deciding if ABM is an appropriate approach for the question at hand; (2) designing the model which involves conceptualising and structuring the model; (3) constructing the model and (4) implementing and analysing the model.

1. Deciding if ABM is appropriate

ABM is appropriate for investigating situations in which there are groups of autonomous, heterogeneous decision-making entities operating in a dynamic environment and where the interactions of these entities results in an emergent phenomenon (Rand and Rust, 2011). While there are no set rules for when ABM is applicable, there is general consensus on the contexts for which ABM is useful. These include:

- When the unit of analysis is the individual and representing the system from the perspective of the individual is more natural (Bonabeau, 2002; Garcia, 2005) and this population of agents can be affected by a few important individual interactions (Rand and Rust, 2011).
- When both micro- and macro-level analyses are of interest and emergent phenomena may be observed(Garcia, 2005): For instance, the adoption of a new product which occurs at the micro-level and the diffusion of that product through the population which occurs at the macro-level. The diffusion may be viewed as an emergent phenomenon since it often occurs as a result of the interactions of the agents.
- When individual behaviour is local, potentially complex (Rand and Rust, 2011) or non-linear and heterogeneous (Garcia, 2005): Because the focus of ABM is on the individual, each agent can have unique characteristics, decision-making rules as well

as learning and adaptation behaviour (Garcia, 2005). For example, agents can have different adoption thresholds, can try different strategies based on their experience with a particular product, can make purchase decisions based on recommendations from their friends in their social network or they can adjust their confidence in their friends' opinions (Rand and Rust, 2011).

- When physical or dynamic environments are of interest (Garcia, 2005): Physical or dynamic environments can range from abstract two-dimensional spaces such as a network-based system to a realistic geographic location (Rand and Rust, 2011).
- When temporal aspects are of interest (Rand and Rust, 2011) - Often the temporal nature of a process is central to the research question at hand and ABM lends itself well to examining how complex systems evolve over time (Rand and Rust, 2011).

2. Designing the model

There are several factors to consider when designing an agent-based model. These factors, shown in Table 2.2 (Rand and Rust, 2011), include scoping the model; identifying the agents in the model; specifying the properties and behaviours or the interactions of the agents; defining the environment in which the agents exist; determining the inputs and outputs of the model and determining the order of events in the model.

Table 2.2: Design choices for agent based modelling (source: Rand and Rust, 2011)

Aspect of design	Description
1. Scope of the model:	Description of the aspects of the complex system under consideration.
2. Agents:	Identifying the types of agents in the model.
3. Properties:	Attributes of each agent.
4. Behaviours:	Behaviour or actions each agent possesses.
5. Environment:	External forces that act on each agent.
6. Input and output:	Inputs required for the model and outputs collected from the model.
7. Time step:	Order of events in the model.

As with any other modelling technique, the scope of the model must be decided. This involves identifying the purpose of the model, the questions that the model is intended to answer and which aspects of the complex system under consideration to model and which aspects to ignore.

An agent-based model can have several diverse classes of agents in the same model. The general classes of agents as well as the quantity of each type of agent has to be identified. Although there is no universal definition of what an agent is, it is widely accepted that agents are heterogeneous, autonomous and dynamic entities with their own attributes and behavioural rules (Bonabeau, 2002; Garcia, 2005; Macal and North, 2010; Rand and

Rust, 2011). Macal and North (2010) suggest that an agent can be considered as:

- Being identifiable, discrete and self-contained with a set of characteristics and rules governing its behaviour and decision-making processes. In other words, it should be easy to identify what is or is not part of an agent and what is a shared characteristic.
- Being situated in an environment along with other agents which it interacts with. Agents are assigned behavioural rules which govern the manner in which they interact with other agents or their environment.
- Being goal-directed thus allowing the agent to compare the outcome of its behaviour to its goals.
- Being self-directed, autonomous and functioning independently of other agents within its environment.
- Being flexible or having the ability to learn and adapt its behaviour based on its experiences.

Each agent is given a set of attributes as well as a set of behavioural rules which govern how they behave in their environment and how they interact with other agents. Behavioural rules can be simple or highly sophisticated.

ABM is rooted in modelling social and organisational behaviour (Macal and North, 2008). This means that the interactions between agents as well as the structure governing the nature of these interactions need to be defined. The environment defines the interaction topology of the agents. This environment can be a physical environment such as a geographic location; a social environment such as a network of friends or a conceptual environment such as a product space.

In designing an agent based model, it is also necessary to define which inputs feed into the model and which outputs the model will generate.

Agent based models generally have two phases: an initialisation phase and an iteration phase. The initialisation step involves creating the agents and the environment in which the agents reside. In each iteration step, agents execute their respective set of behavioural rules. The appropriate properties are then updated. This process is repeated until some condition that terminates the model is reached.

3. Constructing the model

Model construction involves creating a version of the conceptual model that can be executed computationally (Rand and Rust, 2011). While the model can be constructed in programs such as Excel, C, Java or Python, there are several ABM toolkits such as

Repast, Swarm, Netlogo and Mason that can also be used .

4. Implementation and analysis

Model implementation involves conducting a series of experiments by running the model over a range of input combinations to determine how changes in the system affect the outputs. Due to the stochastic nature of ABM, a model has to be run several times with the same inputs so that an event can be observed enough times to make statistical inferences about the relationship between the inputs and the outputs. ABM toolkits usually have a facility that can be used to systematically iterate through the possible combinations of inputs and run the model repeatedly for each treatment.

Once the model has been run, the results can then be analysed using statistical tests or regression analysis of input and output variables.

2.2 Model verification and validation

As with all models, an agent-based model needs to be verified and validated. Although it is not possible to completely verify or validate any model, verification and validation ensure that the model is rigorous (Rand and Rust, 2011). Verification which is carried out during the model design and construction phases determines the extent to which the implemented model corresponds to the conceptual model and validation which is carried out during the analysis phase determines the extent to which the implemented model corresponds to the real-world.

Model verification involves: (Rand and Rust, 2011)

- Documenting the conceptual and implemented models at a level of detail that facilitates a comparison of the implemented model against the conceptual models.
- Testing that the code does what it is intended to do. This can be done by
  - Testing each section of code.
  - Describing what the code is supposed to do to other researchers.
  - Running the code step by step and ensuring that each step generates the correct results.
- Testing certain cases and scenarios to ensure that the model functions as expected. This entails
  - Testing extreme values of the inputs to ensure that the model behaves as expected.

  - Testing a subset of input values to ensure that outputs do not exceed the range of possible outputs.
  - Testing specific inputs for which the output is known.
  - Determining whether changing certain inputs affects output as expected.

Model validation entails ensuring that: (Rand and Rust, 2011)

- The mechanisms and properties of the model such as the characteristics and behaviour of agents correspond to the real-world.
- The aggregate patterns of the model correspond to patterns observed in the real-world. Describing the relationship between the model and the real-world is usually sufficient to show that the model has been verified at face value.
- The input data for the model is as accurate as possible and corresponds to the real-world. This can be done by calibrating the inputs of the model to actual data from the real-world whenever possible and by also conducting a sensitivity analysis to determine the sensitivity of the model to different sets of inputs.
- The output of the implemented model is in line with what is observed in the real-world. If the model is an exploratory model then it can be validated against a stylised fact derived from the knowledge of field experts. If the model is a predictive model then the model should be validated against real-world data. This involves showing that a relevant real-world data set is a possible outcome of the model.
- The model produces similar results to a previous model that has already been validated even if the previous model uses another methodology. This validation step is optional although it can be conducted to increase the validity of the model.

2.3 Limitations of ABM

As with any other modelling technique, ABM has limitations. Building a model at the right level of description with the right amount of detail may not always be easy (Bonabeau, 2002). Because of the flexibility of agent-based models, the temptation is always to make a model as realistic as possible which has the drawback of making a model complicated and difficult to interpret. The model should not have too much detail as to render it too complicated and it should not have too little detail as to render it too simplistic. There should be a balance between accuracy and complexity.

Soft factors such as the irrational behaviour, subjective choices or psychology of human agents are often difficult to quantify, calibrate and sometimes justify (Bonabeau, 2002) which can complicate the development of a model and the interpretation of its outcomes. The varying degrees of accuracy and completeness in model inputs results in output that can range from purely qualitative results that provide useful insight to quantitative results that can be used for decision-making and implementation (Bonabeau, 2002). Thus agent-based models are not always useful as predictive tools.

Agent-based models can be conceptualised in a myriad ways since there are relatively few general principles that can be applied to the construction of models (Rand and Rust, 2011). They have been criticised for having so many parameters that they can fit any data (Rand and Rust, 2011). Also, the impact of many of these parameters may not be fully understood (Rand and Rust, 2011). Agent-based models are sensitive to initial conditions and small variations in interaction rules (Fung and Vemuri, 2003) which can lead to surprising outcomes that have been criticised for not corresponding to the real-world (Epstein, 2006). It is thus important for a model to be based on appropriate and valid assumptions and inputs (Rand and Rust, 2011). A sensitivity analysis can be conducted to determine the sensitivity of the model to changes in a particular set of inputs (Rand and Rust, 2011). By systematically changing certain inputs while holding others constant, it is possible to see how sensitive model results are to different inputs (Rand and Rust, 2011). If the model is very sensitive to changes in a particular input, then it may be necessary to investigate what the causes of the sensitivity are and if it is not very sensitive to changes in a particular input, then the input can be set to a standard value (Rand and Rust, 2011).

Finally, ABM can be extremely computationally intensive and time consuming (Bonabeau, 2002) especially when the system being modelled is rather large and complex.

Despite these limitations, ABM remains a useful tool for exploring complex systems.

Chapter 3

Literature Review

A brief overview of the work that has been done regarding innovation diffusion for a monopolistic context and for a competitive context is presented in this chapter. Work done regarding consumer satisfaction; switching constraints; word-of-mouth (WoM) and network structure as it pertains to the diffusion of innovations within a competitive market is also examined.

3.1 Innovation diffusion

Innovation diffusion models are used to investigate how innovations are adopted by a society over time. In traditional innovation diffusion models the diffusion of an innovation is modelled from the perspective of the system as a whole. As such, they are commonly referred to as macro-level or aggregate models (Kiesling et al., 2012). These models do not "explicitly consider consumers' heterogeneity and the complex dynamics of the social processes that shape the diffusion" of an innovation (Kiesling et al., 2012).

Most aggregate models are a variant of the Bass (1969) diffusion model which is a predictive model based on a differential equation formulation that seeks to forecast the total number of adopters of a new product in each time period (Rogers, 2010). In these models, the diffusion of an innovation is conceptualised as a contagious process driven by information stemming from external sources – external to the social system – such as advertising or mass media as well as information stemming from internal sources such as WoM exchanged by consumers.

Aggregate models "provide a parsimonious and analytically tractable" (Kiesling et al., 2012) means of modelling market dynamics. However, they have limitations. Firstly, aggregate models assume that all consumers are homogeneous (Delre et al., 2007b; Kiesling et al., 2012) in terms of their susceptibility to social influence, their personal preferences and in turn their propensity to adopt an innovation which is not necessarily the case in reality. Secondly, aggregate models imply a fully-connected social network (Kiesling et al., 2012) in which each consumer is connected to every other consumer in the population and can thus potentially be influenced by and influence all others (Kiesling et al., 2012). Real-world social networks are, however, not fully connected (Newman, 2003b). Individuals in a social network are not connected to all or even the majority of the population (Newman, 2003b; Bohlmann et al., 2010) and thus only communicate with and can therefore only influence or be influenced by a small fraction of the population (Bohlmann et al., 2010). Thirdly, they do not truly reflect the mechanisms that drive the diffusion process (Kiesling et al., 2012) since they do not specify how consumers communicate and influence each other and how consumers' decision-making changes over time (Delre et al., 2007b). Because of the shortcomings of aggregate models, innovation diffusion modelling has moved towards an agent-based modelling (ABM) approach.

ABM provides a methodology for investigating how processes at the micro-level influence outcomes at the macro-level. It has the potential of capturing complex non-linear dynamics that influence the diffusion of an innovation. Because ABM allows for the explicit modelling of consumers' decision-making processes, the influence that they may exert on each other and the structure of their social environment, it is able to overcome the shortcomings of aggregate innovation diffusion models and has gained popularity in innovation diffusion modelling in recent years.

Innovation diffusion models can generally be grouped into three broad classes: contagion models (commonly found in the marketing literature), social influence models (commonly found in the sociology literature) and social learning models (commonly found in the economics literature) (Young, 2009). In these models, consumers get their cue to adopt from the adoption of an innovation by others. The premise of these models is that people do not live in isolation but in communities in which they may influence each other's actions and behaviour.

Contagion models posit that people adopt an innovation as soon as they come into contact with at least one other individual who has adopted it (e.g. Delre et al., 2007b). An example of this would be a fashion that spreads within a social system because people imitate those who have already adopted it (Young, 2009). These models are rooted in epidemiology. The innovation spreads through the population much like a contagious epidemic since consumers need only come into contact with one other individual who has adopted the innovation in order for them to adopt it. Contagion models are commonly used in aggregate diffusion models such as the Bass model.

Models based on social influence as a driver of the diffusion process focus on the influence that those that have adopted exert on those that have not adopted the innovation. These models are rooted in concepts such as herd behaviour, group conformism and social comparison. For example, some people may need to see only a few others using a certain brand whereas others may wait until the use of the brand is widespread (Young, 2009; Janssen and Jager, 2003). The innovation spreads through the population as a result of social pressure or people wanting to conform. "Adoption depends on the popularity of the innovation" (Young, 2009). These models are commonly referred to as threshold models since agents are each assigned a threshold which determines whether or not they will adopt the innovation.

In threshold models individuals adopt an innovation once a certain proportion of other people in the population have adopted it. The threshold is defined as the number of other individuals that have already adopted the innovation that are required for an individual to adopt it. It can be thought of as the degree to which individuals are susceptible to social influence (Young, 2009). The threshold is usually varied across the population and can either be deterministic (e.g. Alkemade and Castaldi, 2005) or probabilistic (e.g. Bohlmann et al., 2010; Goldenberg et al., 2010).

The premise of social learning models is that people adopt an innovation when the value or benefit of them adopting it increases as more individuals adopt the innovation. "Adoption depends on how good or desirable the innovation has proven to be" (Young, 2009). In these models, the innovation spreads because of what is referred to as network effects or network externalities. Network externalities can be direct as is the case if the value of adopting the product is directly affected by the number of other users of the same product (e.g. cellphones, email, social media applications) or indirect as is the case if the value of adopting it increases with the number of users of another, complimentary product (e.g. DVD titles for DVD players, compatible software for a particular operating system).

In social influence models individuals with low thresholds adopt the innovation earlier since only a few individuals are required for the threshold to be exceeded whereas individuals with high thresholds adopt after a large proportion of the population has adopted it. In social learning models, consumers see more benefit in adopting the innovation when there are a large number of consumers that have already adopted it. Thus the innovation diffuses more extensively when a higher number of individuals adopt it in the early stages. Thus, in these models, because consumers get their cue to adopt an innovation from the number of other consumers that have already adopted it, a critical mass of adopters is required for the innovation to diffuse extensively otherwise it falls into a trap of under-adoption (Delre et al., 2007a; Choi et al., 2010).

The aim in modelling the diffusion of an innovation is to determine the speed and the extent (or pattern) of the adoption of an innovation. This is measured with an adoption curve which shows the cumulative number of adopters over time. Diffusion patterns are mainly influenced by the model describing how and when consumers adopt an innovation. Thus adoption curves can take on several different shapes. Using a mean-field approach (which assumes an infinitely large population which interacts randomly), Young (2009) showed that processes driven by:

- Inertia decelerate from start to finish and thus exhibit strictly concave adoption curves;
- Contagion initially accelerate and then decelerate as they approach saturation and thus exhibit sigmoid adoption curves;
- Social influence may decelerate or accelerate. In the case where they accelerate, they accelerate at super-exponential rates;
- Social learning begin slowly and may even initially decelerate resulting in what is referred to as a saddle effect in the early stages of the adoption curve. If the processes eventually accelerate then they do so at super-exponential rates.

Many of the diffusion processes in the literature exhibit S-shaped diffusion curves when plotted on a cumulative basis as illustrated in figure 3.1. This is consistent with the fact that the diffusion of a new product generally follows a gradual pattern which results in a bell-shaped curve when plotted as a function of time. In the early stage a few consumers adopt the innovation (innovators and early adopters), then consumers in contact with them adopt and consumers in contact with those consumers adopt and the process continues until eventually the more conservative consumers (laggards) adopt it (Alkemade and Castaldi, 2005).

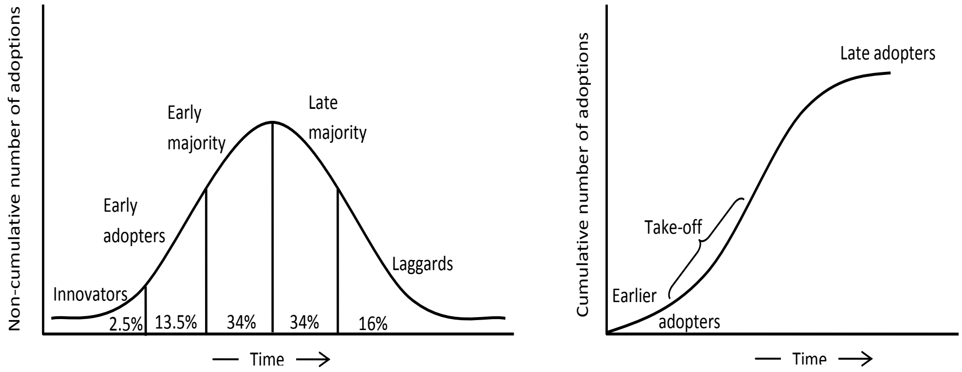


Figure 3.1: The diffusion process (source: Rogers, 2010)

3.2 Competition and diffusion

The studies presented in the innovation diffusion literature (Table 3.1) have largely focused on the first-time purchase of a single product (Peres et al., 2010) while studies that model competitive markets (Table 3.2) tend not to consider the diffusion of a new product or service within those markets. In other words, the competition that a new product may face in the marketplace is rarely considered in simulation models.

Janssen and Jager (2001) present an agent-based model that allows for new products to be introduced into a competitive market. However, their main concern is not the actual diffusion of the new products but whether or not products remain in the market. Products remain in the market if their market share stays at or exceeds a certain level. They find that only a few products remain in the market when consumers imitate each other or repeat their previous product choice because this limits the number of products that consumers consider when making their choices and that a high number of products remain in the market when consumers socially compare or deliberate because they frequently change their product choices and thus consider more products when deciding which products to use making it easier to introduce a new product.

A key characteristic of competitive markets is that consumers switch between products (churn) in search of products that will meet or exceed their expectations. Churn can have important implications for the market penetration of a new product or service (Libai et al., 2009a) in the sense that it influences the number of adopters of a product as well as how much the product is used over time (Rogers, 2010) which, in turn, influences the profitability of a firm. However, as Libai et al. (2009a) point out, "customer attrition has not been formally integrated into models of the diffusion of innovation."

Libai et al. (2009a) present an innovation diffusion model that extends the Bass diffusion model by incorporating customer attrition. They define attrition as any case of a customer who terminates a relationship with a service provider either by leaving the service category (disadoption) or by defecting to a competitor (churn). Focusing on services that entail regular repurchases, they show that neglecting customer attrition at both the category and brand level can have important implications for the market growth and long-term profits of new services. They show that ignoring customer attrition at the category level (category disadoption) can bias the estimation of the parameters of the diffusion curve. They also show that neglecting attrition at the brand level (customers switching to competitors and category disadoption) leads to the underestimation of a firm's customer equity (the revenue a firm derives from its long-term relationships with its customers). This bias and underestimation affects the decisions a firm makes regarding investments pertaining to customer acquisition and retention. It also affects the firm's perceptions of the effect of factors such as consumer satisfaction or attrition on its long-term profitability all of which influence the marketing strategy that a firm implements when introducing a new service into the market.

As the complexity of competition and the costs associated with it increase, firms are increasingly forced to focus attention on effective customer acquisition and retention strategies (Jones et al., 2000; Peres et al., 2010). A firm's ability to acquire and retain customers depends on how well its product offerings can satisfy consumers' needs and preferences (Jager, 2007) and thus prevent them from switching to a competitor. In other words, a firm's ability to satisfy consumers' needs and preferences influences the rate of churn in the market. The rate of churn in the market is influenced by several factors including consumer satisfaction; the switching constraints that consumers may face switching between products and WoM communication, the propagation of which is influenced by the structure of consumers' social networks.

Table 3.1: Agent-based models of monopolistic markets

Reference	Decision rules	Interaction topologies	Findings
Alkemade and Castaldi (2005)	Adopt if the fraction of neighbours that have adopted exceeds exposure-threshold and stop using the product if the fraction of neighbours that have adopted exceeds over-exposure-threshold.	k-regular; random; small-world	Consumers with the same exposure threshold: cascades occur more easily in less regular networks when the advertising strategy is random and occur more often in regular networks when the advertising strategy is directed. Consumers with different exposure thresholds: the diffusion starts off faster and the occurrence of a cascade is quicker in a small-world network. When the firm uses a directed advertising strategy that takes into account the topology of consumers' social networks and consumers' characteristics then it is able to reach more consumers than when it uses a random advertising strategy.
Bohlmann et al. (2010)	Adopt with a certain probability if the fraction of neighbours that have adopted exceeds a given threshold	Random; cellular automata; small-world; scale-free	The diffusion of an innovation is affected by different factors such as the position of early adopters in the network and the adoption thresholds of consumers. The network structure plays an important role in the diffusion process and its pattern.
Choi et al. (2010)	Adopt if the benefits of adopting exceed a reservation utility (which can be regarded as a threshold)	Small-world	A new product is less likely to fall into a trap of under-adoption in cliquish networks than in random networks i.e. in small-world networks. While random links make it more difficult for the diffusion to build up momentum in the early stages, once a critical mass is reached, the diffusion is more rapid in networks with a higher number of random links. The diffusion is slower in highly cliquish (i.e. regular) networks.
Deffuant et al. (2005)	Adopt based on interest and information states	Small-world	Extreme opinions can lead to a significant diffusion of innovations which initially had a low social opinion. High levels of uncertainty may generate a lot of interest but lead to poor diffusion. A low social opinion prevents good diffusion of information which can block the diffusion of innovations.
Delre et al. (2007a)	Adopt if at least one neighbour has already adopted	Small-world	Targeting small cohesive groups of consumers in distant areas of the network is the optimal strategy for launching a new product. The timing of promotional activities is important for the takeoff of the diffusion and for a high market penetration to be reached.

Continued on next page

Table 3.1 – *Continued from previous page*

Reference	Decision rules	Interaction topologies	Findings
Delre et al. (2007b)	Adopt if at least one neighbour has already adopted	Small-world	When consumers are socially susceptible, the speed of the diffusion depends on how clustered groups are. Innovations diffuse faster in clustered networks than in random networks. Large personal networks slow down the diffusion. Consumer heterogeneity speeds up the diffusion.
Delre et al. (2010)	Adopt if the utility derived from the product exceeds a minimum utility requirement	Regular lattice; scale-free with cut-off parameter; undirected/directed and unweighted/weighted	Diffusion is less likely to happen in markets without network hubs (consumers with a large number of connections). The innovation penetrates the market more when the weights for neighbors with more relationships are higher. The direction of the relationships among consumers does not have a substantial effect on the final market penetration of the innovation.
Goldenberg et al. (2007)	Adoption based on probabilities of being influenced by advertising, positive word-of-mouth or negative word-of-mouth	Dynamic small-world	An increase in the number of dissatisfied customers increases the harm caused by negative word-of-mouth. Advertising increases the number of disappointed customers even though it increases the number of adopters. Because weak ties connect otherwise distant parts of the network, they have a stronger effect on the destructive power of negative word-of-mouth than strong ties.
Goldenberg et al. (2010)	Adopt if receive product related communication and if overall level of adoption exceeds personal threshold level	Cellular automata	Network externalities cause a loss of over half of the discounted profits of the growth process which implies that network externalities induce a chilling effect on new product growth and on profit. Network externalities have a stronger effect on profitability early in the product life cycle than they do in later periods.
Kuandykov and Sokolov (2010)	Adopt with a certain probability if a certain fraction of neighbours that have adopted is reached	Random with clusters; scale-free	For random networks, splitting the population into different clusters accelerates the diffusion of the innovation. The innovation takes longer to diffuse in scale-free networks than in random networks. The diffusion is faster when initial adopters are hubs than when they are ordinary vertices.

Table 3.2: Agent-based models of competitive markets

Reference	Decision rules	Interaction topologies	Findings
Janssen and Jager (2001)	Use a product depending on the level of a need satisfaction (individual and social) and degree of uncertainty. Engage in different cognitive processes when deciding on which product to use.	Small-world	Market dynamics are influenced by the cognitive processes that consumers use when making decisions. It is easier to introduce a new product into a market in which consumers engage in social comparison than into a market in which consumers imitate each other or repeat purchases.
Janssen and Jager (2003)	Use a product depending on the level of a need satisfaction (individual and social) and degree of uncertainty. Engage in different cognitive processes when deciding on which product to use.	Small-world; scale-free	Psychological needs, decision-making processes and network size and shape have important implications for how the market organises itself. A scale-free network yields a market dominated by fewer products than a small-world network with a limited number of random links.
Lee et al. (2006)	Use a product depending on the fraction of neighbours that have adopted; adopt based on the availability of complements	Small-world	Clustered network prevents a lead product from driving out rival products whereas a network with a sufficiently large number of shortcuts results in a lead technology cornering the market.
Durbach and Hofmeyr (2007)	Use a product depending on whether it exceeds a consumer's satisfaction threshold on all attributes	Small-world with preferential attachment	The system converges to a stable state the quickest when the network is random and quicker when the network is a small-world network in which consumers have a few connections than when consumers have a lot of connections. The degree distribution of the network influential on system dynamics than the manner in which consumers are connected. Switching constraints result in increases in negative word-of-mouth which can reduce the market share of leading products when consumers have a high number of connections.
Sengupta and Greetham (2010)	Use a particular product if enough neighbours are using it	Random; small-world; scale-free	Networked (especially scale-free network) markets have a higher likelihood of being polarised in favour of one brand than non-networked markets in which brands co-exist and share the market equally.
Pegoretti et al. (2012)	Adopt a product (innovations) by maximising surplus which is a function of the price charged for an innovation, the willingness to pay for any innovation and the fraction of neighbours that have adopted the product	Small-world	Single innovation: under perfect information random network leads to a cascade and under imperfect information the small-world network leads to a cascade. Competitive market: a weak cliquishness increases the chances of falling into a trap of under adoption. The probability of under adoption is lower when there is imperfect information.

3.2.1 Consumer satisfaction

Consumer satisfaction (utility) is defined as an overall performance evaluation based on all previous experiences with a product or service (Jones et al., 2000). The utility derived from products is generally assumed to be comprised of both individual as well as social preferences for products. Individual preferences are a consumer's preference for product attributes such as price, quality, technical performance and reliability (Jager, 2007). Individual utility depends on how well these attributes meet consumers needs and expectations. Delre et al. (2010) note that the critical mass required for an innovation to be adopted is reached more easily when the innovation is of a higher quality compared to when it is of a lower quality. Although the attributes of a product can have important implications for whether it is adopted or not and whether consumers find the product satisfying or not, simulation models do not usually explicitly include product attributes. Social preferences determine a consumer's susceptibility to his or her acquaintance's behaviour. Social utility depends on the number of other individuals in one's social environment that use the same product (Jager, 2007). A low social preference implies an individualistic consumer whose personal need is more important than his or her social need and as such, is influenced less by how many other individuals are using a particular product. A high social preference implies a socially susceptible consumer whose social need is more important than their personal need and as such, is influenced to use a product because of the pressures to conform. A product is adopted if the utility it provides exceeds a consumer's minimum utility requirement.

The adoption of a product is viewed as a process driven by social interactions such as mimicry and word-of-mouth. As such, simulation models tend to emphasise the social utility rather than the individual utility that products provide. In other words, the social utility of a product tends to outweigh the individual utility it offers.

Consumers may use different strategies when deciding which product to use. Janssen and Jager (2001, 2003) present an approach that takes consumers' different cognitive processes into account. When consumers are satisfied and certain, they use the same product that they used previously (repeat); when they are satisfied and uncertain, they use the same product as their neighbours (imitate); when they are dissatisfied and certain, they evaluate the expected need satisfaction of a product and use the product that is expected to satisfy them the most (deliberate) and when they are dissatisfied and uncertain, they evaluate the products that are consumed the most in their social network and use the product that has the highest market share (compare). They find that it is easier to introduce a new product into a market in which consumers engage in social comparison than into a market in which consumers imitate each other or repeat their purchases.

Consumer satisfaction is considered to be an important component of any retention strategy that a firm implements (Burnham et al., 2003; Balabanis et al., 2006; Zhang et al., 2012). Bolton (1998) suggests that when the performance of a product or service meets or exceeds a consumer's expectations, his/her preference for the product increases implying that consumers will continue using a product that they are satisfied with. Dissatisfied consumers may respond to their dissatisfaction with a product by complaining, by disseminating negative word-of-mouth (NWoM) or by switching (Goldenberg et al., 2007) if there are acceptable alternative products in the market and they perceive a substantial benefit to switching (Jones et al., 2000). Thus, firms strive to maintain high consumer satisfaction levels .

3.2.2 Switching constraints

While satisfaction is largely recognised as an important determinant of switching behaviour, it does not account for all of the variation in consumers intentions to continue using a product (Burnham et al., 2003). Switching constraints have also been identified as an important antecedent for switching behaviour and are often punted as being important for retention strategies that firms implement because they have the effect of preventing consumers from switching which gives firms the opportunity to affect price and supply and thus realise more profits. Switching constraints can be defined as any factor that increases the difficultly or cost for consumers to switch from one product or service provider to another (Jones et al., 2000; Burnham et al., 2003). Switching constraints may come about as a consequence of the heterogeneity in product and market characteristics (Burnham et al., 2003) or they may be imposed by firms (Durbach and Hofmeyr, 2007) by means of contracts or benefit schemes that encourage repeat purchases.

Switching constraints are generally considered to be multidimensional and have been conceptualised and measured in various ways (as shown in Table 3.3) that encompass both economic (or financial) and relational (or psychological) facets. For instance, Burnham et al. (2003) develop a switching cost typology that distinguishes between three types of switching constraints, namely procedural, financial and relational switching constraints. Procedural switching costs include uncertainty about the outcome of switching; the time and effort associated with searching for a new product or service; the time and effort required for learning how to use an alternative product or service; the time and effort required to setup an alternative product or to establish a relationship with a new service provider. Financial switching costs include losing the benefits associated with continuing to use a particular product or remaining loyal to a particular service provider and the monetary loss made due to an additional financial outlay that may need to be made when switching products or service providers. Relational switching costs include the loss of relationships made with service staff or loss of brand identification.

Little effort has been dedicated to the development of simulation models that investigate the effects that switching constraints have on market dynamics or the market penetration of a new product or service, especially from an ABM perspective. Empirical studies, which are generally conducted through surveys of service industries, focus on measuring switching constraints and determining how the dimensions of switching constraints affect customer retention and interact with factors such as satisfaction (e.g. Jones et al., 2000; Ranaweera and Prabhu, 2003; Patterson and Smith, 2003; Burnham et al., 2003; Balabanis et al., 2006; Woisetschläger et al., 2011), trust (Ranaweera and Prabhu, 2003), habits (Woisetschläger et al., 2011), and social ties (Woisetschläger et al., 2011). Switching constraints are generally found to be a stronger deterrent to switching than satisfaction especially when those switching constraints are high.

Consumers usually become aware of or become affected by switching constraints when they have a reason to consider switching (Burnham et al., 2003) which often happens as a consequence of satisfaction falling below a certain level (Jones et al., 2000). When switching costs are high and/or the attractiveness of alternatives low, consumers are forced to continue using a product that they are dissatisfied with and may see themselves as "hostages" in a less than ideal situation (Sharma and Patterson, 2000). Consumers may respond to being locked-in by switching as soon as the opportunity arises (Sharma and Patterson, 2000) and/or disseminating NWoM (Jones et al., 2007). Durbach and Hofmeyr (2007) find that NWoM increases as a result of switching constraints and this has the effect of reducing market share of leading brands because it prevents consumers that would have otherwise tried a product and found it satisfying from using the product. Conversely, when switching costs are low, the customer's option to stay or leave is based on the level of satisfaction, which would reflect a relatively strong psychological affinity to a product (Woisetschläger et al., 2011).

Klemperer (1995) argues that entry into a market where consumers have switching constraints may be difficult when the rate of churn in that market is low and may be easier when the rate of churn is high. High switching constraints have the effect of lowering the rate of churn in the market by locking consumers in for extended periods which, in turn, can make it difficult for a new product to obtain sufficient market share. Switching constraints can thus have important implications for the market penetration of a new product since they influence the rate at which consumers switch between products thus affecting the available pool of potential consumers which, in turn, can lead to a lower market share.

Table 3.3: Examples of different types of switching constraints and their effects

Reference	Switching constraints dimensions	Findings
Balabanis et al. (2006)	Time, effort and money associated with the switching process	At low levels of satisfaction, satisfaction has more of an impact on loyalty than switching barriers whereas at high and moderate levels of satisfaction switching barriers have more of an impact on loyalty intention. Loyalty decreases as satisfaction increases.
Burnham et al. (2003)	Procedural switching costs: economic risk, evaluation, learning and setup costs Financial switching costs: benefits loss, financial loss costs Relational switching costs: personal relationship loss, brand relationship loss costs	Satisfaction drives consumer intentions to stay with a service provider. However, switching costs have an even stronger effect on customer retention. All three switching cost types drive consumers' intentions to stay with their current service provider. Procedural and relational switching costs have the biggest impact when consumers consider switching while financial switching costs have the weakest impact.
Fullerton (2005)	Affective commitment (when customers stay with a service provider because they like their service provider, regardless of the type of the service that is being consumed) Continuance commitment (when customers stay with a service provider because they feel that ending the relationship involves an economic or social sacrifice or because they have no choice but to maintain the current relationship)	Affective commitment is negatively related to switching intentions and positively related to advocacy intentions. Continuance commitment has a weakly negative effect on switching intentions and may heighten switching intentions. It has a negative effect on advocacy intentions.
Jones et al. (2000)	Interpersonal relationships, perceived switching costs(time, money and effort), and the attractiveness of competing alternatives	Core-service satisfaction has a reduced influence on repurchase intentions when switching barriers are high. Switching barriers have no influence on repurchase intentions when satisfaction is high and have a positive influence on repurchase intentions when satisfaction is low.
Jones et al. (2002)	Pre-switching search and evaluation costs, costs of lost performance, uncertainty costs, post-switching behavioral and cognitive costs, sunk costs, setup costs	The relationship between repurchase intentions and switching costs varies by industry. In the banking industry pre-switching search and evaluation costs, and setup costs are not significantly associated with repurchase intentions while in the hairstylist/barber industry, all switching cost dimensions except for uncertainty costs are significantly associated with repurchase intentions.
Jones et al. (2007)	Affective commitment and calculative (continuance) commitment	Procedural switching costs increase calculative commitment, which, in turn, results in negative emotions and negative word-of-mouth. Social and lost benefits costs have a positive effect on affective commitment which increases positive emotions and repurchase intentions resulting in a lower potential for negative word-of-mouth.

Continued on next page

Table 3.3 – *Continued from previous page*

Reference	Switching constraints dimensions	Findings
Patterson and Smith (2003)	Search costs, loss of social bonds, setup costs, functional risk, attractiveness of alternatives, loss of benefits	For travel, the loss of special treatment benets and need to explain preferences; for medical services the loss of special treatment benets and an interpersonal relationship and for hairdressing the loss of an interpersonal relationship are the major barriers to switching. There are no signicant interaction effects between satisfaction and switching barriers. Switching barriers are a stronger disincentive to switching than satisfaction.
Ranaweera and Prabhu (2003)	Investment of time, money and effort that, in customers perception, make it difficult to switch	In a low customer contact, mass service setting, satisfaction is the strongest driver of customer retention. Trust is a weaker predictor of retention than satisfaction. In the absence of trust, satisfaction has less impact on retention, and thus, may not be adequate to retain customers. The retention rate of customers with low levels of satisfaction is higher when they perceive high levels of switching barriers than when they perceive low levels of switching barriers.
Sharma and Patterson (2000)	Economic costs, psychological barriers	Without experiencing a fair level of satisfaction, clients do not develop commitment. The impact of satisfaction on commitment is weaker under conditions of high switching costs. When many alternatives are available, the impact of satisfaction on commitment is higher than in situations of few or no alternatives.
Whitten and Wakefield (2006)	Uncertainty costs, post-switching costs, setup costs, hiring and retraining costs systems upgrade costs, lost benefits costs, search and evaluation costs, sunk costs	Switching costs are a multi-dimensional construct. As switching costs increase, the risks or costs associated with performance level are most likely to increase. Uncertainty costs are also strongly correlated with lost benefits and post-switching costs.
Woisetschläger et al. (2011)	Economic switching barriers	Satisfaction and economic switching barriers are the strongest drivers of customer loyalty. Social ties and habits are less important as antecedents of customer loyalty. Social ties are the strongest antecedent of word-of-mouth intention, followed by satisfaction, and then economic switching barriers. Economic switching barriers and social ties mediate the impact of habits on loyalty indicating that habits lead to an increase in these two types of switching barriers, which in turn influence loyalty. Economic switching barriers show a negative moderating effect on the link between satisfaction and loyalty intention. Satisfaction is a strong predictor of customer loyalty when economic switching barriers are low, and is less important when customers perceive high levels of such barriers. Social ties have a negative moderating effect on the relationship between satisfaction and loyalty intention. and have a positive moderating effect of the link between satisfaction and word-of-mouth intention.

3.2.3 Word-of-mouth

WoM relates to the information that consumers exchange about their product experiences. It is the informal, interactive, commercially unbiased and ephemeral advice exchanged by consumers (Buttle, 1998; East et al., 2008). It has the effect of shaping consumer "awareness, perceptions, expectations, attitudes" (Buttle, 1998) and their decision-making. Consumers gather opinions from other consumers, assimilate them and in turn pass them along to other consumers in their social circles (Allsop et al., 2007). As such, WoM is recognised as one of the most important and influential factors affecting consumer behaviour and, in turn, the adoption of new or mature products and services (Buttle, 1998; East et al., 2008).

Because simulation models tend to investigate how processes such as social influence and network externalities influence product adoption, the focus of these models is generally on non-verbal communication rather than verbal communication. When communication is non-verbal, the attractiveness of a product depends on the number of others that have adopted it. No other information regarding the product is included. Thus, products are adopted as the result of imitation or mimicry. When communication is verbal, on the other hand, product specific information such as the importance of certain attributes (Jager, 2007) or the risks involved in adopting it (Peres et al., 2010) is communicated. As some authors point out, a consumer's adoption of a product is often influenced more by the opinions and choices of his or her acquaintances than by the number of other people using it (e.g. Janssen and Jager, 2001; Lee et al., 2006).

Potential consumers can be influenced to adopt a particular product because of communication with the users of that product i.e. a within-brand effect or because of communication with users of a competing product or service i.e. a cross-brand effect (Libai et al., 2009b). The extent to which information pertaining to a particular brand affects perceptions of other brands depends on factors such as the similarity between the brands, price, a match of their needs and the nature of decision-making processes (Libai et al., 2009b).

Positive WoM (PWoM) and negative WoM (NWoM) plays an important role in terms of product perceptions since it may influence the attitude that consumers develop towards a particular product (East et al., 2008). WoM can be positive, in favour of a particular product and may thus influence consumers to develop a favourable attitude towards the product or it can be negative, against a particular product and may thus influence consumers to develop an unfavourable attitude towards the product (East et al., 2008). Traditional innovation diffusion models assume that all adopters of an innovation disseminate PWoM (Goldenberg et al., 2007).

PWoM is assumed to be disseminated by satisfied consumers while NWoM is assumed to be disseminated by dissatisfied consumers. The general assumption in the literature is that NWoM has more impact than PWoM on purchasing behaviour (East et al., 2008; Goldenberg et al., 2007). For example, Goldenberg et al. (2007), find that each additional percentage point of dissatisfied consumers increases the harm caused by NWoM by 1.82%. East et al. (2008) argue that PWoM and NWoM are similar behaviours with similar origins and have similar effects on attitudes when brands are familiar. Contrary to the view held in the literature, they find that PWoM is usually more influential on purchasing behaviour than NWoM.

WoM has important implications for the market penetration of a new product. Libai et al. (2009b) present a study that uses a Bass-type model to investigate the effect of within-brand and cross-brand communication on the growth of the market for a new product in a competitive market. They find that within-brand and cross-brand communication influence the market penetration of a new product in several ways. The first entrant has the advantage of being able to acquire more new customers as a result of a larger number of initial customers who become a self-reinforcing competitive advantage for the product because of within-brand effects. In order for the new product to overcome this advantage that the first entrant has, consumers' perceptions of the new product have to be considerably better than those of the first entrant.

3.2.4 Network structure

It has been suggested that consumers' consumption behaviour is, to a large extent, influenced by social processes (Janssen and Jager, 2003; Peres et al., 2010; Kiesling et al., 2012). The social networks that consumers belong to play an important role in their purchase decisions (Allsop et al., 2007). For some products consumers' social networks may comprise only a few contacts while for other products consumers' social networks may comprise a large number of contacts and may even contain a few individuals that have many contacts (hubs) that influence the consumption behaviour of a large proportion of the market (Janssen and Jager, 2003; Allsop et al., 2007).

The structure of the social system becomes of particular interest given that consumers exchange WoM and the view that the main catalyst of the diffusion of an innovation is the propagation of information through a given social system (Bohlmann et al., 2010; Kiesling et al., 2012). Watts and Strogatz (1998) argue that while the local interactions between members of a network have global implications, the relationships between local and global dynamics are governed by the structure of the network. The number of people that an individual communicates with and can thus influence or be influenced by is a function of his/her social network.

Social networks are networks in which the vertices represent people or groups of people and the edges represent the social interactions or relationships between them (Newman, 2003b). These interactions can be friendship, business or professional relationships or communication patterns (Newman, 2003b) to name a few.

Mathematically, a network can be represented as an undirected (directed) graph, $G = (V, E)$, composed of a set of vertices $V = \upsilon_1, \upsilon_2, ..., \upsilon_N$ joined together by a set of edges, $E = e_1, e_2, ..., e_M$ (Boccaletti et al., 2006; Newman, 2003b). By letting an edge between vertices i and j be denoted by (i, j), the complete network can be specified by giving the number of vertices, N and a list of all the edges (Newman, 2010). Two vertices joined together by an edge are said to be adjacent or neighbouring (Boccaletti et al., 2006). Several metrics can be used to describe the structure of social networks such as the degree distribution, average path lengths, clustering and degree-degree correlations (Newman, 2003b). The salient features of real-world social networks are believed to include short average path lengths, broad-scale degree distributions, high levels of clustering, assortativity and community structure (Newman, 2003b; Toivonen et al., 2006; Boccaletti et al., 2006) which are described in Box 1.

Average path length: A path in a network is any sequence of consecutive pairs of vertices which are each connected by an edge (Newman, 2010). The path length is the number of edges between any sequence of consecutive pairs of vertices that are connected by an edge (Newman, 2010). The average path length is the mean distance between two vertices, averaged over all pairs of vertices.

Small-world property Most real-world networks exhibit a property referred to as the small-world effect which means that they have short average path lengths despite the fact that they are often comprised of hundreds of thousand or even millions of vertices (Newman, 2003b; Boccaletti et al., 2006). Mathematically, the small-world effect means that the value of the average geodesic distance between vertex pairs scales logarithmically or slower with network size for fixed mean degree (Newman, 2003b).

Degree distribution: The degree k_i of a vertex i is the number of edges connected to the vertex (Newman, 2003b), i.e. $k_i = \sum_j a_{ij}$. The degree distribution, $P(k)$ is the probability distribution of the degrees of the vertices in the graph. It gives the probability that a vertex in the network, chosen uniformly at random, has degree k (Newman, 2003b). Most real-world networks have been found to have power-law shaped degree distributions, $p(k) \sim Ak^{-\alpha}$ with exponents typically in the range $2 \leq \alpha \leq 3$. These networks are often referred to as scale-free networks because power-law distributions have the same functional form at all scales (Boccaletti et al., 2006). When networks have truncated power-law degree distributions then they are referred to as having broad-scale degree distributions (Amaral et al., 2000).

Clustering: Transitivity refers to the presence of a high number of triangles in a graph (Newman, 2003a). That is, a connection between vertices A and B and a connection between vertices B and C makes it highly likely that there will also be a connection between vertices A and C, forming a triangle ABC. This property is also referred to as clustering.

Clustering can be quantified by first defining the local clustering coefficient of each vertex (Watts and Strogatz, 1998)

$$\begin{aligned} C_i &= \frac{\text{number of triangles connected to vertex } i}{\text{number of triples centred on vertex } i} \\ &= \frac{2e_i}{k_i(k_i-1)} \end{aligned}$$

where $0 \leq C_i \leq 1$, e_i is the number of triangles connected to vertex i and $k_i(k_i-1)/2$ is the maximum possible number of triangles that vertex i can belong to given its degree (Toivonen et al., 2009). The local clustering coefficient measures the extent to which vertices connected to vertex i are connected to each other. Thus, $C_i = 0$ if none of them are connected and $C_i = 1$ if all of them are connected (Toivonen et al., 2009). The clustering coefficient is not defined for vertices with degree $k < 2$. Hence, C_i is set to zero for vertices with degree 0 or 1. The clustering coefficient for the whole network is then obtained by averaging C_i over all vertices (Newman, 2003b)

$$\bar{C} = \frac{1}{N}\sum_i C_i.$$

Assortative mixing by degree (degree-degree correlations): In a network that is assortatively mixed by degree, high-degree vertices tend to be connected to other high-degree vertices and low-degree vertices tend to be connected to other low-degree vertices (Newman, 2010). A network that is disassortatively mixed by degree has high-degree vertices that are connected to low-degree vertices.

The assortativity coefficient which is given by the Pearson correlation coefficient of the degrees at either ends of an edge (Newman, 2002)

$$r = \frac{\frac{1}{M}\sum_i j_i k_i - [\frac{1}{M}\sum_i \frac{1}{2}(j_i + k_i)]^2}{\frac{1}{M}\sum_i \frac{1}{2}(j_i^2 + k_i^2) - [\frac{1}{M}\sum_i \frac{1}{2}(j_i + k_i)]^2}$$

where M is the number of edges in the network and j_i, k_i are the degrees of the vertices at the ends of the ith edge, with $i = 1, ..., M$.

Community structure: Social networks exhibit community structure because of people's tendency to divide themselves into groups. One way of defining the community structure of a social network is as groups of vertices that have a higher number of edges within them and a lower number of edges between the groups (Boccaletti et al., 2006).

Box 1: A short glossary of terms

Several studies in the literature investigate how the network structure influences market dynamics or the diffusion of a new product. There is general consensus that the structure of the social system that characterises the interactions between individuals, whether verbal or non-verbal, does indeed have an effect on the speed and extent of the diffusion of an innovation (Table 3.1) and market dynamics (Table 3.2). Despite the numerous network models that have been developed - some developed to reproduce some of the topological features observed in real-world networks and others developed to capture the dynamics which result in those features - the studies in the literature almost invariably use the small-world (Watts and Strogatz, 1998), and to a lesser extent, the scale-free (Barabási and Albert, 1999; Amaral et al., 2000); random and regular lattice network models.

The diffusion process depends on the behavioural rules used to characterise interactions between consumers as well as the network used as a platform for these interactions. Rogers (2010) points out that "it is rather complicated to untangle the effects of a system's structure on diffusion, independent from the effects of the characteristics of individuals that make up the system". Most of the diffusion models in the literature are based on social utility. According to Jager (2007), the calculation of social utility is very susceptible to the type of network model used to characterise the interactions between consumers. Because social utility depends on the number of other people in a consumer's social circle that are using the product, the role of the network structure becomes more pronounced. For instance, in the small-world model, the diffusion is faster and more extensive as the number of random links in the network increases. The diffusion is facilitated by random links between vertices (Choi et al., 2010) because as the randomness in the arrangement of the edges in the network increases, otherwise distant sections of the network become connected meaning that influence is not localised to an individual's immediate neighbourhood. Scale-free networks, on the other hand, transmit information efficiently (Delre et al., 2010) since they are comprised of hubs (vertices which have high degrees) that can spread and receive information to and from many individuals.

Using small-world networks, Durbach and Hofmeyr (2007) argue that the degree distribution of a network may be more important in influencing system dynamics than the way in which individuals are connected to each other. Two studies in particular confirm this notion. In order to determine the effects of varying personal network size, Delre et al. (2007a) examine the differences in the speed of the diffusion of an innovation when consumers are affected by their immediate neighbours (small personal network) and when they are affected by both their immediate neighbours and by their neighbours' neighbours (large personal network). They find that in regular and small-world networks, the critical mass required for a consumers' threshold to be reached is lower when consumers have a small personal network and thus the diffusion happens quickly whereas when consumers have a large personal network, the critical mass required is higher which results in a slower diffusion. In a random network, on the other hand, a small personal network results in a fast diffusion and a large personal network results in the critical mass being reached much later than in a regular or small-world network because the lack of clustering in the network reduces the effect of social influence thus slowing down the diffusion. Janssen and Jager (2001) also examine the effects of personal network size except that they do this by increasing the number of edges in the network. They find that when there are more edges in the network, fewer products remain in the market. In their study, products need to maintain a certain level of market share to remain in the market. Consumers have access to more information when they have more connections which influences their behaviour and this, in turn, leads to a faster dominance of one or a few products and the remainder of the products being forced out of the market.

The level of clustering in the network has been found to have an effect on the diffusion of an innovation (Kuandykov and Sokolov, 2010). However, it is rarely explicitly investigated in the literature. Peres et al. (2010) point out that clustering may have two types of effects on the diffusion of an innovation: Within a cluster, the speed of the diffusion is expected to increase if the clustering coefficient of the cluster is high. Between clusters, the role of vertices that connect different clusters (weak ties) is expected to become more pronounced when the clustering coefficient of a cluster is high since the only way for information to leave a cluster with a high clustering coefficient is through weak ties. Kuandykov and Sokolov (2010) present a study that examines the diffusion of an innovation in networks composed of different clusters. They find that an innovation spreads faster through a network with several clusters than through a network with a single cluster. Their study shows that when agents have more connections with agents in the same cluster than with agents from other clusters, the diffusion of an innovation is quicker within the cluster. They also show that weak ties play an important role in spreading the innovation to other clusters.

Random, small-world and scale-free network models have found widespread use despite being criticised for their basic nature (Goldenberg et al., 2010) and not capturing all of the salient features of real-world social networks (Toivonen et al., 2006). An important point that Bohlmann et al. (2010) make is that the choice of the network topology used should be made with care. "Without such care, artifactual results from an invalid choice of network topology might result." These network models have become the default mainly because of the fact that there is scant empirical evidence of the exact structures of the social networks of consumers in different markets (Janssen and Jager, 2003; Goldenberg et al., 2010) which is due to the difficulty of simultaneously mapping networks, collecting individual-level data and tracking the diffusion of products (Peres et al., 2010).

3.3 Conclusion

Market dynamics are influenced by the interaction of consumer satisfaction, switching constraints, WoM communication and the network structure. However, these factors rarely appear together in a single simulation model, more especially one that investigates the diffusion of a new product. In their study, Durbach and Hofmeyr (2007) present a model that offers useful insight into how these factors affect product consumption within a competitive market. The model presented in this dissertation extends their study by investigating how these factors affect the market penetration of a new product.

The next chapter discusses the agent-based model presented in this dissertation.

Chapter 4

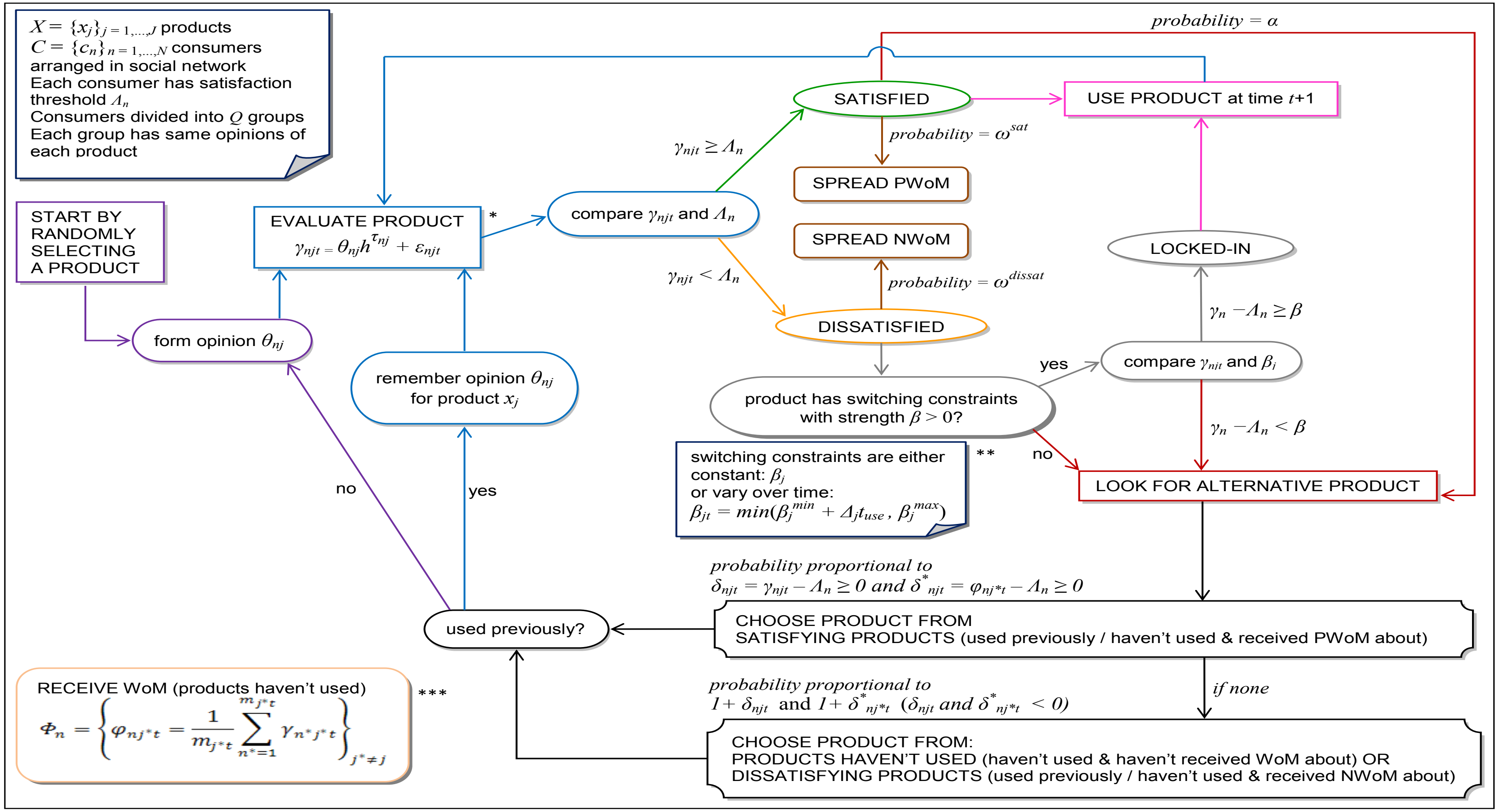
Model Framework

The model that is used to answer the research question of this dissertation is presented in this chapter. It is summarised in a flow diagram in 4.1.

4.1 Product evaluation

The model consists of a set of $C = \{c_n\}_{n=1,...,N}$ consumers that are arranged in a social network. In this context, the social network is a graph with vertices representing consumers in an abstract market and edges representing the friendships or acquaintanceships between consumers. Consumers begin by randomly selecting a product from a set of $X = \{x_j\}_{j=1,...,J}$ products. Since consumers have no information about any of the products, each product has an equal chance of being selected. Consumers then form an opinion, $\theta_{nj}, 0 < \theta_{nj} < 1$, about the product's intrinsic performance (or quality). In other words, consumers evaluate products on a single attribute. The intrinsic performance of each product is unknown to them until such time as they try that particular product. Hence, consumers will only have an opinion of a product that they have tried. Let $\Theta_n = \{\theta_{nj}\}_{j=1,...,J}$ be the set containing consumer c_n's opinion of each product they have used.

Consumers are divided into Q groups. This is akin to market segmentation. Each of the Q groups has the same opinions of each product. The opinions that consumers in each group will have once they have tried a product are stored in a $Q \times J$ matrix $\mathbf{O}$, with elements o_{qj} which represent the opinion that a consumer in group $q, q = 1, ..., Q$ will have of product x_j. Once a consumer tries a product their opinion of that particular product, θ_{nj} is set to o_{qj}. These opinions are used to determine consumers' product experiences.



$$\Phi_n = \left\{ \varphi_{nj^*t} = \frac{1}{m_{j^*t}} \sum_{n^*=1}^{m_{j^*t}} \gamma_{n^*j^*t} \right\}_{j^* \neq j}$$

Figure 4.1: Flow diagram of the model. A new product is launched, at time t_{new}, into a market in which $X = \{x_j\}_{j=1,\dots,J}$ products implicitly compete to gain each other's consumers. The market consists of $C = \{c_n\}_{n=1,\dots,N}$ consumers that are arranged in a social network. Consumers search for satisfying products using information gathered from personal product trials as well as information gathered through word-of-mouth (WoM) communication. Consumers choose a product, evaluate its performance and decide whether to continue or discontinue using it depending on whether they found it satisfying or dissatisfying. Consumers disseminate WoM to their acquaintances about their product experiences and accept WoM from their acquaintances about products they have not used before. Satisfied consumers disseminate positive WoM (PWoM) while dissatisfied consumers disseminate negative WoM (NWoM). Products that have switching constraints make it difficult for consumers to switch in the event that they find them dissatisfying, effectively keeping them locked-in.

---

* γ_{njt} is consumer c_n's evaluation of product x_j at time t; θ_{nj} is the consumer's opinion of product x_j; $0 < h \leq 1$ is an habituation factor; $\tau_{nj} \geq 0$ and $\varepsilon_{njt} \sim N(0, \sigma_\varepsilon^2)$ is a random perturbation.

** β_{jt} is the switching constraint of product x_j at time t; β_j^{min} is the switching constraint that is applicable when the product is used for the first time; Δ_j is the increase in the difficulty of switching the longer the product is used; t_{use} is the number of periods that the product has been used for and β_j^{max} is the maximum possible switching constraint for a product.

*** Φ_n the set containing a consumer's WoM information; φ_{nj^*t} is the WoM information received by consumer c_n about product x_{j^*} at time t; $\gamma_{n^*j^*t}$ is consumer c_{n^*}'s experience of product x_{j^*} at time t and m_{j^*t} is the number of acquaintances that consumer c_n has received WoM from about product x_{j^*} up to time t.

Consumer c_n's evaluation of the product that he/she is currently using is calculated as

$$\gamma_{njt} = \theta_{nj} h^{\tau_{nj}} + \varepsilon_{njt} \tag{4.1}$$

where θ_{nj} is the consumer's opinion of product x_j; $0 < h \leq 1$ is an habituation factor and $\varepsilon_{njt} \sim N(0, \sigma_\varepsilon^2)$ is a random perturbation. Consumers' decision-making processes become habitual when they use a product or service repetitively (Jager, 2007). The habituation factor is a mechanism that discounts a consumer's product experience as habituation (or boredom) builds up with repeated use of a product thus ensuring that they eventually switch products. The exponent, $\tau_{nj} \geq 0$, is initially set to zero and subsequently increased (decreased) by one with each period of use (non-use) of product x_j. The random perturbation ensures that consumers have a different experience of a particular product each time they use it.

Consumers compare their product evaluation to their satisfaction threshold Λ_n,
$0 < \Lambda_n < 1$. If $\gamma_{njt} \geq \Lambda_n$ ($\gamma_{njt} < \Lambda_n$) then consumers are considered to be satisfied (dissatisfied) with their current product and may continue (discontinue) using it. Sometimes satisfied consumers may discontinue using a product that they are satisfied with. In this model this occurs with probability α. Hence, there are two instances when satisfied consumers switch. The first is when they use a product long enough that they become habituated with it resulting in dissatisfaction and thus defection. The second is when they randomly switch with probability α.

4.2 Switching constraints

When products have switching constraints, consumers may not switch immediately when they become dissatisfied but rather when their dissatisfaction with a product exceeds some critical level. That is, when $-\delta_{nj} > \beta_j$, where $\delta_{nj} = \gamma_{nj} - \Lambda_n < 0$ and $\beta > 0$ measures the strength of the switching constraint.

Switching constraints do not necessarily have to be constant over time, it is quite possible for them to vary over time and products. When this occurs, they take the general form

$$\beta_{jt} = \min(\beta_j^{min} + \Delta_j t_{use}, \beta_j^{max}) \tag{4.2}$$

where β_j^{min} is the switching constraint that is applicable when product x_j is used for the first time, Δ_j is the increase in the difficulty of switching the longer the product is used, t_{use} is the number of periods that the product has been used for and β_j^{max} is the maximum possible switching constraint for a product. The way in which the switching constraints have been defined here implies that the strength of the switching constraint increases with each period of use of the product until it reaches β_j^{max}.

In a sense, consumers get "locked-in" and are forced to continue using a product that they are dissatisfied with. Because of the habituation factor and the random perturbation term in (4.1), the consumer's dissatisfaction will eventually be high enough that they discontinue using the product. Figure 4.2 (a) illustrates the case when switching costs are constant and Figure 4.2 (b) illustrates the case when they increase over time. In the case of increasing switching constraints, it is easier for consumers to defect before the constraint reaches its maximum whereas in the case of constant switching constraints, consumers would have difficulty defecting from the onset.

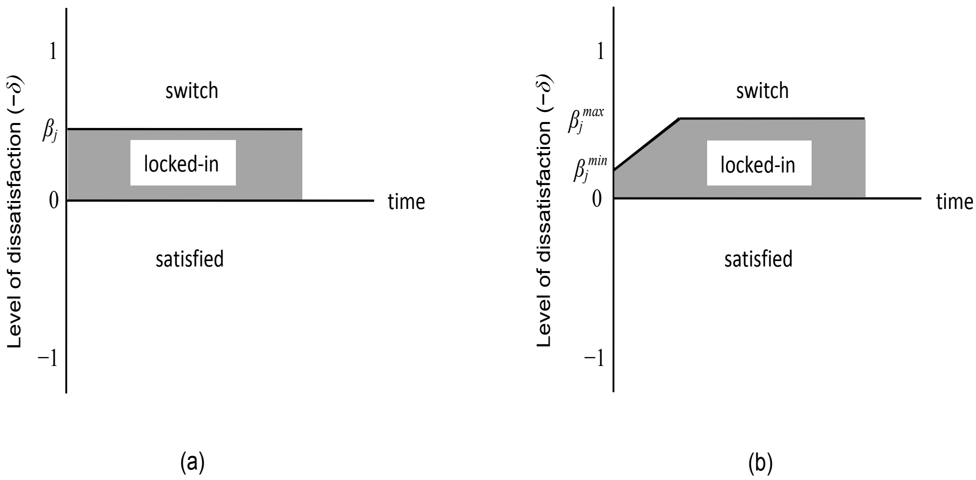


Figure 4.2: Switching constraints that may be applicable to some products in the market

Constant switching constraints represent, for example, the case when consumers enter into a contractual agreement which persists for the duration of the term that they use the product. Increasing switching constraints represent the case, for example, when consumers perceive higher procedural, financial or relational switching constraints (Burnham et al., 2003) the longer they use a particular product.

4.3 Introducing a new product

A new product is introduced into the system at time t_{new}. This product can be of the same, of a superior or of an inferior quality to that of the existing products in the market. The reason for this is to determine the market penetration of a new product that consumers deem to have a performance that is worse, no better or better than that of products that are already available in the market. The new product can also be introduced with different switching constraints.

4.4 Social network

The social network model proposed by Toivonen et al. (2006) (henceforth referred to as the TOSHK model) is used in this dissertation. The TOSHK model is one of a few generative network models that generate networks with all the salient features of real-world social networks. It falls into the category of growing network models since new vertices are added to the network and connected to a certain number of vertices already in the network until the network grows to the desired size N. The network growth of the TOSHK model is governed by two processes: (1) random attachment and (2) implicit preferential attachment. The algorithm for the network growth is as follows:

1. Start with a seed network of N_0 vertices;
2. Add a new vertex to the network and connect it to, on average, $n_{init} \geq 1$ random initial contacts;
3. Connect the new vertex to, on average, $n_{sec} \geq 0$ secondary contacts which are neighbours of each initial contact;
4. Repeat steps 2 and 3 until the network has grown to the desired size.

Any non-negative distribution with expectation value ≥ 1 can be used to generate the number of initial contacts and any non-negative distribution with expectation value ≥ 0 can be used to generate the number of secondary contacts. The number of secondary contacts varies which allows for a community structure to form and sometimes more than one initial contact is chosen which results in connections ("bridges") between communities being formed. Figure 4.3 shows an example of a network with $N = 500$ vertices generated using the following distribution for the number of initial contacts: $P(n_{init} = 1) = 0.95$, $P(n_{init} = 2) = 0.05$ and a $U[0, 3]$ distribution for the number of secondary contacts.

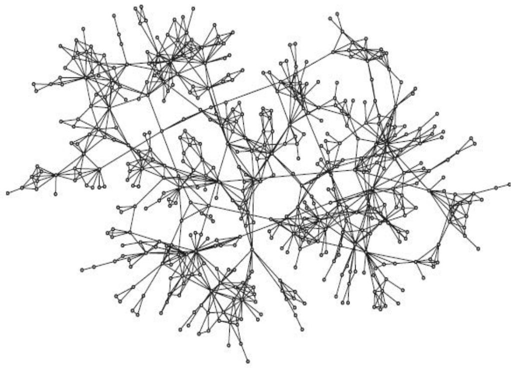


Figure 4.3: Example of a TOSHK network with $N = 500$ vertices (source: Toivonen et al., 2006)

4.5 Word-of-mouth processes

The edges of the social network serve as a conduit for WoM information about products. Consumers share information about their current product experience with their acquaintances in their social circles. Thus, consumers send information to and receive information from k_n other consumers where $k_n < N$ is the number of acquaintances a consumer has. Consumers share information about a satisfying product with probability $\omega_n^{sat}, 0 < \omega_n^{sat} < 1$ and share information about a dissatisfying product with probability $\omega_n^{dissat}, 0 < \omega_n^{dissat} < 1$. Satisfied consumers may be regarded as spreading positive WoM (PWoM) and dissatisfied consumers may be regarded as spreading negative WoM (NWoM).

Consumers may thus receive information about a particular product from zero, one or several sources. Consumers only accept information about products they have not used before and ignore information about a product that they are currently using or have used in the past.

Information received from more than one source about the same product is aggregated. Let $\Phi_n = \{\varphi_{nj^*t} = \frac{1}{m_{j^*t}} \sum_{n^*=1}^{m_{j^*t}} \gamma_{n^*j^*t}\}_{j^* \neq j}$ represent the set containing a consumer's WoM information. Here, φ_{nj^*t} is the WoM information received by consumer c_n about product x_{j^*} at time t (x_{j^*} is used to denote products that consumers are receiving WoM about), $\gamma_{n^*j^*t}$ is consumer c_{n^*}'s experience of product x_{j^*} at time t and m_{j^*t} is the number of acquaintances that consumer c_n has received WoM from about product x_{j^*} up to time t. It is assumed that consumers have infinite memory and can thus keep track of the number of other consumers that they have received WoM from about a particular product as well as the value of $\sum_{n^*=1}^{m_{j^*t}} \gamma_{n^*j^*t}$. For example, if a consumer receives no WoM information about a particular product at time $t+1$ then $\varphi_{nj^*t+1} = \varphi_{nj^*t}$. If he/she receives information from one or more sources then m_{j^*t} is increased by the number of sources that the WoM came from and $\sum_{n^*=1}^{m_{j^*t}} \gamma_{n^*j^*t}$ is updated with the product experiences of each of the sources resulting in $\varphi_{nj^*t+1} = \frac{1}{m_{j^*t+1}} \sum_{n^*=1}^{m_{j^*t+1}} \gamma_{n^*j^*t+1}$.

WoM received about a particular product creates an expectation about the sort of performance that a consumer may derive from that product. This expectation is then used in finding new products in subsequent time periods. Thus, consumers may be influenced to use a product because of PWoM and influenced not to use a product because of NWoM (Goldenberg et al., 2007). When a consumer tries a product, any expectation about its performance created through WoM information is replaced by the actual experience of the product and φ_{nj^*t} is set to zero.

4.6 Product selection

Product experiences are initially set to zero so that products are initially chosen at random. When looking for a different product to use, consumers begin by identifying the set of all products from which they expect to gain a satisfying experience, $X_n^{sat_{exp}} = \{\delta_{njt} = \gamma_{njt} - \Lambda_n \geq 0 \text{ and } \delta^*_{nj^*t} = \varphi_{nj^*t} - \Lambda_n > 0\}$. This set is made up of the products that a consumer has used before and found satisfying as well as the products that a consumer received WoM about and expects a satisfying experience from. A product is selected from $X_n^{sat_{exp}}$ with selection probabilities proportional to δ_{njt} and δ^*_{njt}. If $X_n^{sat_{exp}}$ is empty then consumers choose a product from the set of remaining products excluding their current product, $X_n^{rem} = \{\delta_{njt} < 0 \text{ and } \delta^*_{nj^*t} = \varphi_{nj^*t} - \Lambda_n < 0\}$. The set X_n^{rem} is made up of the products that a consumer has used before and found dissatisfying; the products that a consumer received WoM about and expects a dissatisfying experience from and the products that a consumer has not used before. Consumers select a product from X_n^{rem} with selection probabilities proportional to $1 + \delta_{njt}$ and $1 + \delta^*_{njt}$. Consumers will not necessarily always choose the product with the highest expected performance (Bolton, 1998).

Consumers are not limited to using a product once. In other words, they may defect from a particular product and then use it again at a later stage. Hence, the model also incorporates repeat-purchases.

4.7 Model construction and implementation

The model was programmed in Netlogo[1] (Wilensky, 1999) (version 5.0.3) which is a user-friendly agent-based modelling (ABM) programming environment that runs on all major operating systems (Mac, Window, Linux). It consists of a coding environment that is used to program a model and a front-end graphics-user-interface (GUI) that is used to execute the model. Figure 4.4 shows the Netlogo GUI of the model. Netlogo also comes with a tool called BehaviorSpace which can be used to perform experiments. BehaviorSpace runs a model several times while systematically varying the model's parameter settings (Wilensky, 1999) thus allowing for the exploration of a range of parameter values. The results of each simulation run in Netlogo are written to a Microsoft Excel file allowing for further statistical analysis using an appropriate statistical software package.

The next chapter details the scenarios that were simulated in an experiment that was conducted to answer the research question of this dissertation.

[1]For a tutorial on Netlogo, refer to the website noted in the references.

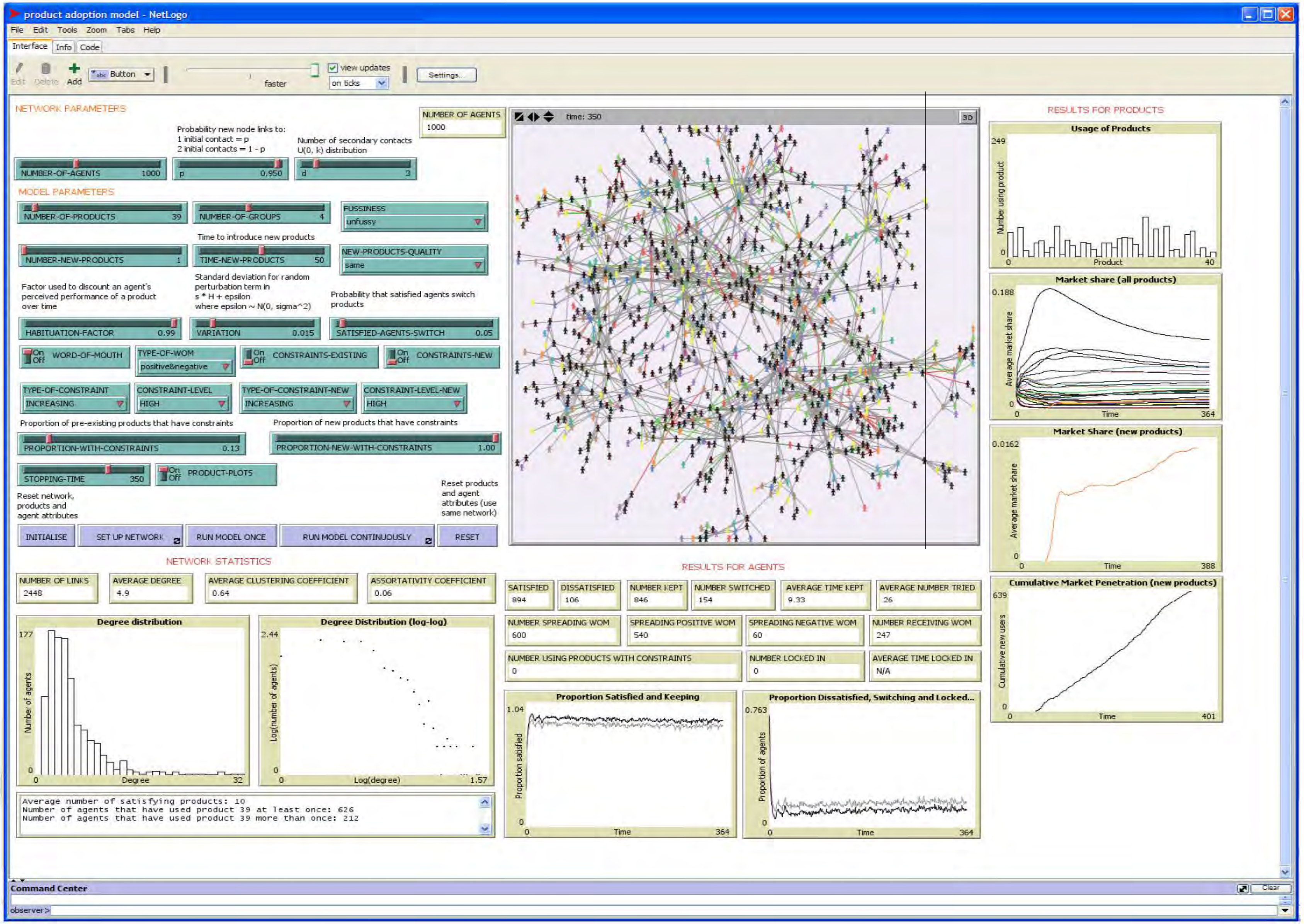


Figure 4.4: Netlogo GUI of the model

Chapter 5

Experimental design

An experiment was conducted to investigate the interaction between product performance, consumer satisfaction, switching constraints, word-of-mouth (WoM)and network structure on the market penetration of a new product. The experiment was executed with BehaviorSpace. Below is a discussion of the hypotheses, the experimental design and the methods of analysis.

5.1 Hypotheses

Figure 5.1 shows the conceptual framework of the model presented in this dissertation. The model is based on the premise that in competitive markets, the market penetration of a new product or service is affected by its quality and by the rate of churn in the market (Libai et al., 2009a; Peres et al., 2010) where the rate of churn is defined as the proportion of consumers that switch in a given period of time. The rate of churn, in turn, is influenced by consumer satisfaction; the switching constraints that consumers may face when they want to switch and WoM, the propagation of which is influenced by the structure of the social network that consumers belong to.

Consumers use a product either because they want to which reflects a relatively strong psychological affinity to a product or because they are forced to which often happens as a consequence of switching constraints. Consumers are likely to continue using a product that they find satisfying and are likely to discontinue using a product that they find dissatisfying provided that there are acceptable alternative products in the market and they find it beneficial to switch.

H1: A higher level of satisfaction results in a lower rate of churn because consumers

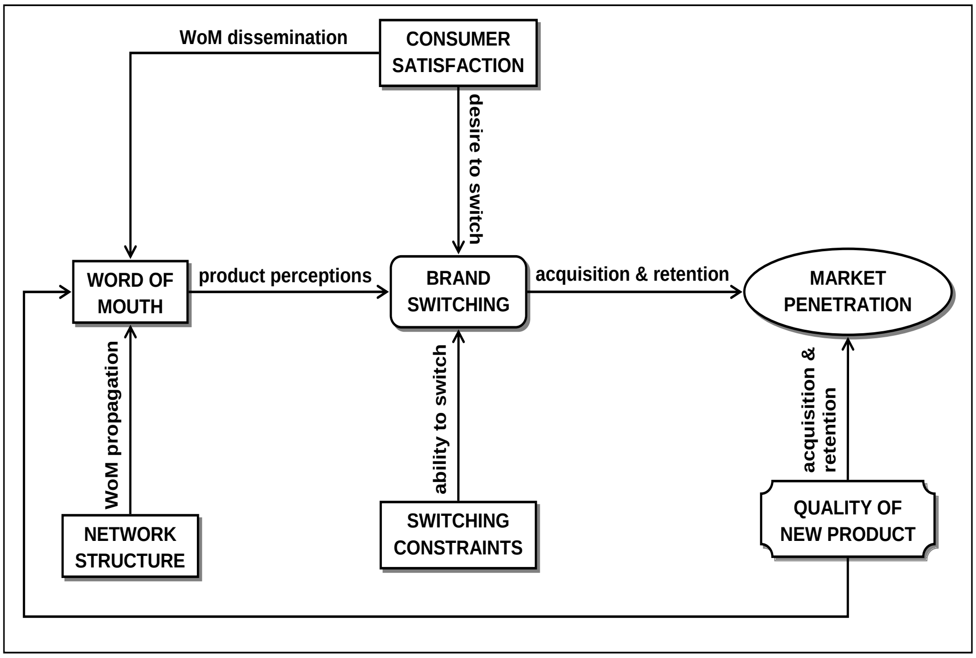


Figure 5.1: Conceptual framework of the model

are likely to use satisfying products for several periods.

Consumers become aware of and affected by switching constraints when they want to switch. Switching constraints make it difficult for consumers to switch and thus have the effect of forcing consumers to continue using a product that they may no longer find satisfying which may result in them disseminating negative WoM (NWoM).

H2: Switching constraints moderate the rate of churn in the market by causing consumers to get locked-in. However, by preventing dissatisfied consumers from defecting, switching constraints increase the dissemination of NWoM which may deter other consumers from using these products and this could result in the moderation being small.

Consumers use WoM communication to exchange information about their product experiences. This information can be positive in favour of a particular product or it can be negative against a particular product. Positive WoM (PWoM) is generally disseminated by satisfied consumers while NWoM is generally disseminated by dissatisfied consumers. WoM influences consumers' perceptions about the products in the market and these perceptions, in turn, influence the products they choose to use. Thus, consumers may be led to use a particular product as a result of the consumers of that particular product who spread PWoM about it or as a result of the consumers of competing products who spread NWoM about them.

H3: A higher level of satisfaction leads to more PWoM being disseminated which leads consumers to use products that yield a satisfying experience and, in turn, results in a lower rate of churn.

Consumers belong to social networks which serve as a means of exchanging information. The propagation of this information is determined by the number of connections that consumers have and the configuration of these connections. A higher number of connections means that consumers have access to more information which improves their ability to determine which products they can expect a satisfying experience from and which ones they can expect a dissatisfying experience from.

H4: A higher average degree increases the number of sources from which consumers can receive information about products in the market. This enables them to find out about products that may yield a satisfying experience which they are more likely to use before using products that they have no experience of or products that they expect a dissatisfying experience from and since they are likely to use satisfying products for several periods, this results in a lower rate of churn.

Churn determines the size of the pool of potential consumers for the products in the market and this influences the market share that a new product would be able to acquire as well as the speed and extent of its diffusion.

H5: A lower rate of churn results in a smaller pool of potential consumers and this leads to a lower market share and a less extensive diffusion of the new product.

Attributes such as price, quality, reliability and technical performance influence the satisfaction that consumers derive from a product (Jager, 2007). The market penetration of a new product would thus also be influenced by its quality. A better quality increases the chances that the product would meet or exceed consumers' expectations thus yielding a more satisfying experience which increases its chances of being used.

H6: A better quality results in a higher market share and a more extensive diffusion of the new product.

Given that switching constraints result in a reduced pool of potential consumers, launching a new product into a market in which there are products that have switching constraints may impede its market penetration. Thus, launching the new product with switching constraints when there are products that have switching constraints in the market may facilitate its market penetration over and above launching it with a quality that is better than that of the existing products.

H7: Because switching constraints make it difficult for consumers to switch, launching a new product with switching constraints when there are products that have switching constraints in the market would enable it to acquire a higher market share and a more extensive diffusion.

5.2 Model Calibration

Calibrating the model was a tedious and time-consuming process that involved running several small-scale simulations using different parameter values and examining the output thereof to ensure that it made sense. Some mechanisms were straightforward to get to work properly while others required more of a trial and error approach. Of particular interest was ensuring that:

- The network was generated properly.
- Consumers' product evaluations did not decrease too quickly and did not vary dramatically with each use of a product. For this, h, had to be set to a value close to one and σ_{ε}^2 had to be set to a value close to zero.
- Consumers select alternative products correctly, particularly when products come from the set of products from which they expect to gain a satisfying experience. When consumers' satisfaction thresholds are high, δ_{njt} and $\delta^*_{nj^*t}$ and are likely to be small which results in a low probability of selecting products that are expected to be satisfying. In order to increase the chances of selecting a satisfying product, δ_{njt} and $\delta^*_{nj^*t}$ were multiplied by 100 when they were greater than zero and left as is when they were less than zero.
- Consumers did not get locked in for too few or too many periods in the event that they use a product that has switching constraints. Also, in the case of increasing switching constraints, the number of periods before the maximum is reached could not be too short or too long.
- Consumers only accept WoM about products that they have not used before and that their WoM information was aggregated correctly.

5.3 Experiment

Various market conditions were simulated using different combinations of the model parameters. Table 5.1 shows the parameter values that were used for the simulations. In each of the simulations, the market consisted of 1000 consumers that were randomly divided into $Q = 4$ equally sized groups. There were 39 existing products and one new product so that there were $J = 40$ products in total in the market. The new product was introduced into the market after 50 time periods. Satisfied consumers discontinued using a satisfying product with probability $\alpha = 0.05$. Each simulation was run for 350 time periods and each market condition with a particular combination of parameter values was run 30 times.

Table 5.1: Parameter values

Network	$\langle k \rangle = 5$ $\langle k \rangle = 15$
Fussiness	$\Lambda_n = 0.7$ $\Lambda_n = 0.85$
$\gamma_{njt} = \theta_{nj} h^{\tau} + \epsilon_{jt}$	$-1 \leq \gamma_{njt} \leq 1$ $\theta_{nj} \in \{0.1, 0.2, ..., 0.9\}$ $h = 0.99$ $\epsilon_{jt} \sim N(0, 0.015^2)$
WoM	PWoM disseminated with probability $\omega^{sat} \in \{0.1, 0.2, ..., 1\}$ NWoM disseminated with probability $\omega^{dissat} \in \{0.1, 0.2, ..., 1\}$
Switching constraints	Low & constant: $\beta_j = 0.2$ Low & increasing: $\beta_j = min(0.04 + 0.04t_{use}, 0.2)$ High & constant: $\beta_j = 0.35$ High & increasing: $\beta_j = min(0.07 + 0.07t_{use}, 0.35)$
Quality of new product	Same Superior: $\theta_{n,newprod} \times 1.1$ Inferior: $\theta_{n,newprod} \times 0.9$

The effect of the network structure on the propagation of information is investigated by varying the degree distribution of the network i.e. by varying the average degree of the network. Varying the average degree of the network affects the density of the cliques within the network. As such, networks with a low average degree of $\langle k \rangle = 5$ (sparse networks) and networks with a high average degree of $\langle k \rangle = 15$ (dense networks) were used for the purposes of investigating the effects of the network structure. Simulations of 100 runs each were conducted to determine which parameters of the TOSHK model would result in networks with these average degrees and still have visible cliques. Networks that have an average degree of $\langle k \rangle = 5$ were generated with a $P(n_{init} = 1) = 0.95$,

$P(n_{init} = 2) = 0.05$ distribution for the initial contacts and a $U[0,3]$ distribution for the secondary contacts and networks that have an average degree of $\langle k \rangle = 15$ were generated with a $P(n_{init} = 1) = 0.95$, $P(n_{init} = 2) = 0.05$ distribution for the initial contacts and a $U[0,17]$ distribution for the secondary contacts.

Table 5.2 shows the basic network statistics, namely the number of edges, M; the average degree, $\langle k \rangle$; the clustering coefficient, $\bar{C}$; the assortativity coefficient, r and the degree distribution $P(k)$ of each network, with standard errors in parentheses, averaged over the 100 realisations of each of the networks. Increasing the average degree from 5 to 15 increases the network density by 200%; the average path length decreases by almost 40%; the clustering coefficient increases by 15% and the assortativity coefficient doubles.

	M	k_{max}	$\langle k \rangle$	$\bar{C}$	r	ℓ	density
sparse networks	2457 (43)	34 (6)	4.91 (0.087)	0.33 (0.009)	0.02 (0.02)	6.2 (0.24)	0.005
dense networks	7634 (225)	89 (15)	15.26 (0.45)	0.38 (0.018)	0.04 (0.021)	3.87 (0.15)	0.015

Table 5.2: Basic statistics of simulated networks. These statistics were averaged over 100 realisations of each network with a low average degree of 5 and a high average degree of 17: total number of vertices = 1000, p = 0.95, total number of edges M; maximum degree k_{max}; average degree $\langle k \rangle$; clustering coefficient $\bar{C}$; average geodesic path length ℓ; degree correlation coefficient r and network density

To determine the effect of consumer satisfaction on market dynamics, two types of markets were simulated: an unfussy market in which consumers were easy to satisfy and a fussy market in which consumers were difficult to satisfy thus making it either easy or difficult for consumers to locate a satisfactory product. In the unfussy market, consumers had a satisfaction threshold of $\Lambda_n = 0.7$ and in the fussy market, consumers had a satisfaction threshold of $\Lambda_n = 0.85$. Consumers were all given the same satisfaction threshold so that they could have similar tastes. When consumers' satisfaction thresholds are $\Lambda_n = 0.7$, the probability that a consumer is satisfied will be $1 - 0.7 = 0.3$. Thus, theoretically, there will be $40 \times 0.3 = 12$ satisfying products. Similarly, when consumers' satisfaction thresholds are $\Lambda_n = 0.85$, theoretically there will be 6 satisfying products. However, because γ_{njt} is stochastic, there can be more than or less than 12 (6) satisfying (dissatisfying) products when consumers are unfussy (fussy).

To simulate a market in which consumers are faced with switching constraints, five of the existing products were made to have switching constraints. Switching constraints could either be weakly binding (low) or strongly binding (high) and could also be either constant or increasing. Hence, products could have switching constraints that were either: low and constant; low and increasing; high and constant or high and increasing.

To determine the effect of the quality of the new product on its market penetration, it could either be of the same quality, of a superior quality or of an inferior quality to that of the existing products. In order to make the new product of a superior quality, consumers opinions of the new product were multiplied by 1.1 and in order to make it of an inferior quality, consumers' opinions were multiplied by 0.9. Thus, on average, consumers' product evaluations were similar to those of the existing products when the new product was of the same quality, were higher than those of the existing products when the new product was of a superior quality and were lower than those of the existing products when the new product was of an inferior quality.

5.3.1 Simulations

Table 5.3 shows a list of the simulations that were conducted. In market condition 1, five of the existing products have switching constraints that are either: low and constant; low and increasing; high and constant or high and increasing and the new product is launched without switching constraints. In market condition 2, none of the existing products have switching constraints and the new product is launched without switching constraints. In market condition 3, consumers do not disseminate WoM; none of the existing products have switching constraints and the new product is launched without switching constraints. This market condition is used as a baseline comparison. Because consumers do not disseminate WoM, the structure of the network is inconsequential. In market condition 4, five of the existing products have switching constraints that are either: low and constant; low and increasing; high and constant or high and increasing and the new product is launched with switching constraints that are either: low and constant; low and increasing; high and constant or high and increasing.

The biggest challenge was in terms of time and resource constraints. Thirty simulations of a single combination of parameters took on average between 15 and 48 hours to run depending on the combination of the parameters. Simulations in which the network had a high average degree generally took longer to run than simulations in which the network had a low average degree.

5.3.2 Methods of analysis

Market dynamics

The effects that consumer satisfaction, WoM and switching constraints have on churn are

Table 5.3: Simulations of various market conditions

Market condition	Consumer satisfaction	Switching constraints	Network	Quality of new product	Simulation runs
1	$\Lambda_n = 0.7$ $\Lambda_n = 0.85$	Existing products: low & constant; low & increasing; high & increasing; high & constant	$\langle k \rangle = 5$ $\langle k \rangle = 15$	same superior inferior	$2 \times 1 \times 4 \times 2 \times 3$
2	$\Lambda_n = 0.7$ $\Lambda_n = 0.85$		$\langle k \rangle = 5$; $\langle k \rangle = 15$	same superior inferior	$2 \times 1 \times 1 \times 2 \times 3$
3	$\Lambda_n = 0.7$ $\Lambda_n = 0.85$		$\langle k \rangle = 5$	same superior inferior	$2 \times 1 \times 1 \times 1 \times 3$
4	$\Lambda_n = 0.7$ $\Lambda_n = 0.85$	Existing products: low & constant; low & increasing; high & increasing; high & constant New product: low & constant; low & increasing; high & increasing; high & constant	$\langle k \rangle = 5$ $\langle k \rangle = 15$	same superior inferior	$2 \times 1 \times 16 \times 2 \times 3$
Market condition	**Consumer satisfaction**	**Type of WoM**	**Network**	**Quality of new product**	**Simulation runs**
5	$\Lambda_n = 0.7$ $\Lambda_n = 0.85$	PWoM only NWoM only	$\langle k \rangle = 5$ $\langle k \rangle = 15$	same	$2 \times 3 \times 1 \times 2 \times 1$

assessed by examining the averages of the results pertaining to: the number of satisfied consumers; number of consumers disseminating WoM; the number of consumers accepting WoM; the number of consumers that are locked-in and the number of consumers that switch products in market conditions 1, 2 and 4. Market condition 5 was simulated to examine the role that PWoM and NWoM play in influencing market dynamics. However, these results are not explicitly examined. Results pertaining to the market share and the extent of the diffusion of the new product obtained from these simulations can be found in Appendix B. Averages are taken for each of the 350 time periods over the 30 runs. These results are compared for unfussy and fussy markets as well as sparse and dense networks.

Launching a new product without switching constraints

The effect that churn has on the market penetration of the new product is assessed by examining the averages of the results pertaining to the market share as well as the extent of the diffusion of the new product for market conditions 1 and 2. The market share is measured as the proportion of consumers that use the new product in each time period. The extent of the diffusion is measured by the total number of consumers that used the new product at least once at the end of each of the 30 runs. Averages are taken for each of the 350 time periods over the 30 runs. These results are compared for unfussy and fussy markets and sparse and dense networks.

An analysis of variance (ANOVA) is performed in order to determine which factors are at play in influencing the market share and extent of the diffusion of the new product. The ANOVA tests the effects of the quality of the new product (*quality*); the fussiness of consumers (Λ_n); the presence of products that have switching constraints in the market ($constraints_{existing}$) and the average degree of the network ($\langle k \rangle$). The results are only considered up to three-way interactions as higher order interactions are difficult to interpret. Here, the control is launching the new product into a market in which there are no products that have switching constraints and the treatments are launching it into a market in which there are products that have various switching constraints.

Launching a new product with switching constraints

The effect that launching the new product with switching constraints has on its market penetration is assessed by examining the averages of the results pertaining to the market share as well as the extent of the diffusion of the new product for market conditions 1 and 4. Averages are taken for each of the 350 time periods over the 30 runs. These results are compared for unfussy and fussy markets and sparse and dense networks.

An analysis of variance (ANOVA) is performed in order to determine which factors are at play in influencing the market share and extent of the diffusion of the new product when it is launched with switching constraints. The ANOVA tests the effects of the quality of the new product (*quality*); the switching constraints of the new product ($constraints_{new}$) the fussiness of consumers (Λ_n); the presence of products that have switching constraints in the market ($constraints_{existing}$) and the average degree of the network ($\langle k \rangle$). Again, the results are only considered up to three-way interactions. Here, the control is launching the new product without switching constraints and the treatments are launching it with various switching constraints.

The results of this experiment are discussed in the next chapter.

Chapter 6

Simulation Results

The results of the experiment are presented in this chapter. Simulation results were analysed in ***R*** which is an open source statistical software package.

6.1 Overview of market dynamics

The typical dynamics of the system as a function of consumer satisfaction, switching constraints, WoM communication and network structure are examined in this section. Figures 6.1 – 6.4 show how these factors evolve over time in unfussy and fussy markets when consumers are sparsely and densely connected. The results pertain to market conditions 1, 2 and 3 (as shown in Box 2). Because of the similarity of the results, only the results of the simulations in which the new product is of the same quality as that of the existing products are presented. Percentages and values quoted pertain to averages taken over time periods $t_{250} - t_{350}$.

Scenario 1: Consumers do not disseminate word of mouth (WoM) and none of the existing products have switching constraints (market condition 3)
Scenario 2: None of the existing products have switching constraints. The new product is introduced without switching constraints (market condition 2)
Scenario 3: The existing products have switching constraints that are low and constant (market condition 1)
Scenario 4: The existing products have switching constraints that are low and increasing (market condition 1)
Scenario 5: The existing products have switching constraints that are high and constant (market condition 1)
Scenario 6: The existing products have switching constraints that are high and increasing (market condition 1)

Box 2: Simulation results

System behaviour is mainly affected by consumer satisfaction and switching constraints while WoM and consequently network structure have a limited effect – more so when consumers are fussy – because consumers only accept WoM about products they have not used before and thus eventually rely less on WoM communication to inform their product choices. As expected, a fussy market generally has fewer satisfied consumers (Figure 6.3); a higher number of consumers disseminating NWoM (Table 6.1); a higher number of consumers switching products (Figure 6.4) and fewer consumers accepting WoM per time period (Figure 6.1) compared to an unfussy market. Also, given that switching constraints prevent dissatisfied consumers from switching, it is not surprising that satisfaction is lower; more NWoM is disseminated; the number of consumers that switch is lower and more WoM is accepted when consumers encounter switching constraints compared to when they do not.

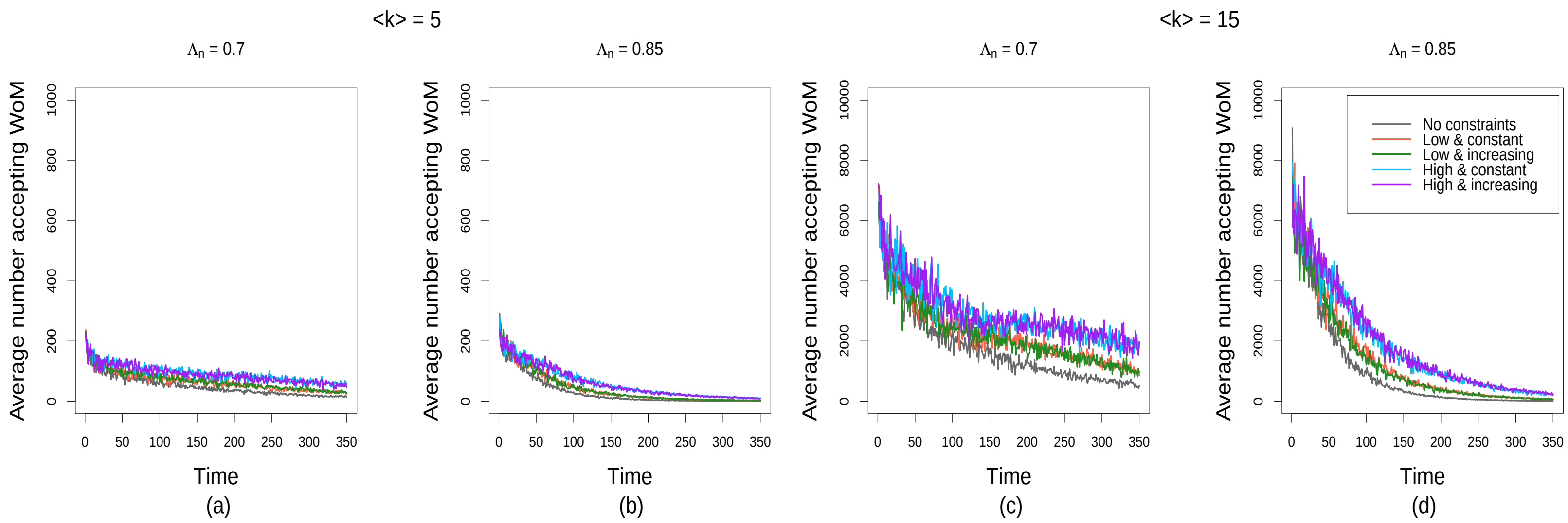


Figure 6.1: Average number of consumers accepting WoM per time period

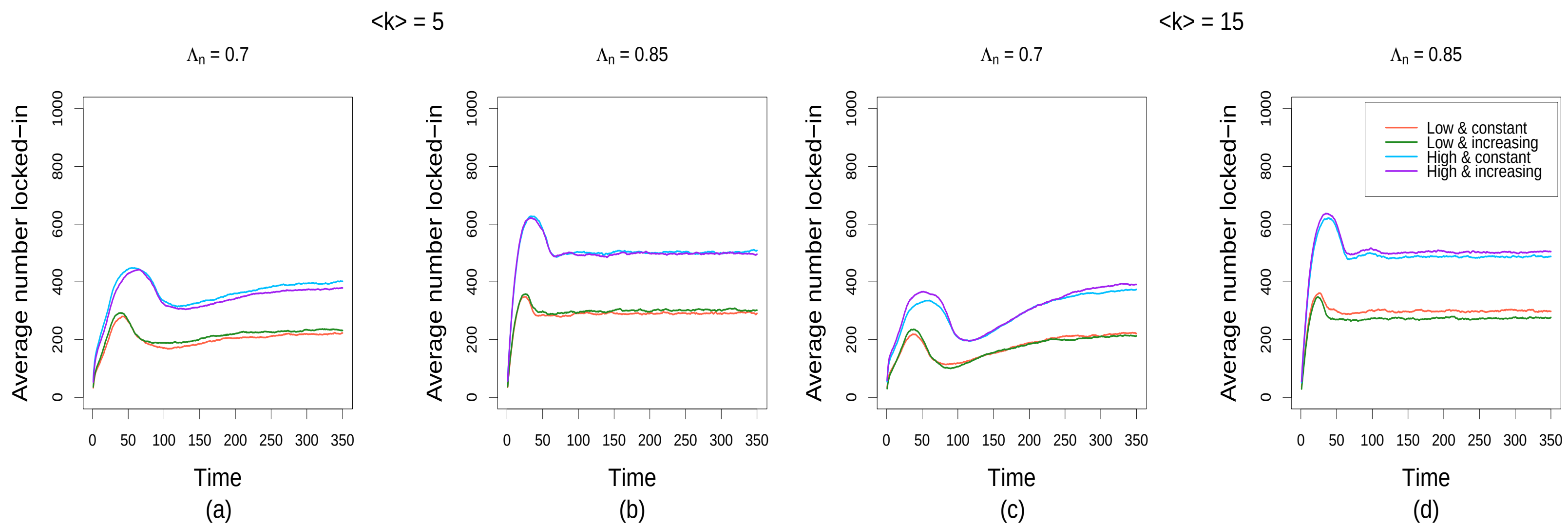


Figure 6.2: Average number of consumers that are locked-in per time period

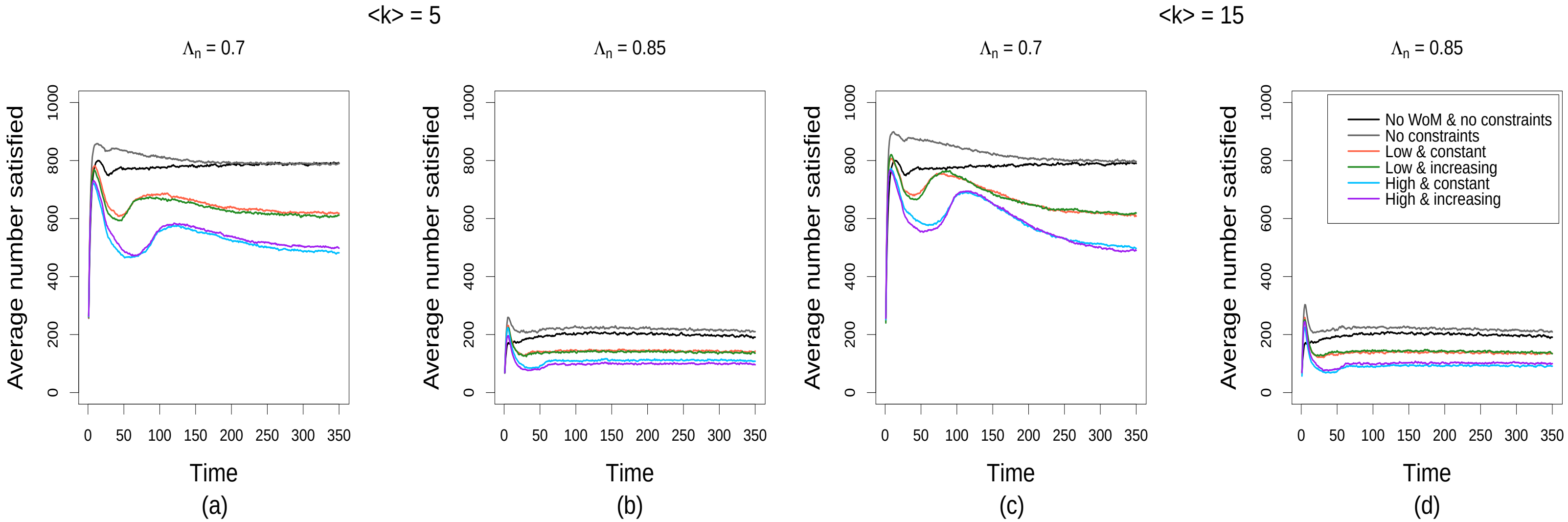


Figure 6.3: Average number of satisfied consumers per time period.

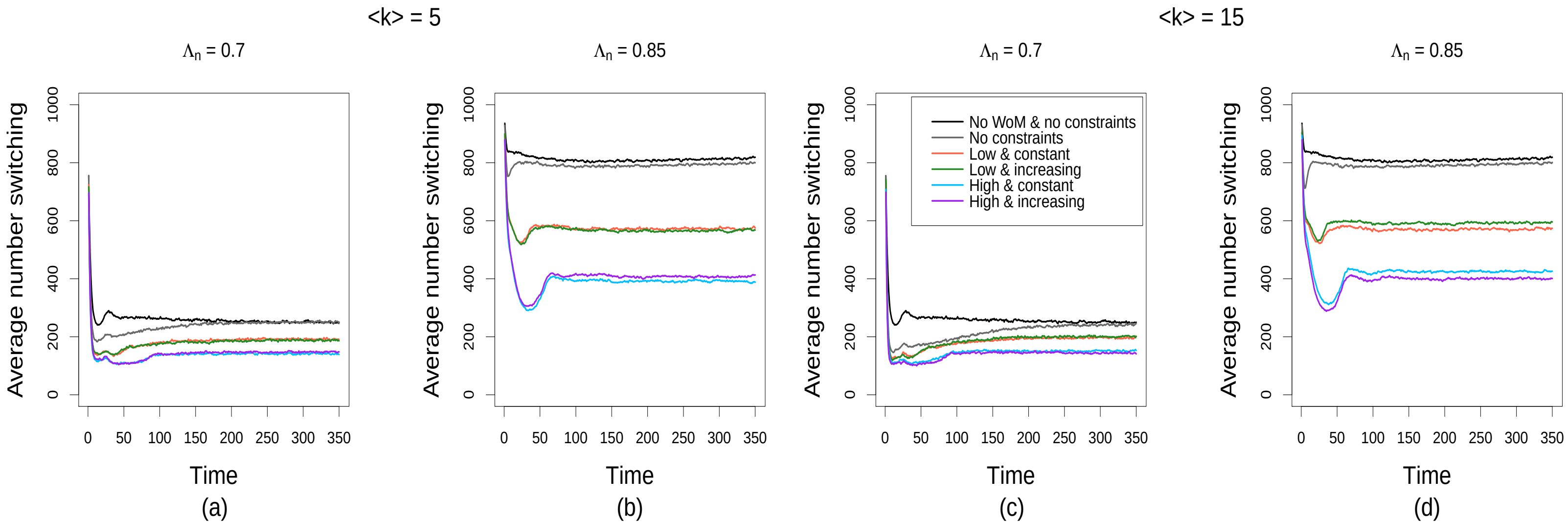


Figure 6.4: Average number of consumers switching products per time period

6.1.1 Role of word-of-mouth

Table 6.1 shows the average number of consumers that disseminate WoM per time period. These averages were obtained by averaging over the 350 time periods for each of the 30 runs and then taking the overall average of the 30 averages. Standard errors are in parentheses. In general, approximately half of the market disseminates WoM at any given time since the probability that consumers disseminate WoM when they are satisfied (dissatisfied), $\omega_n^{sat}(\omega_n^{dissat}) \in \{0.1, 0.2, ..., 1\}$.

As expected, unfussy markets are dominated by PWoM, even when consumers encounter switching constraints, while fussy markets are dominated by NWoM, even more so when there are products that have switching constraints in the market. By preventing dissatisfied consumers from defecting, switching constraints have the effect of increasing the amount of NWoM and simultaneously reducing the amount of PWoM that is disseminated. This happens to a larger extent in an unfussy market than in a fussy market. In an unfussy market, the PWoM:NWoM ratio decreases from approximately 4 when consumers are unconstrained to approximately 2 when there are products that have switching constraints that are low and approximately 1 when there are products that have switching constraints that are high. In a fussy market, on the other hand, the PWoM:NWoM ratio decreases from approximately 0.25 when consumers are unconstrained to approximately 0.15 when there are products that have switching constraints that are low and approximately 0.1 when there are products that have switching constraints that are high.

Table 6.1: Average number of consumers spreading WoM. Standard errors in parentheses

	$\langle k \rangle = 5$				$\langle k \rangle = 15$			
	$\Lambda_n = 0.7$		$\Lambda_n = 0.85$		$\Lambda_n = 0.7$		$\Lambda_n = 0.85$	
Market condition	PWoM	NWoM	PWoM	NWoM	PWoM	NWoM	PWoM	NWoM
Scenario 2	403 (22)	101 (20)	108 (31)	388 (33)	414 (23)	88 (18)	110 (27)	388 (28)
Scenario 3	321 (37)	174 (31)	72 (21)	430 (30)	336 (32)	163 (34)	70 (22)	429 (24)
Scenario 4	316 (24)	181 (27)	70 (17)	429 (24)	335 (37)	162 (31)	71 (22)	425 (24)
Scenario 5	258 (26)	236 (27)	55 (16)	442 (19)	293 (40)	205 (37)	46 (16)	450 (27)
Scenario 6	268 (36)	232 (32)	49 (16)	448 (30)	287 (36)	206 (38)	52 (22)	456 (30)

The presence of WoM has the effect of substantially delaying system convergence in an unfussy market while in a fussy market, it only has a slight effect. In an unfussy market, convergence to a state where approximately 80% of the market is satisfied happens within 50 time periods in scenario 1 compared to almost 200 time periods in scenario 2 (Figure 6.3 a and c). In a fussy market, on the other hand, convergence to a state where approximately 20% of the market is satisfied happens within 50 time periods for both scenarios 1 and 2 (Figure 6.3 b and d). PWoM assists consumers to identify satisfying products much sooner than they would through personal exploration and thus biases product usage towards better performing products as can be seen in the higher number of satisfied consumers in scenario 2. This is can also be seen in the substantially higher market share of the market leading product (Figure 6.5) in the earlier periods when there is PWoM that is disseminated compared to when no WoM is disseminated or when only NWoM is disseminated. These results were obtained from market condition 5.

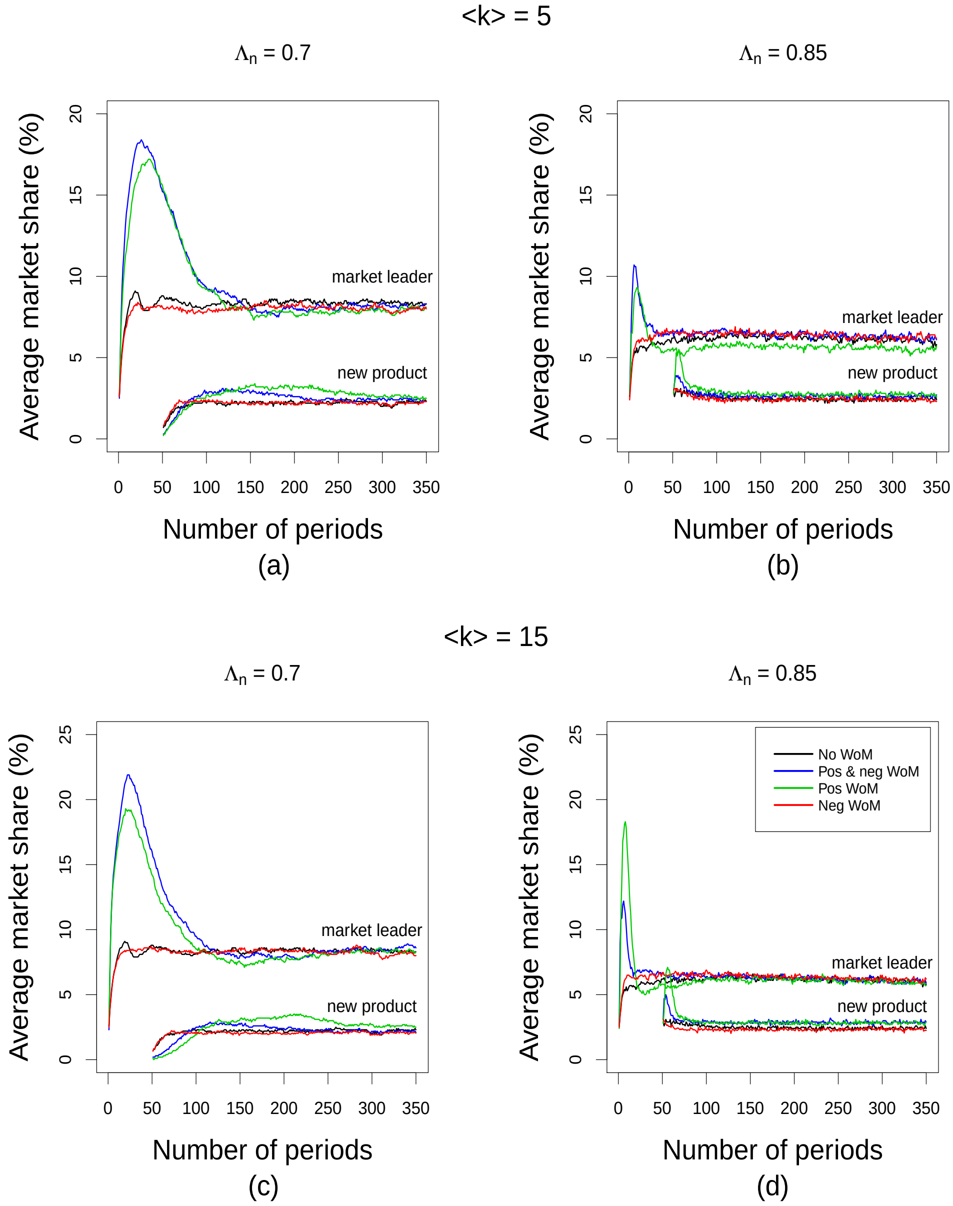


Figure 6.5: Market share of the market leader and of the new product when consumers do not disseminate WoM; disseminate PWoM & NWoM; only disseminate PWoM and only disseminate NWoM

6.1.2 Role of consumer satisfaction

In an unfussy market, satisfaction starts out higher in scenario 2 and eventually declines to the level of scenario 1 because of habituation. The effects of habituation are more obvious in an unfussy market than in a fussy market because a large number of consumers use the products that yield a satisfying experience at the same time. On average, unfussy consumers find ten products satisfying which they use for eight time periods while fussy consumers find five products satisfying which they use for two time periods. In a fussy market, finding a satisfying product is more difficult because most products are considered to offer a dissatisfying experience and thus more NWoM is disseminated. However, the little PWoM that is disseminated results in satisfaction being moderately but consistently higher in scenario 2 than in scenario 1. These results suggest that consumers switch between a particular set of satisfying products once this set has been established.

6.1.3 Role of switching constraints

The increase in the amount of NWoM that is disseminated when consumers encounter switching constraints has the effect of deterring consumers from using the products that have switching constraints. This is more pronounced in an unfussy market as can be seen in the slower increase, in the initial periods, and the subsequent dip in the number of consumers that get locked-in (Figure 6.2 a and c). Also, consumers may not necessarily find the products that have switching constraints to be dissatisfying from the onset which also contributes to the slower increase in the number of consumers that get locked-in in the initial periods.

The convergence of the system is delayed even further when there are products that have switching constraints in the market. The system takes almost 250 time periods to converge to a state in which approximately 60% of the market is satisfied in scenarios 3 and 4 and approximately 50% of the market is satisfied in scenarios 5 and 6. In a fussy market, on the other hand, the system converges within 60 time periods to a state where approximately 15% of the market is satisfied in scenarios 3 and 4 and approximately 10% of the market is satisfied in scenarios 5 and 6. There is NWoM about the majority of products in a fussy market, thus NWoM that is disseminated about products that have switching constraints is less effective in preventing consumers from using these products.

Surprisingly, the number of consumers that get locked-in is determined by whether switching constraints are high or low and not necessarily by whether they are constant or increasing. Increasing switching constraints were expected to result in slightly fewer consumers getting locked-in since there is an opportunity for consumers to switch before the switching constraints reach a maximum. Although only a few products have switching constraints, a substantial proportion of the market gets locked-in when switching constraints are high especially in a fussy market where, on average, approximately 50% of the market gets locked-in (Figure 6.2 b and d). In both fussy and unfussy markets, high switching constraints result in as much as 70% more consumers being locked-in than low switching constraints do. Consumers get locked-in for an average of three time periods when switching constraints are low and an average of nine time periods when switching constraints are high. On average, approximately 40% more consumers get locked-in per time period ($t_1 - t_{350}$) in a fussy market than in an unfussy market which is attributable to fussy consumers switching more frequently and thus being more likely to use products that have switching constraints.

6.1.4 Role of network structure

In the first 60 or so periods, slightly more consumers accept WoM in a fussy market than in an unfussy market (Figure 6.1) because consumers in an unfussy market tend to gravitate towards the same products initially and switch less frequently whereas product usage is more evenly distributed in a fussy market because consumers switch so frequently. Thereafter, the number of consumers accepting WoM becomes higher in an unfussy market than in a fussy market because the frequent switching in a fussy market results in consumers trying more products, on average, and thus accepting less and less WoM. When consumers are sparsely connected, on average, 3% more of consumers accept WoM in an unconstrained market, 4% more when there are products that have switching constraints that are low and 5% more when there are products that have switching constraints that are high. When consumers are densely connected, on the other hand, on average, 9% more of consumers accept WoM in an unconstrained market, 12% more when there are products that have switching constraints that are low and 15% more when there are products that have switching constraints that are high.

The structure of the network is important for the spread of information since the number of edges in the network and the configuration of those edges determines the number of individuals that consumers can disseminate WoM to and receive WoM from and how far the information spreads through the network. Networks in which the average degree, $\langle k \rangle = 15$ have, on average, three times more edges than networks in which $\langle k \rangle = 5$

and thus three times more consumers accepting WoM. Consumers are thus more aware of potentially satisfying (dissatisfying) products which they gravitate towards (avoid), more so when they are densely connected. This is in line with the assertion made by Janssen and Jager (2001) that larger networks lead to faster dominance of one or a few products. More PWoM is disseminated when consumers are unfussy and densely connected than when they are sparsely connected. On average, approximately 2% more of consumers disseminate PWoM in scenario 2, 5% more in scenarios 3 and 4 and 10% more in scenarios 5 and 6.

The effects of having more sources of information are more evident in the first 200 or so time periods in an unfussy market because WoM stays influential for longer in an unfussy market. There are 3% more satisfied consumers in scenario 2 when the network is dense compared to when it is sparse (Figure 6.3 a and c). And, approximately 5% fewer consumers get locked-in in scenarios 3 and 4 and approximately 8% fewer consumers get locked-in in scenarios 5 and 6 when the network is dense compared to when it is sparse (Figure 6.2 a and c) resulting in there being more satisfied consumers of approximately the same percentages. Increases in the average degree plays an important role in improving satisfaction, albeit not substantially, even when switching constraints are high. Switching constraints reduce satisfaction by keeping consumers locked-in and thus reducing switching. An increase in the average degree, on the other hand, also increases satisfaction by reducing switching but in this case by facilitating consumers in finding satisfying products.

Generally speaking, when consumers are easier (more difficult) to satisfy, they find more (fewer) products satisfying and these products stay satisfying for longer (shorter) periods leading to a lower (higher) rate of churn. Also, consumers disseminate more PWoM (NWoM) which results in it being easier (more difficult) to find satisfying products. Consumers use products they have previously had a satisfying experience with or products which they have received PWoM about before they use products they have previously had a dissatisfying experience with; products they have received NWoM about or products they have not tried before. As a result, once a set of satisfying products have been established, consumers tend to switch back and forth between these products. Switching constraints have the effect of reducing the number of consumers that are able to switch. This effect is more substantial when consumers are difficult to satisfy because (1) they are more likely to switch and thus find the products that have switching constraints and (2) they are more likely to find these products dissatisfying and want to switch. These results demonstrate that even a small change in the satisfaction threshold has a

substantial effect on switching behaviour. As can be seen from Figure 6.4, consumer satisfaction, WoM and switching constraints result in approximately 80%, 60% and 40% of consumers switching products in scenarios 1 and 2; scenarios 3 and 4 and scenarios 5 and 6 respectively when the market is fussy compared to approximately 25%, 20% and 15% of consumers switching products in scenarios 1 and 2; scenarios 3 and 4 and scenarios 5 and 6 respectively when the market is unfussy. The number of consumers that switch in each period is slightly less than
1000 – number_switching because satisfied consumers switch with probability $\alpha = 0.05$ even though they are satisfied.

6.2 Launching a new product without switching constraints

6.2.1 Market share

Figures 6.6 and 6.7 show the market share of the new product in each time period. The range of the market share of the new product is generally low since it has to compete with 39 other more established products which may enjoy a higher market share because of switching constraints or because they offer a satisfying experience. In an unfussy market, the top five products comprise three (four) products that have switching constraints in scenarios 3 and 4 (5 and 6) while in a fussy market, the top five products comprise four (five) products that have switching constraints in scenarios 3 and 4 (5 and 6). The top five products have a collective market share of 35% (45%) – 24% (40%) of which is the collective market share of the products that have switching constraints – in scenarios 3 and 4 (5 and 6) when the market is unfussy and a collective market share of 40% (55%) – 35% of which is the collective market share of the products that have switching constraints – in scenarios 3 and 4 (5 and 6) when the market is fussy. In scenarios 1 and 2, the top five products have a collective market share of 30% when the market is unfussy and a collective market share of 25% when the market is fussy. While switching constraints do not necessarily guarantee that a product will have the highest market share – as is the case in an unfussy market where fewer products that have switching constraints capture the market – they do have the effect of substantially eroding the market share of the leading products (as well as that of the other products in the market).

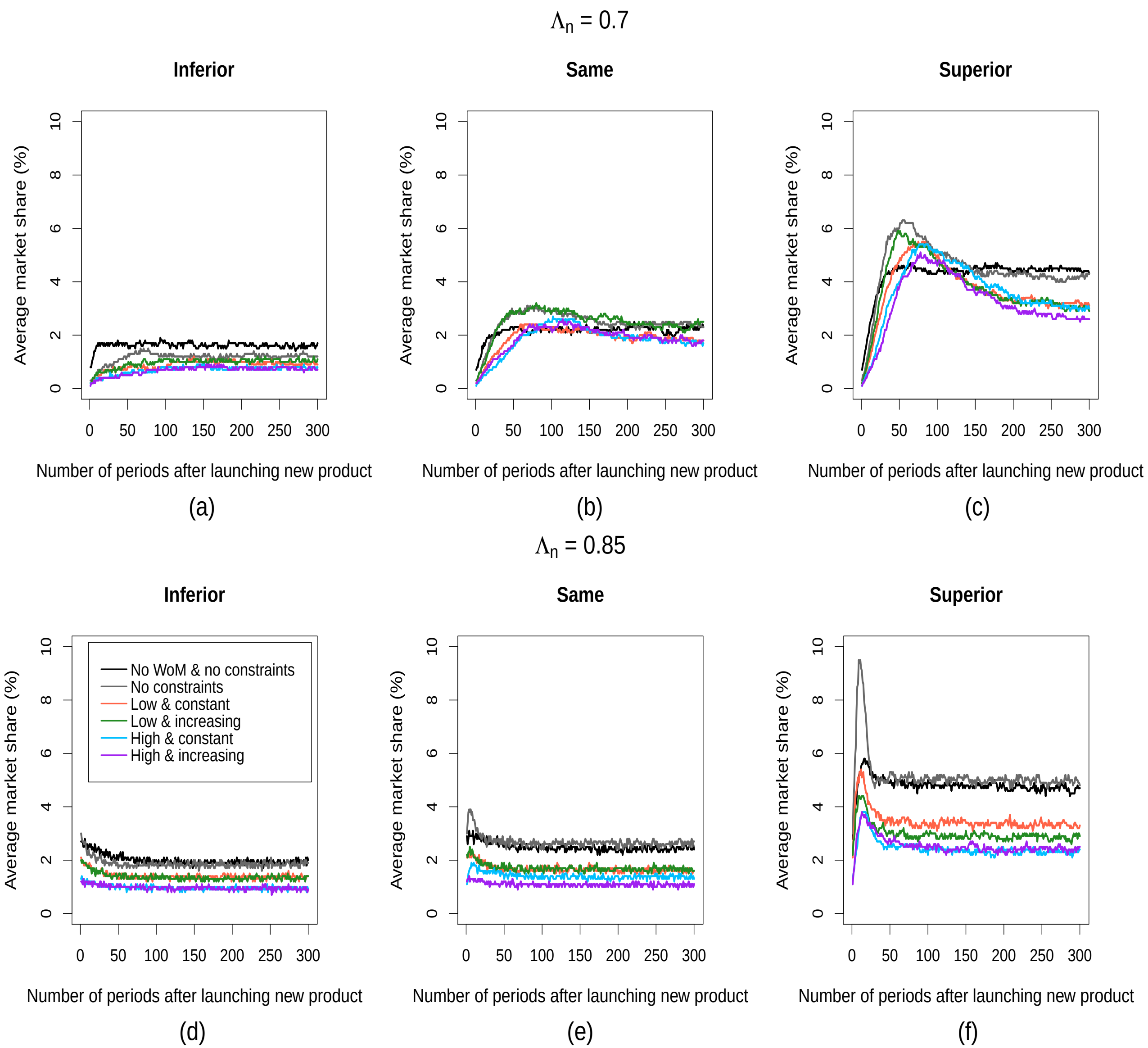


Figure 6.6: Average market share of the new product per time period ($\langle k \rangle = 5$)

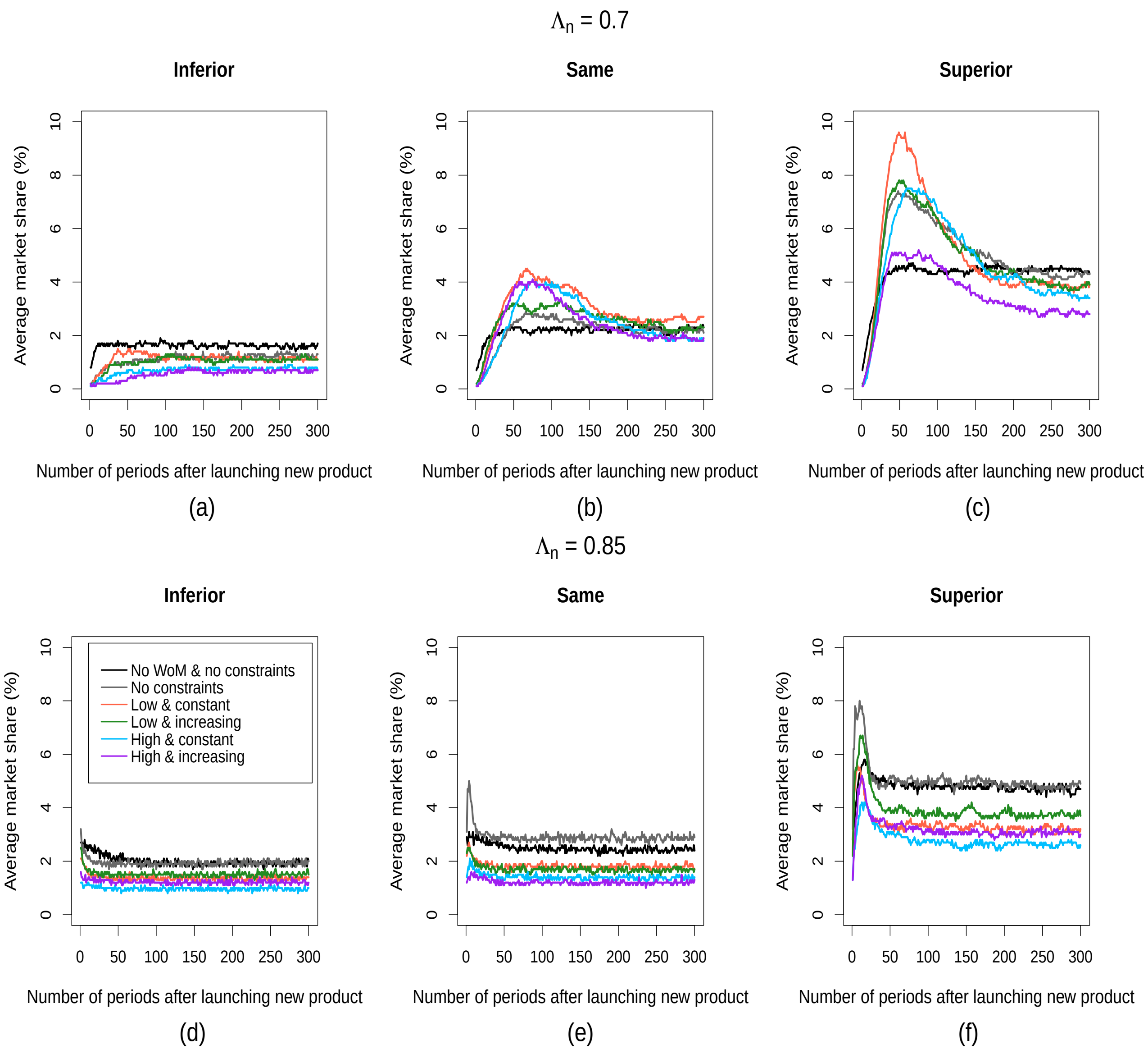


Figure 6.7: Average market share of the new product per time period ($\langle k \rangle = 15$)

Table 6.2 shows the results of the ANOVA that was performed to test (at the 5% significance level) the effects of the quality of the new product (*quality*); the presence of products that have switching constraints ($constraints_{existing}$); the fussiness of consumers (Λ_n) and the average degree of the network ($\langle k \rangle$) on the market share (%) of the new product. The market share was averaged over time periods $t_{250} - t_{350}$. Only the two-way interactions involving *quality*, $constraints_{existing}$ and Λ_n are significant, albeit not highly significant. These are summarised below.

Table 6.2: ANOVA model to test the effects of the quality of the new product (*quality*); the presence of products that have switching constraints ($constraints_{existing}$); the fussiness of consumers (Λ_n) and the average degree of the network ($\langle k \rangle$) on the market share (%) of the new product when it is launched without switching constraints

	Df	Sum Sq	Mean Sq	F value	Pr(> F)
$quality$	2	1597	798.3	270.957	$< 2e-16$
$constraints_{existing}$	4	302	75.5	25.639	$< 2e-16$
Λ_n	1	3	2.5	0.849	0.35698
$\langle k \rangle$	1	17	16.6	5.637	0.0177
$quality \times constraints_{existing}$	8	48	6	2.033	0.03934
$quality \times \Lambda_n$	2	48	23.9	8.117	0.00031
$constraints_{existing} \times \Lambda_n$	4	52	13	4.396	0.00154
$quality \times \langle k \rangle$	2	8	4.1	1.377	0.25265
$constraints_{existing} \times \langle k \rangle$	4	5	1.1	0.387	0.81815
$\Lambda_n \times \langle k \rangle$	1	0	0.1	0.02	0.88754
$quality \times constraints_{existing} \times \Lambda_n$	8	17	2.2	0.74	0.65579
$quality \times constraints_{existing} \times \langle k \rangle$	8	11	1.4	0.475	0.87457
$quality \times \Lambda_n \times \langle k \rangle$	2	1	0.4	0.148	0.86262
$constraints_{existing} \times \Lambda \times \langle k \rangle$	4	8	2.1	0.707	0.58688
$quality \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	8	4	0.5	0.16	0.9958
Residuals	1740	5127	2.9		

$quality \times \Lambda_n$ *interaction*: Launching the new product with a better quality generally results in a higher market share. The increase in its market share is larger in an unfussy market when its quality improves from inferior to to the same as that of the existing products. The quality of the new product has a larger effect on its market share when consumers are unfussy which is counter-intuitive since it would be expected that the fussier the market is, the more important the quality of the product would be.

In general, the market share of the new product is higher in an unfussy market when it is of the same or of a superior quality and lower when it of an inferior quality than it is in a fussy market. In an unfussy market, consumers use satisfying products for longer and WoM continues to be influential for longer periods. Thus, when the product is of a better quality, it can maintain a higher market share because (1) it is likely to be used for several periods and (2) PWoM is likely to be disseminated about it which drives demand for it as can be seen in the higher peaks in its market share when it is of the same or of a superior quality, more especially when the network is dense (Figures 6.6 and 6.7 b, c, e and f). When it is of a worse quality, it is likely to be dissatisfying which makes consumers switch and NWoM is likely to be disseminated about it which deters other consumers from using it. This can also be seen in Figures 1 and 2 in Appendix B. The steady decline in the market share, which is more evident when the new product is of a superior quality, is attributable to habituation. Habituation has the effect of reducing the gains in market share that are as a result of PWoM.

$constraints_{existing} \times \Lambda_n$ *interaction*: Launching the new product into a market in which there are products that have switching constraints generally results in a lower market share compared to when it is launched into a market in which there are no products that have switching constraints. The difference in its market share is larger in a fussy market than in an unfussy market especially when it is launched into a market in which there are products that have switching constraints that are high (be they high and constant or high and increasing).

The market share of the new product is generally higher in a fussy market than it is in an unfussy market when there are no products that have switching constraints in the market and generally lower when there are products that have switching constraints in the market. When there are no products that have switching constraints in the market, the higher rate of churn in a fussy market results in a larger of pool of potential consumers from which the new product can gain market share. When there are products that have switching constraints in the market, on the other hand, the higher rate of churn in a fussy market results in a larger proportion of consumers getting locked-in which reduces the pool of potential consumers for all the products and this in turn results in a smaller pool of potential consumers from which the new product can gain market share.

$quality \times constraints_{existing}$ *interaction*: The increase in the market share of the new product as a result of an improvement in its quality is larger when it is launched into a market in which there are no products that have switching constraints than when it is launched into a market in which there are products that have switching constraints. The increase in it is market share is largest when it is quality improves from the same as to superior to that of the existing products.

$\langle k \rangle$: The network influences the propagation of information. As such, it determines the number of consumers that can find out about the new product through WoM communication. Because three times more consumers accept WoM when the network is dense compared to when it is sparse, the market share of the new product settles at a slightly higher level when the network is dense than it does when the network is sparse. However, this is only a scaling effect as the overall patterns in sparse networks are similar to those in dense networks.

6.2.2 Extent of the diffusion

Figures 6.8 and 6.9 show the diffusion curves of the new product which are the average cumulative number of first time users of the new product in each time period. The diffusion curves are generally concave, with the exception of the diffusion curves of scenarios 3 – 6 when the market is unfussy (Figures 6.8 and 6.9 a - c) which display more of an S-shape. The S-shape is attributable to there being fewer consumers that switch in an unfussy market which is further reduced by the presence of products that have switching constraints. The diffusion of the new product is generally faster and more extensive in a fussy market than in an unfussy market because of the higher rate of churn which results in consumers discovering the new product much sooner than they do in an unfussy market. In terms of diffusion, these results demonstrate that entry into a market in which consumers are faced with switching constraints may be more difficult when the rate of churn in that market is low and may be easier when the rate of churn is high as asserted by Klemperer (1995). In an unfussy market, which already has only a few consumers switching per time period, switching constraints make it difficult for the new product to reach more consumers as can be seen from the slower and less extensive diffusion of the new product. In a fussy market, on the other hand, which has a higher number of consumers switching per time period, the new product reaches at least 80% of the market despite the fact that there are more consumers locked-in than in an unfussy market.

In scenario 2 of an unfussy market, the diffusion of the new product is generally faster in a sparse network than in a dense network when it is of the same or of an inferior quality and similar in both networks when it is of a superior quality. In scenarios 3 – 6 of an unfussy market, the diffusion of the new product is generally faster in a dense network than in a sparse network when it is of the same or of a superior quality and vice versa when it is of an inferior quality. In a fussy market, the diffusion of the new product happens at a similar speed in both dense and sparse networks.

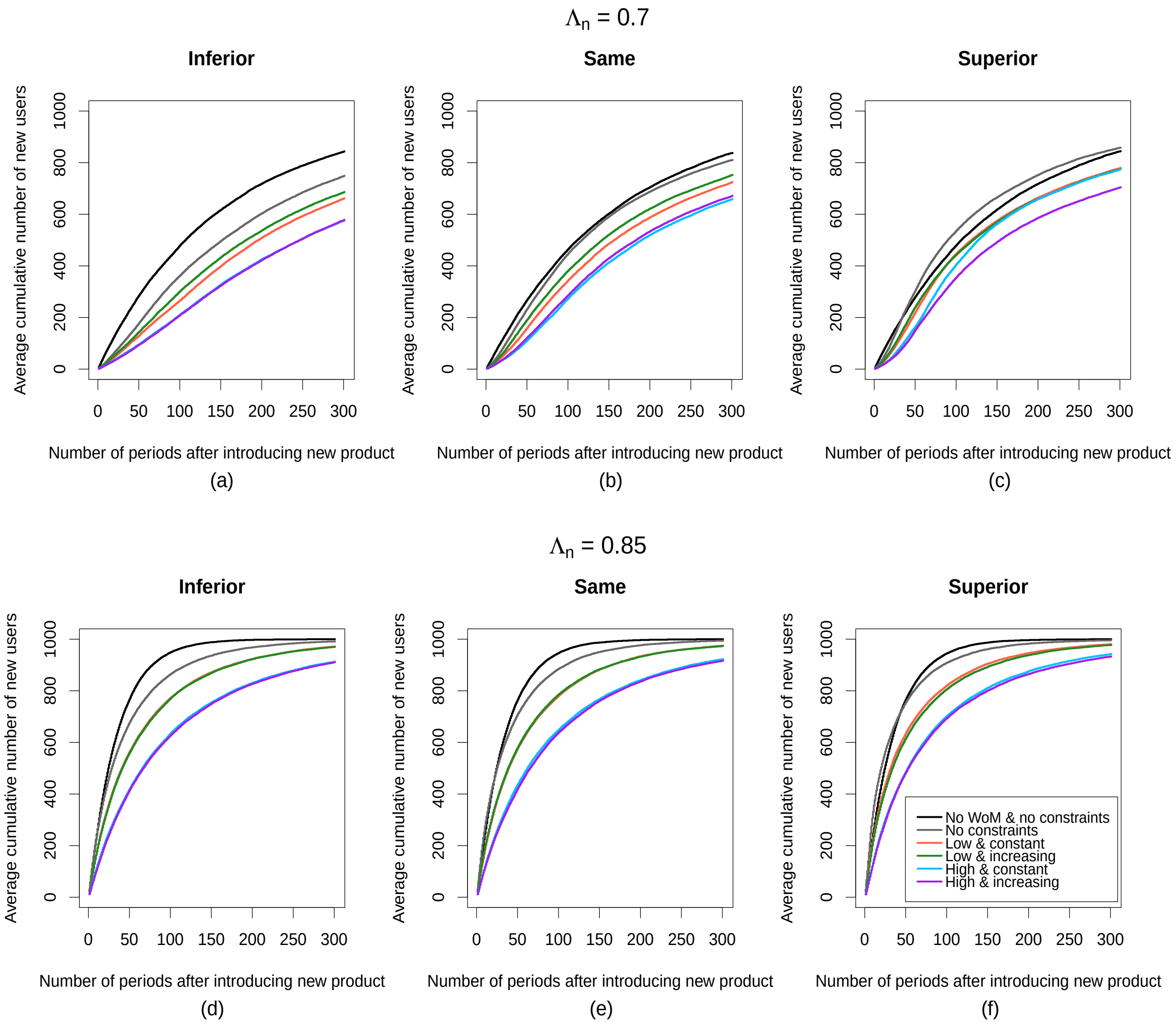


Figure 6.8: Average cumulative number of first time users of the new product ($\langle k \rangle = 5$)

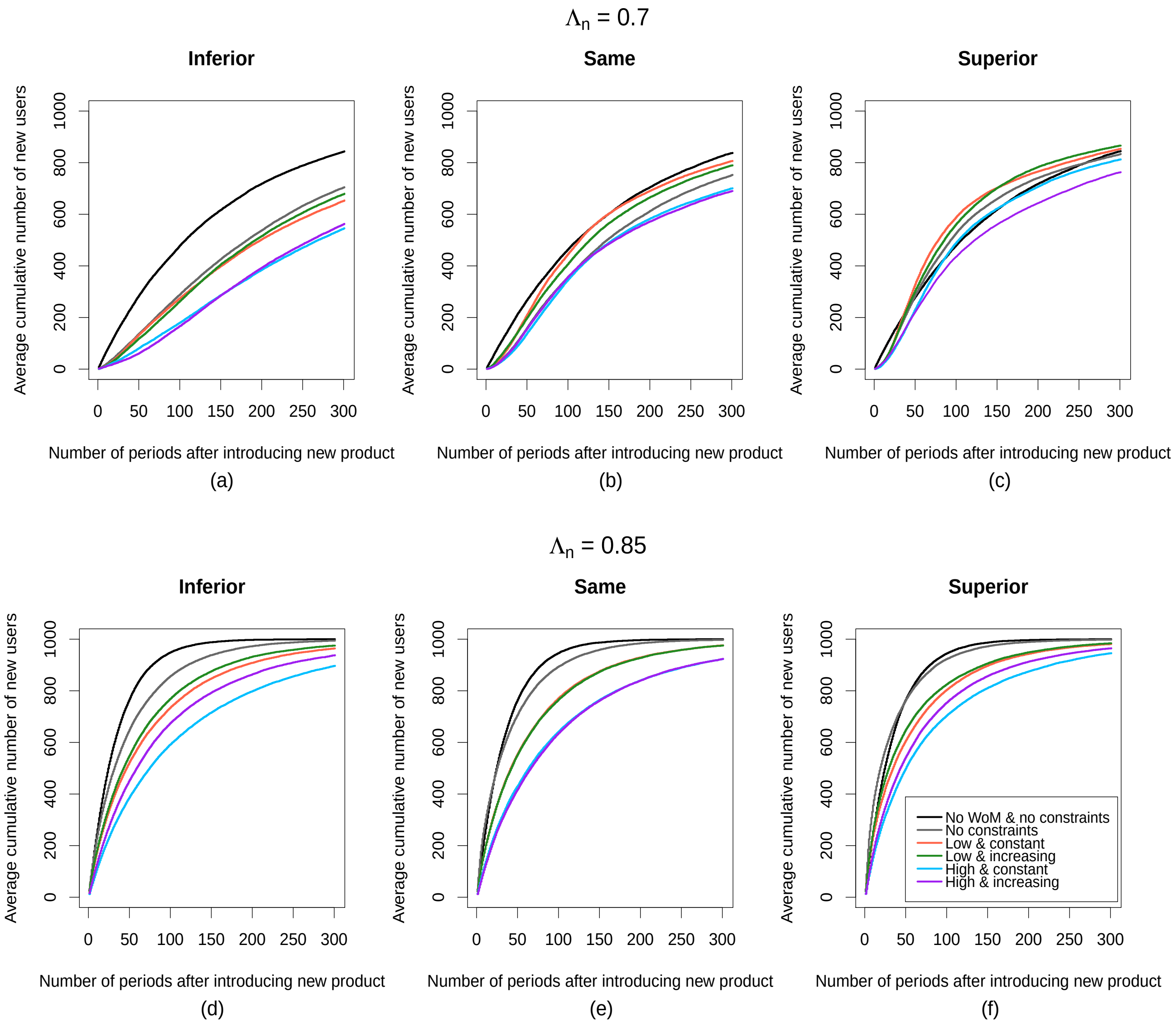


Figure 6.9: Average cumulative number of first time users of the new product ($\langle k \rangle = 15$)

Table 6.3 shows the results of the ANOVA that was performed to test (at the 5% significance level) the effects of the quality of the new product (*quality*); the presence of products that have switching constraints ($constraints_{existing}$); the fussiness of consumers (Λ_n) and the average degree of the network ($\langle k \rangle$) on the extent of the diffusion of the new product. Here, the interactions involving $\langle k \rangle$ are significant which is expected since the network determines the propagation of information and this determines the amount of information that consumers receive about the new product which, in turn, influences whether consumers will try the product or not. Two three-way interactions are significant but again, these interactions are not highly significant. These interactions are summarised below.

Table 6.3: ANOVA model to test the effects of the quality (*quality*) of the new product; the presence of products that have switching constraints ($constraints_{existing}$); the fussiness of consumers (Λ_n) and the average degree of the network ($\langle k \rangle$) on the extent of the diffusion of the new product when it is launched without switching constraints

	Df	Sum Sq	Mean Sq	F value	Pr($> F$)
$quality$	2	2440457	1220229	95.397	$< 2e-16$
$constraints_{existing}$	4	2532034	633009	49.488	$< 2e-16$
Λ_n	1	24655412	24655412	1927.554	$< 2e-16$
$\langle k \rangle$	1	52412	52412	4.098	0.0431
$quality \times constraints_{existing}$	8	209117	26140	2.044	0.03828
$quality \times \Lambda_n$	2	1599013	799507	62.505	$< 2e-16$
$constraints_{existing} \times \Lambda_n$	4	202965	50741	3.967	0.00329
$quality \times \langle k \rangle$	2	107587	53793	4.206	0.01506
$constraints_{existing} \times \langle k \rangle$	4	123626	30906	2.416	0.04687
$\Lambda_n \times \langle k \rangle$	1	16629	16629	1.3	0.25436
$quality \times constraints_{existing} \times \Lambda_n$	8	84814	10602	0.829	0.57708
$quality \times constraints_{existing} \times \langle k \rangle$	8	44838	5605	0.438	0.89857
$quality \times \Lambda_n \times \langle k \rangle$	2	77371	38685	3.024	0.04884
$constraints_{existing} \times \Lambda_n \times \langle k \rangle$	4	127617	31904	2.494	0.04121
$quality \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	8	27281	3410	0.267	0.97659
Residuals	1740	22256407	12791		

$constraints_{existing} \times \Lambda_n \times \langle k \rangle$ *interaction*: Launching the new product into a market in which there are products that have switching constraints generally results in a less extensive diffusion compared to when it is launched into a market in which there are no products that have switching constraints. The difference in the extent of its diffusion is larger when it is launched into a market in which there are products that have switching constraints that are high (be they high and constant or high and increasing). This difference is larger in an unfussy market than it is in a fussy market and is larger in a sparse network than it is in a dense network.

$quality \times \Lambda_n \times \langle k \rangle$ *interaction*: Launching the new product with a better quality generally results in a more extensive diffusion. The difference in the extent of its diffusion as its quality improves is larger in an unfussy market than in a fussy market. This difference is larger in a dense network than in a sparse network.

In a fussy market, the new product reaches relatively the same number of consumers irrespective of its quality. Comparing the extent of its diffusion in a dense network to the extent of its diffusion in a sparse network when the market is unfussy, the new product generally reaches more consumers when it is of the same or of a superior quality and fewer consumers when it is of an inferior quality to that of the existing products. Consumers have more information about the performance they can expect from the products in the market when they are densely connected than when they are sparsely connected. Thus, the new product reaches more consumers when it is of a better quality because more PWoM is likely to be disseminated to more consumers which increases its chances of being discovered. This can also be seen in Figures 3 and 4 in Appendix B.

$quality \times constraints_{existing}$ *interaction*: The increase in the extent of the diffusion of the new product as a result of an improvement in its quality is larger when it is launched into a market in which there are products that have switching constraints that are high and constant.

6.3 Launching a new product with switching constraints

An interesting question is whether launching the new product with switching constraints when there are products that have switching constraints facilitates its market penetration. This is discussed below.

6.3.1 Market share

When there are products that have switching constraints in the market, it is generally beneficial to launch the new product with switching constraints as this results in a higher market share compared to when it is launched without switching constraints (Table 6.4). This is more so the case when it is launched with switching constraints that are high than when it is launched with switching constraints that are low. This can also be seen in Figures 5 – 12 in Appendix C. The maximum market share that it is able to obtain ranges from 2% higher when it is of an inferior quality and it is launched with switching constraints that are low to as much as 20% higher when it is of a superior quality and it is launched with switching constraints that are high. It generally obtains a higher market share when it is launched into a market in which there are products that have switching constraints that are low than when it is launched into a market in which there are products that have switching constraints that are high. When it is launched into a market in which there are products that have switching constraints that are low, its market share settles between 2% and 6% higher as its quality improves when it is launched with switching constraints that are low and between 5% and 12% higher as its quality improves when it is launched with switching constraints that are high. When it is launched into a market in which there are products that have switching constraints that are high, its market share settles between 2% and 4% higher as its quality improves when it is launched with switching constraints that are low and between 5% and 10% higher as its quality improves when it is launched with switching constraints that are high.

Table 6.4: Average market share of the new product (%) from time $t_{250} - t_{350}$ with the maximum market share that it obtains in parentheses

		Quality of new product: Inferior				Quality of new product: Same				Quality of new product: Superior			
		$\langle k \rangle = 5$		$\langle k \rangle = 15$		$\langle k \rangle = 5$		$\langle k \rangle = 15$		$\langle k \rangle = 5$		$\langle k \rangle = 15$	
Switching constraints		$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$
No WoM/constraints		1.6 (1.9)	1.9 (2.8)			2.2 (2.5)	2.4 (3.1)			4.5 (4.7)	4.7 (5.8)		
No constraints		1.2 (1.5)	1.8 (3)	1.3 (1.4)	1.9 (3.2)	2.4 (3.1)	2.6 (3.9)	2.2 (2.9)	2.9 (5)	4.2 (6.3)	5 (9.5)	4.3 (7.4)	4.8 (8)
Existing	New	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$
lc	None	0.9 (1.2)	1.4 (2.1)	1.1 (1.5)	1.4 (2.1)	1.9 (2.4)	1.6 (2.3)	2.6 (4.5)	1.8 (2.7)	3.2 (5.5)	3.3 (5.4)	3.9 (9.6)	3.2 (5.6)
	lc	4 (4.2)	4.7 (6.1)	3.7 (4)	3.6 (4.2)	6 (8.5)	6.1 (8.1)	4.2 (4.4)	6.4 (8.2)	7.8 (13.5)	10.7 (17.1)	6.1 (10.9)	10.1 (15.6)
	li	4.4 (4.6)	4.3 (5.4)	4.5 (4.7)	4 (4.7)	6.7 (9.6)	7.5 (10.5)	4.4 (4.6)	6.7 (8.5)	7.9 (14.7)	8.7 (13.6)	6.2 (13.3)	8.5 (11.8)
	hc	8.1 (8.3)	8.9 (13)	8.1 (8.4)	9.5 (12.6)	9.5 (13.5)	13.6 (19.9)	9.2 (11.5)	13.9 (20.1)	9.9 (15.8)	16.6 (26.3)	10.8 (16.4)	14.6 (21.8)
	hi	8.2 (8.5)	10 (14.1)	7.6 (7.9)	10.3 (13.4)	8.9 (11.8)	9.2 (14)	10.1 (12.8)	10.9 (15.7)	11.2 (16.1)	13.1 (20.4)	11.2 (15.3)	16 (25.5)
li	None	1.1 (1.2)	1.3 (2)	1.1 (1.3)	1.5 (2.5)	2.4 (3.2)	1.7 (2.5)	2.3 (3.3)	1.7 (2.5)	3.1 (5.9)	2.9 (4.4)	3.9 (7.8)	3.7 (6.7)
	lc	3.3 (3.6)	4.1 (5.3)	4.8 (5.1)	4.1 (4.8)	3.7 (4)	6 (9)	5 (5.2)	7.9 (11.5)	6.6 (9.9)	8.6 (13.2)	6.4 (9.8)	11.3 (18)
	li	4.9 (5.1)	4 (5.1)	3.8 (4.2)	2.6 (3.1)	4.9 (5.7)	6.4 (8.9)	5.1 (7.4)	4.9 (6.4)	6.1 (10.4)	8.2 (13.2)	7.3 (16.5)	6.2 (9.4)
	hc	6.6 (6.8)	10.7 (14.6)	8.1 (8.2)	10.2 (13.9)	9.5 (12.3)	12.5 (18.3)	9 (11)	12.3 (18.2)	11.7 (21.9)	17.2 (26.9)	11.3 (20.4)	16.1 (26.2)
	hi	5.8 (6.3)	7.1 (10.6)	7.2 (7.5)	4.6 (6)	9.4 (13.7)	8.1 (12.5)	7.4 (13.2)	9.6 (15)	10.7 (24.4)	13.6 (25.1)	8.8 (17.8)	12.8 (21)
hc	None	0.8 (0.9)	0.9 (1.4)	0.8 (0.9)	1 (1.2)	1.8 (2.7)	1.4 (1.9)	2 (4.1)	1.4 (2.1)	3.1 (5.4)	2.3 (3.8)	3.7 (7.5)	2.7 (4.2)
	lc	3.7 (3.9)	4.1 (4.9)	2.9 (3.1)	3.6 (3.9)	5.1 (6.3)	4.9 (6)	4.3 (4.7)	5.6 (7)	4.7 (5.5)	7.6 (11.1)	5.7 (12.5)	6.7 (9.9)
	li	3.5 (3.8)	2.3 (2.7)	2.5 (2.8)	2.9 (3.3)	3.2 (3.5)	4.4 (5.5)	3.4 (4.8)	5.2 (6.7)	5.6 (6.9)	9 (14.8)	5.7 (13.3)	7.3 (10.8)
	hc	6.3 (6.6)	6.3 (8.3)	7.6 (7.9)	6.4 (8)	10.2 (12.4)	10.9 (15.2)	7.5 (7.8)	11.2 (15)	9.3 (15.1)	12.4 (19.7)	9.7 (16.3)	13.6 (20.5)
	hi	5.8 (6)	8.1 (11)	7.4 (7.7)	6.4 (7.7)	7.9 (8.4)	9.9 (14.2)	8.6 (9.5)	10.1 (14.6)	9.1 (15)	13.1 (20)	9.2 (15.7)	11.4 (16.5)
hi	None	0.7 (0.9)	0.9 (1.3)	0.7 (0.8)	1.2 (1.6)	1.8 (2.6)	1.1 (1.4)	1.9 (4.1)	1.2 (1.6)	2.7 (5.1)	2.4 (3.8)	2.9 (5.2)	3.1 (5.2)
	lc	2.7 (3)	3 (3.5)	3.4 (3.6)	4.1 (4.9)	4.8 (5.8)	4.1 (5.3)	4.5 (5.9)	5.4 (6.7)	5.1 (6.7)	5.2 (6.9)	5.4 (10.9)	6.6 (9.6)
	li	2.9 (3.1)	2.2 (2.6)	3.4 (3.7)	1.9 (2.2)	4.2 (4.4)	4.8 (5.9)	3.3 (4.9)	3.9 (5)	5.4 (8.4)	7.2 (10.6)	4.7 (8.3)	7.6 (11.7)
	hc	6.8 (7)	6.9 (9.1)	6.5 (6.8)	9 (11.9)	7.4 (8.7)	10.1 (15)	8 (8.9)	8.7 (11.8)	9.3 (14.3)	12.6 (19)	9.6 (18.7)	11.7 (18.4)
	hi	4.5 (4.7)	5.2 (7.1)	6.1 (6.6)	4.8 (6.4)	8.2 (12)	6.9 (10.4)	8.1 (12.5)	8 (11.8)	8 (12)	12.4 (19.8)	6.7 (13.7)	9.1 (15.5)

Note: lc = low & constant, li = low & increasing, hc = high & constant, hi = high & increasing

Table 6.5 shows the results of the ANOVA that was performed to test (at the 5% significance level) the effects of the quality of the new product (*quality*); the switching constraints of the new product ($constraints_{new}$); the presence of products that have switching constraints ($constraints_{existing}$); the fussiness of consumers (Λ_n) and the average degree of the network ($\langle k \rangle$) on the market share (%) of the new product. The market share was averaged over $t_{250} - t_{350}$. Each of the factors are involved in significant three-way interactions with $quality \times constraints_{new} \times \Lambda_n$ being highly significant. These interactions are summarised below.

Table 6.5: ANOVA model for the effects of the quality of the new product (*quality*); the switching constraints of the new product ($constraints_{new}$); the presence of products that have switching constraints ($constraints_{existing}$); Λ_n and $\langle k \rangle$ on the market share (%) of the new product when it is launched with switching constraints

	Df	Sum Sq	Mean Sq	F value	Pr($> F$)
$quality$	2	15123	7561	429.605	$< 2e-16$
$constraints_{new}$	4	60782	15195	863.348	$< 2e-16$
$constraints_{existing}$	3	3731	1244	70.654	$< 2e-16$
Λ_n	1	2538	2538	144.182	$< 2e-16$
$\langle k \rangle$	1	3	3	0.17	0.68028
$quality \times constraints_{new}$	8	841	105	5.971	1.16e-07
$quality \times constraints_{existing}$	6	195	32	1.846	0.08625
$constraints_{new} \times constraints_{existing}$	12	1243	104	5.886	2.79e-10
$quality \times \Lambda_n$	2	1109	554	31.495	2.42e-14
$constraints_{new} \times \Lambda_n$	4	1717	429	24.382	$< 2e-16$
$constraints_{existing} \times \Lambda_n$	3	202	67	3.823	0.00948
$quality \times \langle k \rangle$	2	15	8	0.43	0.65081
$constraints_{new} \times \langle k \rangle$	4	141	35	2.006	0.09076
$constraints_{existing} \times \langle k \rangle$	3	9	3	0.169	0.91728
$\Lambda_n \times \langle k \rangle$	1	0	0	0	0.98319
$quality \times constraints_{new} \times constraints_{existing}$	24	700	29	1.657	0.02289
$quality \times constraints_{new} \times \Lambda_n$	8	717	90	5.095	2.42e-06
$quality \times constraints_{existing} \times \Lambda_n$	6	45	8	0.428	0.86075
$constraints_{new} \times constraints_{existing} \times \Lambda_n$	12	438	37	2.075	0.01545
$quality \times constraints_{new} \times \langle k \rangle$	8	181	23	1.283	0.24702
$quality \times constraints_{existing} \times \langle k \rangle$	6	40	7	0.382	0.89115
$constraints_{new} \times constraints_{existing} \times \langle k \rangle$	12	400	33	1.894	0.03035
$quality \times \Lambda_n \times \langle k \rangle$	2	92	46	2.607	0.07386
$constraints_{new} \times \Lambda_n \times \langle k \rangle$	4	48	12	0.682	0.6043
$constraints_{existing} \times \Lambda_n \times \langle k \rangle$	3	34	11	0.636	0.59176
$quality \times constraints_{new} \times constraints_{existing} \times \Lambda_n$	24	462	19	1.095	0.33969
$quality \times constraints_{new} \times constraints_{existing} \times \langle k \rangle$	24	293	12	0.693	0.86328
$quality \times constraints_{new} \times \Lambda_n \times \langle k \rangle$	8	167	21	1.188	0.30195
$quality \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	6	74	12	0.704	0.6463
$constraints_{new} \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	12	245	20	1.161	0.30498
$quality \times constraints_{new} \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	24	484	20	1.146	0.28243
Residuals	6960	122500	18		

$quality \times constraints_{new} \times \Lambda_n$ and $quality \times constraints_{new} \times constraints_{existing}$ interactions: As noted above, launching the new product with a better quality generally results in a higher market share. The difference in its market share as its quality improves is larger when it is launched with switching constraints that are high and constant. This difference is larger in a fussy market than in an unfussy market and when it is launched into a market in which there are products that have switching constraints that are low

and constant.

A better quality increases the chances of the new product being used while switching constraints prevent consumers from switching, especially when they are high. Thus the switching constraints of the new product enable it to maintain a higher market share in a fussy market where satisfying products very quickly become dissatisfying.

$constraints_{new} \times constraints_{existing} \times \Lambda_n$ and $constraints_{new} \times constraints_{existing} \times \langle k \rangle$ *interactions*: Launching the new product with switching constraints that are high and constant into a market in which there are products that have switching constraints that are low and constant results in a larger increase in its market share. This effect is larger in a fussy market than in an unfussy market and when the network is dense than when it is sparse.

6.3.2 Extent of the diffusion

The new product generally reaches fewer consumers when it is launched with switching constraints than when it is launched without switching constraints (Table 6.6). This is more so the case when it is launched with switching constraints that are high than when it is launched with switching constraints that are low. This can also be seen in Figures 13 – 20 in Appendix C. It generally reaches more consumers when it is launched into a market in which there are products that have switching constraints that are low than when it is launched into a market in which there are products that have switching constraints that are high.

Table 6.6: Extent of the diffusion of the new product with standard errors in parentheses

		Quality of new product: Inferior				Quality of new product: Same				Quality of new product: Superior			
		$\langle k \rangle = 5$		$\langle k \rangle = 15$		$\langle k \rangle = 5$		$\langle k \rangle = 15$		$\langle k \rangle = 5$		$\langle k \rangle = 15$	
Switching constraints		$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$
No WoM/constraints		843 (39)	1000 (0)			837 (39)	1000 (1)			844 (45)	1000 (0)		
No constraints		748 (112)	991 (7)	704 (130)	994 (5)	810 (98)	994 (7)	752 (167)	997 (4)	858 (103)	996 (6)	833 (179)	998 (2)
Existing	New	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$	$\Lambda_n = 0.7$	$\Lambda_n = 0.85$
lc	None	661 (96)	971 (20)	652 (166)	964 (29)	724 (133)	975 (17)	806 (169)	976 (22)	779 (149)	981 (14)	853 (161)	981 (18)
	lc	651 (79)	972 (19)	582 (99)	975 (15)	714 (99)	978 (17)	610 (133)	979 (18)	774 (108)	982 (16)	697 (131)	986 (10)
	li	648 (105)	975 (14)	618 (112)	968 (26)	733 (96)	978 (17)	625 (136)	978 (20)	760 (126)	981 (15)	713 (155)	982 (20)
	hc	637 (59)	971 (20)	581 (92)	978 (17)	685 (99)	972 (23)	608 (116)	981 (14)	691 (120)	979 (21)	659 (133)	983 (15)
	hi	629 (75)	968 (32)	561 (114)	975 (16)	652 (105)	969 (22)	634 (132)	978 (14)	699 (99)	982 (13)	658 (127)	985 (13)
li	None	685 (102)	970 (18)	678 (121)	975 (22)	752 (142)	973 (20)	737 (154)	980 (17)	775 (154)	977 (17)	866 (137)	982 (19)
	lc	643 (96)	971 (20)	628 (111)	971 (25)	649 (78)	970 (20)	624 (99)	978 (23)	726 (117)	982 (12)	704 (158)	985 (11)
	li	678 (81)	977 (24)	625 (117)	977 (21)	699 (79)	987 (11)	673 (122)	979 (17)	749 (102)	978 (21)	764 (147)	982 (23)
	hc	613 (75)	977 (15)	550 (95)	976 (20)	674 (86)	980 (9)	610 (118)	977 (17)	740 (106)	982 (17)	719 (125)	984 (13)
	hi	663 (96)	977 (19)	602 (107)	973 (27)	703 (106)	978 (14)	674 (127)	986 (13)	780 (118)	986 (12)	705 (152)	987 (14)
hc	None	575 (125)	912 (38)	545 (151)	896 (43)	658 (173)	922 (39)	700 (227)	923 (51)	774 (137)	942 (36)	812 (201)	945 (40)
	lc	571 (106)	928 (39)	514 (76)	920 (40)	620 (121)	930 (37)	558 (136)	935 (40)	612 (123)	935 (41)	664 (154)	948 (39)
	li	540 (82)	918 (37)	487 (103)	918 (52)	560 (102)	917 (44)	538 (126)	911 (63)	640 (106)	957 (23)	667 (151)	952 (35)
	hc	533 (73)	924 (42)	509 (103)	916 (58)	593 (106)	934 (32)	533 (99)	927 (52)	616 (127)	927 (49)	587 (136)	947 (25)
	hi	486 (62)	922 (36)	502 (109)	923 (35)	566 (98)	933 (36)	559 (126)	933 (40)	642 (114)	943 (27)	592 (144)	938 (36)
hi	None	577 (118)	911 (47)	562 (150)	937 (41)	642 (123)	916 (41)	690 (238)	953 (29)	704 (207)	933 (41)	699 (232)	964 (30)
	lc	526 (90)	913 (43)	487 (97)	932 (41)	615 (101)	923 (36)	566 (130)	934 (43)	628 (137)	935 (40)	622 (164)	945 (34)
	li	586 (118)	946 (28)	539 (110)	932 (38)	605 (91)	948 (40)	561 (129)	952 (43)	684 (124)	961 (29)	627 (181)	965 (31)
	hc	532 (85)	910 (36)	477 (108)	925 (44)	546 (99)	925 (46)	531 (116)	930 (39)	610 (105)	939 (25)	624 (151)	932 (35)
	hi	541 (89)	942 (27)	523 (119)	942 (30)	635 (120)	956 (23)	599 (131)	951 (26)	660 (94)	971 (24)	618 (162)	961 (29)

Note: lc = low & constant, li = low & increasing, hc = high & constant, hi = high & increasing

Table 6.7 shows the results of the ANOVA that was performed to test (at the 5% significance level) the effects of the quality of the new product (*quality*); the switching constraints of the new product ($constraints_{new}$); the presence of products that have switching constraints ($constraints_{existing}$); the fussiness of consumers (Λ_n) and the average degree of the network ($\langle k \rangle$) on the extent of the diffusion of the new product. The three-way interactions involving *quality*, $constraints_{new}$, Λ_n and $constraints_{existing}$ are significant with the $constraints_{new} \times \Lambda_n \times \langle k \rangle$ being highly significant.

Table 6.7: ANOVA model for the effects of the quality of the new product (*quality*); the switching constraints of the new product ($constraints_{new}$); the presence of products that have switching constraints ($constraints_{existing}$); Λ_n and $\langle k \rangle$ on the extent of the diffusion of the new product when it is launched with switching constraints

	Df	Sum Sq	Mean Sq	F value	Pr($> F$)
$quality$	2	5475413	2737707	327.295	$< 2e-16$
$constraints_{new}$	4	2312886	578221	69.127	$< 2e-16$
$constraints_{existing}$	3	8070394	2690131	321.608	$< 2e-16$
Λ_n	1	179456828	179456828	21454.234	$< 2e-16$
$\langle k \rangle$	1	209596	209596	25.057	5.70e-07
$quality \times constraints_{new}$	8	355118	44390	5.307	1.17e-06
$quality \times constraints_{existing}$	6	97698	16283	1.947	0.06966
$constraints_{new} \times constraints_{existing}$	12	374379	31198	3.73	1.18e-05
$quality \times \Lambda_n$	2	3146866	1573433	188.105	$< 2e-16$
$constraints_{new} \times \Lambda_n$	4	2755456	688864	82.354	$< 2e-16$
$constraints_{existing} \times \Lambda_n$	3	992881	330960	39.567	$< 2e-16$
$quality \times \langle k \rangle$	2	92908	46454	5.554	0.00389
$constraints_{new} \times \langle k \rangle$	4	386512	96628	11.552	2.39e-09
$constraints_{existing} \times \langle k \rangle$	3	32950	10983	1.313	0.2682
$\Lambda_n \times \langle k \rangle$	1	314543	314543	37.604	9.14e-10
$quality \times constraints_{new} \times constraints_{existing}$	24	278237	11593	1.386	0.09918
$quality \times constraints_{new} \times \Lambda_n$	8	272808	34101	4.077	7.41e-05
$quality \times constraints_{existing} \times \Lambda_n$	6	33562	5594	0.669	0.675
$constraints_{new} \times constraints_{existing} \times \Lambda_n$	12	164935	13745	1.643	0.07289
$quality \times constraints_{new} \times \langle k \rangle$	8	144881	18110	2.165	0.02707
$quality \times constraints_{existing} \times \langle k \rangle$	6	10044	1674	0.2	0.97684
$constraints_{new} \times constraints_{existing} \times \langle k \rangle$	12	116286	9691	1.159	0.30725
$quality \times \Lambda_n \times \langle k \rangle$	2	61797	30899	3.694	0.02492
$constraints_{new} \times \Lambda_n \times \langle k \rangle$	4	323096	80774	9.657	8.73e-08
$constraints_{existing} \times \Lambda_n \times \langle k \rangle$	3	43203	14401	1.722	0.16021
$quality \times constraints_{new} \times constraints_{existing} \times \Lambda_n$	24	191448	7977	0.954	0.52651
$quality \times constraints_{new} \times constraints_{existing} \times \langle k \rangle$	24	144957	6040	0.722	0.834
$quality \times constraints_{new} \times \Lambda_n \times \langle k \rangle$	8	106477	13310	1.591	0.12173
$quality \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	6	4987	831	0.099	0.99646
$constraints_{new} \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	12	125571	10464	1.251	0.24107
$quality \times constraints_{new} \times constraints_{existing} \times \Lambda_n \times \langle k \rangle$	24	146842	6118	0.731	0.82379
Residuals	6960	58217856	8365		

$constraints_{new} \times \Lambda_n \times \langle k \rangle$ *interaction*: Launching the new product with switching constraints has a larger effect in an unfussy market than in a fussy market. It results in a less extensive diffusion compared to when it is launched without switching constraints. The difference is larger in a dense network than in a sparse network. Because consumers receive information from more sources when they are densely connected and because more consumers accept WoM per time period in an unfussy market, the NWoM that consumers disseminate when they are locked-in results in fewer consumers trying the new product.

In a fussy market, the new product generally reaches the same number of consumers whether it is launched with switching constraints or it is launched without switching constraints. In an unfussy market, on the other hand, it generally reaches a similar number of consumers when it is launched with switching constraints (be they low or high). The number of consumers that it reaches when it is launched with switching constraints is lower than when it is launched without switching constraints especially when consumers are densely connected.

$quality \times constraints_{new} \times \Lambda_n$ and $quality \times constraints_{new} \times \langle k \rangle$ *interactions*: An improvement in quality has a larger effect on the extent of the diffusion of the new product when it is launched without switching constraints than when it is launched with switching constraints. This effect is larger in an unfussy market than in a fussy market and in a dense network than in a sparse network.

$quality \times \Lambda_n \times \langle k \rangle$ *interaction*: An improvement in quality results in a larger difference in the extent of the diffusion of the new product in an unfussy market than in a fussy market. This difference is larger when the network is dense than when it is sparse.

$constraints_{existing} \times \Lambda_n$ *interaction*: The new product reaches fewer consumers when it is launched into a market in which there are products that have switching constraints that are high compared to when it is launched into a market in which there are products that have switching constraints that are low. The difference in the extent of its diffusion is larger in an unfussy market than in a fussy market.

$constraints_{new} \times constraints_{existing}$ *interaction*: Launching the new product with switching constraints that are high and constant results in a larger difference in the extent of its diffusion compared to when it is launched without switching constraints. This difference is larger when it is launched into a market in which there are products that have switching constraints that are high and increasing.

In sum when the new product is launched without switching constraints:

- The $quality \times \Lambda_n$ interaction is the most significant in influencing both the market share and the extent of the diffusion of the new product. The quality of the new product has less of an effect on its market share when the market is fussy and also when there are products that have switching constraints in the market. It has less of an effect on the extent of its diffusion when the market is fussy and densely connected.
- The presence of products that have switching constraints has less of an effect on the

market share of the new product when the market is unfussy and less of an effect on the extent of its diffusion when the market is fussy and densely connected.

- The network structure plays a larger role in the earlier periods when WoM is influential. The increase in the number of sources of information when consumers are densely connected leads to a higher market share, particularly when the new product is of a better quality. It also results in a faster diffusion.

When the new product is launched with switching constraints:

- The $quality \times constraints_{new} \times \Lambda_n$ interaction is the most significant in influencing its market share. The quality of the new product and launching it with switching constraints has less of an effect on its market share when the market is unfussy.
- The $constraints_{new} \times \Lambda_n \times \langle k \rangle$ interaction is the most significant in influencing the extent of its diffusion. Launching the new product with switching constraints has no effect on the extent of its diffusion when consumers are fussy , be they sparsely or densely connected. When consumers are unfussy, launching the new product with switching constraints has less of an effect on the extent of its diffusion when consumers are sparsely connected.

Chapter 7

Conclusion

Long-term success and profitability in a competitive market depends on a firm's ability to acquire and retain consumers which to a large extent depends on how well its product offerings can satisfy consumers' needs and preferences and thus prevent them from switching to a competitor. This is especially true for a new product that has to overcome the competitive advantage that existing products have.

Market dynamics are influenced by a myriad of complex, interacting factors, the full array of which would be difficult to translate into an analytical model. Agent-based modelling (ABM) provides a method to develop simple simulation models that provide useful insight into and facilitate the understanding of fundamental micro-level processes that give rise to complex macro-level phenomena. The flexibility of ABM makes it easier to design models that reflect real-world scenarios.

7.1 Summary of simulation results

The simulation results demonstrated the importance of considering factors such as product quality, consumer satisfaction, switching constraints, word-of-mouth (WoM) and network structure as there is an intricate interaction between these factors that influences market dynamics and in turn the market penetration of a new product.

The simulation results suggest that the effectiveness of a retention strategy that is aimed at ensuring consumers remain satisfied also depends on how easily consumers are satisfied. When consumers are unfussy, they are likely to find more products satisfying and use these products for a lot longer than they would when they are fussy. They are also more likely to disseminate positive WoM (PWoM) about the products that they use which assists other consumers to identify satisfying products sooner than they would through personal exploration. Also, consumers are likely to go back to using a product that they tried and found satisfying than one that they tried and found dissatisfying. All of this can lead to a dominance of a few products. In a real-world context, consumers would need some motivation to discontinue using these better performing products which would happen either as a consequence of them becoming bored of these products or because they are convinced that the alternatives in the market would yield a more satisfying experience.

In experience-goods markets consumers use WoM to determine the sort of performance that they can expect from products they have no experience of. Thus, in a market where consumers switch more frequently, WoM very quickly becomes less relevant in influencing product choices. Also, when the market is flooded with negative word-of-mouth, as is the case when consumers are fussy, WoM becomes less effective in influencing purchasing decisions. Thus, consumers try products even if they will yield a dissatisfying experience. When consumers switch less frequently, on the other hand, they have more time to gather information about the products in the market. By making it difficult for consumers to switch when they want to, products that impose switching constraints have more NWoM disseminated about them. In a market in which consumers switch more frequently, the NWoM does not deter consumers from using these products resulting in these products acquiring and sustaining a higher market share. In a market in which consumers switch less frequently, the NWoM deters consumers from using these products. Thus, in a turbulent market retention strategies may need to include switching constraints whereas in a stable market, switching constraints may work against a product.

When the market has a lower rate of churn, as is the case when consumers are unfussy or when they are faced with switching constraints, the pool of potential consumers is reduced resulting in a slower and less extensive diffusion of the new product and it acquiring a lower market share. When the new product is of a better quality though, it is able to acquire a higher market share and a more extensive diffusion since more PWoM is disseminated about it which generates demand for it. Also, when there are products that have switching constraints in the market, launching the new product with switching constraints results in a higher market share, especially when its launched with switching constraints that are high. However, it results in a less extensive diffusion, when consumers have more connections because the NWoM that consumers that are locked-in disseminate about it deters consumers that have not used it before from trying it.

7.2 Recommendations for marketing managers

Some factors such as the fussiness of consumers; the shape and size of consumers' social networks; the type of messages that consumers transmit and with whom and how often they communicate about a product may be beyond the control of marketing managers. However, these factors can potentially be influenced through a marketing strategy that encourages consumers to exchange PWoM both with consumers that are familiar with a product and those who are not.

Supposing that a new product is launched into a market in which there are no products that have switching constraints, if it is known that consumers are easy to satisfy, then market share could be maximised by ensuring that the product offers a superior performance to the products that are already in the market. This could generate PWoM which would reach a large number of people if consumers have a high number of connections. Also, this would ensure that consumers repeatedly purchase the product. A marketing strategy that creates a buzz around the product would also be beneficial as this would encourage current consumers to talk about the product to potential consumers which could be helpful in luring consumers that use other products that also yield a satisfactory performance or in luring potential consumers that are not part of the product category or in changing the minds of consumers that may think the product will not yield a satisfactory performance. When consumers are difficult to satisfy, on the other hand, launching the new product with a superior quality may be beneficial at first. However, it may not stay satisfying for long. A possible strategy could involve creating a campaign that encourages consumers to identify with the product or creating a rewards program, thus making it difficult for them to switch. In other words, a possible strategy could involve creating some form of switching constraints. Even when the fussiness of consumers is unknown, using a strategy that creates brand loyalty could maximise market share since if consumers are easy to satisfy they are likely to use the product because it yields a satisfying experience and if consumers are difficult to satisfy, they would find it difficult to switch because they have developed a psychological affinity to the product.

When there are products that have switching constraints in the market, launching a new product with a superior quality and with switching constraints may be the best way to maximise market share. When the existing products have switching constraints that are low, the new product can be launched with switching constraints that are either low or high, although, this can be detrimental if WoM stays influential for long periods. Switching constraints may result in consumers disseminating NWoM which could deter potential consumers that would have otherwise found the product satisfying from trying the product. Thus, this strategy could be coupled with a campaign that encourages consumers to communicate about the product in a positive light. When the existing products have switching constraints that are high, the best strategy would be to launch the new product with switching constraints that are high, particularly if consumers are known to be difficult to satisfy and thus switch frequently.

7.3 Future research

The model presented in this dissertation can be extended in several ways. It was assumed that products had similar attributes and were marketed in a similar way. Future research would entail incorporating different marketing strategies for each of the products in the market which would intensify competition and aid in determining which marketing strategies may work best for launching a new product given the marketing strategies of the other products in the market. Something else that may be of interest is determining whether the timing of the launch of a new product affects its diffusion and market share. Some simplifying assumptions were required in terms of consumer behaviour in order to make the model more tractable. Future research might involve allowing consumers' preferences to change; allowing for WoM to change consumers' opinions about products; allowing consumers to pass on WoM and examining its ripple effects and incorporating the strength of the relationships between consumers which could include consumers learning about the trustworthiness of other consumers over time. Future research could also entail investigating product consumption within different clusters of the network and examining the diffusion of a new product within each of those clusters.

Because the model presented in this dissertation was intended to serve as a generic model that facilitates understanding of certain processes in the marketplace, it remains to be seen how applicable it is to a real-world context. As such, future research entails validating the model assumptions using real-world data in an effort to make it more realistic and more applicable to different product markets.

References

Alkemade, F. and Castaldi, C. (2005). Strategies for the diffusion of innovations on social networks. *Computational Economics*, 25(1-2):3–23.

Allsop, D. T., Bassett, B. R., and Hoskins, J. A. (2007). Word-of-mouth research: principles and applications. *Journal of Advertising Research*, 47(4):398.

Amaral, L. A. N., Scala, A., Barthelemy, M., and Stanley, H. E. (2000). Classes of small-world networks. *Proceedings of the National Academy of Sciences*, 97(21):11149–11152.

Axelrod, R. M. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*. Princeton University Press.

Balabanis, G., Reynolds, N., and Simintiras, A. (2006). Bases of e-store loyalty: Perceived switching barriers and satisfaction. *Journal of Business Research*, 59(2):214–224.

Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *science*, 286(5439):509–512.

Bass, F. (1969). A new product growth for model consumer durables. *Management Sciences*, 15(1):215–227.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., and Hwang, D.-U. (2006). Complex networks: Structure and dynamics. *Physics reports*, 424(4):175–308.

Bohlmann, J. D., Calantone, R. J., and Zhao, M. (2010). The effects of market network heterogeneity on innovation diffusion: An agent-based modeling approach. *Journal of Product Innovation Management*, 27(5):741–760.

Bolton, R. N. (1998). A dynamic model of the duration of the customer's relationship with a continuous service provider: the role of satisfaction. *Marketing science*, 17(1):45–65.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, 99(Suppl 3):7280–7287.

Burnham, T. A., Frels, J. K., and Mahajan, V. (2003). Consumer switching costs: a typology, antecedents, and consequences. *Journal of the Academy of Marketing Science*, 31(2):109–126.

Buttle, F. A. (1998). Word of mouth: understanding and managing referral marketing. *Journal of strategic marketing*, 6(3):241–254.

Candale, T. and Sen, S. (2005). Effect of referrals on convergence to satisficing distributions. In *Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems*, pages 347–354. ACM.

Choi, H., Kim, S.-H., and Lee, J. (2010). Role of network structure and network effects in diffusion of innovations. *Industrial Marketing Management*, 39(1):170–177.

Deffuant, G., Huet, S., and Amblard, F. (2005). An individual-based model of innovation diffusion mixing social value and individual benefit1. *American Journal of Sociology*, 110(4):1041–1069.

Delre, S., Jager, W., Bijmolt, T., and Janssen, M. (2007a). Targeting and timing promotional activities: An agent-based model for the takeoff of new products. *Journal of business research*, 60(8):826–835.

Delre, S. A., Jager, W., Bijmolt, T. H., and Janssen, M. A. (2010). Will it spread or not? the effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management*, 27(2):267–282.

Delre, S. A., Jager, W., and Janssen, M. A. (2007b). Diffusion dynamics in small-world networks with heterogeneous consumers. *Computational and Mathematical Organization Theory*, 13(2):185–202.

Durbach, I. N. and Hofmeyr, J. H. (2007). Interactions between market barriers and communication networks in marketing systems. In Durfee, E. H., Yokoo, M., Huhns, M. N., and Shehory, O., editors, *AAMAS*, page 59. IFAAMAS.

East, R., Hammond, K., and Lomax, W. (2008). Measuring the impact of positive and negative word of mouth on brand purchase probability. *International Journal of Research in Marketing*, 25(3):215–224.

Epstein, J. M. (2006). Remarks on the foundations of agent-based generative social science. *Handbook of computational economics*, 2:1585–1604.

Farrell, J. and Klemperer, P. (2007). Coordination and lock-in: Competition with switching costs and network effects. *Handbook of industrial organization*, 3:1967–2072.

Fullerton, G. (2005). How commitment both enables and undermines marketing relationships. *European Journal of Marketing*, 39(11/12):1372–1388.

Fung, K. K. and Vemuri, S. (2003). The significance of initial conditions in simulations. *Journal of Artificial Societies and Social Simulation*, 6(3).

Garcia, R. (2005). Uses of agent-based modeling in innovation/new product development research*. *Journal of Product Innovation Management*, 22(5):380–398.

Goldenberg, J. and Efroni, S. (2001). Using cellular automata modeling of the emergence of innovations. *Technological Forecasting and Social Change*, 68(3):293–308.

Goldenberg, J., Libai, B., Moldovan, S., and Muller, E. (2007). The npv of bad news. *International Journal of Research in Marketing*, 24(3):186–200.

Goldenberg, J., Libai, B., and Muller, E. (2010). The chilling effects of network externalities. *International Journal of Research in Marketing*, 27(1):4–15.

Jager, W. (2007). The four p's in social simulation, a perspective on how marketing could benefit from the use of social simulation. *Journal of Business Research*, 60(8):868–875.

Janssen, M. A. and Jager, W. (2001). Fashions, habits and changing preferences: Simulation of psychological factors affecting market dynamics. *Journal of economic psychology*, 22(6):745–772.

Janssen, M. A. and Jager, W. (2003). Simulating market dynamics: Interactions between consumer psychology and social networks. *Artificial Life*, 9(4):343–356.

Jones, M. A., Mothersbaugh, D. L., and Beatty, S. E. (2000). Switching barriers and repurchase intentions in services. *Journal of retailing*, 76(2):259–274.

Jones, M. A., Mothersbaugh, D. L., and Beatty, S. E. (2002). Why customers stay: measuring the underlying dimensions of services switching costs and managing their differential strategic outcomes. *Journal of Business Research*, 55(6):441–450.

Jones, M. A., Reynolds, K. E., Mothersbaugh, D. L., and Beatty, S. E. (2007). The positive and negative effects of switching costs on relational outcomes. *Journal of Service Research*, 9(4):335–355.

Kiesling, E., Günther, M., Stummer, C., and Wakolbinger, L. M. (2012). Agent-based simulation of innovation diffusion: a review. *Central European Journal of Operations Research*, 20(2):183–230.

Klemperer, P. (1995). Competition when consumers have switching costs: An overview with applications to industrial organization, macroeconomics, and international trade. *The Review of Economic Studies*, 62(4):515–539.

Kuandykov, L. and Sokolov, M. (2010). Impact of social neighborhood on diffusion of innovation s-curve. *Decision Support Systems*, 48(4):531–535.

Lee, E., Lee, J., and Lee, J. (2006). Reconsideration of the winner-take-all hypothesis: Complex networks and local bias. *Management Science*, 52(12):1838–1848.

Libai, B., Muller, E., and Peres, R. (2009a). The diffusion of services. *Journal of Marketing Research*, 46(2):163–175.

Libai, B., Muller, E., and Peres, R. (2009b). The role of within-brand and cross-brand communications in competitive growth. *Journal of Marketing*, 73(3):19–34.

Macal, C. M. and North, M. J. (2008). Agent-based modeling and simulation: Abms examples. In *Proceedings of the 40th Conference on Winter Simulation*, pages 101–112. Winter Simulation Conference.

Macal, C. M. and North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*, 4(3):151–162.

Newman, M. (2010). *Networks: an introduction*. Oxford University Press.

Newman, M. E. (2002). Assortative mixing in networks. *Physical review letters*, 89(20):208701.

Newman, M. E. (2003a). Properties of highly clustered networks. *Physical Review E*, 68(2):026121.

Newman, M. E. (2003b). The structure and function of complex networks. *SIAM review*, 45(2):167–256.

Patterson, P. G. and Smith, T. (2003). A cross-cultural study of switching barriers and propensity to stay with service providers. *Journal of retailing*, 79(2):107–120.

Pegoretti, G., Rentocchini, F., and Marzetti, G. V. (2012). An agent-based model of innovation diffusion: network structure and coexistence under different information regimes. *Journal of economic interaction and coordination*, 7(2):145–165.

Peres, R., Muller, E., and Mahajan, V. (2010). Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing*, 27(2):91–106.

Ranaweera, C. and Prabhu, J. (2003). The influence of satisfaction, trust and switching barriers on customer retention in a continuous purchasing setting. *International journal of service industry management*, 14(4):374–395.

Rand, W. and Rust, R. T. (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing*, 28(3):181–193.

Rogers, E. M. (2010). *Diffusion of innovations*. Simon and Schuster.

Sengupta, A. and Greetham, D. V. (2010). Dynamics of brand competition: Effects of unobserved social networks. *Journal of Economic Dynamics and Control*, 34(12):2391–2406.

Sharma, N. and Patterson, P. G. (2000). Switching costs, alternative attractiveness and experience as moderators of relationship commitment in professional, consumer services. *International journal of service industry management*, 11(5):470–490.

Toivonen, R., Kovanen, L., Kivelä, M., Onnela, J.-P., Saramäki, J., and Kaski, K. (2009). A comparative study of social network models: Network evolution models and nodal attribute models. *Social Networks*, 31(4):240–254.

Toivonen, R., Onnela, J.-P., Saramäki, J., Hyvönen, J., and Kaski, K. (2006). A model for social networks. *Physica A: Statistical Mechanics and its Applications*, 371(2):851–860.

Watts, D. J. and Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393(6684):440–442.

Whitten, D. and Wakefield, R. L. (2006). Measuring switching costs in it outsourcing services. *The Journal of Strategic Information Systems*, 15(3):219–248.

Wilensky, U. (1999). Netlogo. Available at: http://ccl.northwestern.edu/netlogo. Center for connected learning and computer-based modeling. Evanston, IL: Northwestern university.

Woisetschläger, D. M., Lentz, P., and Evanschitzky, H. (2011). How habits, social ties, and economic switching barriers affect customer loyalty in contractual service settings. *Journal of Business Research*, 64(8):800–808.

Young, H. P. (2009). Innovation diffusion in heterogeneous populations: Contagion, social influence, and social learning. *The American economic review*, pages 1899–1924.

Zhang, X., Zhu, J., Xu, S., and Wan, Y. (2012). Predicting customer churn through interpersonal influence. *Knowledge-Based Systems*, 28:97–104.

Appendix A. Software

Netlogo http://ccl.northwestern.edu/netlogo

R http://cran.r-project.org

Appendix B. Effects of word-of-mouth

Figures 1 – 2 show the market share of new product and Figures 3 – 4 show the diffusion curves of the new product when consumers do not disseminate word-of-mouth (WoM); disseminate PWoM & NWoM; only disseminate PWoM and only disseminate NWoM.

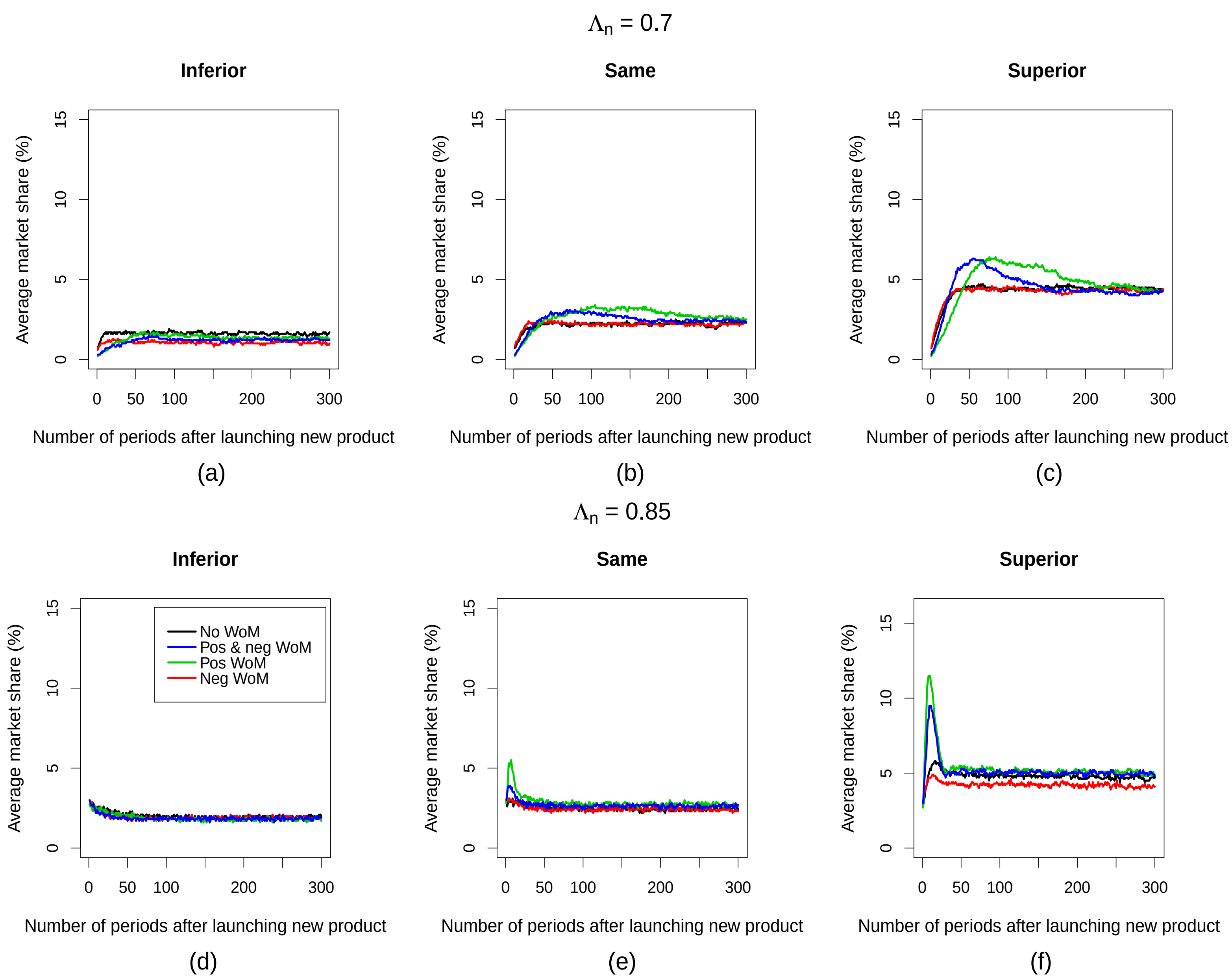


Figure 1: Market share of new product when consumers do not disseminate WoM; disseminate PWoM & NWoM; only disseminate PWoM and only disseminate NWoM ($\langle k \rangle = 5$)

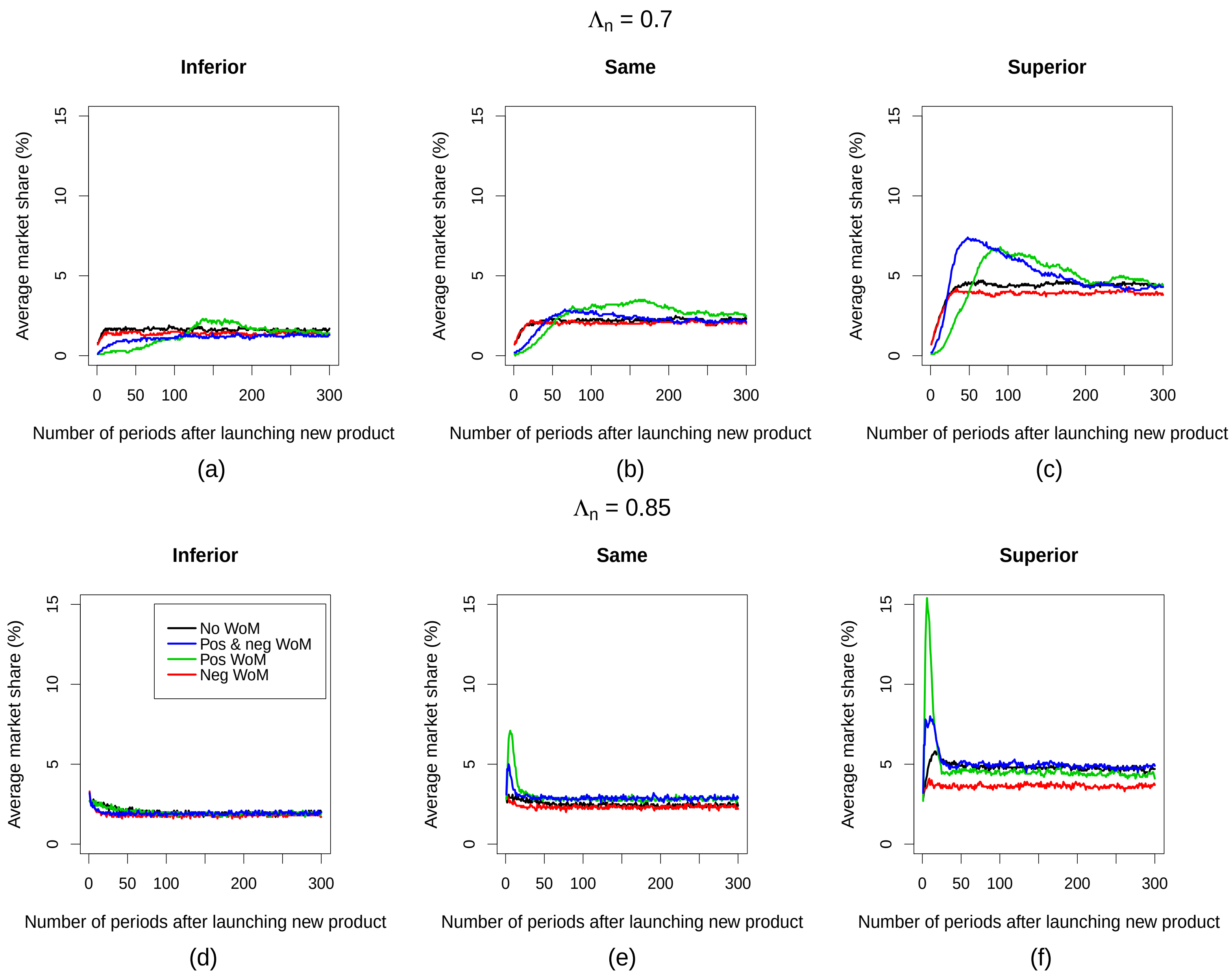


Figure 2: Market share of new product when consumers do not disseminate WoM; disseminate PWoM & NWoM; only disseminate PWoM and only disseminate NWoM ($\langle k \rangle = 15$)

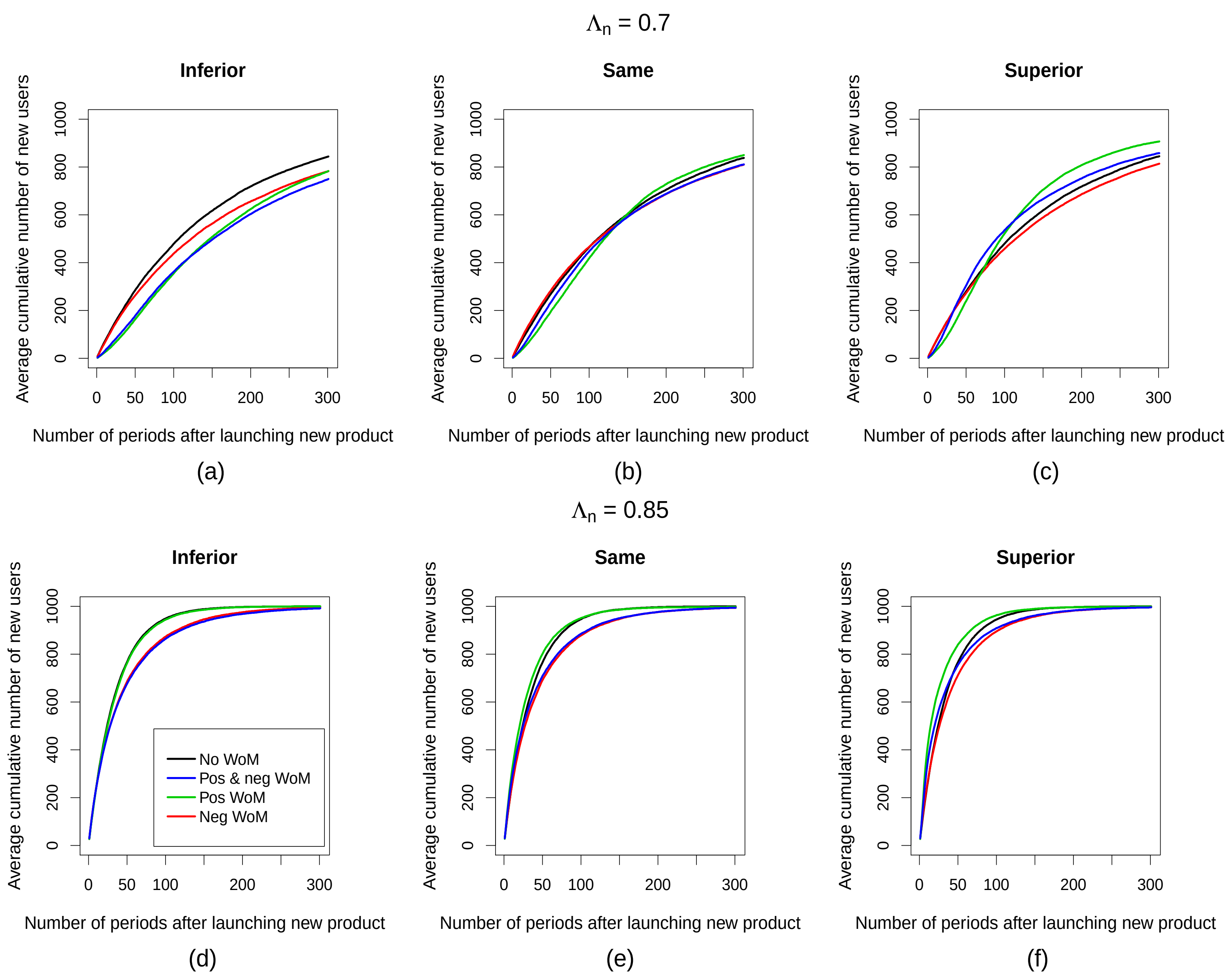


Figure 3: Average cumulative number of first time users of the new product when consumers do not disseminate WoM; disseminate PWoM & NWoM; only disseminate PWoM and only disseminate NWoM ($\langle k \rangle = 5$)

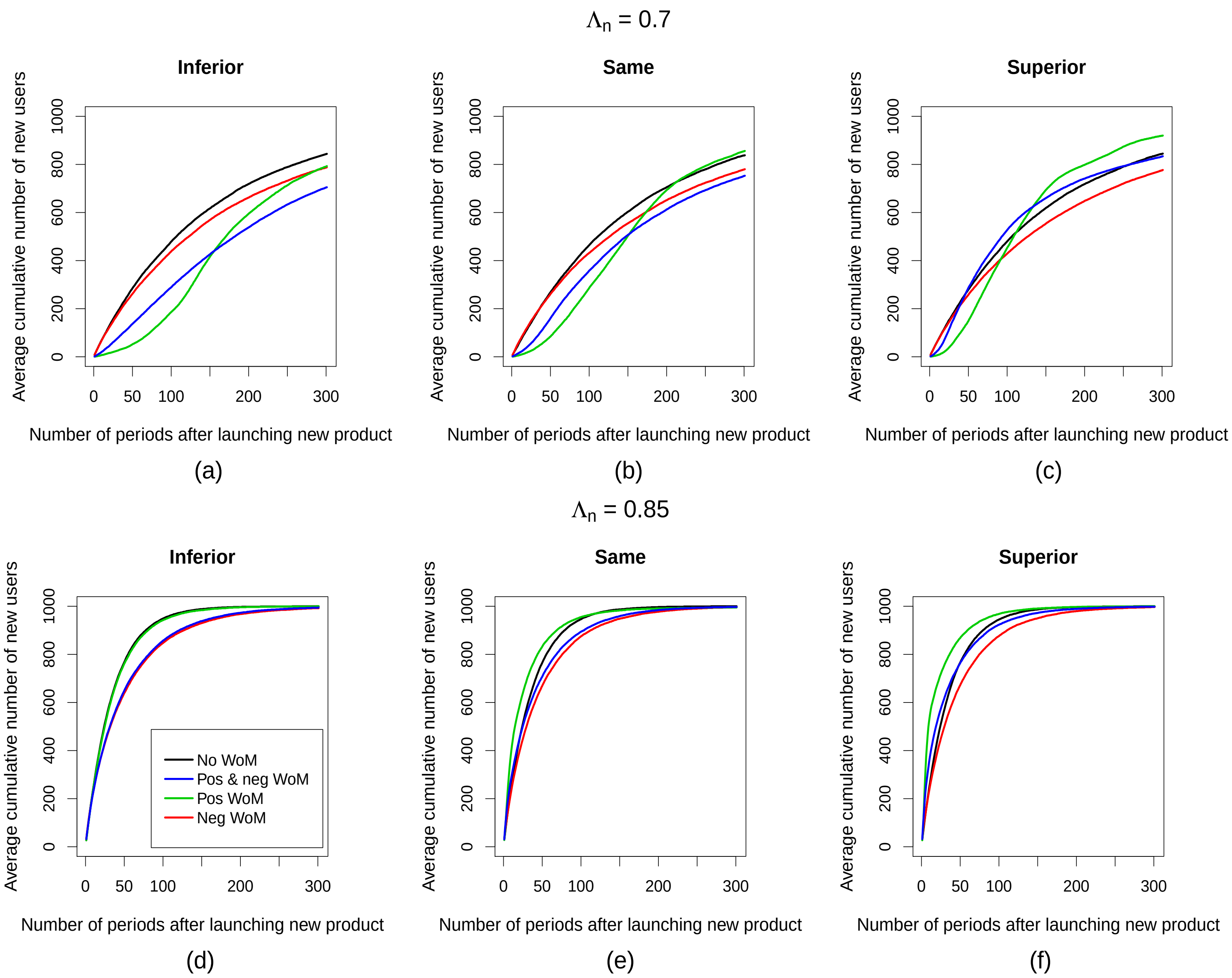


Figure 4: Average cumulative number of first time users of the new product when consumers do not disseminate WoM; disseminate PWoM & NWoM; only disseminate PWoM and only disseminate NWoM ($\langle k \rangle = 15$)

Appendix C. Effects of launching the new product with switching constraints

Figures 5 – 12 show the market share of the new product and Figures 13 – 20 show the diffusion curves of the new product when it is launched with and without switching constraints into a market in which there are products that have switching constraints.

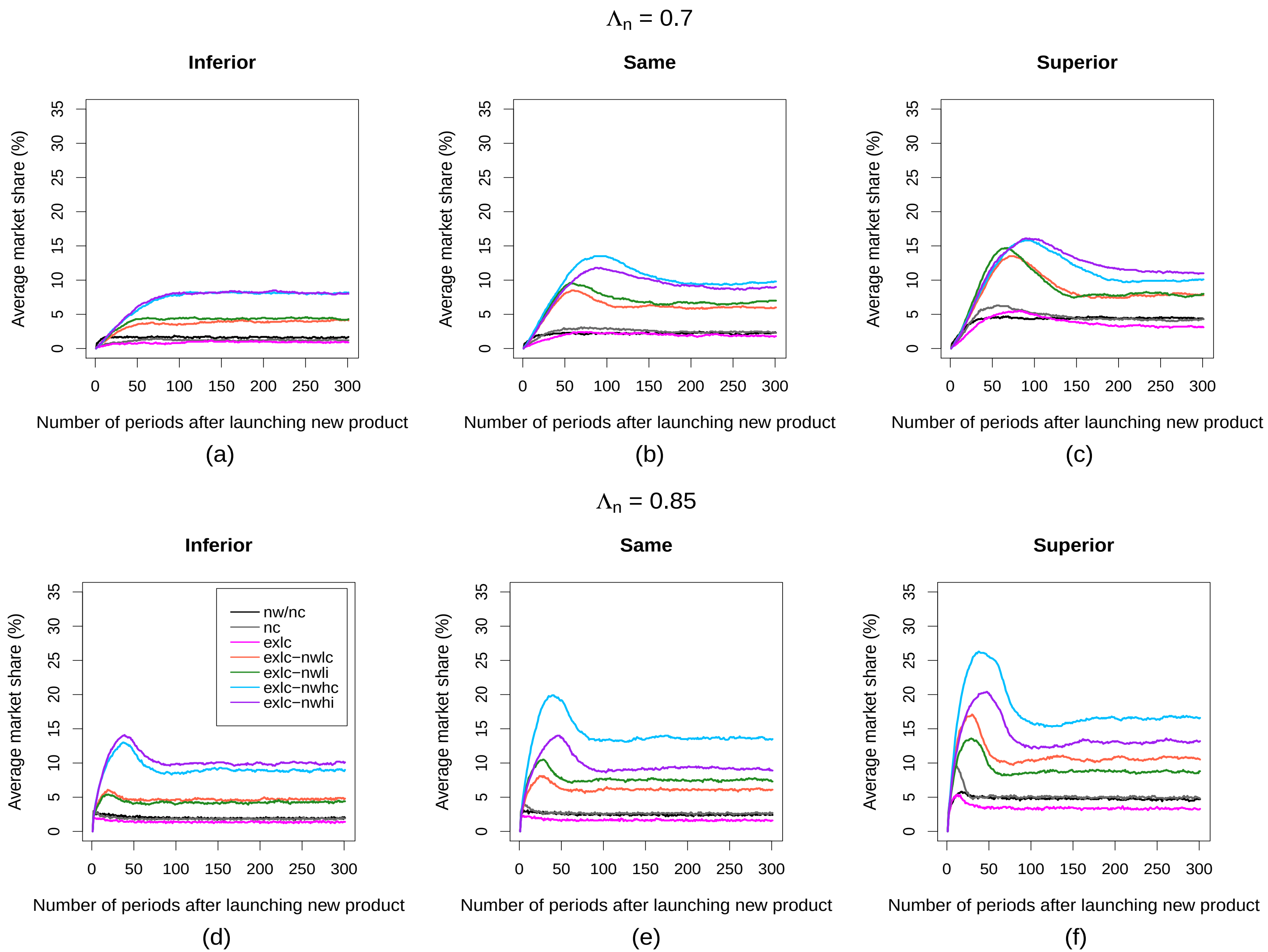


Figure 5: Average market share of the new product (%) when there are products that have switching constraints that are low & constant (lc) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exlc: only existing products have constraints; exlc-nwlc: new product has constraints that are low & constant; exlc-nwli: new product has constraints that are low & increasing; exlc-nwhc: new product has constraints that are high & constant; exlc-nwhi: new product has constraints that are high & increasing

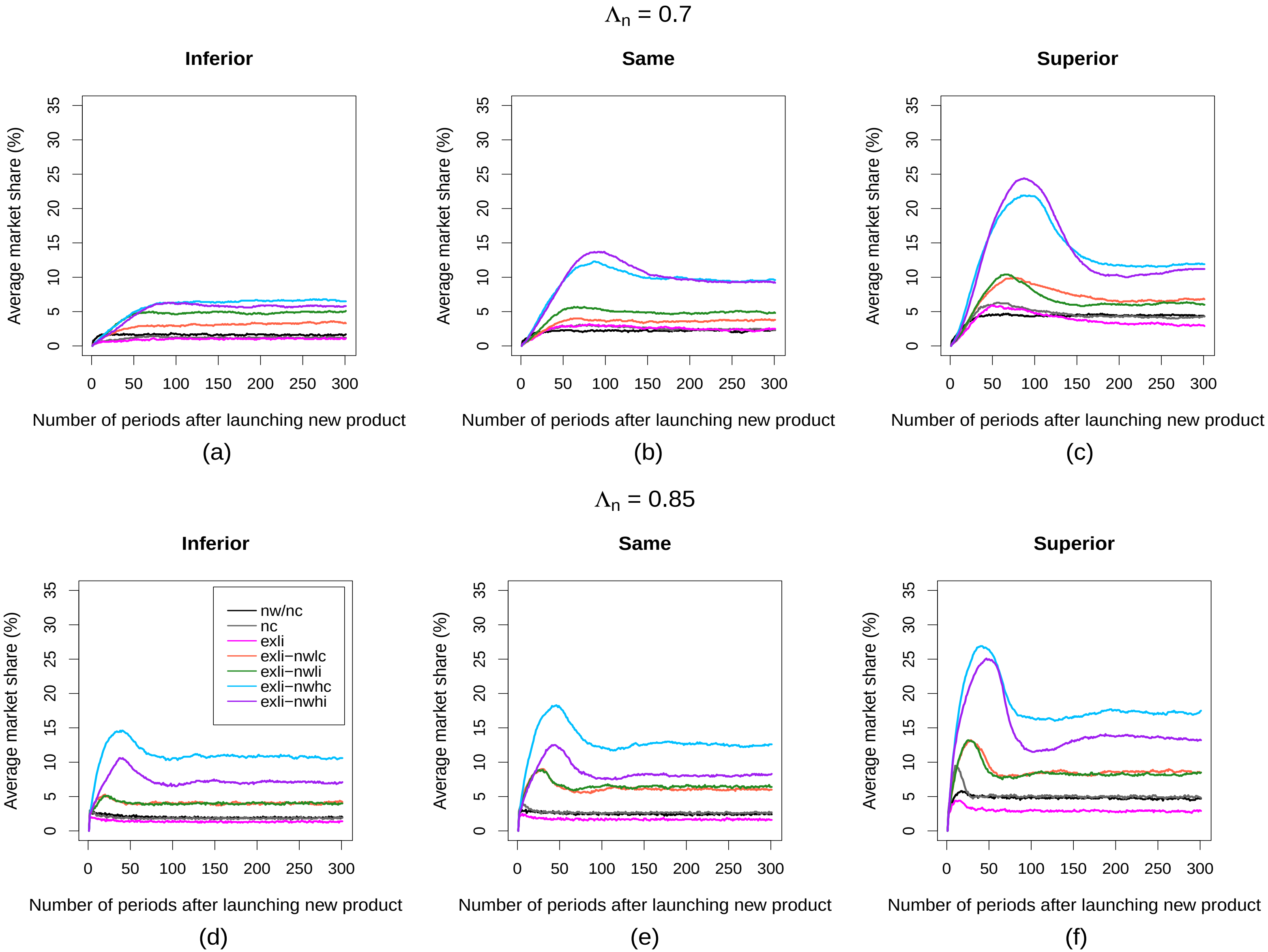


Figure 6: Average market share of the new product (%) when there are products that have switching constraints that are low & increasing (li) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exli: only existing products have constraints; exli-nwlc: new product has constraints that are low & constant; exli-nwli: new product has constraints that are low & increasing; exli-nwhc: new product has constraints that are high & constant; exli-nwhi: new product has constraints that are high & increasing

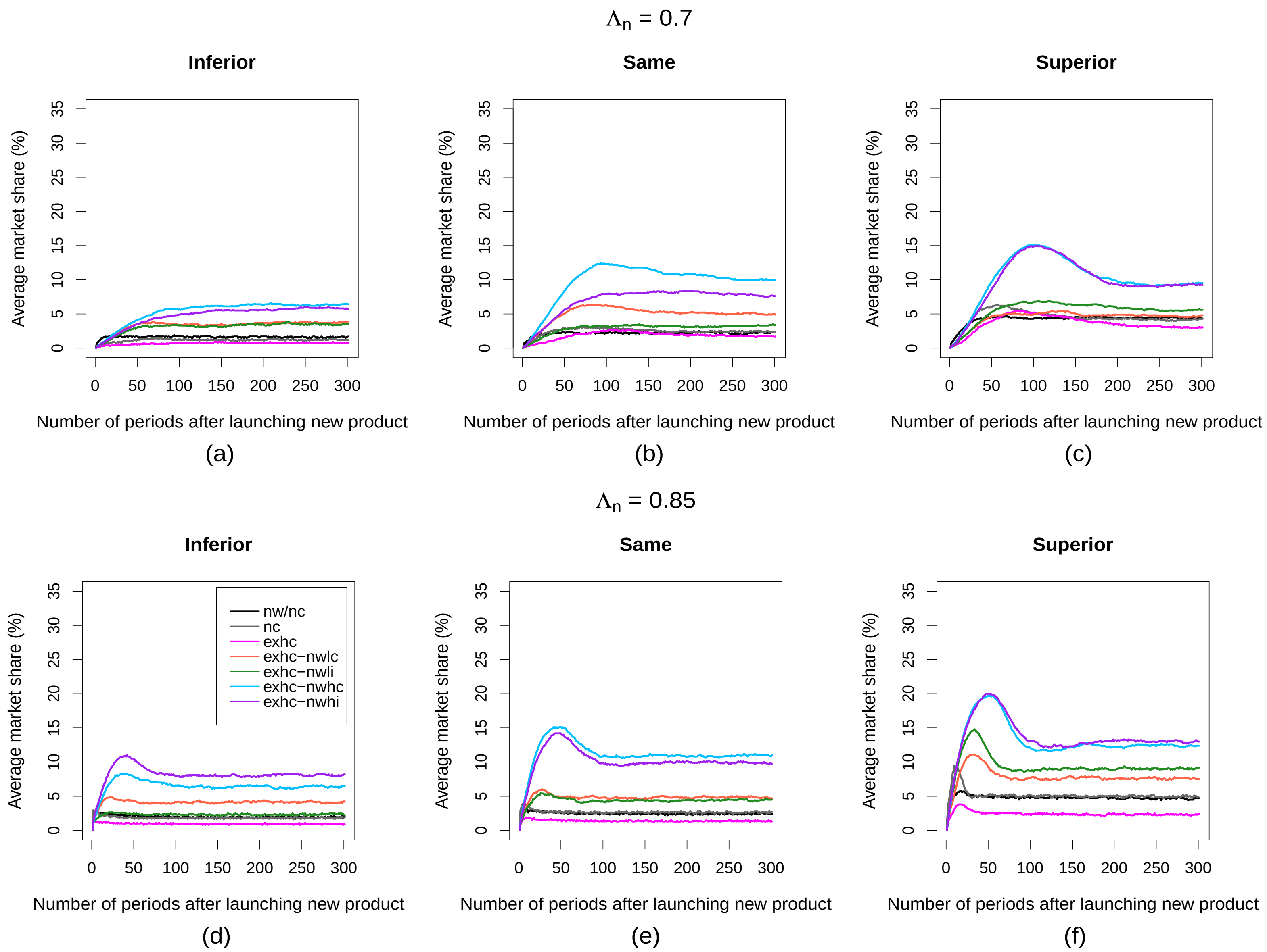


Figure 7: Average market share of the new product (%) when there are products that have switching constraints that are high & constant (hc) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exhc: only existing products have constraints; exhc-nwlc: new product has constraints that are low & constant; exhc-nwli: new product has constraints that are low & increasing; exhc-nwhc: new product has constraints that are high & constant; exhc-nwhi: new product has constraints that are high & increasing

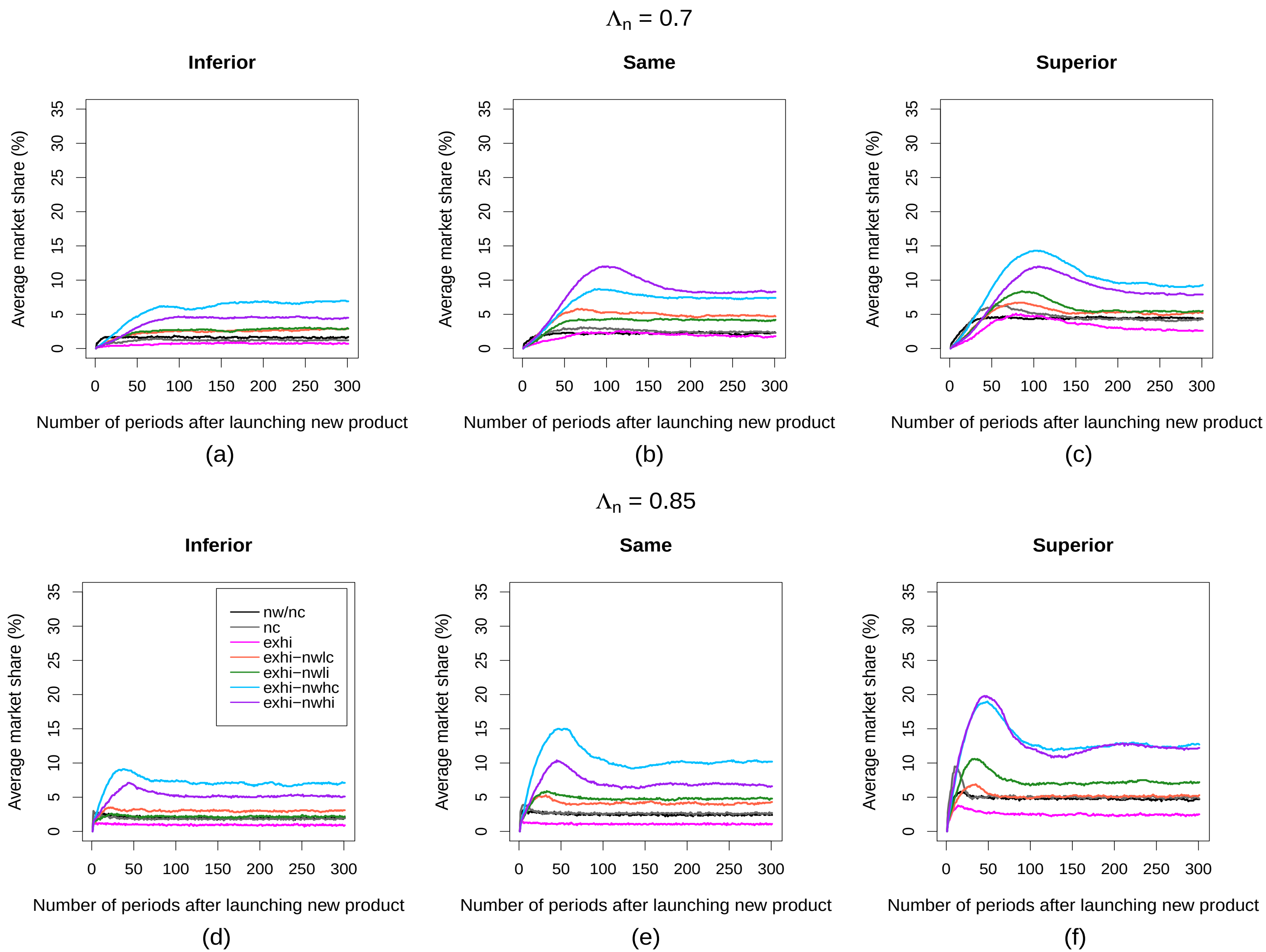


Figure 8: Average market share of the new product (%) when there are products that have switching constraints that are high & increasing (hi) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exhi: only existing products have constraints; exhi-nwlc: new product has constraints that are low & constant; exhi-nwli: new product has constraints that are low & increasing; exhi-nwhc: new product has constraints that are high & constant; exhi-nwhi: new product has constraints that are high & increasing

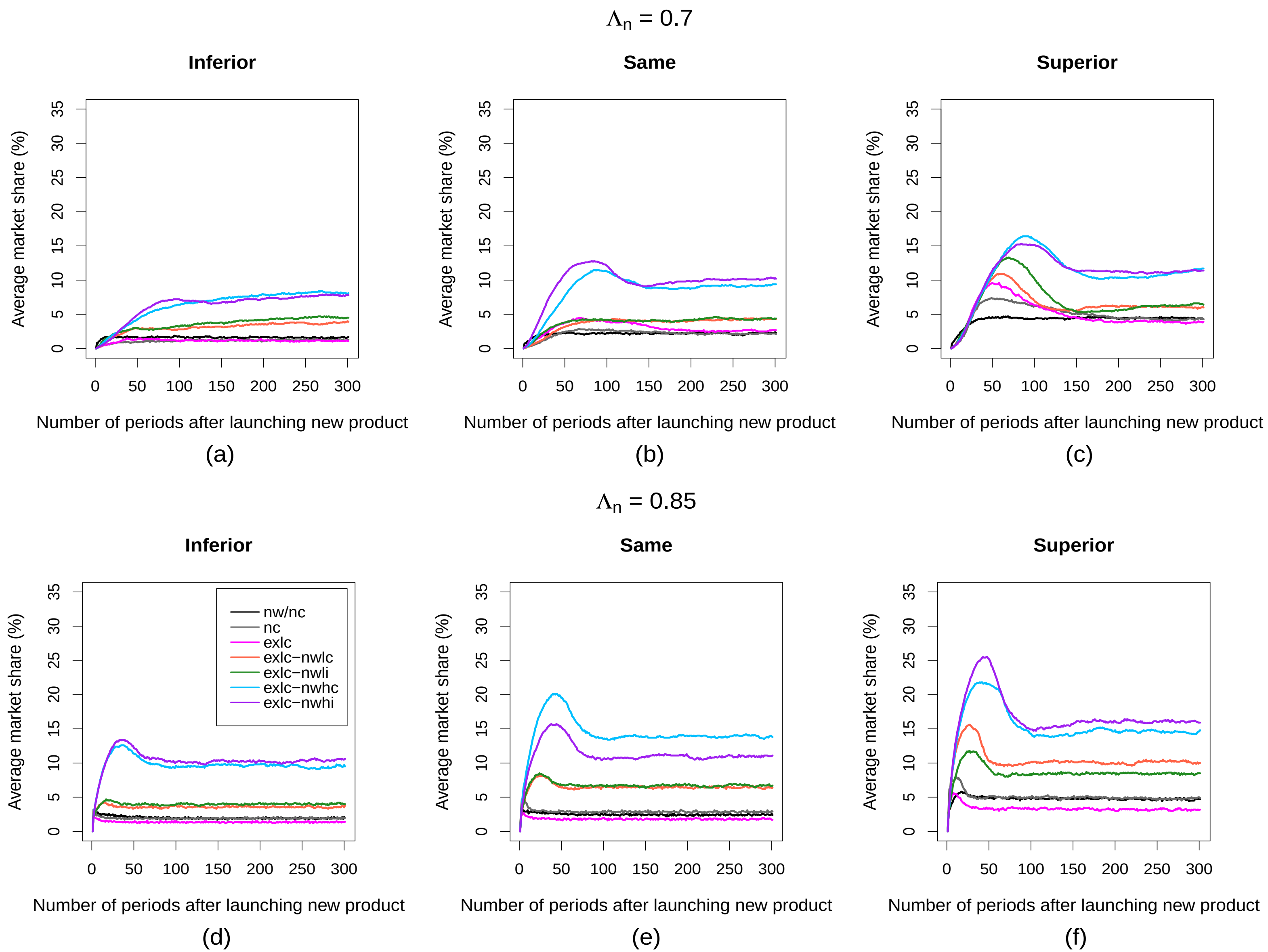


Figure 9: Average market share of the new product (%) when there are products that have switching constraints that are low & constant (lc) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exlc: only existing products have constraints; exlc-nwlc: new product has constraints that are low & constant; exlc-nwli: new product has constraints that are low & increasing; exlc-nwhc: new product has constraints that are high & constant; exlc-nwhi: new product has constraints that are high & increasing

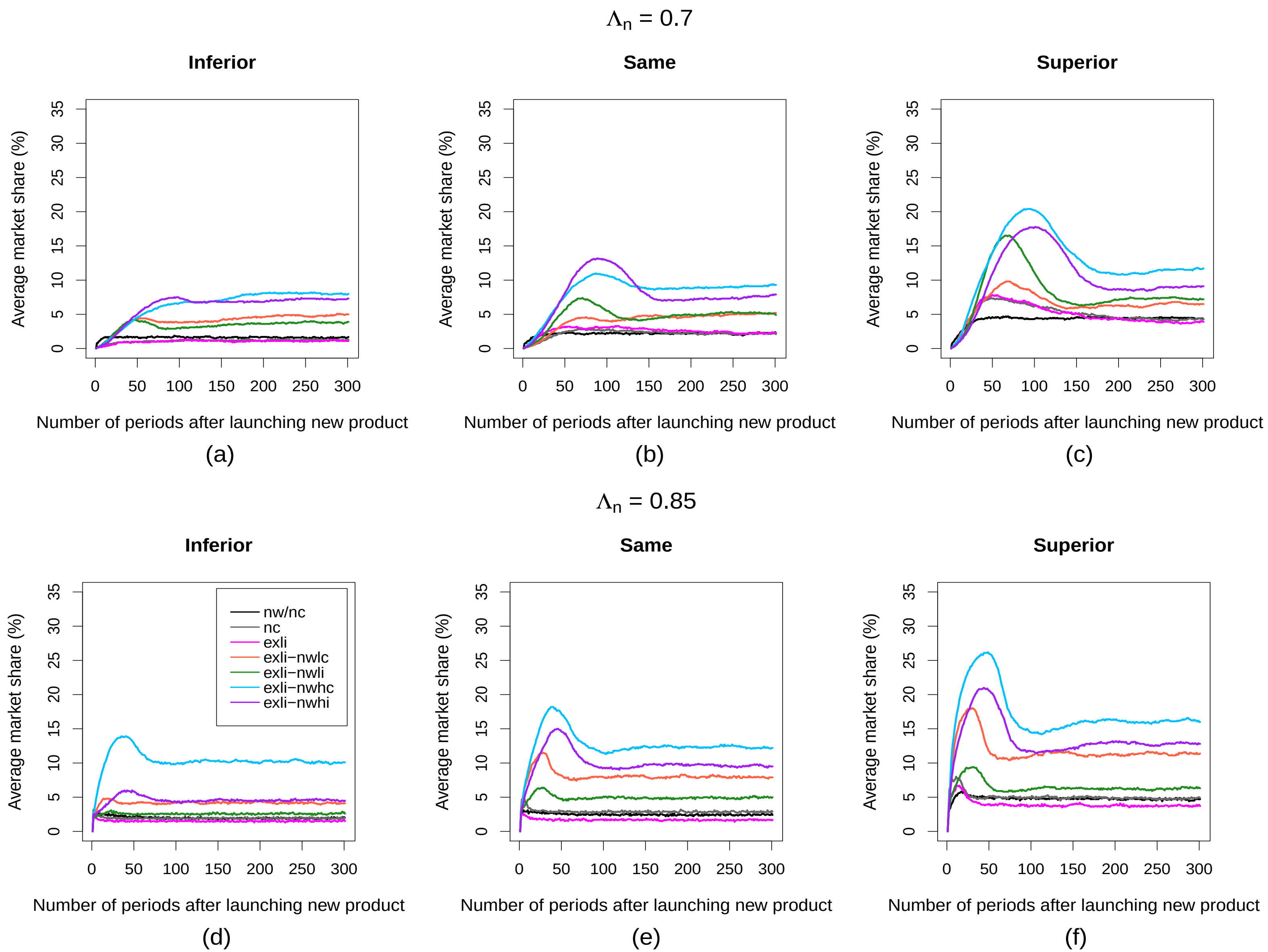


Figure 10: Average market share of the new product (%) when there are products that have switching constraints that are low & increasing (li) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exli: only existing products have constraints; exli-nwlc: new product has constraints that are low & constant; exli-nwli: new product has constraints that are low & increasing; exli-nwhc: new product has constraints that are high & constant; exli-nwhi: new product has constraints that are high & increasing

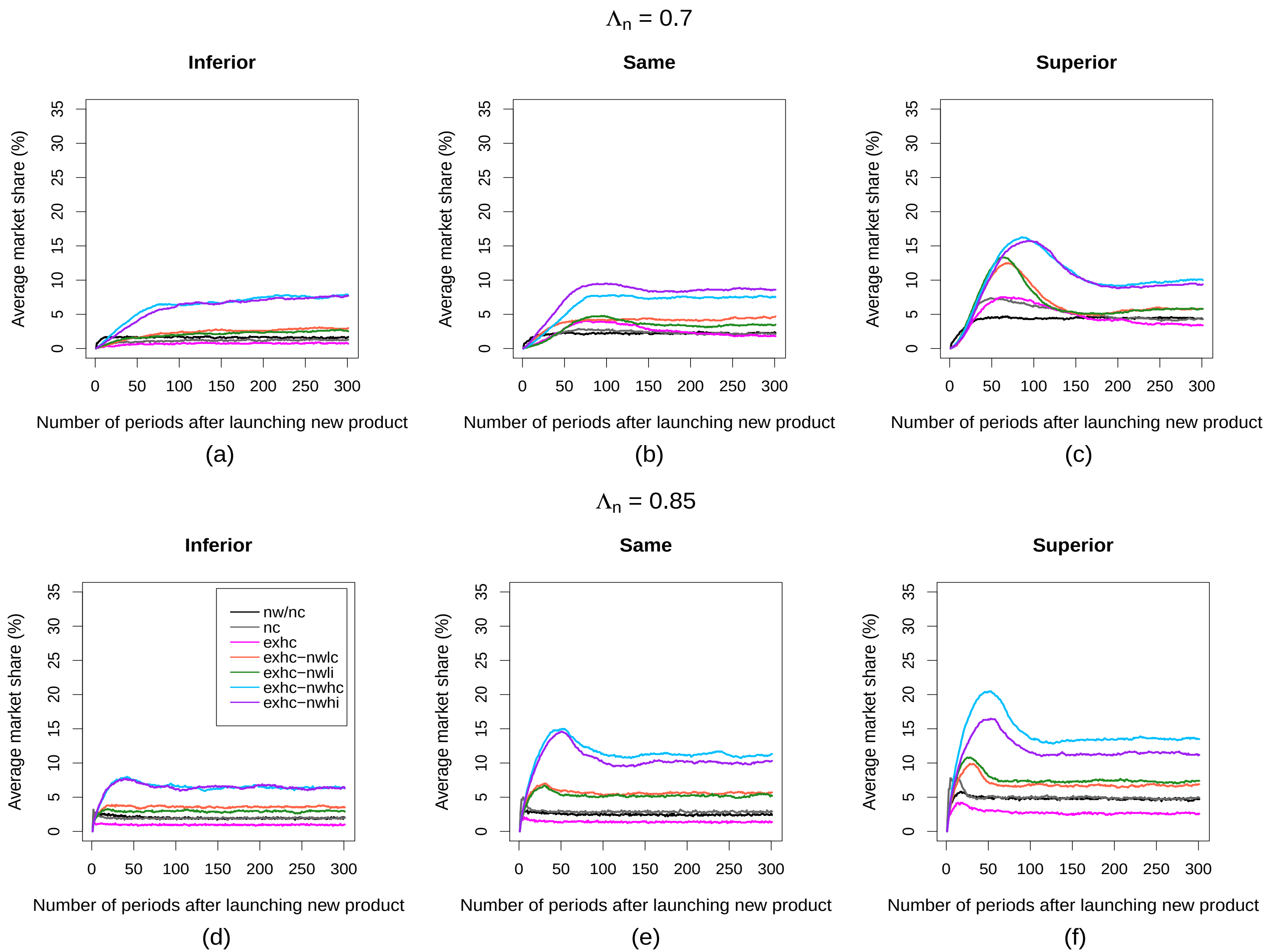


Figure 11: Average market share of the new product (%) when there are products that have switching constraints that are high & constant (hc) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exhc: only existing products have constraints; exhc-nwlc: new product has constraints that are low & constant; exhc-nwli: new product has constraints that are low & increasing; exhc-nwhc: new product has constraints that are high & constant; exhc-nwhi: new product has constraints that are high & increasing

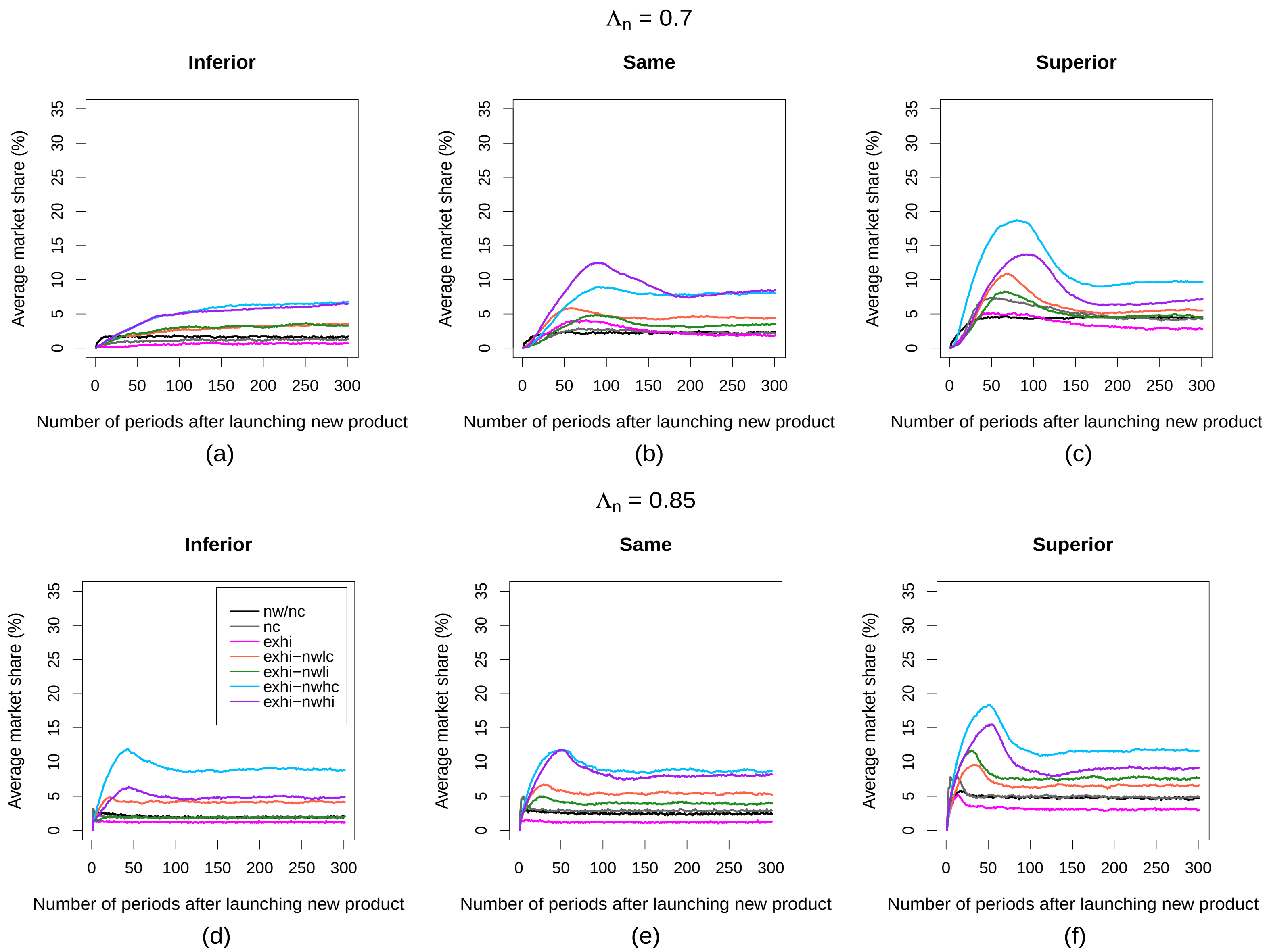


Figure 12: Average market share of the new product (%) when there are products that have switching constraints that are high & increasing (hi) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exhi: only existing products have constraints; exhi-nwlc: new product has constraints that are low & constant; exhi-nwli: new product has constraints that are low & increasing; exhi-nwhc: new product has constraints that are high & constant; exhi-nwhi: new product has constraints that are high & increasing

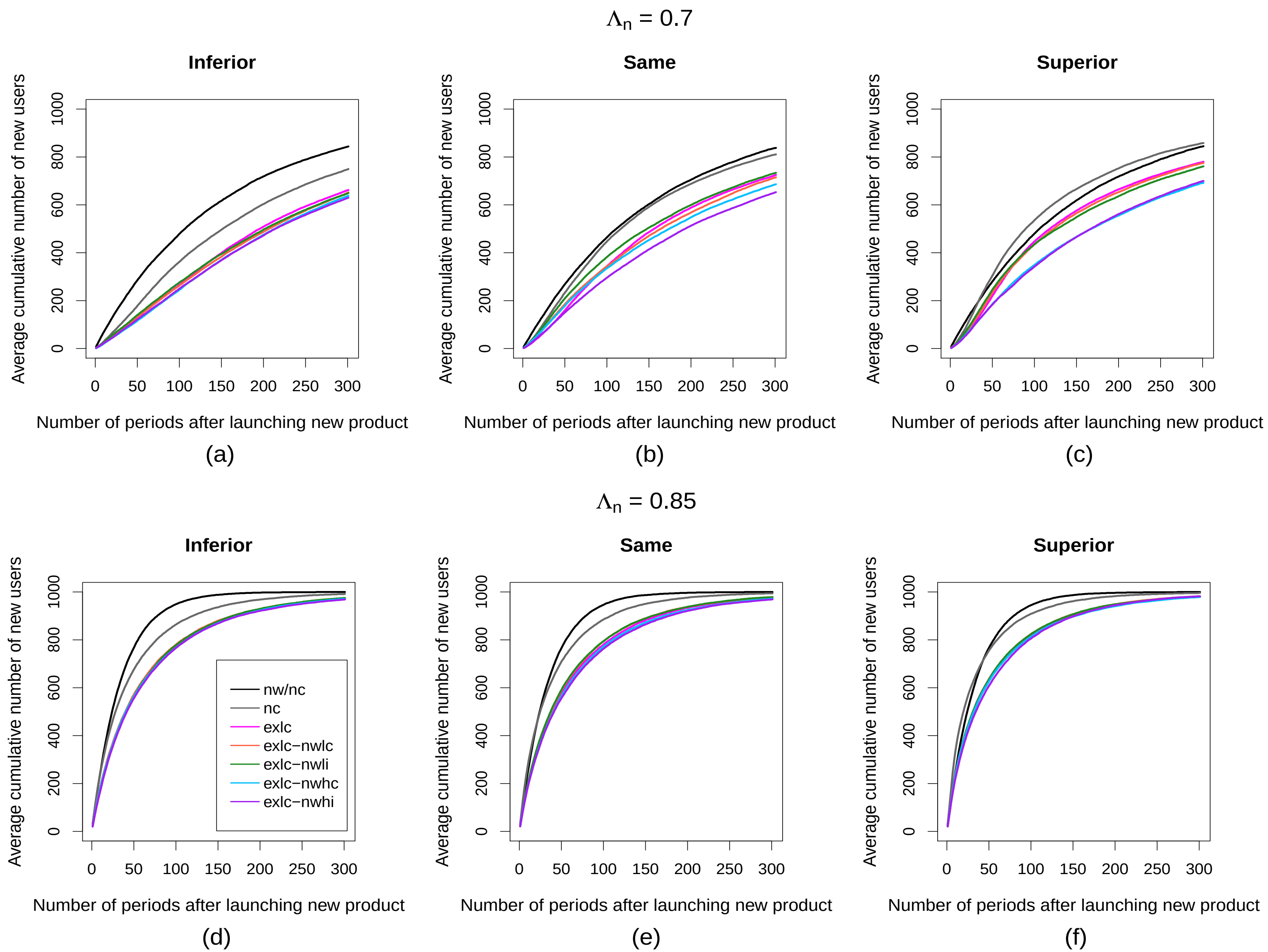


Figure 13: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are low & constant (lc) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exlc: only existing products have constraints; exlc-nwlc: new product has constraints that are low & constant; exlc-nwli: new product has constraints that are low & increasing; exlc-nwhc: new product has constraints that are high & constant; exlc-nwhi: new product has constraints that are high & increasing

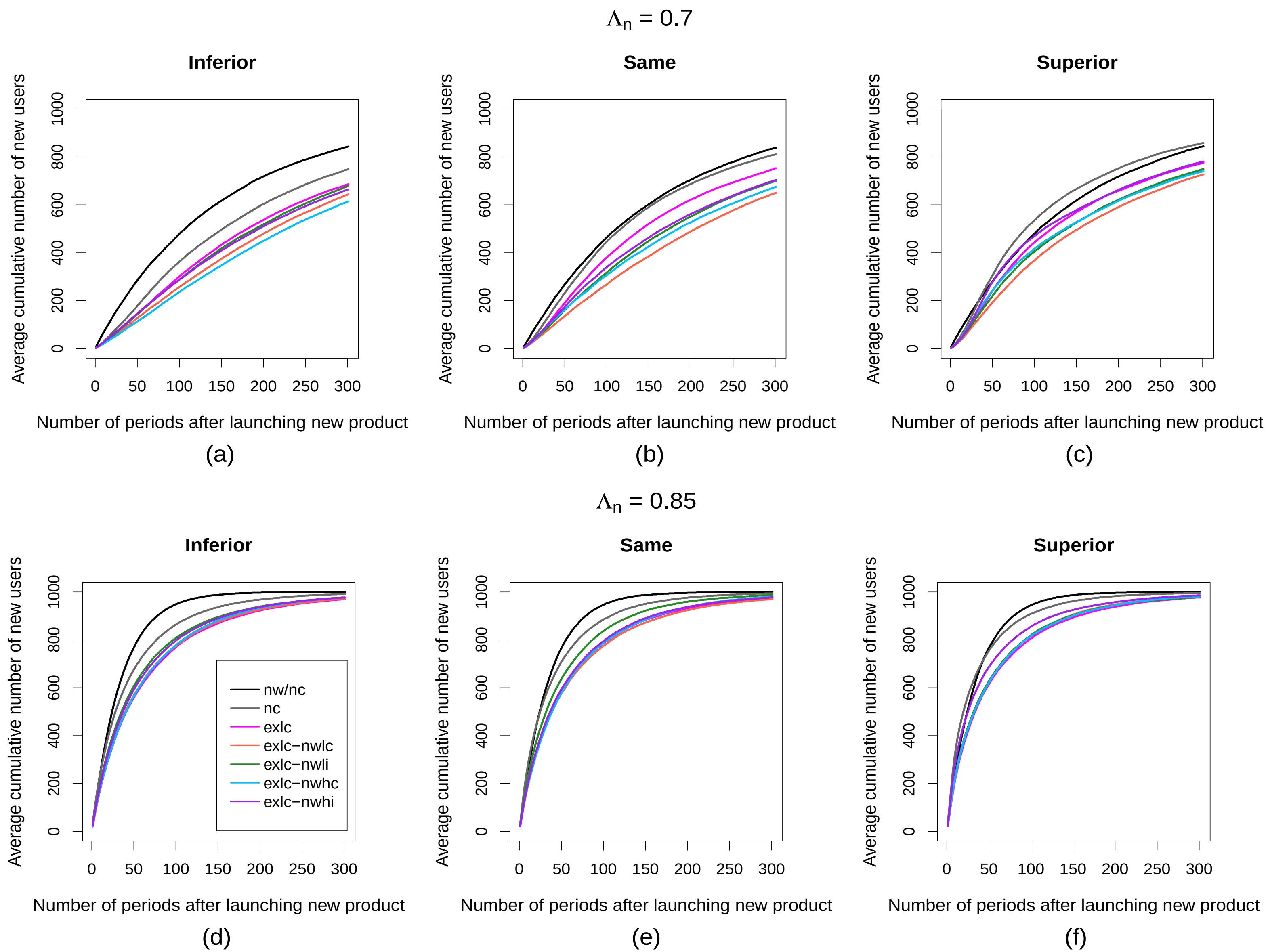


Figure 14: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are low & increasing (li) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exli: only existing products have constraints; exli-nwlc: new product has constraints that are low & constant; exli-nwli: new product has constraints that are low & increasing; exli-nwhc: new product has constraints that are high & constant; exli-nwhi: new product has constraints that are high & increasing

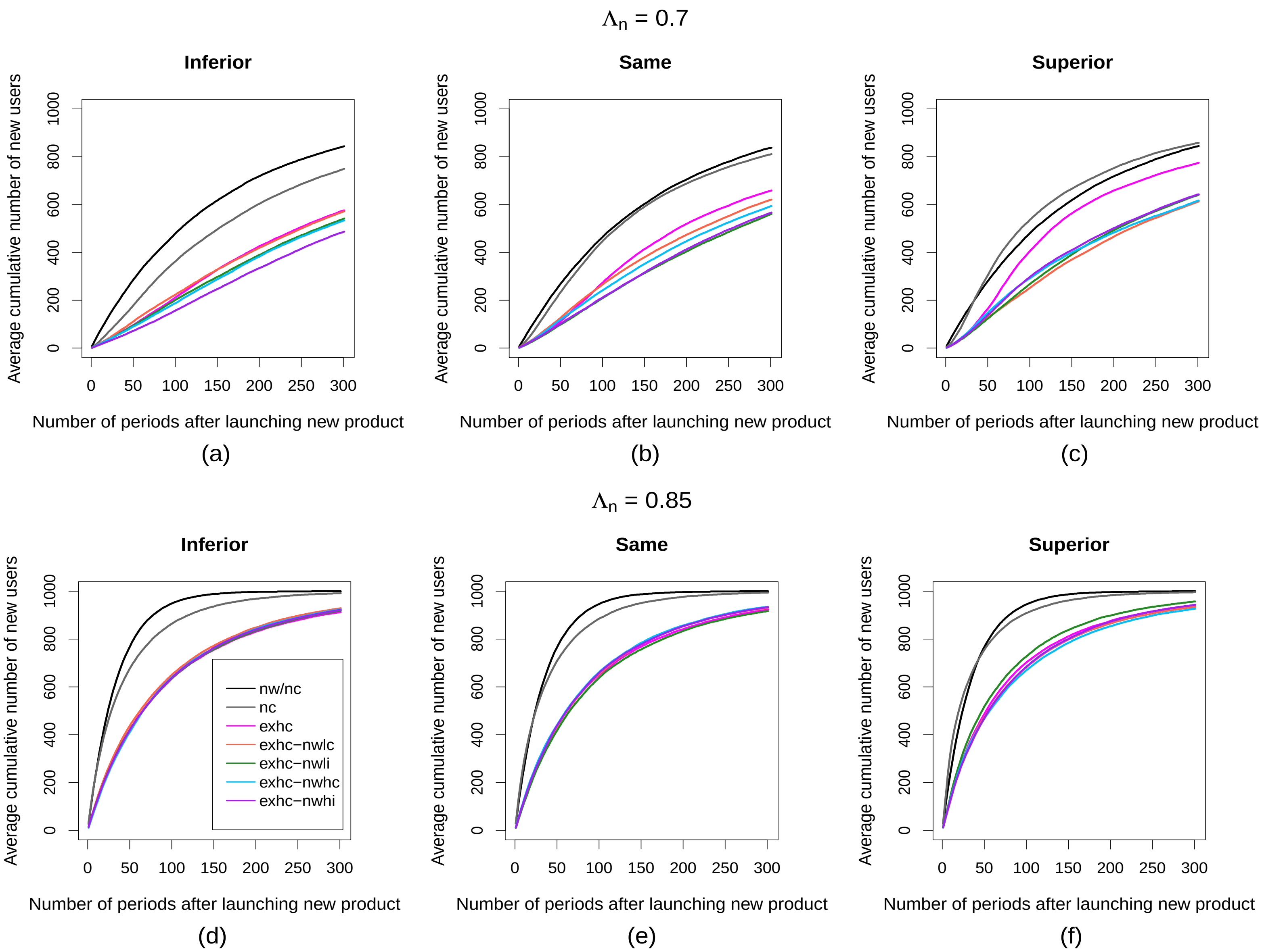


Figure 15: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are high & constant (hc) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exhc: only existing products have constraints; exhc-nwlc: new product has constraints that are low & constant; exhc-nwli: new product has constraints that are low & increasing; exhc-nwhc: new product has constraints that are high & constant; exhc-nwhi: new product has constraints that are high & increasing

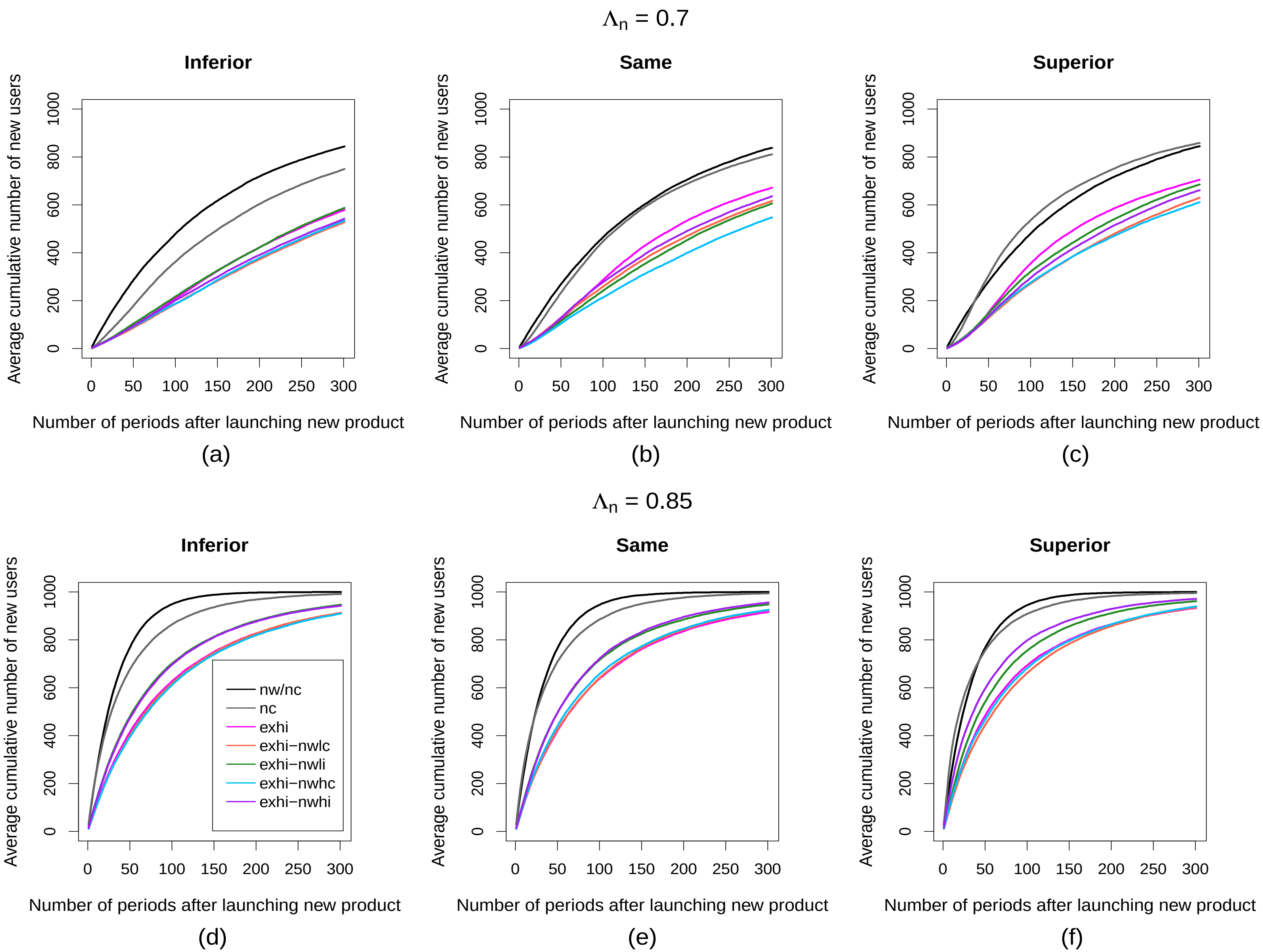


Figure 16: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are high & increasing (hi) in the market ($\langle k \rangle = 5$).

nw/nc:no wom & no constraints; nc: no constraints; exhi: only existing products have constraints; exhi-nwlc: new product has constraints that are low & constant; exhi-nwli: new product has constraints that are low & increasing; exhi-nwhc: new product has constraints that are high & constant; exhi-nwhi: new product has constraints that are high & increasing

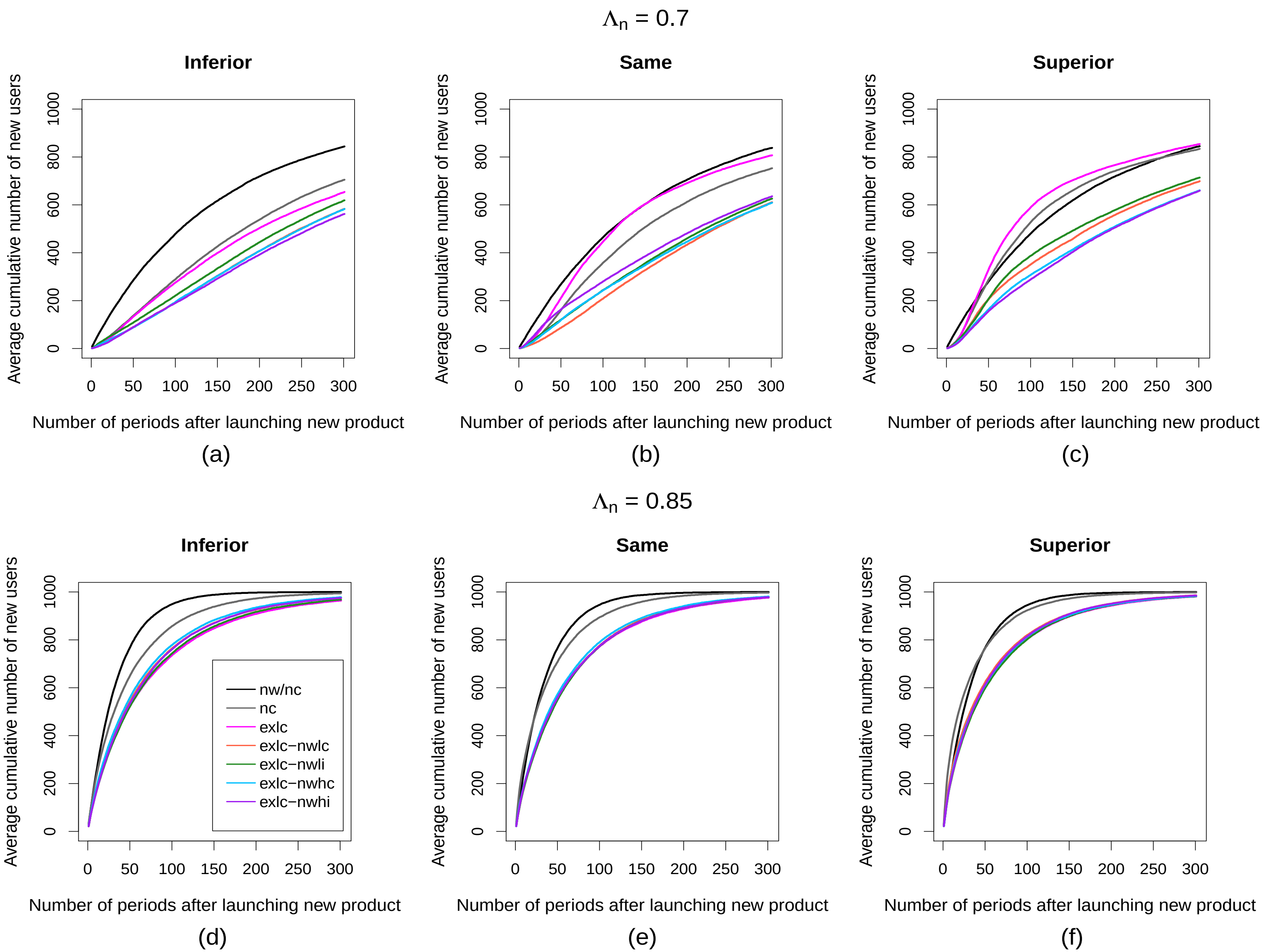


Figure 17: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are low & constant (lc) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exlc: only existing products have constraints; exlc-nwlc: new product has constraints that are low & constant; exlc-nwli: new product has constraints that are low & increasing; exlc-nwhc: new product has constraints that are high & constant; exlc-nwhi: new product has constraints that are high & increasing

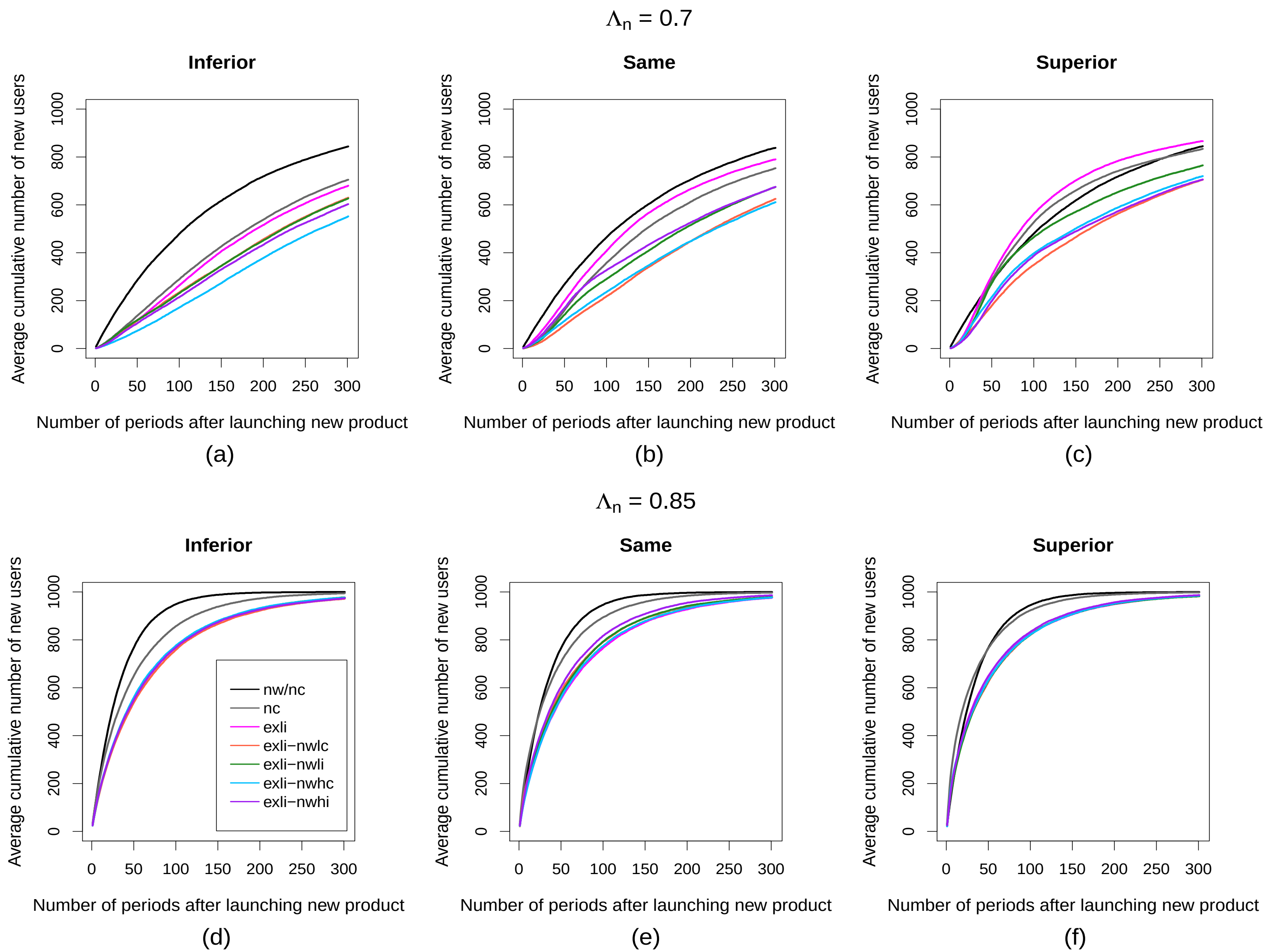


Figure 18: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are low & increasing (li) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exli: only existing products have constraints; exli-nwlc: new product has constraints that are low & constant; exli-nwli: new product has constraints that are low & increasing; exli-nwhc: new product has constraints that are high & constant; exli-nwhi: new product has constraints that are high & increasing

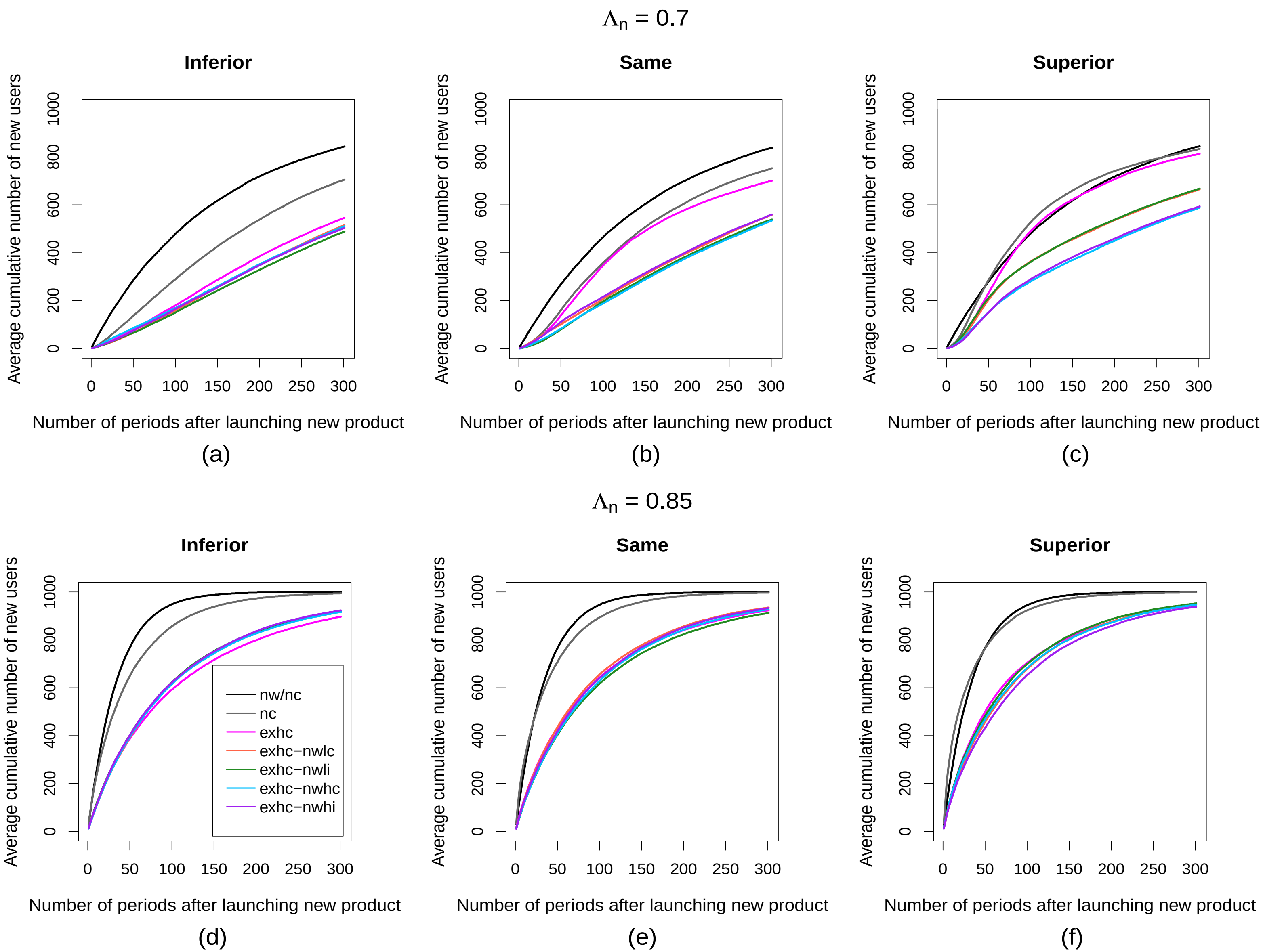


Figure 19: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are high & constant (hc) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exhc: only existing products have constraints; exhc-nwlc: new product has constraints that are low & constant; exhc-nwli: new product has constraints that are low & increasing; exhc-nwhc: new product has constraints that are high & constant; exhc-nwhi: new product has constraints that are high & increasing

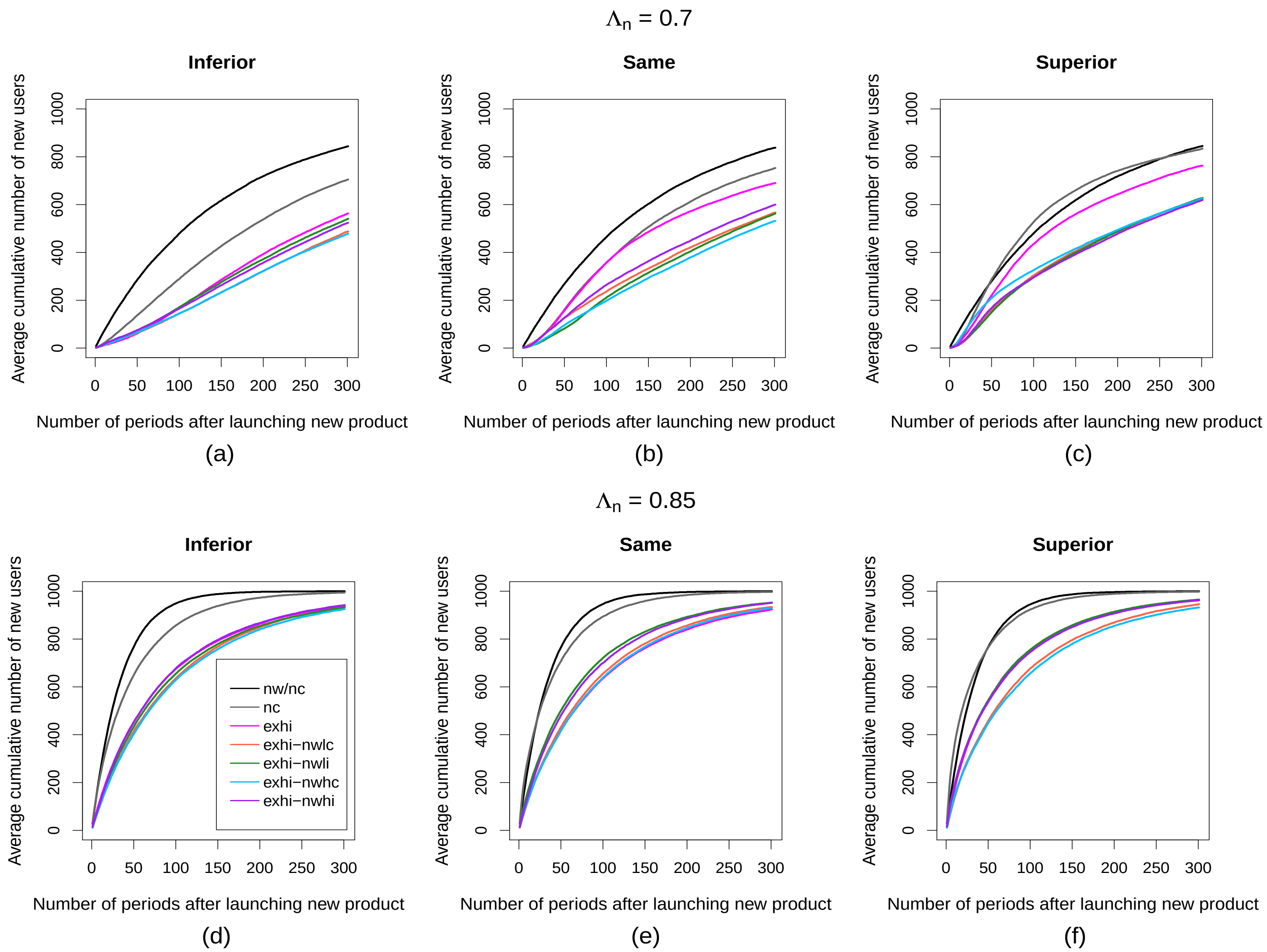


Figure 20: Average cumulative number of new users of the new product (%) when there are products that have switching constraints that are high & increasing (hi) in the market ($\langle k \rangle = 15$).

nw/nc:no wom & no constraints; nc: no constraints; exhi: only existing products have constraints; exhi-nwlc: new product has constraints that are low & constant; exhi-nwli: new product has constraints that are low & increasing; exhi-nwhc: new product has constraints that are high & constant; exhi-nwhi: new product has constraints that are high & increasing