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# Tariff-Mediated Network Effects With Incompletely Informed Consumers

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# Tariff-Mediated Network Effects With Incompletely Informed Consumers[1]

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*January 2016*

**ABSTRACT**

I explore the competitive effects of on-net/off-net differentiation in a market with two asymmetric networks by combining the literature on on-net/off-net differentiation with research on costly consumer search in an agent-based simulation model. All consumers in the market are subscribed to one of two networks, whereby, initially, clusters of subscribers to network B exist. A priori, consumers lack information on the market shares of both network and, hence, have to engage in costly fixed-sample search. With respect to the extent of search costs, I distinguish between three types of consumers: (1) fully informed consumers (FICs) have non-positive search costs and, accordingly, are always perfectly informed about networks' market shares; (2) partly informed consumers (PICs) have moderate search costs, which allow them to observe market shares within a circular sensing field; and (3) locally informed consumers (LICs) have high search costs and, hence, only observe market shares among their immediate eight neighbours. Irrespective of their type, consumers maximize their expected utility by subscribing to the network offering the lowest expected cost for a call to a random consumer. The results of a systematic variation of the key parameters of the model show that the larger network's probability to increase its market share or to corner the market is negatively affected by the fraction of PICs and LICs, whereas it is positively affected by PICs's sensing radius, the larger network's initial market share, and the number of clusters. The introduction of calling clubs reveals that the probability of calling a friend inflicts a negative effect while the size of the calling clubs has a positive effect. These findings highlight the pivotal role of the amount of information available to consumers for the distribution of market shares.

JEL codes: C63, D83; K23, L14, L96

Keywords: on-net/off-net differentiation; tariff-mediated network effects; agent-based computational economics; search costs

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# INTRODUCTION

Over the past decades, telecommunications markets around the globe have been liberalized with the consequence that in modern economies typically several mobile telecommunications networks coexist. Since subscribers expect to be able to make both on-net calls (which originate and terminate on the same network) as well as off-net calls (which originate and terminate on different networks) networks are interconnected (Peitz 2003, p.734, Berger 2005, p. 2, Gabrielsen and Vagstad 2008, p. 100). Typically, network operators charge each other for terminating a call originating from a rival's network. These access charges directly increase operators' costs for off-net calls and, thereby, increase the tariffs for off-net calls (Blonski 2002, p. 96, Peitz 2003, p. 732, Hoernig 2008, p. 9, Gabrielsen and Vagstad 2008, p. 5, Cabral 2011, p. 103, Lopez and Rey 2012, p. 1). Accordingly, access charges are one reason why network operators often price discriminate between on-net and off-net calls ("on-net/off-net differentiation"), whereby on-net calls are cheaper than off-net calls.

On-net/off-net differentiation generates tariff-mediated network effects (Laffont, Rey, and Tirole 1998b, p. 39). Under the standard assumption of a "balanced" or "uniform" calling pattern (Laffont, Rey, and Tirole 1998b, Armstrong 1998, Hoernig, Bourreau, and Cambini 2014), i.e., calls are placed randomly, the probability that a subscriber to network A makes an on-net call equals A's market share. Hence, the higher A's market share, the higher subscribers' probability of making a cheaper on-net call and, therefore, the lower the expected costs of a call which ultimately translates into a higher utility of being subscribed to network A. Accordingly, rational consumers striving to maximize their utility by minimizing their telephone bill have an incentive to join the largest network. Tariff-mediated network effects are particularly important if network sizes are asymmetric, i.e., if a large incumbent network competes with one or several smaller entrants. In this case, tariff-mediated network effects exacerbate the already superior competitive position that large incumbent networks enjoy, for instance, due to cost advantages (for instance, because of economies of scale) or higher network quality (for instance, broader network coverage) (Peitz 2003, p. 735).

Inspired by the seminal articles of Armstrong (1998) and Laffont, Rey, and Tirole (1998a, 1998b), numerous scholars have investigated the competitive effect of tariff-mediated network effects (for a summary see Harbord and Pagnozzi 2010). One key result of this abundant literature is that on-net/off-net differentiation benefits large networks and harms small ones. In their survey of the theoretical literature Harbord and Pagnozzi summarize that on-net/off-net differentiation "can be used strategically by incumbent operators to either prevent entry or to reduce competition from new entrants into their markets" (2010, p. 7).

This unanimously agreed-upon result is somewhat puzzling given the mixed empirical observations regarding the effect of on-net/off-net differentiation on small networks. On the one hand, evidence from the French mobile telecommunications industry corroborates the findings of the extant literature. In December 2012, the French Competition Authority announced that the two largest network operators, Orange, and SFR, had been found guilty of abusing their dominant position in the market for mobile telecommunications by engaging in "excessive rate differentiation between 'on-net' calls (made within their own network) and 'off-net' calls (to a rival network)" (Autorité de la concurrence 2012, p. 1). The on-net/off-net differentiation practiced by Orange and SFR led to a "freezing [of] the market by drawing consumers to the two biggest networks" and acted to "weaken the third operator - Bouygues Télécom - which had to strike back by launching offerings that significantly increased its costs" (Autorité de la concurrence 2012, p. 1) so that ultimately "there was a great danger of Bouyges being driven out of the market" (Autorité de la concurrence 2012, p. 3). The fine for Orange's and SFR's anti-competitive conduct was set to €183 million.

On the other hand, evidence from the German and Austrian mobile telecommunication markets challenge the prevailing paradigm that on-net/off-net differentiation is harmful for small networks. In 2007 Germany's second smallest-network operator, E-Plus, filed a complaint with the European Commission that the on-net/off-net differentiation practiced by Germany's two largest network operators, T-Mobile and Vodafone, put E-Plus at an unfair competitive disadvantage due to its smaller market share (KPN 2007). The German Federal Cartel Office, entrusted with the investigation of KPN's complaint, found insufficient evidence of anti-competitive effects of on-net/off-net differentiation and therefore stopped its investigation in 2009 (Haucap, Heimeshoff, and Stühmeier 2011, Haucap and Heimeshoff 2011, German Federal Cartel Office 2010). Even more surprisingly, in the Austrian mobile telecommunications market, the first competitor of incumbent A1 Telekom Austria, T-Mobile Austria (formerly max.mobil), successfully introduced a calling plan with substantial on-net/off-net differentiation shortly after its market entry to gain a competitive advantage over A1 (pressetext.com 1999). Contrary to the standard theory which predicts that consumers would have no incentive to subscribe to the small network of T-Mobile Austria, this strategy proved very successful and led to the rapid growth of T-Mobile Austria (wirtschaftsblatt.at 2012, p. 1). With a market share of 31% in 2012, T-Mobile has become Austria's second largest mobile network operator after A1 Telekom Austria which has a market share of 42%.

A possible explanation for the divergence between the theoretical findings and the empirical observations could be that some of the assumptions of the theoretical models are not met in real-world telecommunications markets. In particular, two assumptions appear to be crucial for tariff-mediated network effects to occur. These are, first, the assumption of a uniform calling pattern which implies that consumers know (at least in expectation) whom they will be calling, and which ensures that the number of calls to a network is proportional to its market share. Secondly, the assumption of fully informed consumers guarantees that consumers know (at least in expectation) the networks of their callees.

Recently, first attempts have been made to relax the assumption of a uniform calling pattern by studying models which use more realistic calling patterns (Kamiński and Latek 2008, 2010). Yet, relaxing the assumption of a uniform calling pattern by introducing real-word call graph topologies also suffers from severe shortcomings. This approach implicitly assumes that at the time a consumer decides to subscribe to a particular network she can either perfectly foresee her future calling pattern or perfectly infer it from her past behavior – both of which are quite unrealistic assumptions. Hence, assuming a balanced calling pattern which links calling probabilities to market shares appears to be a reasonable approximation.

However, to the best of my knowledge, the assumption that consumers have full information about the market shares of all networks has not yet been challenged in the existing literature. This gap is surprising given the fact that there exists a large body of literature which argues that consumers ex-ante lack information about important market parameters which they can acquire by costly search. Following the seminal work of Stigler (1961), numerous scholars have investigated the consequences of costly information acquisition (for an overview of the recent literature see Baye, Morgan, and Scholten 2006; for recent advances in this literature see Janssen and Parakhonyak 2013, 2014). The key premise of the literature on search costs is that consumers are uninformed about prices and have to incur costs to obtain this information. As a result, a certain fraction of utility-maximizing consumers decide to remain only partially informed because of prohibitively high search costs.

This paper aims at challenging the assumption of fully informed consumers by combining the literature on tariff-mediated network effects with the literature on search costs. By combining these two previously separated literature streams, I aim at answering the following research question: *Do tariff-mediated network effects still unfold detrimental effects for small networks if (at least some) consumers are imperfectly informed about the true market shares of the networks?*

To answer this question, I study an agent-based simulation model of a mobile telecommunications market with two asymmetric networks and three types of consumers with unit demand who differ with respect to their search costs. Fully informed consumers (FICs) have non-positive search costs (i.e., search costs are either negative or zero) and, accordingly, are perfectly informed about the true market shares of both networks. Partially informed consumers (PICs) have moderate search costs and, therefore, are assumed to observe market shares within a circular sensing field. Finally, locally informed consumers (LICs) have high search costs and are assumed to be able to only observe their immediate neighbors. Consumers maximize their expected utility by subscribing to the network with the lowest expected costs for a call which they calculate based on the market shares they observe.

The remainder of this paper is structured as follows. In section two, I briefly review the theoretical literature on tariff-mediated network effects as well as the literature on search costs. In section three, I describe the methodology used and the setup of the simulation model. Section four discusses how the model was analyzed and section five presents the results of the baseline model. Section six presents the results of two extensions of the baseline model while section seven discusses the results. Chapter eight summarizes and concludes the paper.

## TARIFF-MEDIATED NETWORK EFFECTS AND COSTLY INFORMATION ACQUISITION

### *Tariff-Mediated Network Effects*

The literature on on-net/off-net differentiation has two different foci. While some scholars study how on-net/off-net differentiation affects competition among network operators in a market, others explore networks' incentives to use access charges as a device for facilitating collusion. In the following review of the extant literature I will focus on the competitive effect of on-net/off-net differentiation and in particular on the effect of on-net/off-net differentiation on the viability of small networks. In doing so, I do not distinguish between studies which solely derive equilibrium results with respect to the access charges set by networks and those which also derive the equilibrium on-net/off-net pricing structure. This is due to the fact that access charges are typically assumed to raise off-net tariffs (see, for instance, Blonski 2002, p. 96, Peitz 2003, p. 732, Hoernig 2008, p. 9, Gabrielsen and Vagstad 2008, p. 5, Cabral 2011, p. 103, Lopez and Rey 2012, p. 1)

The first paper which theoretically explores the competitive effect of on-net/off-net differentiation is the seminal work of Laffont, Rey, and Tirole (1998b, henceforth LRT). They study a Hotelling duopoly in which networks set reciprocal access charges and price discriminate between on-net and off-net calls. One insight of their analysis is that "a full-coverage incumbent can squeeze a small-coverage entrant by insisting on a high access price. The high access charge translates into high off-net prices, creating a de facto lack of interconnection" which, in turn, raises "serious anticompetitive concerns under price discrimination" (Laffont, Rey, and Tirole 1998b, p. 40-41).

Using the same setup, Gans and King (2001) find that with asymmetric access charges, the network setting the higher access charge can increase its market share at the expense of its rival (Gans and King 2001, p. 417). This might be the case if, for instance, one network has a higher bargaining power vis-á-vis its competitors, possibly due to higher initial market shares caused by an incumbency advantage.

Blonski (2002) studies a duopoly market with (exogenous or endogenous) network externalities in which consumers are assumed to be heterogeneous with regards to their taste for the network good. Assuming that network effects are exogenous, he notes that "it is realistic to assume that there is only one equilibrium […] namely the incumbent remaining monopolist" (Blonski 2002, p. 103). Moreover, with endogenous network externalities (whose origin is not explored further), he finds that under linear pricing only corner equilibria exist with the incumbent being more likely to corner the market (Blonski 2002, p. 106). Although under nonlinear pricing shared-market equilibria also exist, the incumbent's prevalence remains if access charges are sufficiently high. Based on these results Blonski concludes that "network externalities represent a force towards uniformity and therefore towards monopoly" (2002, p. 109).

In his review of the European legislation concerning the interconnection between telecommunications network operators, Peitz posits that by setting high access charges incumbents can deter entry and retain their dominant position (2003, p. 730). Furthermore, "in an infant market […] cost-based access prices maintain the asymmetry between operators" (Peitz 2003, p. 737).

Cambini and Valletti (2003) build on the LRT framework and study the effect of reciprocal access charges on networks' investment incentives. However, their study does not pertain to the competitive effect of on-net/off-net differentiation since they explicitly consider only symmetric equilibria (Cambini and Valletti 2003, p. 3).

Another extension of the LRT setup is the model by Jeon, Laffont, and Tirole (2004) who study a Hotelling duopoly with call externalities, i.e., consumers also derive utility from being called. Their key result is that a connectivity breakdown can occur, i.e., networks charge excessively high tariffs for off-net calls so that consumers only make on-net calls, irrespective of whether or not networks levy a reception charge. As a result, consumers on the rival's network do not receive utility from being called by subscribers to the rival network. However, Jeon, Laffont, and Tirole only consider the case of symmetric networks so the question of whether their results extend to the case of asymmetric networks remains unanswered.

Elliot (2004) provides an early review and extension of the literature on on-net/off-net differentiation by means of an Excel-based simulation model. He shows that "it is possible for the larger network to increase its market share if it can force up reciprocal access charges" while also pointing out that "it is almost certainly more cost effective for the dominant firm to cut retail prices than to force up reciprocal access charges" (Elliot 2004, p. 26).

A further simulation study is provided by Cricelli, Di Pillo, Levialdi, and Gastaldi (2004). They consider a triopoly with one fixed network and two mobile networks (an incumbent and an entrant) which are differentiated á la Hotelling. The two mobile networks price differentiate between mobile-to-mobile on-net and off-net calls. Their analysis shows that the incumbent mobile network can increase its market share by price discriminating between on-net and off-net calls. Therefore, the authors conclude that "this price discrimination strategy presents a threat for the other carriers, especially for the smallest ones" (Cricelli, Di Pillo, Levialdi, and Gastaldi 2004, p. 197).

In two related papers, Berger (2004, 2005) studies the model of LRT with call externalities. By means of a graphical analysis, he posits that symmetric equilibria only exist if networks are sufficiently differentiated (Berger 2004, p. 14). Moreover, in the case of asymmetric market shares, "it is optimal for network i to deter any off-net call" (Berger 2005, p. 6) if its market share is sufficiently high which, apparently, would harm the smaller network.

Another series of articles on on-net/off-net differentiation is provided by Hoernig (2007, 2008, 2009). Building on the model of LRT with call externalities and explicitly allowing for asymmetric networks, Hoernig shows that the larger network has an incentive to "limit off-net calls in order to make the smaller network less attractive" (2007, p. 185). Moreover, he explicitly studies the larger network's incentive for predatory pricing and concludes that large on-net/off-net differentials can indicate such anti-competitive conduct (Hoernig 2007, p. 185). The starting point of Hoernig's (2008) study is the assertion that on-net/off-net differentiation "creates inefficiencies and disadvantages for small networks" (Hoernig 2008, p. 1). Subsequently, he analyzes the effectiveness of different regulatory measures for alleviating market share asymmetries. These measures include limiting on-net/off-net differentials, limiting off-net margins, lowering access charges, and allowing for asymmetric access charges. A key insight is the conclusion that the effect of the regulatory measures under consideration on total welfare is ambiguous and depends on the characteristics of demand. Hoernig (2009) extends the findings of his study from 2007 to the case of N networks with asymmetric costs.

Calzada and Valletti (2008) analyze an oligopolistic market with logit demand in which firms compete in prices or utilities, set reciprocal industry-wide access charges, and face the threat of additional entry. Calzada and Valleti show that, if allowed to, incumbents will set higher access charges for entrants than for other incumbents thereby foreclosing the market (2008, p. 1234). However, even with non-discriminatory access charges, incumbents "may decide to use the access charge to deter entry completely" (Calzada and Valletti 2008, p. 1243). While their results are contingent on the extent of the fixed cost of entry, they are robust to the introduction of asymmetric calling patterns, i.e., consumers call some of their peers (their calling club) more frequently than others.

The consequences of calling clubs is also explored in the work of Gabrielsen and Vagstad (2008) who study a non-differentiated duopoly in which both networks have zero marginal cost and offer two-part tariffs with on-net/off-net differentiation. Consumers do not receive utility from receiving calls, have unit demand, incur exogenous switching costs, and are members of non-overlapping calling clubs. Initially, all members of a calling club are subscribed to the same network. Gabrielsen and Vagstad conclude that "a markup on access and resulting price discrimination between on- and off-net calls creates endogenous switching costs and thereby reduces competition between networks" (2008, p. 111).

In a similar vein, Geoffron and Wang (2008) study an extension of the LRT framework with call externalities and linear tariffs in which the second network enjoys an incumbency advantage and consumers are members of calling clubs. The starting point of their analysis is the observation that large or incumbent networks can strategically use access charges to gain a competitive advantage over entrant networks (Geoffron and Wang 2008, p. 60). These scholars then set out to explore the effectiveness of different regulatory measures in alleviating the entrant's disadvantage. They find that regulators should decrease the access charge of the incumbent network rather than increase the access charge of the entrant. From this they conclude that an "appropriate asymmetric regulation may contribute to balancing market shares and, in such a way, compensate for first-mover advantages" (Geoffron and Wang 2008, p. 58).

The analysis of Stennek and Tangerås (2008) builds on a non-differentiated duopoly without call externalities in which networks charge linear tariffs. Absent any regulatory intervention, an incumbent will monopolize the market with the help of three related actions: First, by setting prohibitively high access charges for calls terminating in his network; second, by charging very low off-net tariffs; and third, by paying a very low access charge for calls terminating on the rival's network (Stennek and Tangerås 2008, p. 14). To restore competition, regulators should mandate the interconnection of both networks at reciprocal access charges and should ban on-net/off-net differentiation.

The first agent-based model which explicitly accounts for on-net/off-net differentiation is provided by Schade, Frey, and Mahmoud (2009). They study a mobile telecommunications market with four network operators and a total of 30 different mobile contracts, both pre- and post-paid. Furthermore, with respect to mobile usage intensity, the model accommodates three different consumer types ("infrequent callers," "average callers," and "frequent callers"). When studying which pricing strategy a new entrant should adopt to maximize his probability of successful market entry, Schade, Frey, and Mahmoud find that "a new provider has to accept a considerable cut in prices to successfully establish on the market" and that a "low off-net fee for prepaid contracts has a higher chance of success than a low fee for landline calls" or a cut in the on-net fees (Schade, Frey, and Mahmoud 2009, p. 296).

Cabral (2011) studies a dynamic oligopoly market with a constant fluctuation of consumers. More specifically, in each period one consumer dies and is replaced ("birth"). Having chosen their network after birth, consumers are not allowed to switch anymore. Furthermore, they derive positive utility from the presence of other subscribers on their network. However the source of these positive network effects is not explored explicitly. Cabral demonstrates that "if network effects are sufficiently strong, then the larger network tends to increase in its size" (2011, p. 84) and that "high markups of termination charges over marginal cost imply greater market dominance and possibly the switch from a unimodal to a bimodal stationary distribution of market shares" (2011, p. 104).

The case of an asymmetric Hotelling duopoly with two-part tariffs and switching costs in which initially all consumers are subscribed to the incumbent network is studied by López and Rey (2012). They submit that an incumbent network can use tariff-mediated network effects to "keep the entrant out of the market and still charge monopoly prices by setting a large enough mark-up (or subsidy) on the access charges even if access charges are reciprocal" (López and Rey 2012, p. 4). Hence, the authors conclude that on-net/off-net differentiation "is a key factor in foreclosing competition" (López and Rey 2012, p. 5).

Hoernig, Inderst, and Valletti (2014) study a model with nonuniform calling-patterns in which the probability of calling a specific consumer decreases in the distance between the caller and the callee on the Hotelling line. These scholars show that "if calling patterns are sufficiently concentrated […] profit maximizing access charges are set above cost because sustaining high off-net prices becomes relatively more important than suppressing network effects" (Hoernig, Inderst, and Valletti 2014, p. 172).

The first study to investigate the competitive effects of on-net/off-net differentiation in the context of calls between fixed and mobile networks is the work of Hoernig, Bourreau, and Cambini (2014). Their model comprises one fixed and two mobile network operators, whereby the fixed line operator and one mobile network are integrated and customers of the fixed and mobile networks, respectively, do not overlap. Consumers derive utility from receiving calls, and mobile networks set nonlinear prices. In equilibrium "FTM [fixed-to-mobile] calls to the rival mobile network are priced significantly above marginal cost, while those to the integrated mobile network are priced below cost" which, in turn, "creates an additional disadvantage for the non-integrated mobile network, in terms of market shares and profits, and even magnifies any prior asymmetries" (Hoernig, Borreau, and Cambini 2014, p. 59). Since it is typically the mobile network incumbents which are integrated with the fixed line operator (Hoernig, Burreau, and Cambini 2014, p. 58), the pricing structure of the integrated network especially harms small network operators.

In summary, the theoretical literature on tariff-mediated network effects by and large shows that on-net/off-net differentiation can strategically be used to harm smaller networks. This is also echoed in Harbord and Pagnozzi's review of the literature on on-net/off-net differentiation who conclude that "tariff-mediated network effects create barriers to entry" (2010, p. 6) and that "high mobile-to-mobile termination charges, coupled with high charges for off-net calls, can be used strategically by incumbent operators to either prevent entry or reduce competition from new entrants into their market" (2010, p. 7).

***Costly Information Acquisition***

Research on the consequences of costly information acquisition by consumers started in 1961 with Stigler's seminal paper 'The Economics of Information.' The key premise underlying the stream of literature kindled by Stigler's work is that consumers ex-ante lack information about prices charged by individual firms. In order to obtain this information, consumers have to costly search for prices. Possible sources of search costs are, for instance, “the material cost of time and travel involved” or “behavioural biases such as status quo bias or choice overload” (Fletcher 2013, p. 108). Since a comprehensive review of the literature on search costs is beyond the scope of this paper, I focus on those papers which closely follow the research agenda outlined by Stigler and which analyze the impact of costly information acquisition on equilibrium prices charged by firms. For a comprehensive review of the recent theoretical and empirical literature on search costs see Baye, Morgan, and Scholten (2006).

A standard assumption in this literature is that consumers differ with respect to the extent of their search costs. In particular, this literature distinguishes between two basic types of consumers. On the one hand, a fraction μ of consumers is assumed to have non-positive search costs (i.e., search costs are either negative or zero) to account for the empirical observation “that there is a non-negligible measure of consumers who seem to derive enjoyment form shopping [i.e., searching for prices] itself” (Stahl 1989, p. 701). Accordingly, these consumers, typically labeled “shoppers,” always obtain full information about all prices in a market. On the other hand, the remaining fraction 1- μ of “non-shoppers” have positive search costs which are either assumed to be homogeneous among consumers (see, e.g., Burdett and Judd 1983, Stahl 1989, Janssen and Non 2008, Janssen and Parakhonyak 2013, 2014, Astorne-Figari and Yankelevich 2014), or drawn from some distribution function (see, e.g., Braverman 1980, Rob 1985, Stiglitz 1987, Stahl 1996, Chandra and Tappata 2011). Typically, search costs are assumed to be high enough so that it is optimal for non-shoppers to search only a fraction of all prices in the market and, hence, remain only partially informed. In fact, some consumers may even decide to “remain uninformed, as they prefer to avoid search costs” (Chandra and Tappata 2011, p. 681).

With respect to the extent of consumers’ prior information, Stahl (1996) distinguishes between models following the ‘Stackelberg paradigm,’ under which “consumers know the ‘market distribution’ of actual prices being charged but do not know which store is charging which price,” and models adhering to the ‘Nash paradigm,’ under which “consumers have no information (before search) about the market distribution M(p)” (Stahl 1996, p. 244-245). Moreover, Stahl posits that “the Nash paradigm is the preferred modeling choice” (1996, p. 246).

Furthermore, the literature on search costs also differs according to the process of consumer search. More specifically, consumers are either assumed to search sequentially or use a fixed sample size search strategy. In sequential search models, consumers search the first firm provided that their valuation for the good exceeds the search costs. After learning the price charged by the first firm, consumers decide whether to buy or continue searching. Consumers keep on searching if and only if the expected gain from additional search exceeds the cost of search. Based on this optimization behavior, it is possible to calculate a reservation price r such that if the price at a firm is lower than r, consumers buy at the firm and otherwise they keep on searching. This implies that consumers always buy at the firm last visited (unless they have searched all firms). Sequential consumer search is only viable under the Stackelberg paradigm since consumers are required to know (or have an estimate of) the probability distribution of the prices charged to be able to form an expectation about the probability of finding a lower price than the one currently observed. On the other hand, if consumers use a fixed sample size search strategy, they ex-ante decide to visit a fixed number of firms to obtain price quotes. After having visited each firm in their sample, consumers buy from the firm with the lowest price. The two crucial assumptions underlying this search strategy are that, first, consumers have perfect recall of all prices observed and that, second, prices remain fixed between the time of search and the time of purchase. Although most theoretical models assume that consumers search sequentially, empirical evidence from a recent study of De Los Santos, Hortaçsu, and Wildenbeest (2012) suggests that this assumption is invalid. These scholars use data on the actual browsing behavior of more than 150,000 internet users to analyze search behavior in the market for online books. They formulate three hypotheses which allow them to test whether the observed search behavior is consistent with sequential or fixed sample size search strategy. In all three tests, their data does not support the null hypothesis of sequential search and, hence, the authors conclude that "the fixed sample size search strategy outperforms the sequential search model in terms of explaining observed search behavior" (De Los Santos, Hortaçsu, and Wildenbeest 2012, p. 2979).

The major theme of this literature stream is whether costly information acquisition can explain the persistent price dispersion observed in many markets. (Stahl 1996, p. 260, Carlton and Perloff 2005, p. 445). Price dispersion occurs if price differentials between firms exist which are not rooted in differing product characteristics or transportation costs. Accordingly, there exists an abundant literature studying whether and under which conditions costly consumer search leads to a market equilibrium with dispersed prices. Recently, scholars have begun to enrich standard models of search behavior (Wollinsky 1986, Stahl 1989) by allowing for firms offering price matching guarantees (Janssen and Parakhonyak 2013), costly revisits of firms (Janssen and Parakhonyak 2014), or asymmetric price sampling by consumers (Astorne-Figari and Yankelevich 2014).

The key insight from this literature stream is that under quite general conditions, costly information acquisition by consumers leads to equilibrium prices being consistently above marginal costs as long as the fraction of shoppers does not exceed a certain threshold. Moreover, costly search might also induce firms to randomize over prices in equilibrium which, in turn, leads to price dispersion. Therefore, as Stahl concludes, “costly information acquisition almost surely implies a departure from the first-best setting” (1996, p. 259) and, accordingly, a welfare loss.

## A COMPUTATIONAL MODEL OF TARIFF-MEDIATED NETWORK EFFECTS WITH INCOMPLETELY INFORMED CONSUMERS

To study the competitive effects of tariff-mediated network effects with costly information acquisition for consumers, I employ an agent-based simulation model. Two key features of agent-based simulations make this methodology particularly useful for answering the research question. First of all, agents in the model are autonomous, i.e., act according to individual rules and objectives. Secondly, agents are heterogeneous regarding their characteristics and decision rules. This allows for an investigation of different types of consumers who differ with respect to their search costs without necessarily imposing simplifying assumptions on the distribution of search costs, such as, for instance, that search costs are identical or uniformly distributed among consumers. Moreover, modeling autonomous agents allows me to study models which are characterized by complex interactions and feedback loops among consumers’ behavior. These interactions and feedback loops, in turn, lead to emergent system-level behavior, “that is, properties arising from the interactions of the agents that cannot be deduced simply by aggregating the properties of the agents.” (Axelrod and Tesfatsion 2006, p. 1649). Being able to study models which allow for interactions and feedback loops is particularly important in the context of a consumer’s decision to subscribe to a telecommunication network. This decision strongly depends on the market shares of the networks which, in turn, depend on other consumers’ decisions to join a particular network which, again, depends on other consumers’ decision and so on.

The description of the model proceeds in four steps. First, I describe the key features of the telecommunications market modeled before explaining the characteristics and behavior of consumers in the second step. The third step comprises an explanation of how the model is initialized and, finally, in the fourth step I describe the scheduling of the simulation.

***The Market***

The market for telecommunications is modeled as a rectangular grid of 1,000 (50x20) cells with each cell accommodating exactly one consumer. The grid is toroidal, i.e., the world wraps both horizontally and vertically so that each consumer has exactly eight neighbors. Telecommunication services are provided by two network operators offering linear tariffs and price discriminating between on-net and off-net calls. Networks sizes are assumed to be asymmetric with a large incumbent network A facing competition from a small entrant B. Furthermore, in line with standard models of tariff-mediated network effects (see, e.g., LRT 1998b), I assume full market participation so that each consumer is subscribed to exactly one network in every period.

The representation of the market as a two-dimensional grid is open to different interpretations. First of all, the market could be interpreted spatially, where the Euclidean distance between two consumers represents the spatial distance between the two. Alternatively, the two-dimensional grid can also be interpreted as a social space where individuals differ along two social dimensions. An example for such a social space would be the so-called Sinus-Milieus, which classify consumers into ten different social groups along two basic dimensions (SINUS Markt -und Sozialforschung GmbH 2011, p. 14). These are, first, "basic values," indicating whether an individual is primarily oriented toward "tradition," "modernization and individualization," or "re-orientation," and, second, "social class," indicating whether an individual belongs to the "lower," "middle," or "higher" class.

***The Consumers***

The models studied in the literature on search costs assume that consumers' decision to buy a good depends on their *actual* expenditure for the good, i.e., on the quantity to be purchased and on firms' prices. In contrast, the literature on tariff-mediated network effects postulates that the decision to subscribe to a telecommunications network is contingent on the *expected* expenditures for the good which depend on consumers' forecast of their future demand and the actual prices set by the firms. To facilitate this forecast, it is typically assumed that calling patterns are uniform, i.e., that the probability of calling a specific network equals its market share. Accordingly, in search models consumers face only one source of uncertainty, namely the prices charged by firms, whereas in the present model, in principal two different sources of uncertainty exist. Similar to search cost models, consumers could lack knowledge of the prices charged by each network. However, additionally consumers might lack information about networks' market shares and, hence, the probabilities of calling each network. While it would in principle be possible to allow for both sources of uncertainty simultaneously, it seems advisable to only consider one source of uncertainty at a time in order to establish a clear between the type of uncertainty and the outcome of the model.

I assume that consumers in the model are perfectly informed of the tariffs charged by each network, while they have to search for information regarding networks' market shares. This decision is based on the observation that the advertising of prices is ubiquitous in telecommunications markets, as exemplified, for instance, by the overwhelming success of T-Mobile Austria's famous "Ein-Schilling-Tariff" (see pressetext.com 1999). Since advertising can be considered a substitute for consumer search (Perloff and Salop 1986, p. 187, Janssen and Non 2008, p. 355), it seems reasonable to assume that consumers are informed of the prices charged by different telecommunication networks. On the other hand, information about networks' market shares is not readily available to consumers via advertising or other sources. Hence, I assume that consumers have to search costly for networks' market shares. An alternative argumentation would be that the costs of searching for tariffs charged by networks are negligible compared to the costs which consumers incur when searching for networks' market shares.

In the model, a central agency selling perfect information about networks' market shares does not exist. Therefore, in order to obtain information about networks' market shares, consumers have to approach other consumers and ask them about their current network subscription. This assumption roughly parallels the setup in standard search models where consumers have to visit a firm to learn about its price. For each visit consumers incur constant costs which are assumed to be independent of the distance traveled. Hence, the number of other consumers visited by a specific consumer depends on the realization of her search costs.

In line with Stahl who postulates that "it is important to have a model that can accommodate an atom of shoppers" (1996, p. 146), I assume that a fraction $\alpha$ of consumers are shoppers with non-positive search costs. As a result, they always approach all other consumers and, hence, become 'fully informed consumers' (FICs). To get a more fine-grained picture of the influence of costly information acquisition on the competitive effect of tariff-mediated network effects, I allow the fraction $1-\alpha$ of non-shoppers to differ with respect to the extent of search costs. More specifically, I assume that a fraction $\beta \leq 1-\alpha$ has moderate search costs, whereas the remaining $\gamma = 1 - \alpha - \beta$ consumers have high search costs.

In line with the empirical findings of De Los Santos, Hortaçsu, and Wildenbeest (2012) consumers in the model use a fixed sample size search strategy to collect information about networks' market shares. I do not explicitly model how consumers' search costs translate into an optimal sample size for fixed sample size search. Instead, I assume that the moderate extent of search costs allows the fraction β of consumers to approach other consumers within a specific radius which is decreasing in the search costs. This assumption establishes a clear link between consumers' search cost and the radius of their sensing field. Since these consumers only observe a fraction of the market, I label them 'partially informed consumers' (PICs). Finally, I assume that the remaining fraction γ of consumers with high search costs find it optimal to only infer market shares from their immediate eight neighbors, which makes them 'locally informed consumers' (LICs).

Both partially and locally informed consumers use the observed market shares as estimates for firms' true market shares. This assumption parallels the model of Perloff and Salop (1986) in which consumers form an estimate of firms' prices which is based on, among other factors, their observation of prices (see also Carlton and Perloff 2005, p. 464).

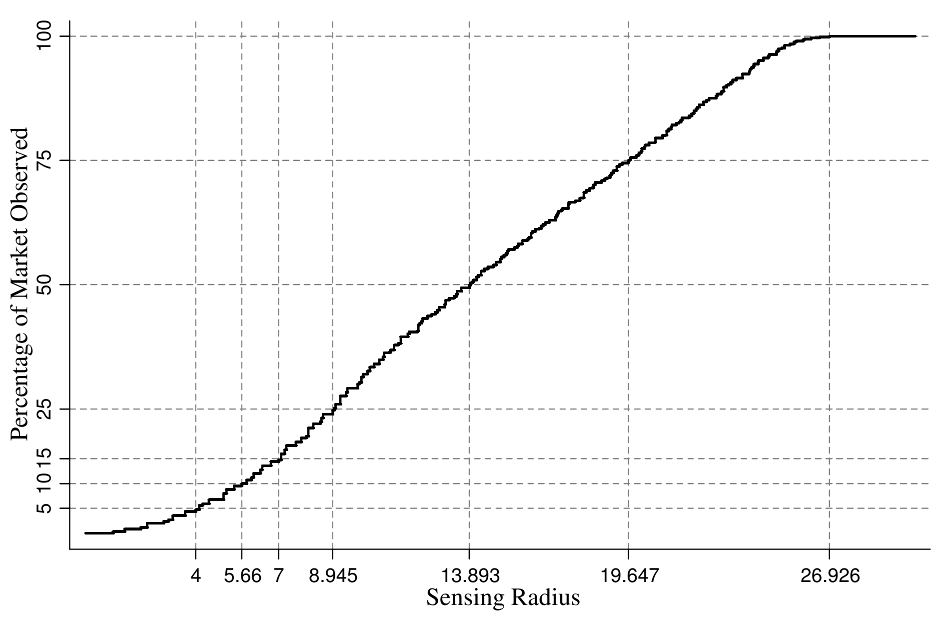



**Figure 1: Effect of sensing radius on percentage of market observed**

The modeling of consumers' search behavior implies that FICs and LICs span a continuum of different levels of information on firms' market shares. PICs are located within this continuum and their exact position depends on their sensing radius. As their radius increases, they approach FICs in behavior, while they converge to the behavior of LICs as their sensing radius decreases. Figure 1 further illustrates the relationship between the sensing radius of PICs and percentage of market observed.

This flexible specification allows for an investigation of the consequences of different levels of information among consumers on the competitive effect of tariff-mediated network effects.

Following Stahl, I assume that "consumers are effectively identical except for search costs" (1989, p. 701). Each consumer strives to be subscribed to the network offering the highest expected utility. The expected utility of consumer i from being subscribed to network j in period t is given by:

(1) $U_{ijt} = v_{0i} - E(c_{ijt})$,

that is, the expected utility is given by a baseline utility derived from being able to communicate over the network net of the expected cost of a call to a random consumer. The baseline utility is assumed to be large enough so that consumers always subscribe to one of the two networks (Calzada and Valletti 2008, p. 1227, Cabral 2011, p. 88, López and Rey 2012, p. 6). Note that the specification of the utility function contains three implicit assumptions about consumers' behavior. First, I assume that consumers have unit demand, which is a common assumption in models of costly consumer search (see, for instance, Rob 1985, Janssen and Non 2008, Janssen and Parakhonyak 2013, Astorne-Figari and Yankelevich 2014) but has also been used in the literature on on-net/off-net differentiation (Gabrielsen and Vagstad 2008, p. 103). Second, I assume that consumers are myopic, i.e., when deciding which network to subscribe to, consumers do not take the behavior of other consumers into account. This assumption is in line with Cabral who observes that "many of the existing models of network effects assume that consumers are short-lived, myopic, or naïve" (2011, p. 95; see also Gabrielsen and Vagstad 2008, p. 104). The third assumption is that the baseline utility is identical for both networks for a given consumer while it may differ between consumers. Accordingly, the only source of differentiation between the two networks are the tariffs for on-net and off-net calls, respectively. The reason for this seemingly strong assumption is that the present study focuses on the competitive effect of price differentiation rather than on the effect of (horizontal or vertical) product differentiation. Moreover, this assumption is in line with the observation of Gabrielsen and Vagstad (2008, p. 102) that "the extent of product differentiation among different mobile network operators is minimal" (see also Stennek and Tangerås 2008, p. 2). However, this assumption is not overly restrictive as differences in product quality, which would be reflected by different $v_{0i}$, can also be interpreted as an additional cost incurred by subscribers of the network with inferior quality.

In essence, the utility function in (1) implies that consumers minimize their (expected) telephone bill by subscribing to the network which offers the lowest expected cost of a random call. Furthermore, the expected cost of a call is given by:

(2) $E(c_{ijt}) = marketshare_{ijt} * p_{jt}^{onnet} + (1 - marketshare_{ijt}) * p_{jt}^{offnet}$,

where $marketshare_{ijt}$ denotes consumer i's observation of network j's market share in period t and $p_{jt}^{onnet}$ and $p_{jt}^{offnet}$ denote network j's tariffs for on-net and off-net calls in period t, respectively. Note that two consumers may have a different observation of network j's market share at time t depending on their search costs as well as on their location in the market.

This specification implies that, for each network, there exists a critical market share above which a consumer wants to be subscribed to the respective network. For network A the critical market share is given by:

(3) $E(c_{iAt}) < E(c_{iBt})$

which holds whenever

(4) $marketshare_{iAt} > \frac{p_{Bt}^{onnet} - p_{At}^{offnet}}{\left(p_{At}^{onnet} - p_{At}^{offnet}\right) + \left(p_{Bt}^{onnet} - p_{Bt}^{offnet}\right)}$

Typically, the denominator in (4) is negative since networks price on-net calls below off-net calls. If this is the case, an analysis of the effect of tariff-mediated network effects is only interesting if network B's tariff for on-net calls is below A's tariff for off-net calls because otherwise the right-hand side of the inequality is negative and, hence, consumers always join network A regardless of its market share. The analogous result holds for network B. Moreover, equation (4) shows that network A's critical market share increases in its tariffs and decreases in network B's tariffs.

***Initialization of the Market (t=0)***

The initialization of the simulation in t=0 proceeds in three steps. First, the computer creates 1,000 consumers and scatters them across the grid so that each cell accommodates exactly one consumer. In the second step, each consumer is randomly assigned to one of the three types (FIC, PIC, or LIC) based on pre-defined shares. In the third step, membership to networks A and B is distributed based on the market shares pre-defined by the modeler. The distribution is such that clusters of subscribers to network B occur, with the number of clusters being pre-defined by the modeler. The initial clustering of subscribers to the smaller network is in line with Möbius (2011, p. 16) and mirrors the empirical findings of Karacuka, Çatik, and Haucap (2013). These scholars report that in the Turkish mobile telecommunications market regional market shares of mobile networks differ considerably. While the incumbent network operator Turkcell has a dominant position in the densely populated area of Marmara, “surprisingly, the smallest operator, Avea, is the market leader in postpaid services in eastern and south eastern parts of Turkey, and Avea has a share very close to Turkcell in the postpaid market in the Black Sea region” (Karacuka, Çatik, and Haucap 2013, p. 337). Furthermore, Karacuka, Çatik, and Haucap report that Turkish network operators also differ with respect to the social characteristics of their customers. Avea, for instance, is the operator of choice among young consumers (Karacuka, Çatik, and Haucap 2013, p. 343). Hence, these findings corroborate the assumption of a clusterwise distribution of membership to the smaller network regardless of whether the two dimensional grid is interpreted as a geographic or social space. As a side note, this assumption is also reasonable from a technical point of view. If membership to both networks was assigned randomly, then market shares observed by both PICs and LICs would in expectation be equal to the true market share observed by FICs. Hence, with random assignment of network membership, all three types of consumers would behave similarly.

Figure 2 shows an exemplary state of the market after completed initialization. Red cells are occupied by subscribers to network A, while blue cells accommodate subscribers to network B. Membership to network B is distributed in ten clusters. FICs are represented by a dot, PICs by an x, and LICs by a triangle.

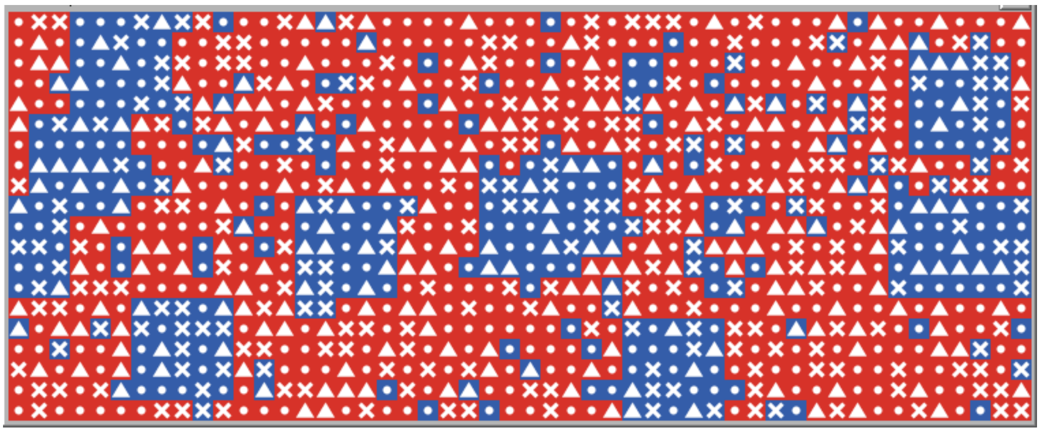


**Figure 2: Exemplary state of the market after successful initialization**

### *The Scheduling (t=1 to 999)*

In the simulation model, time is represented discretely, i.e., time passes in steps. The length of one time step is not explicitly defined. However, it is shorter than the average subscription duration because in each time period only a fraction of subscribers is allowed to decide about whether to stay with the current network or switch to the competitor. This assumption compares to the dynamic model of Cabral (2011). Although in his model, subscribers are not allowed to switch their network after initial subscription, in each period one random consumer dies and is replaced. Technically, this is equivalent to allowing one consumer per period to decide on switching her network. Moreover, allowing only a fraction of all consumers to switch their network in each period mirrors the fact that, in reality, consumers' contract lengths are heterogeneous and not synchronized. Following Cabral (2011, p. 102), I set the maximum simulation length to 1,000 periods. However, the simulation prematurely stops after one of the networks has successfully cornered the market.

**Table 1: Scheduling of the model**

| | |
|---|---|
| 1. Initialization | 1.1. Create and distribute 1,000 consumers |
| | 1.2. Assign consumer types randomly |
| | 1.3. Assign network membership clusterwise |
| 2. Simulation | 2.1. Draw random sample of consumers allowed to decide on network membership |
| | 2.2. Selected consumers update observed market shares<br>• FICs observe true market shares<br>• PICs observe market shares within circular sensing field<br>• LICs observe market shares among their eight neighbours |
| | 2.3. Selected consumers calculate expected utility for both networks, based on equations (1) and (2) |
| | 2.4. Selected consumers switch to competitor if expected utility from competing network is higher |
| 3. Observation | Update plot of true market shares of both networks |

In each period, four actions are executed successively. First, the computer draws a random sample of consumers who are allowed to decide on their network membership. Second, all consumers of this sample update their observed market shares of both networks using their respective behavioral rule. Since I assume full market participation, the market share of network B is simply one minus the market share of network A. Third, all selected consumers calculate the expected utility derived from both networks, while in the fourth step, each consumer of the sample subscribes to the network offering the higher expected utility. As a tie-breaking rule, consumers stay with their current network operator if the expected utilities for both networks are equal. Finally, in the fifth step, a plot is updated which keeps track of the true market shares of A and B. Table 1summarizes the initialization and scheduling of the model.

## DESCRIPTION OF THE EXPERIMENTAL SETUP

Table 2 gives an overview of the variables used in the model. To analyze agent-based models, Railsback and Grimm (2012) recommend identifying the key variables which are likely to have the greatest impact on the model outcome and systematically varying these variables to understand the model's behavior. However, it is important to keep in mind that the number of possible parameter combinations which have to be simulated increases exponentially. For instance, adding a variable with three levels to an analysis which already contains five variables with three levels each increases the number of necessary simulations from $3^5 = 243$ to $3^6 = 729$.

**Table 2: Overview of variables**

| Name | Type | Levels used in analysis |
|---|---|---|
| Market shares at end of simulation | Dependent | n.a. |
| Fraction of fully informed consumers | Independent | 0%, 20%, 40%, 60%, 80%, 100% |
| Fraction of partially informed consumers | Independent | 0%, 20%, 40%, 60%, 80%, 100% |
| Fraction of locally informed consumers | Independent | 0%, 20%, 40%, 60%, 80%, 100% |
| Initial market share of network A | Control | 65%, 75%, 85%, 95% |
| Sensing radius of partially informed consumers | Control | 4, 5.66, 7, 8.945, 13.893, 19.647 |
| Number of clusters | Control | 1, 5, 10 |
| Number of consumers | Fixed | 1000 |
| Maximum simulation length | Fixed | 1000 |
| Probability of network selection | Fixed | 5% |
| On-net price network A | Fixed | 0.5 |
| Off-net price network A | Fixed | 1 |
| On-net price network B | Fixed | 0.25 |
| Off-net price network B | Fixed | 1 |

To keep the model computationally tractable, I decided to keep the size of the market and the length of the simulation constant since these two variables do not significantly affect the model outcome. Increasing the size of the market does not affect the behavior of fully informed consumers, decreases the fraction of the market observed by PICs which is equivalent to a reduction of their sensing radius, and makes LICs' inference about the market shares of A and B even less precise. Setting the maximum simulation length to 1,000 periods ensures that the system will achieve a market equilibrium or steady state before the simulation terminates. Moreover, I fixed the tariffs for off-net calls of networks A and B to 1 and the tariffs for on-net calls to 0.5 and 0.25, respectively. Variation of the tariffs for on-net and off-net calls affects the critical market share of network A below (above) which consumers will choose network B (A) (see equation (4)). Given these tariffs, consumers join network B if their observed market share of network A is below 60%. However, a change in tariffs implies a change in the critical market share and, therefore, necessitates an adjustment of the values of network A's initial market share which, in turn, complicates a comparison of the different simulation runs. Hence, I decided to keep tariffs constant to assure that all simulations can be run on the same parameter space. However, in the second extension of the model (see chapter 6.2) I allow for endogenous price setting.

To investigate the effects of on-net/off-net differentiation on the market shares of small networks, I systematically vary the remaining six variables of the model, whereby the main focus is on how differing fractions of FICs, PICs, and LICs affect the model outcome. I vary these fractions in six equidistant steps of 20%, of course assuring that the three shares sum to one. As control variables, I systematically permute the initial market share of A (and hence of B), the sensing radius of partially informed consumers, and the number of (and hence the size of) clusters of subscribers to network B. For network A's market share, I choose four equidistant steps starting from 65% to ensure that tariff-mediated network effects still favor the larger network A. The values for PICs' sensing radius were chosen such that they observe 5%, 10%, 15%, 25%, 50%, and 75% of the market, respectively. The number of clusters was set somewhat arbitrarily to 1, 5, and 10, respectively.

In total, the combination of all values for each of the six variables results in 1,152 possible parameter combinations, taking into account that the shares of consumer types sum to one and that the sensing radius need not be varied if the share of PICs is 0%. Despite this vast parameter space, I decided to use a full factorial design for the analysis of the model to be able to detect nonlinearities in the model's response surface. By using fractional factorial designs, such as Plackett-Burman designs (Plackett and Burman 1946) or Latin Hypercubes (Siebertz, van Bebber, and Hochkirchen 2010, p. 159-190) it is not possible to estimate higher-order nonlinearities (Siebertz, van Bebber, and Hochkirchen 2010, p. 25-56) or it might even be the case that nonlinear regions in the response surface of the model are overlooked if exactly those parameter combinations leading to nonlinear behavior are skipped.

In order to minimize the influence of stochastic elements of the model, such as the random initialization of the market or the order in which consumers are selected to decide on network membership, I simulated each parameter combination 500 times. Although it is possible to observe both equilibrium and off-equilibrium behavior in an agent-based simulation, the focus of this paper is on the model's equilibrium or steady state given a specific combination of parameters. Hence, for each parameter combination and each repetition, I only analyze the market shares of networks A and B in the last period and the average number of times in which a consumer switches her network. The final data set consists of the average of these two statistics over the 500 repetitions as well as the average simulation length for each of the 1,152 parameter combinations.

## SIMULATION RESULTS

As described in the previous section, I simulated each parameter combination 500 times to ensure that stochastic elements in the model do not affect the simulation results. Accordingly, the results reported below are based on the averaged dataset, i.e., for each parameter combination the results are averaged over the 500 repetitions.

To check whether 500 repetitions are sufficient to ensure that stochastic elements in the model do not affect the analysis, the experimental error variance should be calculated (Lorscheid, Heine, and Meyer 2012, p. 33). The experimental error variance is a measure of the variability in the model's response variable(s) which arises if the model is run repeatedly using the same parameter settings (Lorscheid, Heine, and Meyer 2012, p. 33). As a measure of the experimental error variance, Lorscheid, Heine, and Meyer suggest using the coefficient of variation, which is defined as

(5) $c_v = \frac{s}{\mu}$

where s denotes the standard deviation of a response variable and μ denotes its arithmetic mean (Hendricks and Robey 1936). The necessary number of repetitions is given by the point where $c_v$ no longer changes with an increasing number of repetitions.

Figure 3 shows the experimental error variance after 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 repetitions for 20 different parameter combinations which showed the highest coefficient of variation in network A's market share after 500 repetitions and, accordingly, represent those combinations which are most sensitive to random influences.

As Figure 3 illustrates, in 15 parameter combinations the coefficient of variation stabilizes after 400 to 450 repetitions. The explanation for the increasing coefficient of variation for the remaining five parameter combinations is of a statistical nature. In four parameter combinations network A corners the market in all but one repetition, while for the fifth parameter combination A corners the market 498 times. Due to the fact that with an increasing number of repetitions the mean market share decreases faster than the standard deviation, these rare events lead to an increasing coefficient of variation. However, since the events that impede the coefficient of variation from stabilizing are so rare, even significant increases in the number of repetitions for all parameter combinations would not lead to a significant increase in the amount of information available. Therefore, I decided to not increase the number of repetitions per parameter combination further.

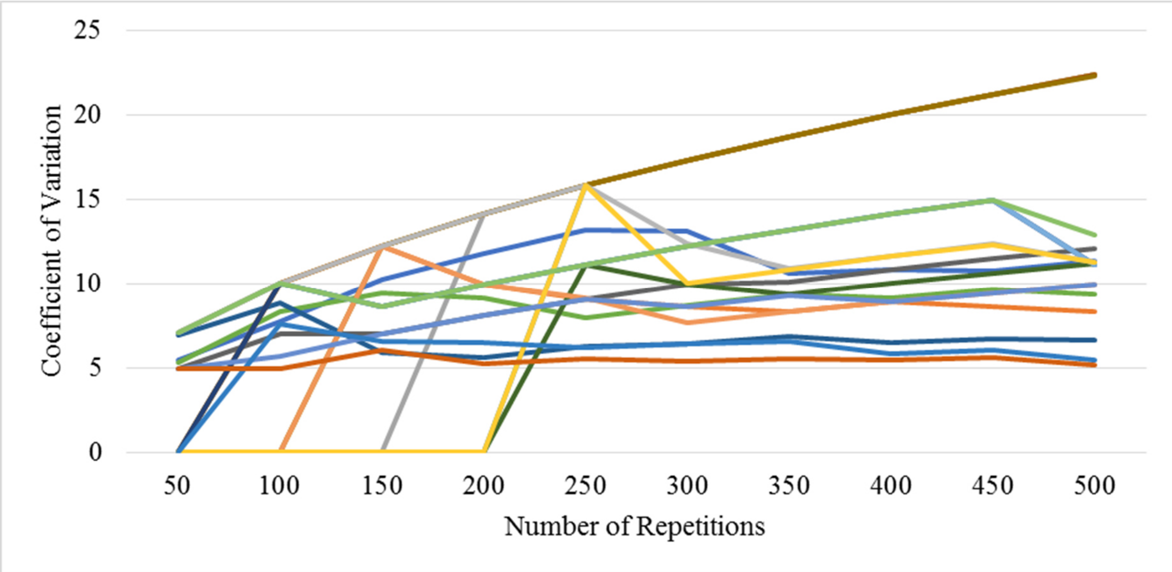



**Figure 3: Development of Coefficient of Variation**

***Descriptive Statistics***

Table 3 summarizes the descriptive statistics of the results. On average, consumers switch their network 0.26 times during one simulation run. In extreme cases, the market either shows hardly any dynamics, with consumers switching only 0.01 times, or turns out to be very turbulent, with all consumers switching their network once. Furthermore, on average, a simulation run stops after 266 periods since one of the networks corners the market. However, for 24 parameter combinations the market never converges to a corner equilibrium so that all 999 periods are simulated in all 500 repetitions. The mean market share of network A at the end of a simulation run is 0.88. Over all parameter combinations, network A increases its initial market share with a probability of 89%, i.e., in 445 repetitions, while the corresponding probability for network B is 11%. Furthermore, network A corners the market with a probability of 80%, i.e., in about 400 repetitions, while network B corners the market with a probability of 9%.

The fact that the probabilities of increasing the initial market share and of cornering the market are pretty close implies that for most parameter combinations market share growth is monotonic, i.e., if a network increases its initial market share it typically also corners the market.

**Table 3: Descriptive statistics**

| | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| No. of network switches per consumer | 0.26 | 0.23 | 0.01 | 1.00 |
| Simulation length | 266.24 | 270.74 | 85.78 | 999.00 |
| Final market share of network A | 0.88 | 0.29 | 0.00 | 1.00 |
| Probability of A increasing its market share | 0.89 | 0.30 | 0.00 | 1.00 |
| Probability of B increasing its market share | 0.11 | 0.30 | 0.00 | 1.00 |
| Probability of A cornering the market | 0.80 | 0.36 | 0.00 | 1.00 |
| Probability of B cornering the market | 0.09 | 0.27 | 0.00 | 1.00 |

However, these statistics can only provide a first rough understanding of the simulation results since they are based on the average of 500 repetitions for all parameter combinations. Therefore, Table 4 shows the number of parameter combinations in which the number of runs in which either network increases its initial market share exceeds a certain threshold.

In 1,026 out of 1,152 parameter combinations, network A increases its market share in at least 250 out of 500 repetitions, whereas for network B this is only the case in 126 parameter combinations. In 898 (65) parameter combinations, all 500 repetitions result in network A (B) increasing its initial market share.

The corresponding analysis for corner equilibria is displayed in Table 5. In 932 out of 1,152 parameter combinations, network A corners the market in at least half of all repetitions, while in still 675 combinations, A always corners the market. For network B, the corresponding figures are 102 and 48, respectively. This analysis again shows that if one of the networks increases its initial market share it most likely also corners the market.

**Table 4: Frequency of market share growth**

| | | Number of parameter combinations in which… | |
|---|---|---|---|
| | | ...network A increases its initial market share in at least… | ...network B increases its initial market share in at least… |
| 250 | repetitions | 1026 | 126 |
| 300 | | 1022 | 123 |
| 350 | | 1013 | 115 |
| 400 | | 1003 | 110 |
| 450 | | 980 | 102 |
| 500 | | 898 | 65 |

**Table 5: Frequency of monopolization**

| | | Number of parameter combinations in which… | |
|---|---|---|---|
| | | ...network A corners the market in at least… | ...network B corners the market in at least… |
| 250 | repetitions | 932 | 102 |
| 300 | repetitions | 912 | 98 |
| 350 | repetitions | 887 | 89 |
| 400 | repetitions | 866 | 83 |
| 450 | repetitions | 818 | 75 |
| 500 | repetitions | 675 | 48 |

To investigate the effect of the independent variables, Lorscheid, Heine, and Meyer (2012, p. 38) recommend the use of an effect matrix which contains the main effects as well as all possible pairwise interactions between all levels of the independent variables. In Table 6, the values on the main diagonal denote the unconditional mean of the final market share of network A for each level of all independent variables. Furthermore, for all levels of the independent variables, the mean of the final market of network A conditional on the level of another independent variable is shown in the lower triangle matrix.

Across all parameter combinations in which the share of FICs is 0, the average market share of network A at the end of the simulation is 67%. However, A's market share drastically increases to an average of 96% if the share of FICs is 20%. If at least 40% of all consumers are fully informed, network A always corners the market. In contrast to that, network A's final market share (almost) monotonically decreases with an increase in the fraction of PICs (LICs). On average, network A's market share is 66% across all parameter combinations in which all consumers are partially informed, while A's average market is 79% if all consumers are locally informed. Not surprisingly, an increase in A's initial market share also leads to an increase in its final market share. Moreover, the sensing radius of PICs also has a positive effect on A's final market share which increases from 82% for a sensing radius of 4 to an average of 96% if the radius is 19.65. Finally, if the number of clusters of network B at t=0 increases from 1 to 10, network A's average market share increases from 83% to 92%.

## Table 6: Matrix of one-way and two-way effects

| | | FIC | | | | | | PIC | | | | | | LIC | | | | | | Initial Market Share | | | | Sensing Radius | | | | | | Number of Clusters | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 0.00 | 0.20 | 0.40 | 0.60 | 0.80 | 1.00 | 0.00 | 0.20 | 0.40 | 0.60 | 0.80 | 1.00 | 0.00 | 0.20 | 0.40 | 0.60 | 0.80 | 1.00 | 0.65 | 0.75 | 0.85 | 0.95 | 4.00 | 5.66 | 7.00 | 8.95 | 13.89 | 19.65 | 1 | 5 | 10 |
| FIC | 0.00 | 0.67 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | 0.20 | | 0.96 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | 0.40 | | | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | 0.60 | | | | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | 0.80 | | | | | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | | |
| | 1.00 | | | | | | 1.00 | | | | | | | | | | | | | | | | | | | | | | | | | |
| PIC | 0.00 | 0.79 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 | 0.95 | | | | | | | | | | | | | | | | | | | | | | | | |
| | 0.20 | 0.68 | 0.98 | 1.00 | 1.00 | 1.00 | | | 0.93 | | | | | | | | | | | | | | | | | | | | | | | |
| | 0.40 | 0.67 | 0.97 | 1.00 | 1.00 | | | | | 0.91 | | | | | | | | | | | | | | | | | | | | | | |
| | 0.60 | 0.66 | 0.96 | 1.00 | | | | | | | 0.87 | | | | | | | | | | | | | | | | | | | | | |
| | 0.80 | 0.66 | 0.94 | | | | | | | | | 0.80 | | | | | | | | | | | | | | | | | | | | |
| | 1.00 | 0.66 | | | | | | | | | | | 0.66 | | | | | | | | | | | | | | | | | | | |
| LIC | 0.00 | 0.66 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.94 | 0.66 | 0.92 | | | | | | | | | | | | | | | | | | |
| | 0.20 | 0.66 | 0.96 | 1.00 | 1.00 | 1.00 | | 1.00 | 1.00 | 1.00 | 0.96 | 0.66 | | | 0.91 | | | | | | | | | | | | | | | | | |
| | 0.40 | 0.66 | 0.97 | 1.00 | 1.00 | | | 1.00 | 1.00 | 0.97 | 0.66 | | | | | 0.88 | | | | | | | | | | | | | | | | |
| | 0.60 | 0.67 | 0.98 | 1.00 | | | | 1.00 | 0.98 | 0.67 | | | | | | | 0.83 | | | | | | | | | | | | | | | |
| | 0.80 | 0.68 | 0.94 | | | | | 0.94 | 0.68 | | | | | | | | | 0.71 | | | | | | | | | | | | | | |
| | 1.00 | 0.79 | | | | | | 0.79 | | | | | | | | | | | 0.79 | | | | | | | | | | | | | |
| Initial Market Share | 0.65 | 0.19 | 0.87 | 1.00 | 1.00 | 1.00 | 1.00 | 0.90 | 0.82 | 0.77 | 0.68 | 0.48 | 0.17 | 0.80 | 0.77 | 0.71 | 0.59 | 0.29 | 0.54 | 0.70 | | | | | | | | | | | | |
| | 0.75 | 0.54 | 0.97 | 1.00 | 1.00 | 1.00 | 1.00 | 0.94 | 0.91 | 0.88 | 0.83 | 0.74 | 0.54 | 0.90 | 0.88 | 0.84 | 0.77 | 0.62 | 0.73 | | 0.84 | | | | | | | | | | | |
| | 0.85 | 0.94 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.98 | 0.99 | 0.99 | 0.98 | 0.96 | 0.93 | 0.99 | 0.98 | 0.98 | 0.98 | 0.95 | 0.90 | | | 0.98 | | | | | | | | | | |
| | 0.95 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 | | | | 1.00 | | | | | | | | | |
| Sensing Radius | 4.00 | 0.48 | 0.96 | 1.00 | 1.00 | 1.00 | | | 0.92 | 0.87 | 0.80 | 0.69 | 0.42 | 0.87 | 0.84 | 0.80 | 0.73 | 0.62 | | 0.64 | 0.71 | 0.91 | 1.00 | 0.82 | | | | | | | | |
| | 5.66 | 0.58 | 0.95 | 1.00 | 1.00 | 1.00 | | | 0.91 | 0.88 | 0.84 | 0.75 | 0.59 | 0.90 | 0.88 | 0.84 | 0.76 | 0.60 | | 0.63 | 0.77 | 0.98 | 1.00 | | 0.85 | | | | | | | |
| | 7.00 | 0.63 | 0.95 | 1.00 | 1.00 | 1.00 | | | 0.92 | 0.89 | 0.86 | 0.78 | 0.64 | 0.91 | 0.90 | 0.86 | 0.79 | 0.61 | | 0.64 | 0.82 | 0.99 | 1.00 | | | 0.86 | | | | | | |
| | 8.95 | 0.66 | 0.95 | 1.00 | 1.00 | 1.00 | | | 0.92 | 0.91 | 0.87 | 0.80 | 0.67 | 0.92 | 0.90 | 0.88 | 0.82 | 0.64 | | 0.65 | 0.85 | 1.00 | 1.00 | | | | 0.87 | | | | | |
| | 13.89 | 0.74 | 0.96 | 1.00 | 1.00 | 1.00 | | | 0.94 | 0.93 | 0.90 | 0.84 | 0.74 | 0.93 | 0.93 | 0.91 | 0.87 | 0.72 | | 0.73 | 0.88 | 1.00 | 1.00 | | | | | 0.90 | | | | |
| | 19.65 | 0.90 | 0.98 | 1.00 | 1.00 | 1.00 | | | 0.97 | 0.98 | 0.96 | 0.93 | 0.91 | 0.97 | 0.97 | 0.97 | 0.95 | 0.86 | | 0.85 | 0.99 | 1.00 | 1.00 | | | | | | 0.96 | | | |
| Number of Clusters | 1 | 0.53 | 0.92 | 1.00 | 1.00 | 1.00 | 1.00 | 0.95 | 0.90 | 0.87 | 0.80 | 0.68 | 0.49 | 0.88 | 0.86 | 0.82 | 0.76 | 0.62 | 0.80 | 0.63 | 0.73 | 0.95 | 1.00 | 0.77 | 0.80 | 0.81 | 0.81 | 0.81 | 0.90 | 0.83 | | |
| | 5 | 0.72 | 0.97 | 1.00 | 1.00 | 1.00 | 1.00 | 0.96 | 0.94 | 0.92 | 0.89 | 0.83 | 0.71 | 0.94 | 0.92 | 0.90 | 0.86 | 0.75 | 0.79 | 0.72 | 0.89 | 0.99 | 1.00 | 0.83 | 0.86 | 0.88 | 0.90 | 0.93 | 0.99 | | 0.90 | |
| | 10 | 0.76 | 0.98 | 1.00 | 1.00 | 1.00 | 1.00 | 0.96 | 0.95 | 0.94 | 0.92 | 0.87 | 0.77 | 0.95 | 0.94 | 0.92 | 0.89 | 0.78 | 0.78 | 0.76 | 0.92 | 1.00 | 1.00 | 0.84 | 0.88 | 0.90 | 0.92 | 0.96 | 1.00 | | | 0.92 |

Furthermore, Table 6 shows that if the fraction of FICs is at least 40%, network A always corners the market irrespective of the levels of the other independent variables. If the fraction of FICs is at most 20%, A's market share in most cases decreases with an increase in the fraction of PICs or LICs, while it increases with an increase in A's initial market share, PICs' sensing radius, or the number of clusters. The interaction effects between the share of PICs and the share of LICs show that network A always corners the market if the combined fraction of PICs and LICs is below 80%. For all levels of the fraction of PICs, A's final market share monotonically increases in A's initial market share. Besides, for a given fraction of PICs, network A's market share increases with either an increase in the sensing radius or in the number of clusters, albeit these effects gain in strength with an increase in the fraction of PICs. The same pattern can be observed for the fraction of LICs, albeit with one exception: If all consumers are locally informed, an increase in the number of clusters from 1 to 10 slightly lowers A's average market share from 80% to 78%. For values of A's initial market share of 85% or above, A almost always corners the market, irrespective of the values of the other independent variables. An increase in PICs' sensing radius or in the number of clusters increases the positive effect of A's initial market share on A's final market share and this positive effect is larger for higher values of the initial market share. The number of clusters have only a minor positive influence on the effect of the sensing radius on A's final market share.

Overall, Table 6 also shows that for some combinations, network A faces a substantial loss in market shares to an average of less than 50%. This is the case in the following seven combinations: (1) FIC = 0% and initial market share = 65%; (2) FIC = 0% and sensing radius = 4; (3) PIC = 80% and initial market share = 65%; (4) PIC = 100% and initial market share = 65%; (5) PIC = 100% and sensing radius = 4; (6) PIC = 100% and number of clusters = 1; and (7) LIC = 80% and initial market share = 65%.

However, since Table 6 only illustrates the main effects and two-way interactions, the preceding analysis only conveys a partial picture of the effects of the independent variables on network A's final market share. A more comprehensive picture is provided by the graphical analysis in the following section.

***Graphical Analysis***

Figure 4 shows the averaged results for all 1,152 parameter combinations in a matrix of four-dimensional scatter plots (Mazza 2009, p. 50-51). The rows of the matrix denote the six different levels of the fraction of FICs used in the simulation, while the columns denote the

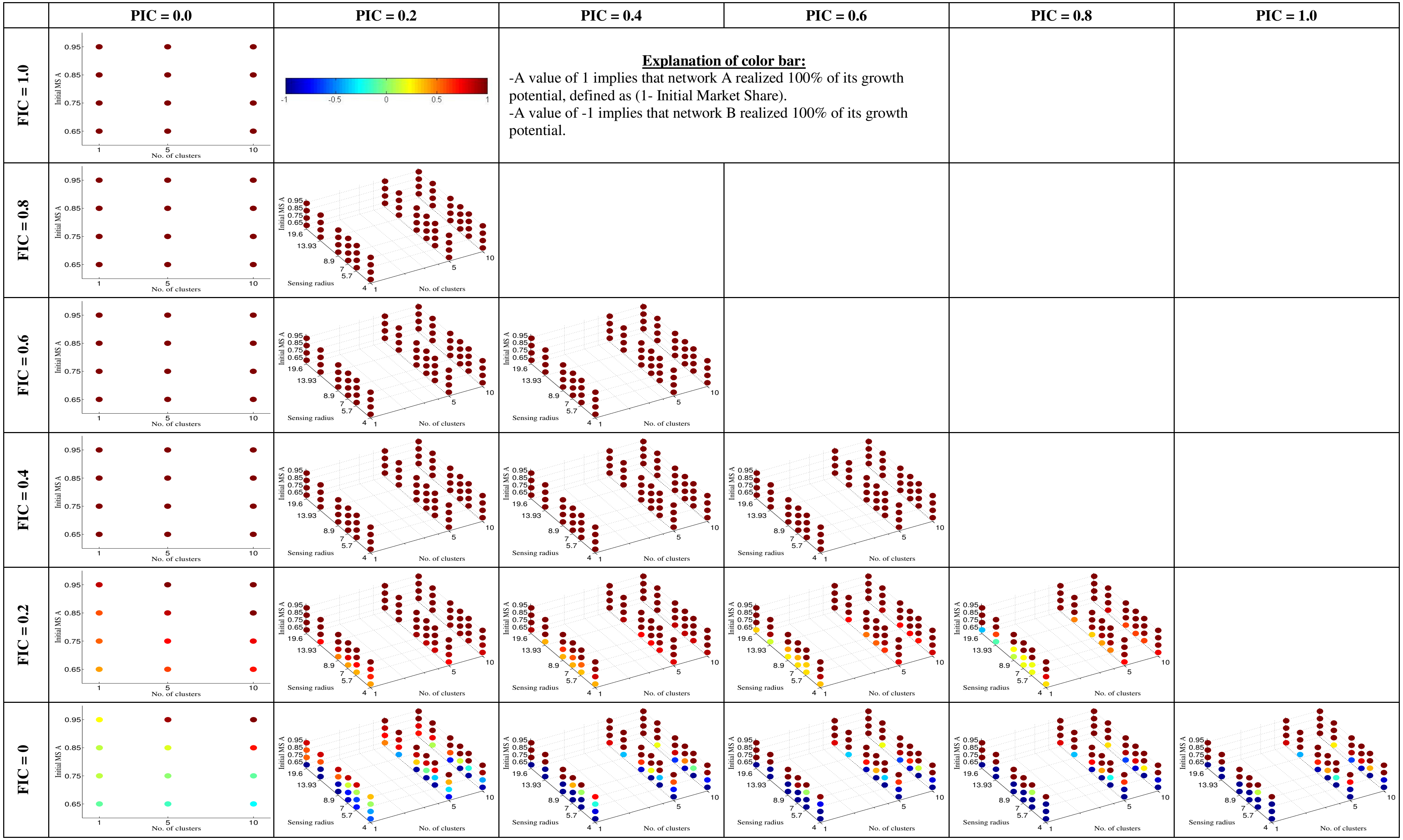



**Figure 4: Graphical representation of simulation results**

six different levels of the fraction of PICs. Since the sum of FICs and PICs cannot exceed 1, only the lower triangle of the matrix is filled. Apart from the first column, each cell contains a four-dimensional scatter plot. In each plot, the x-axis represents the number of clusters, the y-axis represents the sensing radius of PICs, and the z-axis represents network A's initial market share. Since I used a full factorial design for the simulation, each plot contains a total of 72 parameter combinations, each represented by a bullet. In the plots in the first column the sensing radius is missing as an additional dimension since the fraction of PICs is zero for that column. The value of the dependent variable is depicted by the color of the bullets. The dependent variable in the plots is defined as the ratio of the actual change in network A's market share to the maximum possible change, i.e.,

$$(6)\ change = \begin{cases} \frac{marketshare_{end} - marketshare_{intial}}{1 - marketshare_{initial}} & if\ marketshare_{end} \geq marketshare_{initial} \\ \frac{marketshare_{end} - marketshare_{intial}}{marketshare_{initial}} & if\ marketshare_{end} < marketshare_{intial} \end{cases}$$

Accordingly, the value of the dependent variable is bound on the interval [-1;1]. A value of 1 implies that network A realized 100% of its growth potential, i.e., cornered the market. On the other hand, a value of -1 implies that A realized 100% of its possible shrinkage or, put differently, network B realized 100% of its growth potential. Values close to zero can have two different meanings. They occur either if networks A and B take turns in cornering the market or if predominantly market sharing equilibria occur in the respective parameter combination so that neither network realizes its full growth potential. By using the ratio of the actual change and the maximum possible change in A's market share instead of the mean market share, all graphs are immediately comparable. When using the mean market share instead, a value of 80% would imply an *increase* in A's market share if its initial share was 75% but a *decrease* if its initial share was 85%. When using the ratio between actual change and maximum possible change, the respective values would be +0.2 in the former case and -0.06 in the latter.

The scatter plots in Figure 4 illustrate that network A always realizes 100% of its maximum growth potential, i.e., corners the market, if the fraction of FICs is at least 40%. Furthermore, even if the fraction of FICs is below 40%, network A always corners the market if its initial market share exceeds a certain threshold, whereby this threshold varies between 75% and 95%, depending on the value of the othervariables. If the fraction of FICs is at most 20%, Figure 4 illustrates that, generally, network A's fraction of realized growth potential decreases with an increasing fraction of PICs or LICs but increases if either A's initial market, the number of clusters, or PICs' sensing radius increases. Furthermore, network B's odds of increasing its market share drastically increase if the fraction of FICs decreases from 20% to 0%, regardless of whether this decrease leads to an increase in the fraction of PICs or LICs.

More specifically, if the fraction of FICs is 20%, network A's initial market share is below 75% (in some cases below 85%), and the number of clusters is 1 (in some cases 5 or 1), in most cases market sharing equilibria emerge. For instance, if the fraction of FICs and PICs is 20% each, network A's initial market share is 65%, and only one cluster exists, the mean ratio of the number of runs in which A corners the market to the number of runs in which B corners the market (henceforth called *monopolization ratio*) over the six different radii is 96 : 0. This means that over these six parameter combinations, network A monopolizes the market in 96 out of 500 runs on average, while network B never monopolizes the market. If, ceteris paribus, the fraction of PICs gradually increases to 80%, the average monopolization ratio takes on the values 111 : 1 (PIC = 40%), 52 : 14 (PIC = 60%) and 16 : 64 (PIC = 80%). If the fraction of FICs is 20%, network B can only increase its market share substantially if four conditions are fulfilled simultaneously: First, the fraction of PICs is 80%; second, initially only one cluster of subscribers to network B exists; third, the initial market share of network A does not exceed 65%; and fourth, PICs observe 50% or 75% of the market, i.e., the sensing radius is either 13.893 or 19.647.

If no consumer is fully informed, network B realizes a large fraction of its growth potential or even corners the market over a wide range of parameter combinations. If, for instance, the fraction of PICs is 60% or higher, network A's initial market share is 65%, and only one cluster exists, the average monopolization ratio is 0 : 500, i.e., B always corners the market in all 500 repetitions, regardless of PICs' sensing radius. If, ceteris paribus, the fraction of PICs decreases to 40% or 20%, the average monopolization ratios are still 0 : 434 and 0 : 250, respectively. An increase in the number of clusters changes the monopolization ratio in favor of network A. As an example, consider the case in which the fraction of PICs is 60% and network A's initial market share is 65%. A change in the number of clusters from 1 to 5 or 10 changes the monopolization ratio from 0 : 500 to 106 : 394 or 153 : 345, respectively. But even if network A's initial market share is 75%, network B can increase its market share and may even corner the market if the number of clusters is small enough and/or the fraction of PICs is large enough. Network B can corner the market even if network A has an initial market share of 85%, provided that initially only one cluster exists, PICs' sensing radius is only 4 and the fraction of PICs exceeds 40%.

*Regression Results*

To further explore how the fraction of consumer types, PICs' sensing radius, network A's initial market share, and the number of initial clusters affect the market shares of both networks, I estimated five different regressions (see Table 7) in which the dependent variable is network A's final market share, as before averaged over the 500 repetitions for each parameter combination.

**Table 7: Regression results**

| | ( I ) | | ( II ) | | ( III ) | | ( IV ) | | ( V ) | |
|---|---|---|---|---|---|---|---|---|---|---|
| PIC | -0.50 | *** | -0.25 | ** | -3.90 | *** | -0.83 | | -0.83 | *** |
| LIC | -0.43 | *** | -0.32 | *** | -3.27 | *** | -1.76 | *** | -1.76 | *** |
| Radius | 0.01 | *** | 0.00 | | 0.00 | * | -0.01 | * | -0.01 | *** |
| Initial MS | 1.02 | *** | 5.86 | *** | -1.77 | *** | 3.52 | *** | 3.52 | *** |
| Clusters | 0.01 | *** | 0.03 | *** | 0.00 | | 0.02 | *** | 0.02 | *** |
| $PIC^2$ | | | -0.23 | ** | | | -2.95 | *** | -2.95 | *** |
| $LIC^2$ | | | -0.16 | * | | | -1.57 | *** | -1.57 | *** |
| $Radius^2$ | | | 0.00 | * | | | 0.00 | | 0.00 | *** |
| $(Initial\ MS)^2$ | | | -3.02 | *** | | | -3.02 | *** | -3.02 | *** |
| $Clusters^2$ | | | 0.00 | ** | | | 0.00 | *** | 0.00 | *** |
| PIC x LIC | | | | | -0.41 | *** | 1.20 | * | 1.20 | *** |
| PIC x Radius | | | | | 0.01 | *** | 0.02 | | 0.02 | *** |
| PIC x (Initial MS) | | | | | 4.01 | *** | 1.77 | *** | 1.77 | *** |
| PIC x Clusters | | | | | 0.03 | *** | 0.00 | | 0.00 | *** |
| LIC x (Initial MS) | | | | | 3.69 | *** | 2.77 | *** | 2.77 | *** |
| $PIC^2$ x LIC | | | | | | | -2.96 | *** | -2.96 | *** |
| $PIC^2$ x Radius | | | | | | | 0.00 | | 0.00 | |
| $PIC^2$ x Clusters | | | | | | | 0.02 | | 0.02 | *** |
| $PIC^2$ x (Initial MS) | | | | | | | 2.27 | *** | 2.27 | *** |
| $LIC^2$ x PIC | | | | | | | -2.97 | *** | -2.97 | *** |
| $LIC^2$ x (Initial MS) | | | | | | | 1.27 | ** | 1.27 | *** |
| Constant | 0.28 | *** | -1.66 | *** | 2.59 | *** | 0.02 | | 0.02 | |
| N | 1152 | | 1152 | | 1152 | | 1152 | | 576000 | |
| R-sq | 0.37 | | 0.40 | | 0.56 | | 0.66 | | 0.59 | |
| adj. R-sq | 0.37 | | 0.39 | | 0.55 | | 0.65 | | 0.59 | |

* p<0.1, ** p<0.05, *** p<0.01

Model I only contains the levels of the independent variables. Since the fractions of the three different consumer types sum to one and including all three variables would lead to perfect multicollinearity, I decided to exclude the fraction of FICs from the regression. Hence, the coefficients for the fraction of PICs and LICs denote the effect of increasing the fraction of PICs or LICs at the expense of the fraction of FICs. In line with the analysis of the preceding sections, the results indicate that network A's final market share decreases if either the fraction of PICs or the fraction of LICs increases. On the other hand, PICs' sensing radius, network A's initial market share, and the number of clusters positively affect A's final market share. However, the low $R^2$ of 0.37 suggests that this simple linear model misses out on important nonlinearities and/or interactions in the model's behavior.

Therefore, models II and III introduce squares and interaction terms, respectively. The decision as to which interactions to include in model III was based on the fact that PICs' sensing radius and the number of clusters is only relevant for the behavior of PICs, while network A's initial market share is relevant to both PICs and LICs. According to model II, the fraction of PICs, the fraction of LICs, and network A's initial market share have an inverted u-shaped effect on network A's final market share. In contrast, the number of clusters exerts a u-shaped effect on A's final market share, while PICs' sensing radius does not seem to have a nonlinear effect. The results for Model III suggest that the negative effect of the fraction of PICs (LICs) on A's final market share is larger the larger the fraction of LICs (PICs) or, put differently, the lower the fraction of FICs. Besides, the influence of the fraction of PICs decreases in, first, an increase in PICs' sensing radius; second, an increase in A's initial market share; and, third, an increase in the number of clusters. Similarly, the effect of the fraction of LICs is lower the higher A's initial market share.

Due to the presence of both statistically significant nonlinearities and interactions, model IV combines both the squared and the interaction terms. Despite the fact that a combination of squares and interactions significantly complicates the interpretation of the regression coefficients, model IV is the preferred specification since it offers by far the highest adjusted $R^2$. Overall, model IV explains 66% of the variance in network A's final market share. However, in model IV several coefficients are insignificant. A possible explanation for that could be the moderate sample size of 1,152 in conjunction with the very high multicollinearity present in model IV: While the maximum variance inflation factor (VIF) is 895.45, the mean VIF is 330.14. Since the problem of multicollinearity vanishes in very large samples, I reestimated model IV using the dataset which contains the original simulation data prior to averaging, i.e., 500 observations for each parameter combination. The results for model V demonstrate that the increase in sample size to 576,000 successfully mitigates the problem of multicollinearity as all coefficients except for the interaction between $PIC^2$ and Radius and the Constant are now statistically different from zero. While all coefficient estimates remain the same, the $R^2$ slightly decreases to 0.59. This is not very surprising since the original dataset contains much more randomness than the averaged dataset which, in turn, makes it more difficult to explain changes in the dependent variable.

The fraction of PICs and the fraction of LICs continue to have an inverted U-shaped effect which implies that the marginal effect is a downward-sloping line which intersects the x-axis at some point. Figure 5 shows how the course of the marginal effect of the fraction of PICs is affected by the fraction of LICs (upper-left panel), the sensing radius (upper-right panel), network A's initial market share (lower-left panel), and the number of clusters (lower-right panel).

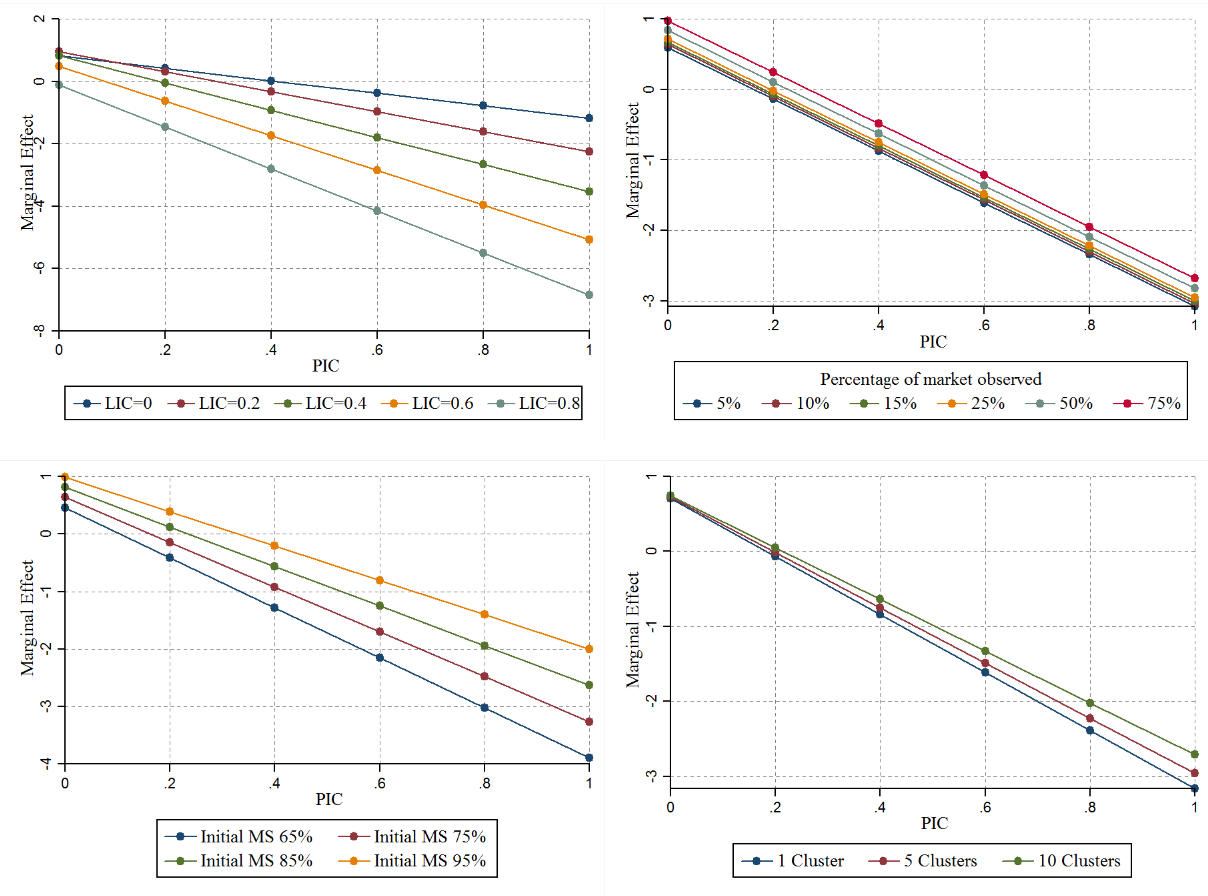



**Figure 5: Marginal effect of PIC conditional on the other independent variables**

The fraction of LICs as well as network A's initial market share have a strong effect on both the intercept and the slope of the marginal effect of the fraction of PICs. While an increase in the fraction of LICs decreases the intercept and increases the absolute value of the slope of the marginal effect, the reverse is true for an increase in network A's initial market share. On the other hand, PICs' sensing radius increases the intercept slightly but hardly affects the slope of the marginal effect, whereas the number of clusters does not change the intercept but decreases the absolute value of the slope. Also note that in many cases the marginal effect is already negative if the fraction of PICs is at least 20% while it is negative in all cases as soon as the fraction of PICs reaches 40%.

Figure 6 contains the marginal effect of the fraction of LICs for different fractions of PICs (left panel) and different values for network A's initial market share (right panel). An increase in the fraction of PICs decreases the intercept and increases the absolute value of the slope of the marginal effect of the fraction of LICs. Network A's initial market share increases the slope of the marginal effect but hardly affects its slope. Moreover, the marginal effect becomes negative in all cases as soon as the fraction of LICs is at least 40%.

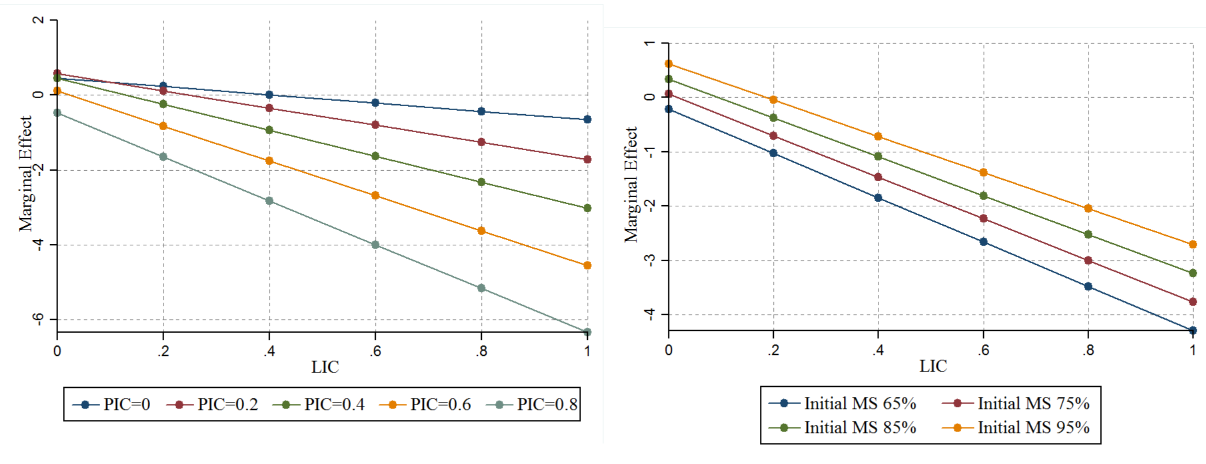



**Figure 6: Marginal effect of LIC conditional on PIC and Initial MS**

To further quantify the effect of the independent variables on network A's final market share, Table 8 shows the estimated average marginal effects for models I to IV. The results for model IV imply that if the fraction of PICs increases by 10% points, on average network A's final market share decreases by 6.7% points, while a similar increase in the fraction of LICs leads to a decrease of A's final market share of 6.3% points on average. Furthermore, if PICs' sensing radius increases by 1 or if the number of clusters increases by 1, A's average market share increase is estimated to be a 1% point. Finally, a 10% points increase in network A's market share increases A's final market share, on average, also by 10% points.

To check how sensitive the estimated regression coefficients are to the random initialization of the market and to other random elements in the model, I repeatedly estimated model IV, while using only the simulation results of one repetition for each parameter combination at a time. As a result, I obtained 500 coefficient estimates for each independent variable. Table 9 shows the mean, 95% confidence interval, as well as the minimum and maximum estimate for each coefficient and the $R^2$. Overall, the standard deviation of the estimated coefficients is

**Table 8: Average marginal effects for models I to IV**

| | ( I ) | | ( II ) | | ( III ) | | ( IV ) | |
|---|---|---|---|---|---|---|---|---|
| PIC | -0.50 | *** | -0.45 | *** | -0.55 | *** | -0.67 | *** |
| LIC | -0.43 | *** | -0.41 | *** | -0.50 | *** | -0.63 | *** |
| Radius | 0.01 | *** | 0.01 | *** | 0.01 | *** | 0.01 | *** |
| Initial MS | 1.02 | *** | 1.02 | *** | 1.02 | *** | 1.02 | *** |
| Clusters | 0.01 | *** | 0.01 | *** | 0.01 | *** | 0.01 | *** |

* p<0.1, ** p<0.05, *** p<0.01

**Table 9: Descriptive statistics of the estimates of the repeated regressions**

| | Mean | Std. Error | 95% Conf. Interval | | Min. | Max. |
|---|---|---|---|---|---|---|
| PIC | -0.83 | 0.25 | -0.85 | -0.81 | -1.73 | -0.06 |
| LIC | -1.76 | 0.21 | -1.78 | -1.74 | -2.37 | -1.24 |
| Radius | -0.01 | 0.00 | -0.01 | -0.01 | -0.02 | 0.00 |
| Initial MS | 3.52 | 0.43 | 3.48 | 3.56 | 2.20 | 4.83 |
| Clusters | 0.02 | 0.00 | 0.02 | 0.02 | 0.01 | 0.03 |
| $PIC^2$ | -2.94 | 0.29 | -2.97 | -2.92 | -3.82 | -1.77 |
| $LIC^2$ | -1.57 | 0.30 | -1.60 | -1.54 | -2.38 | -0.62 |
| $Radius^2$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| $(Initial MS)^2$ | -3.02 | 0.27 | -3.04 | -3.00 | -3.91 | -2.25 |
| $Clusters^2$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| PIC x LIC | 1.20 | 0.29 | 1.17 | 1.22 | 0.38 | 2.11 |
| PIC x Radius | 0.02 | 0.01 | 0.02 | 0.02 | 0.00 | 0.05 |
| PIC x (Initial MS) | 1.77 | 0.32 | 1.74 | 1.80 | 0.74 | 2.67 |
| PIC x Clusters | 0.00 | 0.01 | 0.00 | 0.00 | -0.02 | 0.03 |
| LIC x (Initial MS) | 2.77 | 0.24 | 2.75 | 2.79 | 2.14 | 3.43 |
| $PIC^2$ x LIC | -2.96 | 0.35 | -2.99 | -2.93 | -4.22 | -1.94 |
| $PIC^2$ x Radius | 0.00 | 0.01 | 0.00 | 0.00 | -0.02 | 0.02 |
| $PIC^2$ x Clusters | 0.02 | 0.01 | 0.02 | 0.02 | -0.01 | 0.05 |
| $PIC^2$ x (Initial MS) | 2.27 | 0.37 | 2.23 | 2.30 | 1.07 | 3.42 |
| $LIC^2$ x PIC | -2.97 | 0.29 | -2.99 | -2.94 | -3.68 | -2.10 |
| $LIC^2$ x (Initial MS) | 1.27 | 0.33 | 1.24 | 1.30 | 0.24 | 2.19 |
| Constant | 0.02 | 0.17 | 0.00 | 0.03 | -0.45 | 0.57 |
| $R^2$ | 0.59 | 0.01 | 0.59 | 0.59 | 0.56 | 0.62 |

quite low: For 18 out of 22 regressors, the ratio of the mean to the standard deviation is greater than 2. Additionally, the 95% confidence intervals of all variables do not enclose 0, i.e., they do not contain a sign switch. Moreover, the $R^2$ shows only a very low standard deviation and ranges within the quite narrow interval [0.56;0.62]. Taken together, this suggests that the regression results are robust to random elements in the model.

## EXTENSIONS OF THE BASELINE MODEL: CALLING CLUBS AND ENDOGENOUS PRICE SETTING

### *Incorporating Calling Clubs*

Evidence from empirical studies suggests that the network membership of close friends and family members has a great influence on consumers' decision to join a specific network (Birke and Swann 2006, Calzada and Valletti 2008, Gabrielsen and Vagstand 2008). Therefore, the first extension of the model tests whether the existence of so-called calling clubs affects the results of the baseline model. To this end, consumers in the model consecutively befriend with x random other consumers. As a result, each consumer has at least x friends, the expected mean number of friends is 2x, and the expected modus is 2x-1. Figure 7 shows the resulting distribution of the number of friends among all consumers for x = 10.

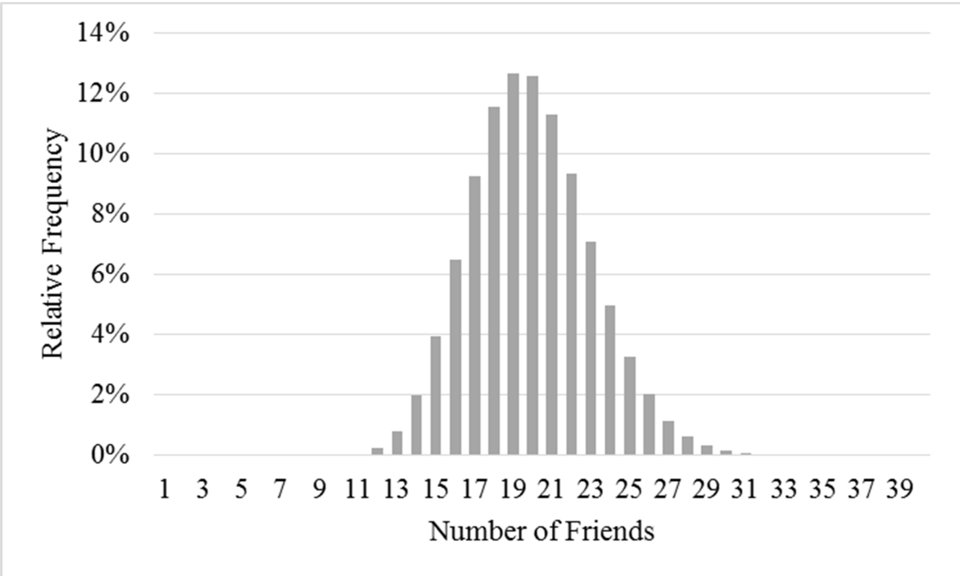



**Figure 7: Distribution of the number of friends for x = 10**

Irrespective of their type, all consumers know which network their friends are subscribed to. This assumption is in line with the literature on costly consumer search which argues that friends can serve as a costless source of information (Janssen and Parakhonyak 2013, p. 3, Perloff and Salop 1986, p. 187, Carlton and Perloff 2005, p. 463). Moreover, following Geoffron and Wang (2008, p. 63), Calzada and Valletti (2008, p. 1240), and Gabrielsen and Vagstad (2008, p. 104), I assume that consumers call one of their friends with probability q and a random stranger with probability (1-q). Accordingly, the expected cost of a call to a random consumer in the model with calling clubs is denoted by (recall that consumers have unit demand):

(7) $E\left(c_{ijt}\right) = q(E\left(c_{ijt}^{friends}\right)) + (1-q)(E\left(c_{ijt}^{strangers}\right))$

Furthermore, the expected costs for calls to friends and strangers are given by:

(8) $E\left(c_{ijt}^{friends}\right) = marketshare_{ijt}^{friends} * p_{jt}^{onnet} + \left(1 - marketshare_{ijt}^{friends}\right) * p_{jt}^{offnet}$

and

(9) $E\left(c_{ijt}^{strangers}\right) = marketshare_{ijt}^{strangers} * p_{jt}^{onnet} + \left(1 - marketshare_{ijt}^{strangers}\right) * p_{jt}^{offnet}$,

respectively.

For the simulation of the extended model I chose values of 5 and 10 for the minimum number of friends. Furthermore, for the probability of calling a friend, q, the values 50%, 75%, and 95% were used, which is in line with Gabrielsen and Vagstad (2008, p. 104) who assume that the probability of calling friends is at least 50% as well as with Möbius (2011, p. 8) who postulates that the probability is 75% (see also Fischer 1992, p. 226). Similar to the baseline model, I used a full factorial design for the simulation which included eight variables and a total of 6,912 parameter combinations, each of which was again simulated 500 times to mitigate the effect of random elements.

Table 10 gives an overview of the descriptive statistics of the results for the extended model with calling clubs. Compared to the baseline model, the average number of network switches remains at 0.26, albeit with a slightly lower standard deviation of 0.21. More interestingly, with an average simulation length of 122 periods, the extended model converges to a corner equilibrium more than twice as fast as the baseline model. Furthermore, the maximum average simulation length is below 999 which implies that in the extended model no parameter combination was simulated for 999 periods in all 500 repetitions, i.e., corner equilibria occur in each parameter combination. Across all parameter combinations, network A's final market share increases to an average of 95% and also shows less variability with a standard deviation of 0.14. Likewise, the average probability that network A corners the market also increases across all parameter combinations. In the extended model, A corners the market in 475 out of 500 repetitions, i.e., with a probability of 95%. In contrast, the probability of network B cornering the market decreases to 4%. In line with the baseline model, the probability that a network increases its market share closely resembles the respective probability of cornering the market. Hence, also in the extended model, growth in market share typically leads to a corner equilibrium.

**Table 10: Descriptive statistics of the model with calling clubs**

| | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| No. of networks switches per consumer | 0.26 | 0.21 | 0.05 | 0.89 |
| Simulation length | 121.83 | 35.13 | 84.25 | 399.08 |
| Final market share of network A | 0.95 | 0.14 | 0.01 | 1.00 |
| Probability of A increasing its market share | 0.95 | 0.14 | 0.01 | 1.00 |
| Probability of B increasing its market share | 0.05 | 0.14 | 0.00 | 0.99 |
| Probability of A cornering the market | 0.95 | 0.15 | 0.01 | 1.00 |
| Probability of B cornering the market | 0.04 | 0.14 | 0.00 | 0.99 |

Table 11 illustrates that the number of parameter combinations in which network A increases its initial market share in a significant number of repetitions substantially increases for the model with calling clubs. In 6,628 of 6,912 (96%) parameter combinations, network A increases its initial market share in at least 250 of 500 repetitions. In still 5,540 (80%) parameter combinations, network A increases its market share in all 500 repetitions. On the other hand, no parameter combination exists in which network B always increases its market share, and only 288 combinations (4%) exist in which B increases its market share in at least 250 repetitions.

**Table 11: Frequency of market share growth for the model with calling clubs**

| | | Number of parameter combinations in which… | |
|---|---|---|---|
| | | ...network A increases its initial market share in at least… | ...network B increases its initial market share in at least… |
| 250 | repetitions | 6628 | 288 |
| 300 | | 6524 | 176 |
| 350 | | 6427 | 55 |
| 400 | | 6332 | 7 |
| 450 | | 6245 | 4 |
| 500 | | 5540 | 0 |

Almost the same holds for the number of parameter combinations in which either network corners the market (see Table 12). While in 6,607 (5,540) combinations network A corners the market in at least 250 (500) repetitions, this is the case for network B in 283 and 0 parameter combinations, respectively. A comparison of Tables 11 and 12 again demonstrates that there are only very few parameter combinations in which either network increases its market share without cornering the market. Hence, shared-market equilibria become less likely if calling clubs exist.

**Table 12: Frequency of monopolization for the model with calling clubs**

| | | Number of parameter combinations in which… | |
|---|---|---|---|
| | | ...network A corners the market in at least… | ...network B corners the market in at least… |
| 250 | repetitions | 6607 | 283 |
| 300 | repetitions | 6506 | 166 |
| 350 | repetitions | 6424 | 48 |
| 400 | repetitions | 6332 | 7 |
| 450 | repetitions | 6244 | 4 |
| 500 | repetitions | 5540 | 0 |

Appendix C graphically illustrates the results for the extended model with calling clubs. Since the extended model contains two additional variables, the number of friends and the probability of calling a friend, with two and three levels, respectively, Appendix C contains six different graphs each of which shows the simulation results for a specific combination of number of friends and probability of calling a friend.

If the minimum number of friends is 5 and consumers call friends and strangers with equal probability (see Figure 11), network A always corners the market if the fraction of FICs is at least 40%. The same holds for all parameter combinations in which the fraction of FICs is 20% and network A's initial market share is above 65%. Network B has a small probability of cornering the market if the fraction of FICs is 20% and A's initial market share is 65%. For example, if the number of clusters is 1, the average monopolization ratios range between 443 : 56 (PIC = 0%) and 458 : 42 (PIC = 80%). If, however, no consumers are fully informed, network B corners the market in most cases if the following three conditions are fulfilled simultaneously: First, network A's initial market share is 65%; second, initially only one cluster of subscribers to network B exists; and, third, PICs observe at most 50% of the market, i.e., the sensing radius does not exceed 13.893.

If the probability of calling a friend increases to 75%, i.e., friends become more important relative to strangers, network A still always corners the market if its initial market share is above 65% (see Figure 12). Yet, if A's initial market share is 65%, network B is generally more likely to corner the market. In fact, both networks take turns in cornering the market whereby the probability that network A corners the market decreases if the fraction of LICs increases at the expense of the fraction of FICs. Furthermore, it increases (decreases) if the fraction of PICs increases at the expense of the fraction LICs (FICs). Besides, network A is more likely to corner the market if the number of clusters or PICs' sensing radius increases. To further illustrate these effects, consider the following examples. For instance, if the fraction of LICs is 0%, the fraction of PICs is 20%, and the number of clusters is 1, the average monopolization ratio over the six different radii is 405 : 95. This ratio decreases to 323 : 176 and 172 : 322 if the fraction of LICs increases to 40% and 80% while the fraction of FICs decrease accordingly. If, instead, the fraction of FICs is fixed at 20% and the number of clusters is 1, the average monopolization ratios become 214 : 280 if the fraction of PICs is 0%, 287 : 210 if the fraction of PICs is 40%, and 331 : 168 if the fraction of PICs is 80%. If the fraction of PICs increases while the fraction of LICs is fixed to 20%, the respective ratios are: 388 : 111, 341 : 158, and 255 : 242. Setting the fraction of FICs to 20% and the fraction of PICs to 40% leads to average monopolization ratios of 287 : 210 (1 cluster), 319 : 180 (5 clusters), and 342 : 156 (10 clusters), or alternatively, if the ratios are averaged over the number of clusters, they become 288 : 209 (radius = 4), 311 : 186 (radius = 8.945), and 351 : 147 (radius = 19.647).

Almost the same results apply if the probability of calling a friend further increases to 95% (see Figure 13). Increasing the fraction of LICs or PICs at the expense of the fraction of FICs decreases the probability that network A corners the market, while increasing the number of clusters or PICs' sensing radius increases the probability. However, the effect of increasing the fraction of PICs at the expense of the fraction of LICs now depends on the number of clusters: If initially only one cluster exists, increasing the fraction of PICs decreases the probability that A corners the market, while the reverse is true if the number of clusters is either 5 or 10. For instance, if the number of clusters is 1, the fraction of FICs is 20%, and the fraction of PICs increases from 0.2 to 0.8, the average monopolization ratio decreases from 165 : 322 to 152 : 335. For the case of 10 clusters and 20% FICs, the average monopolization ratios are 176 : 308 (PIC = 0.2) and 226 : 261 (PIC = 0.8).

For all parameter combinations in which the minimum number of friends is 10 and the probability of calling a friend is 50% (see Figure 14), network B has a sizeable probability of cornering the market only if the following five conditions hold: First, the fraction of FICs is 0; second, the fraction of PICs is at least 60%; third, network A's initial market share is 65%; fourth, the number of clusters is 1; and fifth, the sensing radius is neither too small nor too large. For instance, in the parameter combination FIC = 0%, PIC = 80%, initial market share = 65%, clusters = 1, and sensing radius = 13.93, network B corners the market in 216 out of

500 repetitions, while A corners the market in the remaining 284 repetitions. If, ceteris paribus, the fraction of PICs increases to 100%, B (A) corners the market in 444 (56) repetitions.

If the probability of calling a friend increases to 75% or 95% (see Figures 15 and 16), network A virtually always corners the market. The average monopolization ratio across all parameter combinations in which consumers call a friend with 75% probability is 499.5 : 0.5 and slightly decreases to 496 : 4 if the probability increases to 95%.

Table 13 shows the regression results for the extended model with calling clubs. In contrast to the baseline model, the independent variables do not have significant quadratic effects on the dependent variable (results available upon request). Instead, the preceding graphical analysis suggests that the effects of the fraction of PICs and LICs, the sensing radius, and the number of clusters depend on three factors: First, whether or not network A's initial market share is above 65%, second, whether the minimum number of friends is 5 or 10; and third, the probability of calling a friend. Therefore, in models II, III, and IV the independent variables are interacted with a dummy indicating whether network A's initial market share is above 65%, a dummy indicating whether the minimum number of friends is 10, and the probability of calling a friend, respectively. Since all interactions except for two in model IV are statistically significant, model V contains the full set of interactions. Achieving the highest adjusted $R^2$, model V is also the preferred specification.

In line with the results from the graphical analysis, model II shows that the main effects of the independent variables are completely neutralized by their respective interactions with the dummy variables indicating whether A's initial market share is above 65%. This implies that the independent variables do not affect network A's final market share if its initial market share is above 65%. Almost the same holds true for the results from model III, albeit with one exception: The coefficient for the dummy indicating whether A's initial market share is above 65% switches its sign, depending on whether the minimum number of friends is 5 or 10. In the former case, the effect on A's final market share is positive, while in the latter it is negative, albeit of comparable magnitude. In model IV, the interaction effects are not large enough to offset the main effects or to cause a switch in the effect sign.

**Table 13: Regression results of model with calling clubs**

| | ( I ) | | ( II ) | | ( III ) | | ( IV ) | | ( V ) | |
|---|---|---|---|---|---|---|---|---|---|---|
| PIC | -0.05 | *** | -0.18 | *** | -0.08 | *** | -0.09 | *** | -0.26 | *** |
| LIC | -0.06 | *** | -0.23 | *** | -0.11 | *** | -0.08 | *** | -0.31 | *** |
| Radius | 0.00 | *** | 0.00 | *** | 0.00 | *** | 0.00 | | 0.00 | *** |
| Initial MS > 65% | 0.18 | *** | -0.11 | *** | 0.18 | *** | 0.18 | *** | -0.11 | *** |
| Clusters | 0.00 | *** | 0.01 | *** | 0.00 | *** | 0.00 | *** | 0.01 | *** |
| Friends = 10 | 0.08 | *** | 0.33 | *** | -0.13 | *** | 0.08 | *** | 0.11 | *** |
| Weight of friends | -0.13 | *** | -0.52 | *** | -0.26 | *** | -0.14 | *** | -0.66 | *** |
| PIC x (Initial MS > 65%) | | | 0.18 | *** | | | | | 0.18 | *** |
| LIC x (Initial MS > 65%) | | | 0.23 | *** | | | | | 0.23 | *** |
| Radius x (Initial MS > 65%) | | | 0.00 | *** | | | | | 0.00 | *** |
| Clusters x (Initial MS > 65%) | | | -0.01 | *** | | | | | -0.01 | *** |
| (Friends = 10) x (Initial MS > 65%) | | | -0.33 | *** | -0.33 | *** | | | -0.33 | *** |
| Weight of friends x (Initial MS > 65%) | | | 0.52 | *** | | | 0.52 | *** | 0.52 | *** |
| PIC x (Friends = 10) | | | | | 0.06 | *** | | | 0.06 | *** |
| LIC x (Friends = 10) | | | | | 0.10 | *** | | | 0.10 | *** |
| Radius x (Friends = 10) | | | | | 0.00 | *** | | | 0.00 | *** |
| Clusters x (Friends = 10) | | | | | 0.00 | *** | | | 0.00 | *** |
| Weight of friends x (Friends = 10) | | | | | 0.25 | *** | 0.25 | *** | 0.25 | *** |
| PIC x Weight of friends | | | | | | | 0.06 | * | 0.06 | ** |
| LIC x Weight of friends | | | | | | | 0.03 | | 0.03 | * |
| Radius x Weight of friends | | | | | | | 0.00 | | 0.00 | |
| Clusters x Weight of friends | | | | | | | 0.00 | * | 0.00 | *** |
| Constant | 0.89 | *** | 1.11 | *** | 1.00 | *** | 0.90 | *** | 1.22 | *** |
| N | 6912 | | 6912 | | 6912 | | 6912 | | 6912 | |
| $R^2$ | 0.42 | | 0.78 | | 0.69 | | 0.53 | | 0.81 | |
| adjusted $R^2$ | 0.42 | | 0.78 | | 0.69 | | 0.52 | | 0.81 | |

* p<0.1, ** p<0.05, *** p<0.01

To facilitate the interpretation of the results of model V, which contains the full set of interactions, Figure 8 illustrates the marginal effects of the fraction of PICs (left panel) and LICs (right panel), depending on the probability of calling a friend for different values of A's initial market share and the minimum number of friends.

The marginal effects of the fraction of PICs and the fraction of LICs are negative as long as network A's initial market share is 65% and/or the minimum number of friends is 5. Moreover, the probability of calling a friend slightly increases both marginal effects. On the other hand, the marginal effect of PICs' sensing radius is very small and positive unless network A's initial market share is larger than 65% and the minimum number of friends is 10. The marginal effect of the number of clusters is also quite small, decreases in the probability of calling a friend, and is also positive except for the case when A's initial market share is larger than 65% and the minimum number of friends is 10.

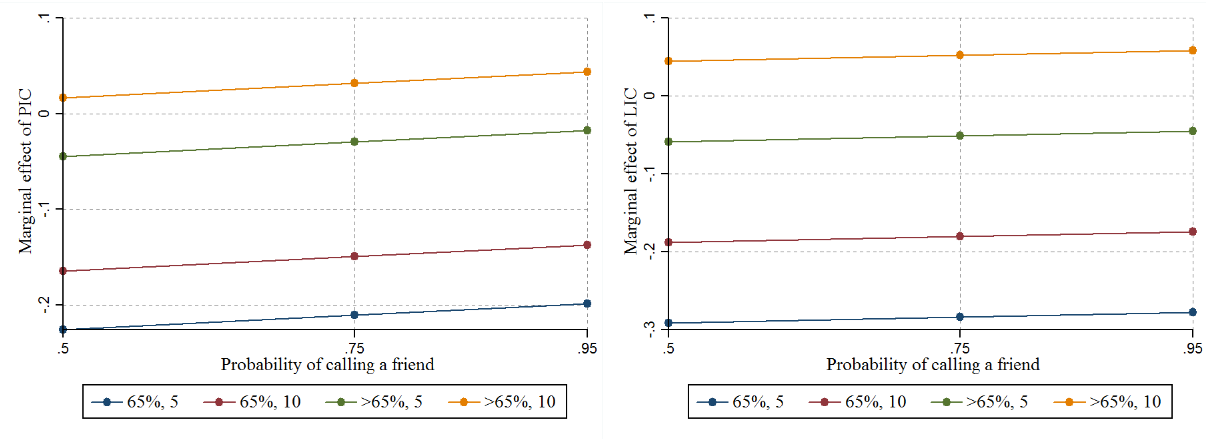



**Figure 8: Marginal effects of PIC and LIC for model with calling clubs**

The average marginal effects of all seven independent variables are shown in Table 14.

**Table 14: Average marginal effects for model with calling clubs**

| | ( I ) | ( II ) | ( III ) | ( IV ) | ( V ) |
|---|---|---|---|---|---|
| PIC | -0.05 *** | -0.05 *** | -0.05 *** | -0.05 *** | -0.05 *** |
| LIC | -0.06 *** | -0.06 *** | -0.06 *** | -0.06 *** | -0.06 *** |
| Radius | 0.00 *** | 0.00 *** | 0.00 *** | 0.00 *** | 0.00 *** |
| Initial MS > 65% | 0.18 *** | 0.18 *** | 0.18 *** | 0.18 *** | 0.18 *** |
| Clusters | 0.00 *** | 0.00 *** | 0.00 *** | 0.00 *** | 0.00 *** |
| Friends = 10 | 0.08 *** | 0.08 *** | 0.08 *** | 0.08 *** | 0.08 *** |
| Weight of friends | -0.13 *** | -0.13 *** | -0.13 *** | -0.13 *** | -0.13 *** |

* p<0.1, ** p<0.05, *** p<0.01

At first sight, it might be surprising that the marginal effects are identical for all models. However, the explanation for that is rather straightforward. Due to the full factorial design of the simulation, all independent variables are uncorrelated with each other. Furthermore, since model I does not account for any interaction effects, these are lumped into the coefficients of the main effects. On the other hand, this is not the case for models II to V which explicitly account for different kinds of interaction effects. However, by calculating the average marginal effects for models II to V, both the main effects and the interaction effects are again "lumped together," which leads to the very same results as model I due to the strict independence of all variables.

According to the estimated average marginal effects, network A's final market share decreases by 0.5 (0.6) % points if the fraction of PICs (LICs) increases by 10% points. Furthermore, if A's initial market share is above 65%, its final market share is on average 18% points higher and if the minimum number of friends increases from 5 to 10, the average increase in A's final market share is 8% points. A 25% points increase in the probability of calling a friend decreases A's final market share by 3% points. Finally, the results in Table 14 suggest that the effects of PICs' sensing radius and the number of clusters are negligible in the extended model with calling clubs.

***Endogenous Price Setting***

In both the baseline model as well as in the model with calling clubs, both networks were not allowed to react to changes in their market shares by adjusting their tariffs for on-net and off-net calls. While the assumption of fixed tariffs ensures that the study of the effects of costly information acquisition by consumers is not blurred by supply-side effects, i.e., the price setting behavior of networks, this restrictive assumption heavily weakens the empirical relevance of the study. In order to test whether the previous results generalize to the case of endogenous pricing where networks aim at increasing their profits by adjusting their prices, the second extension of the model allows for endogenous price setting.

Similar to consumers, both networks are assumed to lack perfect information about all market conditions. In particular, I assume that networks lack information on consumers' individual search costs (while they may know the fraction of FICs, PICs, and LICs in the population of consumers). Accordingly, networks in the model are not able to explicitly maximize their profits by setting tariffs, since this would require perfect knowledge of each consumer's type and each consumer's immediate environment. Instead, both networks try to estimate the consequences of different pricing strategies in order to implement the strategy associated with the highest expected profit.

When deciding on changing their tariffs, I assume that both operators can choose among five generic strategies (see Figure 9). Each network can either increase its tariff for on-net calls (strategy A) or decrease it (strategy B), or increase or decrease its tariffs for off-net calls (strategies C and D, respectively). Of course, networks can also decide to keep their prices unchanged (strategy E). To keep the model computationally trackable, networks are not allowed to combine several strategies. However, this assumption is not particularly restrictive since every change in one tariff (on-net or off-net) can profit-neutrally be substituted by an appropriate change in the other tariff (see Appendix B for details).

| | **tariff on-net** | **tariff off-net** |
|---|---|---|
| **increase** | strategy A | strategy C |
| **decrease** | strategy B | strategy D |

Keep prices: strategy E

**Figure 9: Price setting strategies of networks**

Despite their lack of full information on consumers' search costs, both networks nevertheless aim at increasing their profit by implementing the strategy resulting in the highest expected profit. To evaluate the effectiveness of the five pricing strategies, networks use a variant of a recursive algorithm (Łatek, Axtell, and Kamińsky 2009). The basic idea of a recursive algorithm is that an agent simulates the outcome of an action by anticipating certain actions of all other agents who, themselves, may anticipate certain action of all other agents, and so on. How many iterations of anticipated actions are simulated is described by the concept of n-th order rationality (Michihiro 1997). For n = 0, an agent simulates the consequences of an action under the assumption that all other agents do not change their current behavior (Łatek, Axtell, and Kamińsky 2009, p. 458). On the other hand, for n = 1, an agent simulates the consequences of an action given an explicitly defined set of actions for all other agents, while for n = 2 each action of all other agents is again contingent on the actions chosen by all other agents (Łatek, Axtell, and Kamińsky 2009, p. 457).

To simplify the computation, I assume that both networks use the simplest possible variant of the recursive algorithm in which n is set to 0. Hence, for each of the four strategies, both networks calculate the expected profit under the assumption that the rival network will not change its tariffs. If, instead, n was set to 1, the number of strategies that each network would have to simulate would quadruple which, in turn, would result in a significant increase in computation time. Since this paper is primarily interested in the consequences of costly search on the consumer side rather than in the price setting behavior of firms, I decided to keep the computational burden stemming from the price setting behavior of networks at a minimum by setting n = 0.

Both networks implement the recursive algorithm by executing six consecutive actions. First, each network draws a random sample of its subscribers as well as a random sample of subscribers to the rival network. For simplicity, both sample sizes are assumed to be equal and fixed. If the market share of one network is too small so that the targeted sample size exceeds the number of available consumers, all available consumers are sampled. Second, for each of the five strategies, consumers in both samples indicate their decision (switch or stay) should the respective strategy be implemented. Note that each strategy has four possible outcomes: Consumers already subscribed to the network can decide to either renew their subscription or switch to the rival network, and subscribers to the rival network can either switch to the network or renew their subscription to the rival. In the third step, for each strategy networks calculate the fraction of subscribers in the first sample who indicated that they would leave the network as well as the fraction of consumers in the second sample who indicated they would join the network. Step four involves an extrapolation of the findings from the two samples to the whole population. To illustrate the process of extrapolation, consider the following numerical example. Assume network A has a market share of 60% and that in each period 5% of all consumers are allowed to switch their network. Assume further that in A's first sample 50% of its subscribers indicated that they would join the rival network if strategy C was implemented. In this case, network A expects 50% of its total subscribers would leave if they were allowed to decide on their network membership in the next period, i.e., it expects that it would lose 600*0.5*0.05=15 consumers. Likewise, if 30% of consumers in A's second sample indicate that they would join network A under strategy C, then A expects to gain 400*0.3*0.05=6 consumers. In step five, each network calculates the balance of joining and leaving consumers and the resulting potential market share for each strategy. In the final step, for each strategy the expected profits are calculated based on the potential market shares using the following formula:

(10) $\Pi_{jts} = 1000 * marketshare_{jts}(marketshare_{jts} * p_{jts}^{onnet} + \left(1 - marketshare_{jts}\right) * p_{jts}^{offnet})$,

where $marketshare_{jts}$ denotes the expected market share for network j in period t when implementing strategy s, $p_{jts}^{onnet}$ and $p_{jts}^{offnet}$ denote network j's tariffs for on-net and off-net calls in period t under strategy s respectively, and networks' cost are normalized to zero.

Following Calvo (1983) I assume that networks' tariffs are sticky, i.e., in every period firms are allowed to change their prices with an exogenously determined probability $\lambda < 1$. For the analysis of the extended model, I fixed $\lambda$ at 5% so that, in expectation, whenever a consumer is allowed to decide about her network membership, both networks have changed their tariffs once. Furthermore, to avoid the occurrence of negative prices, I assume that networks change their prices by a constant fraction which I fixed at 5% for the analysis. Finally, I decided to set the two sample sizes of the recursive algorithm to 50 for both networks, i.e., I assume that both networks rely on the same amount of market intelligence when estimating the consequences of each strategy. In total, this results in 8,064 different parameter combinations (1,152 combinations without and 6,912 combinations with calling clubs) each of which was simulated 500 times to mitigate the effect of random elements in the model.

Table 15 gives an overview of the descriptive statistics for the model with endogenous price setting, both for the case without calling clubs and with calling clubs.

**Table 15: Descriptive statistics for the model with endogenous price setting**

| | Without calling clubs | | | | With calling clubs | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Min. | Max. | Mean | Std. Dev. | Min. | Max. |
| No. of networks switches per consumer | 0.29 | 0.22 | 0.05 | 0.94 | 0.26 | 0.21 | 0.05 | 0.81 |
| Simulation length | 198 | 145 | 86 | 827 | 118 | 25 | 85 | 212 |
| Final market share of network A | 0.93 | 0.15 | 0.04 | 1.00 | 0.95 | 0.12 | 0.43 | 1.00 |
| Prob. of A increasing its market share | 0.92 | 0.16 | 0.04 | 1.00 | 0.95 | 0.12 | 0.43 | 1.00 |
| Prob. of B increasing its market share | 0.08 | 0.16 | 0.00 | 0.96 | 0.05 | 0.12 | 0.00 | 0.57 |
| Prob. of A cornering the market | 0.92 | 0.17 | 0.04 | 1.00 | 0.95 | 0.12 | 0.43 | 1.00 |
| Prob. of B cornering the market | 0.06 | 0.13 | 0.00 | 0.96 | 0.05 | 0.12 | 0.00 | 0.57 |
| A's on-net tariff in final period | 0.79 | 0.23 | 0.51 | 2.38 | 0.67 | 0.02 | 0.59 | 0.73 |
| A's off-net tariff in final period | 1.31 | 1.00 | 1.00 | 8.21 | 1.03 | 0.08 | 1.00 | 1.45 |
| B's on-net tariff in final period | 0.25 | 0.01 | 0.25 | 0.32 | 0.25 | 0.01 | 0.25 | 0.29 |
| B's off-net tariff in final period | 1.85 | 1.15 | 1.18 | 8.80 | 1.33 | 0.06 | 1.23 | 1.56 |

Compared to the baseline model, consumers switch slightly more frequently (0.29 times on average) in the model with endogenous price setting. On the other hand, with a value of 198, the average simulation run takes 68 periods less to converge to a corner equilibrium and no parameter combination exists which is simulated for all 1,000 periods in all 500 repetitions. This implies that in contrast to the baseline model, corner equilibria exist in all parameter combinations even if no calling clubs exist. On average, network A’s final market share is 93%, which is a slight increase compared to the baseline model, while, simultaneously, the standard deviation of A’s average market share almost bisects. Similarly, A’s probability of increasing its market share rises to 92%, while the respective value for network B decreases to 8%. Besides, on average, network A (B) has a 92% (6%) probability of cornering the market in each simulation run. Hence, the finding that whenever a network increases its initial market share it typically also corners the market continues to hold in the second extension of the model. Finally, Table 15 shows that, on average, network A increases both its on-net and its off-net tariff to 0.79 and 1.31, respectively, whereas B only increases its off-net tariff to 1.85 while the on-net tariff remains at 0.25, on average. Moreover, both networks never find it profitable to decrease their tariffs below the respective initial values. With respect to the extent of on-net/off-net differentiation, the results show that, except for 74 parameter combinations, network A always prices on-net calls below off-net calls, while network B does so in all 1,152 combinations. Finally, only 95 (0) parameter combinations exist in which A's (B's) on-net/off-net differential is smaller than 0.1.

If calling clubs are included in the model with endogenous price setting, consumers switch 0.26 times on average during a simulation run with a mean duration of 118 periods. These values are roughly equivalent to the ones from the model with calling clubs but without exogenous price setting. Quite surprisingly, the descriptive statistics of the remaining variables, i.e., for network A's final market share and the probabilities of networks A and B to increase their market share or to corner the market, are also almost identical to the statistics from the first extension. Besides, network A's (B's) tariff for on-net and off-net calls are, on average, 0.79 and 1.31 (0.25 and 1.85), respectively, which is slightly lower than in the case without calling clubs. However, even in the case with calling clubs, both networks never find it profitable to decrease their tariffs below their initial values, and in all parameter combinations both networks price on-net calls below off-net calls. The minimum on-net/off-net differential is 0.29 for network A and 0.98 for network B.

**Table 16: Frequency of market share growth for model with endogenous price setting**

| | | Number of parameter combinations in which… | | | |
|---|---|---|---|---|---|
| | | ...network A increases its initial market share in at least… | | ...network B increases its initial market share in at least… | |
| | | without calling clubs | with calling clubs | without calling clubs | with calling clubs |
| 250 | repetitions | 1087 | 6873 | 66 | 44 |
| 300 | | 1072 | 6590 | 40 | 0 |
| 350 | | 1060 | 6422 | 11 | 0 |
| 400 | | 1040 | 6244 | 6 | 0 |
| 450 | | 930 | 5827 | 2 | 0 |
| 500 | | 366 | 4380 | 0 | 0 |

Compared to the baseline model, the number of parameter combinations in which network A increases its initial market share in at least 250 repetitions slightly increases to 1,087 in the model with endogenous price setting, whereas the number of parameter combinations in which A increases its share in all 500 repetitions more than bisects to a value of 366 (see Table 16). On the other hand, the number of parameter combinations in which network B increases its market share in at least 250 repetitions almost bisects to 66, and no parameter combination exists in which B increases its market share in all 500 repetitions. Similar results pertain if calling clubs are included in the model with endogenous price setting. In 6,873 parameter combinations, A increases its market share in at least 250 repetitions, which represents a slight increase compared to the model with exogenous price setting. The number of combinations in which A increases its market share in all 500 repetitions decreases to 4,380. Moreover, the parameter space in which B can increase its initial market share drastically shrinks: Only 44 combinations exist in which B increases its market share in at least 250 combinations, while there is no case in which B always increases its market share.

Table 17 shows that the number of parameter combinations in which network A corners the market at least 250 (500) times increases (decreases) to 1,078 (366) compared to the baseline model. In contrast, network B is less likely to corner the market in either 250 or 500 repetitions if networks adjust their tariffs to changes in market shares. Again, the same applies if calling clubs are included in the model. More parameter combinations exist in which network A corners the market at least 250 times (6,873 combinations), but less combinations exist in which this happens in all 500 repetitions (4,380). Network B is less likely to corner the market at least 250 times (44 combinations) and never corners the market in all 500 repetitions.

**Table 17: Frequency of monopolization for model with endogenous price setting**

| | | Number of parameter combinations in which… | | | |
|---|---|---|---|---|---|
| | | ...network A corners the market in at least… | | ...network B corners the market in at least… | |
| | | no calling clubs | calling clubs | no calling clubs | calling clubs |
| 250 | repetitions | 1078 | 6873 | 27 | 44 |
| 300 | | 1066 | 6590 | 13 | 0 |
| 350 | | 1059 | 6422 | 8 | 0 |
| 400 | | 1032 | 6244 | 6 | 0 |
| 450 | | 926 | 5827 | 2 | 0 |
| 500 | | 366 | 4380 | 0 | 0 |

Also in the model with endogenous price setting, market share growth typically leads to a corner equilibrium as a comparison of Tables 16 and 17 reveals. In fact, if calling clubs are included in the model with endogenous price setting, market share growth by either network always leads to a corner equilibrium.

The graphical results of the model with endogenous price setting are shown by Figures 16 to 21 in Appendix D. If no calling clubs exist in the model, the general results are qualitatively similar to the results from the baseline model, albeit in general the results are more favorable to network A (see Figure 16). Network A always realizes its full growth potential if the fraction of FICs is at least 40% or if network A's initial market share exceeds a certain threshold, which varies between 65% and 75%. Furthermore, the fraction of network A's realized market share growth decreases with an increasing fraction of PICs or LICs and increases if either A's initial market share, the number of clusters, or PICs' sensing radius increases. Besides, similar to the baseline model, network B is much more likely to increase its market share if the fraction of FICs decreases from 20% to 0%.

Yet, a closer inspection of the graphical results reveals not only similarities with the baseline model but also some interesting differences. While in the baseline model mostly corner equilibria occurred if the fraction of FICs is 20%, network A's initial market share is 65%, and 1 cluster exists, this is no longer the case if networks adjust their prices. In these parameter combinations, the average monopolization ratios range between 437 : 62 (PIC = 20%), 429 : 71 (PIC = 40%), 405 : 95 (PIC = 60%), and 376 : 123 (PIC = 80%).

If the fraction of FICs decreases to 0%, networks A and B take turns in cornering the market as long as network A's initial market share is 65%, with network A being more likely to corner the market the lower the fraction of PICs is. For instance, the average monopolization ratio across the six parameter combinations in which the fraction of PICs is 20%, A's initial market share is 65%, and 1 cluster exists, is 170 : 155, while it is 90 : 330 if, ceteris paribus, the fraction of PICs is 100%. On the other hand, with an increasing number of clusters network A is more likely to corner the market. This is illustrated, for example, by the monopolization ratios for the case in which the fraction of PICs is 60% and network A's initial market share is 65%. If the number of clusters increases from 1 to 10, the average monopolization ratio changes from 108 : 283 to 280 : 160. Moreover, Figure 16 reveals that even if no consumer is fully informed, network B is substantially less likely to increase its market share or to corner the market if A's initial market share exceeds 65%.

If calling clubs are included in the model with endogenous price setting, network A still always corners the market if its initial market share exceeds 65%, irrespective of the number of friends and the probability of calling a friend. Therefore, the following analysis only considers the parameter combinations in which A's initial market share is 65%.

For the case in which consumers have at least five friends which are called with a probability of 50%, network B generally has a higher probability of cornering the market as compared to the model with fixed prices. Network B already has a non-negligible probability of cornering the market if the fraction of FICs is 40% with monopolization ratios ranging between 488 : 12 and 433 : 67. If the fraction of FICs decreases to 20%, the average monopolization ratios are slightly less favorable for network B if the number of clusters is 1 and slightly more favorable if the number of clusters is 5 or 10.

Increasing the probability of calling a friend to 75% leads to qualitatively similar results as the model with fixed tariffs, albeit with slightly more (less) favorable monopolization ratios for network B if the fraction of FICs is 40% or higher (20% or lower). Still, the probability that network A corners the market decreases if the fraction of LICs or the fraction of PICs increases at the expense of the fraction of FICs and increases if the fraction of PICs increases at the expense of the fraction of LICs, if the number of clusters increases, or if PICs' sensing radius increases. However, contrary to the model with fixed tariffs, no parameter combination exists in which network B has a higher probability of cornering the market than network A.

Further increasing the probability of calling a friend to 95% again largely confirms the results from the model with fixed tariffs. For values of the fraction of FICs below 80%, the average monopolization ratios are generally less favorable for network B while the opposite is true for values of 80% and above. An increase in the fraction of PICs or LICs at the expense of the fraction of FICs still decreases network A's probability of cornering the market, while an increase in the number of clusters or in PICs' sensing radius in most cases increases it. Contrary to the model with fixed tariffs, the effect of increasing the fraction of PICs at the expense of the fraction of LICs is inconclusive since some parameter combinations result in an increase of network A's probability to corner the market, while others result in a decrease.

In all parameter combinations in which the minimum number of friends is 10, network A always corners the market if its initial market share is higher than 65%, which confirms the findings from the model with fixed prices. However, if A's initial market share is 65%, different results for the model with endogenous price setting s emerge. Network B has a higher probability of cornering the market as indicated by an increase in the average monopolization ratio to 467 : 33 if the probability of calling a friend is 75% and to 432 : 68 if the respective probability is 95%. If, on the other hand, consumers call friends and strangers with equal probability, the monopolization ratios of the model with endogenous price setting correspond to the ones of the model with fixed prices if the fraction of FICs is 40% or higher.

Setting the fraction of FICs to 20% or 0% changes the monopolization ratios in favor of network B, albeit with one exception: While in the model with fixed prices B has a substantial probability of cornering the market if the fraction of FICs is 0, the fraction of PICs is 80% or 100%, and the number of clusters is 1, this probability is significantly reduced in the model with endogenous price setting.

The regression results for the model with endogenous prices setting are shown in Table 18 for the case without calling clubs and in Table 20 for the case with calling clubs while Tables 19 and 21 show the estimated average marginal effects of the respective regression models.

**Table 18: Regression results of the model with endogenous price setting and without calling clubs**

| | ( I ) | | ( II ) | | ( III ) | | ( IV ) | |
|---|---|---|---|---|---|---|---|---|
| PIC | -0.83 | | -0.83 | *** | 0.06 | | 0.06 | * |
| LIC | -1.76 | *** | -1.76 | *** | -1.55 | *** | -1.55 | *** |
| Radius | -0.01 | * | -0.01 | *** | -0.01 | *** | -0.01 | *** |
| Initial MS | 3.52 | *** | 3.52 | *** | 4.29 | *** | 4.29 | *** |
| Clusters | 0.02 | *** | 0.02 | *** | 0.01 | *** | 0.01 | *** |
| $PIC^2$ | -2.95 | *** | -2.94 | *** | -2.22 | *** | -2.22 | *** |
| $LIC^2$ | -1.57 | *** | -1.57 | *** | 0.03 | | 0.03 | |
| $Radius^2$ | 0.00 | | 0.00 | *** | 0.00 | ** | 0.00 | *** |
| $(Initial\ MS)^2$ | -3.012 | *** | -3.02 | *** | -3.07 | *** | -3.07 | *** |
| $Clusters^2$ | 0.00 | *** | 0.00 | *** | 0.00 | *** | 0.00 | *** |
| PIC x LIC | 1.20 | * | 1.20 | *** | 0.40 | | 0.40 | *** |
| PIC x Radius | 0.02 | | 0.02 | *** | 0.01 | | 0.01 | *** |
| PIC x (Initial MS) | 1.77 | *** | 1.77 | *** | 0.38 | | 0.38 | *** |
| PIC x Clusters | 0.00 | | 0.00 | *** | 0.00 | | 0.00 | |
| LIC x (Initial MS) | 2.77 | *** | 2.77 | *** | 2.09 | *** | 2.09 | *** |
| $PIC^2$ x LIC | -2.96 | *** | -2.96 | *** | -1.18 | *** | -1.18 | *** |
| $PIC^2$ x Radius | 0.00 | | 0.00 | | 0.00 | | 0.00 | *** |
| $PIC^2$ x Clusters | 0.02 | | 0.02 | *** | 0.02 | | 0.02 | *** |
| $PIC^2$ x (Initial MS) | 2.27 | *** | 2.27 | *** | 1.99 | *** | 1.99 | *** |
| $LIC^2$ x PIC | -2.97 | *** | -2.97 | *** | -0.99 | *** | -0.99 | *** |
| $LIC^2$ x (Initial MS) | 1.27 | ** | 1.27 | *** | -0.34 | | -0.34 | *** |
| Constant | 0.02 | | 0.02 | | -0.48 | *** | -0.48 | *** |
| N | 1152 | | 576000 | | 1152 | | 576000 | |
| R-sq | 0.66 | | 0.59 | | 0.70 | | 0.25 | |
| adj. R-sq | 0.65 | | 0.59 | | 0.70 | | 0.25 | |

* p<0.1, ** p<0.05, *** p<0.01

To facilitate an easier comparison with the regression results of the baseline model, Table 18 states the regression results of models IV and V from Table 7 in columns I and II, while columns III and IV show the results of the regressions for the extended model without calling clubs using the averaged data set and the full data set, respectively. Compared to model I, model III shows a slightly better fit with an $R^2$ of 0.70. As before, several coefficients in model III are insignificant, possibly due to the high multicollinearity induced by the regression specification. Therefore, model IV uses the full data set containing 500 repetitions per parameter combination. While this does not change the estimated coefficients due to the strict independence of all variables, all but two coefficients in model IV are significant at least at the 10% level. On the other hand, model IV can only explain 25% of the variance of network A's final market share, which is less than half the value achieved by model II. This worse model fit might be caused by additional random elements injected into the model by the endogenous price setting. A comparison of the estimated coefficients of models I and III shows that most of the findings from the model with fixed tariffs extend to the model with endogenous price setting since almost all coefficients have the same sign and are of comparable magnitude. Three exceptions are worth mentioning. First, the coefficient for the fraction of PICs is slightly positive and only significant at the 10% level. Second, $LIC^2$ is insignificant and, third, the interaction between $LIC^2$ and Initial MS is negative in model III. However, this does not lead to a qualitative change in the results for two reasons. First, the increase of the coefficient for PIC is at least somewhat compensated by the decrease of the coefficient of the interaction between PIC and LIC. Second, the substantial increase of the coefficient of $LIC^2$ is neutralized by a substantial decrease of the coefficient for the interaction between $LIC^2$ and Initial MS and, therefore, the fraction of LICs continues to exert an inverted U-shaped effect on network A's market share (see also Table 19).

**Table 19: Average marginal effects of the model with endogenous price setting and without calling clubs**

| | ( I ) | | ( II ) | |
|---|---|---|---|---|
| PIC | -0.67 | *** | -0.29 | *** |
| LIC | -0.63 | *** | -0.33 | *** |
| Radius | 0.01 | *** | 0.00 | |
| Initial MS | 1.02 | *** | 0.61 | *** |
| Clusters | 0.01 | *** | 0.01 | *** |

* p<0.1, ** p<0.05, *** p<0.01

The fact that the results of the model with endogenous price setting largely confirm the findings from the model with fixed tariffs can also be inferred from Table 19, which shows the estimated average marginal effects of both models. All coefficients have the same sign and are of comparable magnitude. All variables continue to be highly significant except for PIC's sensing radius which is insignificant due to the very high multicollinearity present in model III, but would be significant at the 1% level if the average marginal effects were calculated based on model IV.

The regression results of the model incorporating both endogenous price setting as well as calling clubs are displayed in Table 20, whereby the results of model V from Table 14 are again included in column I to facilitate an easier comparison of both models. With an $R^2$ of 92%, model II explains the data of the simulation model significantly better than model I. Furthermore, except for the coefficient of the interaction between the number of clusters and the dummy variable indicating whether network A's initial market share is above 65%, all coefficients have the same sign, are of the same magnitude, and are significant at the 1% level. In model II, additionally the coefficients of the interactions between radius and weight and between clusters and weight are significant at the 1% level, albeit the magnitude of their effect can be considered economically insignificant.

Likewise, the estimated average marginal effects of both models demonstrate that the findings from the model with calling clubs but fixed tariffs continue to hold if networks are allowed to adjust their prices (see Table 21). In fact, the estimated marginal effects are even almost numerically identical which, further corroborates the robustness of the results.

**Table 20: Regression results of the model with endogenous price setting and with calling clubs**

| | ( I ) | | ( II ) | |
|---|---|---|---|---|
| PIC | -0.26 | *** | -0.20 | *** |
| LIC | -0.31 | *** | -0.26 | *** |
| Radius | 0.00 | *** | 0.00 | *** |
| Initial MS > 65% | -0.11 | *** | -0.06 | *** |
| Clusters | 0.01 | *** | 0.01 | *** |
| Friends = 10 | 0.11 | *** | 0.12 | *** |
| Weight of friends | -0.66 | *** | -0.54 | *** |
| PIC x (Initial MS > 65%) | 0.18 | *** | 0.12 | *** |
| LIC x (Initial MS > 65%) | 0.23 | *** | 0.16 | *** |
| Radius x (Initial MS > 65%) | 0.00 | *** | 0.00 | *** |
| Clusters x (Initial MS > 65%) | -0.01 | *** | 0.00 | *** |
| (Friends = 10) x (Initial MS > 65%) | -0.33 | *** | -0.22 | *** |
| Weight of friends x (Initial MS > 65%) | 0.52 | *** | 0.44 | *** |
| PIC x (Friends = 10) | 0.06 | *** | 0.02 | *** |
| LIC x (Friends = 10) | 0.10 | *** | 0.04 | *** |
| Radius x (Friends = 10) | 0.00 | *** | 0.00 | *** |
| Clusters x (Friends = 10) | 0.00 | *** | 0.00 | *** |
| Weight of friends x (Friends = 10) | 0.25 | *** | 0.13 | *** |
| PIC x Weight of friends | 0.06 | ** | 0.10 | *** |
| LIC x Weight of friends | 0.03 | * | 0.11 | *** |
| Radius x Weight of friends | 0.00 | | 0.00 | *** |
| Clusters x Weight of friends | 0.00 | *** | 0.00 | *** |
| Constant | 1.22 | *** | 1.14 | *** |
| N | 6912 | | 6912 | |
| $R^2$ | 0.81 | | 0.92 | |
| adjusted $R^2$ | 0.81 | | 0.92 | |

* p<0.1, ** p<0.05, *** p<0.01

**Table 21: Average marginal effects of the model with endogenous price setting and with calling clubs**

| | ( I ) | | ( II ) | |
|---|---|---|---|---|
| PIC | -0.05 | *** | -0.03 | *** |
| LIC | -0.06 | *** | -0.04 | *** |
| Radius | 0.00 | *** | 0.00 | *** |
| Initial MS > 65% | 0.18 | *** | 0.20 | *** |
| Clusters | 0.00 | *** | 0.00 | *** |
| Friends = 10 | 0.08 | *** | 0.06 | *** |
| Weight of friends | -0.13 | *** | -0.11 | *** |

* p<0.1, ** p<0.05, *** p<0.01

## DISCUSSION

The preceding analysis of the simulation results has unearthed five key insights into the effect of different model parameters on the distribution of market shares at the end of a simulation run. First, the findings show that network A's final market share decreases or, alternatively, that network A is less likely to corner the market if the fraction of PICs or the fraction of LICs increases at the expense of the fraction of FICs. Second, in the majority of parameter combinations, increasing the fraction of PICs (LICs) while decreasing the fraction of LICs (PICs) has a positive (negative) effect on network A's final market share and on its probability of cornering the market. Third, introducing calling clubs into the model generally increases A's ability to either increase its market share or to even corner the market. Yet, if consumers have only a limited number of friends which are very important to them, i.e., consumers almost exclusively call their friends, the probability that network A will increase its market share or corner the market decreases. Fourth, increasing the number of clusters also has a positive effect on A's probability to increase its market share or to corner the market. Finally, as a fifth insight, these findings largely extend to the case in which both networks are allowed to adjust their prices to changes in their market shares.

A close inspection of the first three findings reveals that these effects pertain to the amount of information on which consumers base their decision to subscribe to a network. Increasing the fraction of PICs or LICs at the expense of the fraction of FICs generally decreases the total amount of information used in the market since PICs and LICs use less information to decide about their network membership than FICs. Furthermore, since LICs use even less information than PICs, increasing the fraction of PICs (LICs) at the expense of the fraction of LICs (PICs) increases (decreases) the total amount of information in the market. The introduction of calling clubs has two different effects. On the one hand, the existence of friends increases the amount of information available to PICs and LICs: When trying to infer the market shares among strangers, each consumer also relies on the information on the market shares of both networks obtained from her friends. On the other hand, the existence of friends mitigates the problem of costly information acquisition since I assume that consumers always know the network subscription of their friends and call them with a certain probability. The more important friends are relative to strangers, i.e., the higher the probability of calling the friend, the larger the extent of mitigation. In the extreme case in which consumers call their friends with a 95% probability, the problem of costly information acquisition disappears almost completely.

Taken together, these observations indicate that the total amount of information used for consumers' subscription decision plays an important role for networks' final market shares, which leads to the following hypothesis: *The higher the amount of information used by consumers in their decision process the higher network A's final market share will be*.

To test this hypothesis, I created the variable INFORMATION_MASS which contains the total amount of information used by all 1,000 consumers in each parameter combination. Since in the model the amount of information available is represented by the number of other consumers observed by each consumer, the construction of this variable proceeds as follows. FICs always observe the true market share, i.e., each FIC observes 999 consumers. PICs, on the other hand, observe all other consumers within their circular sensing field with the size of the field depending on PICs' sensing radius. Each PIC observes 48, 100, 148, 248, 499, or 749 consumers, depending on whether her sensing radius is 4, 5.66, 7, 8.945, 13.893, or 19.647, respectively. Finally, each LIC observes eight consumers. As explained in section 6.1, in the models with calling clubs, each consumer weights the market share of each network among strangers and among friends with the probability of calling a friend or stranger, respectively. Therefore, in the models with calling clubs, the number of strangers and friends observed is weighted with the respective calling probabilities.[2] The resulting variable, INFORMATION_MASS, ranges from 999,000, if all consumers are fully informed and no calling clubs exist, to 8,000 if all consumers are locally informed and no calling clubs exist.

Regressing INFORMATION_MASS on network A's final market share leads to highly significant results (see Table 22). Models I, II, and III contain the regression results for the baseline model, the model with calling clubs, and the model with endogenous price setting, respectively, while model IV pools the data from all models. To facilitate an easier

[2] In the calculation of the total amount of information available, I use the simplifying assumption that friends are not part of PICs' sensing radius and are not among LICs' eight neighbors.

interpretation, Table 22 reports the standardized beta coefficients since the dimensionality of the four variables varies greatly.

**Table 22: Results of regression with INFORMATION_MASS as explanatory variable**

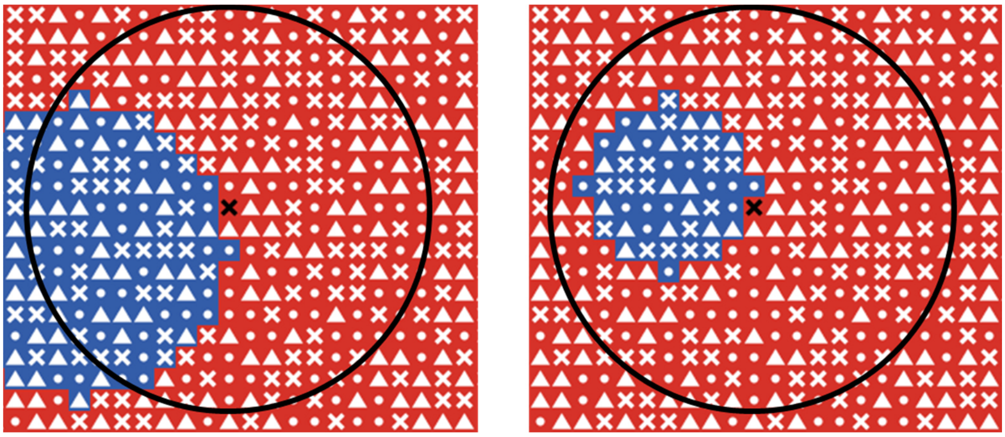
| | ( I ) | | ( II ) | | ( III ) | | ( IV ) | |
|---|---|---|---|---|---|---|---|---|
| Information_Mass | 1.36 | *** | 0.65 | *** | 0.45 | *** | 0.47 | *** |
| Information_Mass$^2$ | -0.97 | *** | -0.46 | *** | -0.29 | *** | -0.32 | *** |
| Initial MS > 65% | 0.36 | *** | 0.54 | *** | 0.68 | *** | 0.55 | *** |
| Clusters | 0.13 | *** | 0.05 | *** | 0.05 | *** | 0.06 | *** |
| N | 1152 | | 6912 | | 8064 | | 16128 | |
| R-sq | 0.40 | | 0.36 | | 0.50 | | 0.35 | |
| adj. R-sq | 0.40 | | 0.36 | | 0.50 | | 0.35 | |

* p<0.1, ** p<0.05, *** p<0.01

The results show that in all four models the total amount of information used by consumers when deciding about their network subscription has a positive decreasing effect on network A's final market share. The explanation for this positive effect is as follows. If a consumer bases her subscription decision on a limited amount of information, i.e., infers networks' market shares from the observation of a small sample of consumers, there is a high probability that the market shares within the sample of observed consumers do not resemble the true market shares. For instance, it might be the case that a LIC happens to be surrounded by six subscribers to network B inducing her to subscribe to network B since it appears to be the dominant network operator with a market share of 75%, while, in fact, B's market share might be much smaller. Of course, the same applies if a PIC happens to observe a disproportionally large number of subscribers to network B within her sensing radius, for instance because she is located adjacent to a cluster of subscribers to network B.

Nevertheless, the results in Table 22 also clearly show that in addition to the amount of information used by consumers, network A's initial market share and the number of clusters have a significant positive effect on network A's final market share. The explanation for this positive effect closely relates to the "deceiving effect" just described. Both network A's initial market share as well as the number of clusters are decisive for the actual size of the clusters: The higher A's initial market share and, hence, the lower B's initial market share, the smaller the size of the clusters since a smaller number of subscribers to network B is allotted to the existing number of clusters. Similarly, an increasing number of clusters implies smaller clusters since the given number of subscribers to network B is allotted to more clusters.

However, with a smaller cluster size it is more likely that PICs located adjacent to a cluster can observe other consumers beyond the cluster's boarder as illustrated by Figure 10.



In the left panel of Figure 10, the size of the cluster is sufficiently large so that the sensing

**Figure 10: Effect of cluster size on PICs' sensing field**

radius of the PIC marked in black does not protrude beyond the cluster. As a result, this consumer perceives network B to have a rather large market share which might be sufficiently high to make her subscribe to network B. In contrast to that, the right panel of Figure 10 shows a situation in which the cluster is substantially smaller so that the sensing radius of the consumer in question spans beyond the cluster. Accordingly, for this consumer network B appears to have a rather small market share and, hence, she most likely decides to remain subscribed to network A.

Therefore, the larger A's initial market share and/or the higher the number of clusters, the more likely it is that PICs located adjacent to a cluster of subscribers to network B observe consumers beyond the cluster's border making it less likely that these consumers perceive network B as having a higher market share than it actually has which, ultimately, negatively affects network B's odds of increasing its market share.

## Summary and Conclusion

The extant literature argues that on-net/off-net differentiation is detrimental for small network operators due to tariff-mediated network effects which provides consumers with an incentive to subscribe to the largest network (Harbord and Pagnozzi 2010). While these studies assume that consumers have perfect information about all relevant market parameters (especially prices and market shares) at zero cost, the literature on search costs posits that consumers have to costly search to obtain such information. As a result, some consumers may choose to remain imperfectly informed or even uninformed due to prohibitively high search costs. This paper aims at combining these two previously separated streams of literature to investigate whether on-net/off-net differentiation is still detrimental for small networks if at least some consumers are incompletely informed about networks' true market shares.

To study this research question, I employ an agent-based simulation model in which the market for mobile telecommunications is represented by a rectangular grid of 1,000 cells each occupied by exactly one consumer. Consumers are subscribed to exactly one of two networks which have asymmetric market shares and offer differentiated linear tariffs for on-net and off-net calls. A priori, consumers lack information on the market shares of both networks. To obtain this information, consumers have to use a costly fixed sample size search strategy, i.e., they observe the market shares of both networks in a sample of other consumers and use them as an estimate for the true market shares. With respect to the extent of search costs, I distinguish between three types of consumers: First, fully informed consumers (FICs) have non-positive search costs and, accordingly, always observe the network membership of all other consumers, which makes them perfectly informed of networks' market shares; second, partially informed consumers (PICs) have moderate search costs and are assumed to observe other consumers within a circular sensing field; and, third, locally informed consumers (LICs) have high search costs and are assumed to only observe their immediate eight neighbors. Irrespective of their type, consumers maximize their expected utility by subscribing to the network offering the lowest expected cost for a call to a random consumer. Furthermore, I assume that, initially, membership to the smaller network B is distributed clusterwise which is line with the empirical observations of Karacuka, Çatik, and Haucap (2013).

To analyze the simulation model, I systematically explore the parameter space spanned by the four key variables of the model. These include, first, the fraction of FICs, PICs, and LICs, second, the initial distribution of market shares, third, the number of clusters of subscribers to network B in $t = 0$, and, fourth, the radius of the circular sensing field of PICs. Using a full factorial design results in 1,152 different parameter combinations, each of which is simulated 500 times to mitigate the effects of random elements in the model.

Subsequently, I check for the robustness of the results by means of two extensions. First, I allow for the existence of calling clubs. More specifically, I assume that each consumer befriends a minimum number of random other consumers (friends) which are called with a probability $q$ whereas the remaining consumers (strangers) are called with probability $1-q$. In the second extension, I allow for endogenous price setting. In each period, each network has an exogenous probability $\lambda$ to be allowed to change its tariffs by choosing among five different pricing strategies. Both networks evaluate the effectiveness of each strategy by using a simple variant of a recursive algorithm and implement the strategy yielding the highest expected profit.

The results of the simulation offer two key insights. First of all, the initially larger network A has a lower final market share or becomes less likely to corner the market the higher the fraction of PICs or LICs, while A is more likely to do so if PICs' sensing radius increases. While these result are robust to the introduction of calling clubs and to endogenous price setting, the results from the models with calling clubs additionally indicate that A's final market share or its probability to corner the market increases if the minimum number of friends increases and decreases if friends become more important relative to strangers.

These findings highlight the crucial role of the amount of information available to consumers when deciding which network to subscribe to. Since PICs and LICs generally use less information than FICs, increasing their fraction in the population of consumers decreases the amount of information used, while a larger sensing radius implies that PICs possess more information when making their subscription decision. Furthermore, incorporating calling clubs generally increases the available information since, first, consumers always know which network their friends are subscribed to and, second, friends can be located anywhere in the market. Yet, the amount of information used by consumers in their subscription decision again decreases as friends become more important than strangers. Taken together this suggests that the amount of information available to consumers positively affects network A's final market share and its probability to corner the market.

Since consumers in the model obtain information about networks' market shares by observing the network membership of other consumers, the total amount of information can be measured as the total number of other consumers observed by each of the 1,000 consumers. A regression of the total amount of information available on network A's final market share confirms its postulated positive effect. Intuitively, this effect can be explained by the fact that the less information a consumer possesses the more likely it becomes that the observed market shares significantly differ from the true ones. Such a misconception could occur, for instance, if a PIC only observes a very small number of other consumers (due to a small sensing radius) but happens to be located adjacent to a cluster of subscribers to network B (see Figure 10). Due to her proximity to the cluster, she will observe a disproportionally large fraction of subscribers to network B, which induces her to think that B has a large market share and might cause her to also subscribe to network B.

The second key insight from the model is that network A's final market share and its probability of cornering the market is positively affected by the initial number of clusters and A's initial market share. An increase in these two variables reduces the size of the clusters. Smaller clusters, in turn, make it more likely that the sensing field of PICs located adjacent to a cluster spans beyond the cluster hence leading to a smaller probability that the market shares observed by these PICs are biased as a result of their proximity to the cluster.

The contributions of this study are threefold. First of all, it contributes to the literature on tariff-mediated network effects by confirming and extending previous findings of the theoretical literature. In line with previous theoretical research in this area, the findings of the simulation model suggest that if consumers have perfect information or are, at least, sufficiently well informed, tariff-mediated network effects harm small networks and might even induce market exit. At the same time, this study extends previous findings by showing that tariff-mediated network effects can also work in favor of small networks if consumers possess only limited information about crucial market parameters, such as, for instance, the market shares of both networks. Hence, contrary to the extant theoretical literature, which unanimously stresses the detrimental effect of tariff-mediated network effects, this study demonstrates that both shared-market equilibria as well as corner equilibria in favor of the initially smaller network can exist under on-net/off-net differentiation.

Moreover, this study also contributes to the literature on costly consumer search. While the extant literature argues that costly information acquisition by consumers decreases total welfare by enabling firms to charge prices above marginal cost, the findings of this study suggest that under certain circumstances search costs can actually improve total welfare, at least in the long run. This is the case if, as a result of costly information acquisition, the existence of incompletely informed consumers decreases barriers to market entry created by tariff-mediated network effects, thereby allowing a new network operator to enter the market. This, in turn, might increase the competitiveness of the market, at least in the long run, thereby leading to lower prices and higher welfare. Of course, this is contingent on the entrant being sufficiently efficient so that prices decline as a result of the competition.

Finally, this study also contributes to an emerging literature which uses agent-based simulation models to study telecommunication markets (Twomey and Cadman 2002, Osnumakinde and Potgieter 2006, Kamiński and Łatek 2008, 2010, Schade, Frey, and Mahmoud 2009, DeMaagd and Bauer 2011, Grove and Baumann 2012, Diedrich and Beltrán 2012). By combining two previously separated research streams, this study demonstrates the ability of agent-based computational models to extend existing theoretical models by relaxing modeling assumptions which, in turn, makes these models analytically intractable. This is especially relevant for research on telecommunication networks which are characterized by interactions among consumers' behavior which lead to feedback loops in the behavior of the system as a whole. Agent-based computational models are exceptionally well suited to address models in which interactions and feedback loops play a prominent role. By providing an analytical framework, this study might serve as a starting point for future endeavors to study less restrictive theoretical models in order to further deepen our knowledge of the functioning of telecommunications markets.

From a practical point of view, the findings of this study imply that better informed consumers do not necessarily lead to improved market outcomes in terms of consumer surplus or total welfare. In fact, the results suggest that under certain conditions it might even be detrimental to foster market transparency, for instance, by means of a public information system as recently implemented in gasoline markets (Dewenter and Heimeshoff 2012). Instead, it might even be desirable to actively limit the amount of information possessed by consumers if this helps to decrease barriers to market entry and to promote long-term competition. Furthermore, this study suggests that entrant network operators should aim at establishing one or more local clusters upon market entry, for instance, by predominantly targeting single cities or regions, or by focusing on distinct social groups. The clusters could then serve as nuclei for further market share growth. A possible point in case might be the strategy of E-Plus, Germany's second smallest mobile network operator, who founded the mobile virtual network operator Ay Yildiz in 2006. The tariffs offered by Ay Yildiz are specifically targeted at the needs of Turkish mobile phone users in Germany, for instance, by offering flat rate tariffs for calls to Turkey (Ay Yildiz 2014).

The findings and implication of this study should be viewed in light of its limitations which could serve as starting points for future research. A first limitation of the study is that it simply assumes that ex-ante both networks price discriminate between on-net and off-net calls without investigating whether or not networks would have an incentive to do so in the first place. Hence, future studies could explore models in which, initially, both networks charge equal tariffs for on- and off-net calls and study whether or not on-net/off-net differentiation emerges endogenously from operators' efforts to maximize profits. Preliminary findings from this study suggest that on-net/off-net differentiation likely also emerged endogenously since in the extension with endogenous price setting both networks did not abandon termination-based price discrimination but continued to price discriminate between on- and off-net calls.

A second starting point for further research could be the assumption that consumers only lack information on the market shares of both networks but are perfectly informed about the tariffs charged by them. Future studies could set out to test whether or not the findings of this study also hold if consumers alternatively or additionally are ex-ante uninformed or only incompletely informed about the tariffs charged by all network operators.

Thirdly, the present model is limited by the assumption that although both networks differ in size, they offer identical services, i.e., both networks offer the same network quality, coverage, and added services. While this allowed me to concentrate on the impact of costly information acquisition on the competitive effect of on-net/off-net differentiation, future studies may find it worthwhile to relax this assumption and allow for horizontal or vertical product differentiation to improve the internal and external validity of the model.

Fourthly, the network structure of the calling clubs appears as a fruitful area for additional studies. Presently, I assume that calling clubs are organized as a random network, i.e., the probability that two random consumers are friends is $\frac{1}{999} \approx 0.1\%$. It might be interesting to check whether more realistic network topologies such as, for instance, small-world networks, would lead to diverging results.

Finally, future research might extend the present model by using real-word data to calibrate the parameters of the variables used in the model, thereby greatly broadening its practical applicability. For instance, laboratory experiments could be designed such that it is possible to infer the amount of information used by consumers when making their decision to subscribe to a mobile network. This information could then be used to estimate the fraction of FICs, PICs, and LICs in the population as well as PICs' sensing radius. Furthermore, the size of calling clubs could be inferred either by conducting surveys among subscribers to mobile networks or by studying the communication behavior of consumers on social networks, such as Facebook. The number of friends with which members of a social network communicate frequently, e.g., at least once a week, could be used as a proxy for the size of a calling club. Information on the tariffs for on- and off-net calls could be inferred from publicly available databases, such as the one provided by the OECD. Finally, the decision on the number of network operators, the extent of market share asymmetry, and the initial number of clusters could be guided by the historic characteristics of the mobile telecommunications market under investigation.

Despite the widespread introduction of flat rate tariffs in recent years, the investigation of tariff-mediated network effects remains both a promising and a relevant research area since the competitive problems raised by on-net/off-net differentiation are not limited to markets in which several mobile network operators compete with each other. Rather, as demonstrated recently by Hoernig, Bourreau, and Cambini (2014), tariff-mediated network effects continue to play a role in markets where an integrated fixed/mobile network operator competes with several mobile operators and price discriminates between calls to the fixed-line network originating on his integrated mobile network and those originating on competitors' mobile networks. Hopefully, this study serves as a starting point for future endeavors to further explore the competitive effects of tariff-mediated network effects.

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## APPENDIX A: DESCRIPTION OF THE MODEL ACCORDING TO THE ODD PROTOCOL

The following section describes the agent based model employed according to the ODD protocol (Grimm et al. 2006, Grim et al. 2010).

*Purpose*. The objective of the model is to study the impact of costly information acquisition on the competitive effect of tariff-mediated network effects.

*Entities, state variables, and scales*. The model consists of two mobile network operators offering linear tariffs with on-net/off-net differentiation as well as 1,000 consumers who maximize their expected utility by subscribing to the network which offers the lowest expected cost for a call to a random other consumer. A priori, consumers lack information on the market shares of both networks. To obtain this information, consumers use a costly fixed sample size search strategy, i.e., they observe the network membership of other consumers and use that information to infer the market shares of both networks. With respect to the extent of the search costs, I distinguish between three types of consumers. Fully informed consumers (FICs) have non-positive search costs and, therefore, always observe the network membership of all other consumers. Partially informed consumers (PICs) have moderate search costs and, therefore, are assumed to observe the network membership of all consumers within a circular sensing field whose radius is exogenously set by the variable "sensing-radius." Finally, locally informed consumers (LICs) face high search costs and, consequently, are assumed to be able to observe only the network membership of their immediate eight neighbors. Key characteristics of all consumers include their position on a two-dimensional grid, a dummy variable "network-a" which takes on the value one if the consumer is currently subscribed to network A and zero if she is subscribed to network B[3], and a variable "search-costs" indicating the consumer type (FIC, PIC, or LIC). The market for mobile telecommunications is represented by a rectangle of 50 x 20 cells and each cell is occupied by exactly one consumer located at the center of the cell. The grid is toroidal, i.e., the world wraps both horizontally and vertically so that all consumers have exactly eight neighbors. The length of one time step is not explicitly defined. However, it is shorter than the average duration of a mobile contract because in each time period only a fraction of consumers, specified by the variable "prob-of-switch", is allowed to decide whether to stay with the current network or switch to the competitor. The model automatically stops after 999 time periods.

[3] I assume full market participation, i.e., all consumers are always subscribed to one of the two networks.

*Process overview and scheduling*. In each period, five actions are executed successively. First, the computer draws a random sample of consumers who are allowed to decide on their network membership. The sample size is determined by the variable “prob-of-switch” which is determined exogenously. Second, all consumers of this sample execute the process “calculate-current-share-a” to calculate the current market share of network A as perceived by each consumer. Since FICs observe the network membership of all other consumers they observe the true market shares. PICs calculate the market share of network A as the fraction of consumers within their sensing field who are subscribed to network A. LICs calculate network A’s market share as the fraction of subscribers to network A among their eight neighbors. Third, all selected consumers execute the process “calculate-utility” to calculate the expected utility from both networks. Fourth, each consumer of the sample executes the process “decide-switching” which induces the consumer to either stay with her current provider if the expected utility from the current network is larger or equal to the expected utility of the competing network or to switch to the competing network otherwise. Therefore, switching takes place simultaneously, and switching costs are assumed to be zero. Fifth, the process “do-plotting” is used to update the plot of market shares of both networks.

*Design concepts*. The focus of the model is on the sizes of networks A and B, which *emerge* endogenously from the interaction of the three different consumer types. The decision of each consumer to join a network depends on the market share of each network, which, in turn, depends on the decisions of all other consumers in previous periods. Due to this feedback loop, network sizes emerge in complex ways and cannot be inferred by simply considering initial market shares and consumers’ search costs. Consumers *adapt* to their environment by either staying with their current network operator or by switching to the competing network. In doing so, consumers pursue the *objective* of being subscribed to the network which offers them the highest expected utility. When calculating the expected utility derived from each network, consumers do not make any *predictions* about the future or about other consumers’ behavior. All consumers *sense* the tariffs for on-net and off-net calls of both networks. Moreover, FICs sense the network membership of all other consumers, whereas PICs sense the network membership of consumers within a circular sensing field and LICs only sense the network membership of their eight neighbors. *Interaction* takes place only indirectly through network externalities that arise from the decision of each consumer to join a specific network. The sole s*tochastic* element of the model is the recurrent sampling of consumers which are allowed to decide on their network membership. The main *observations* of the model are the market share of networks A and B.

*Initialization*. The initialization of the model proceeds in four steps. First, 1,000 consumers are created and distributed across the rectangular grid so that each cell is occupied by exactly one consumer.

Second, each consumer is assigned to exactly one of the two networks so that the actual fraction of subscribers to network A matches the market share of network A as specified exogenously in the variable “initial-share-a.” To this end, the process “distribute-shares-in-clusters” is executed which distributes network membership such that clusters of subscribers to network B occur.

In the third step of the initialization, consumers’ search costs are assigned randomly by setting the variable “search-costs” to one for FICs, to two for PICs, and to three for LICs. The distribution is such that the fraction of FICs and PICs corresponds to the value of the variables “share-fic” and “share-pic,” respectively. The remaining consumers are assigned to be LICs.

Fourth, the values for the variables “prob-of-switch,” “tariff-a-onnet,” “tariff-a-offnet,” “tariff-b-onnet,” and “tariff-b-offnet” are initialized.

*Input Data*. The model does not use input data from external sources.

*Submodels*. In executing the process “calculate-utility”, consumers who have been selected to decide on their network membership calculate the expected utility from both networks according to (2).

The process “distribute-shares-in-clusters” assigns membership to network B in clusters across the rectangular grid and proceeds in six steps. First, the variable “network-a” is set to one for all consumers. Second, the process calculates how many subscribers to network B are needed to mirror the market share of network B as implicitly defined by the variable “initial-share-a.” This number is divided by the number of clusters specified by the variable “number-of-clusters” and subsequently rounded down to approximate the average number of consumers per cluster subscribed to network B. Third, the necessary radius of each cluster is approximated by

(11) $radius = \sqrt{average\ cluster\ population}/2$,

i.e., a cluster is viewed as a square and the cluster radius is approximated by the half of the square’s edge length. Fourth, a number of consumers equal to the number of clusters is randomly chosen as the center of a cluster and all consumers within the calculated radius are assigned to network B (including the consumer located at the center of the cluster). Fifth, the number of consumers actually subscribed to network B is compared to the required number of consumers calculated in step two. If the actual number of subscribers to network B is too small (large) then the computer randomly picks the necessary number of consumers from network A (B) and assigns them to network B (A). In the sixth step, the colors of the cells are updated to correctly display the network membership of the consumer inhabiting the cell.

## APPENDIX B: SUBSTITUTABILITY OF ON-NET AND OFF-NET TARIFF CHANGES

If a network increases its on-net tariff by x-%, the resulting profits are given by

(12) $1000[MS * p^{on}(1 + x) + (1 - MS) * p^{off})]$

Likewise, the expected profit for a y-% increase in the off-net tariff is given by:

(13) $1000[MS * p^{on} + (1 - MS) * p^{off}(1 + y)]$

Equating (12) and (13) and solving for x yields:

(14) $x = \frac{1-MS}{MS} * \frac{p^{off}}{p^{on}} * y$

That is, every y-% increase in the off-net tariff can profit-neutrally be substituted by an appropriate increase in the on-net tariff and vice-versa. The magnitude of the necessary increase in the on-net tariff depends on the relative market shares of both networks and the ratio of tariffs for off- and on-net calls, respectively.

# APPENDIX C: GRAPHICAL VISUALIZATION OF THE SIMULATION RESULTS OF THE MODEL WITH CALLING CLUBS

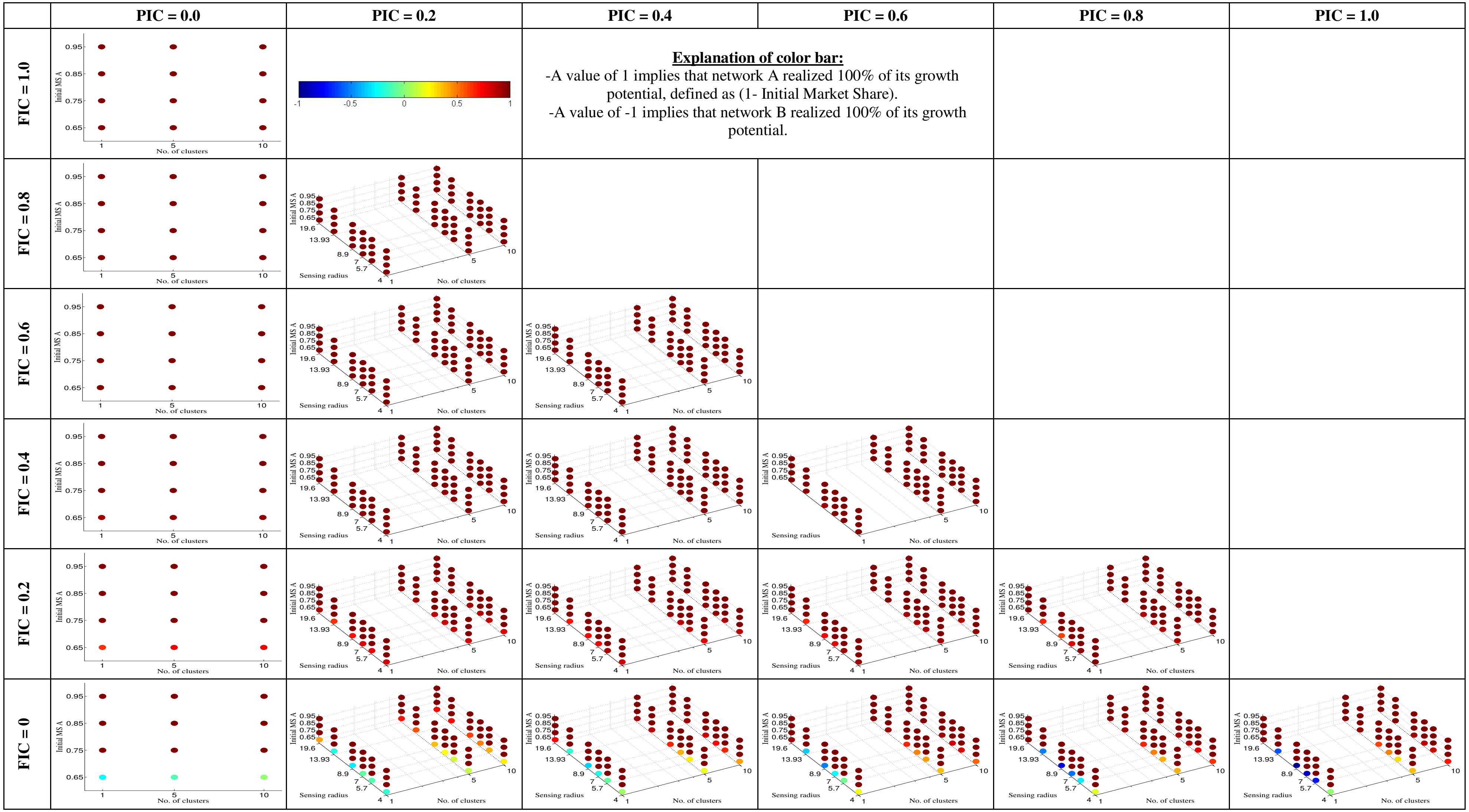


**Figure 11: Graphical visualization of simulation results of model with calling clubs (friends = 5, weight = 50%)**

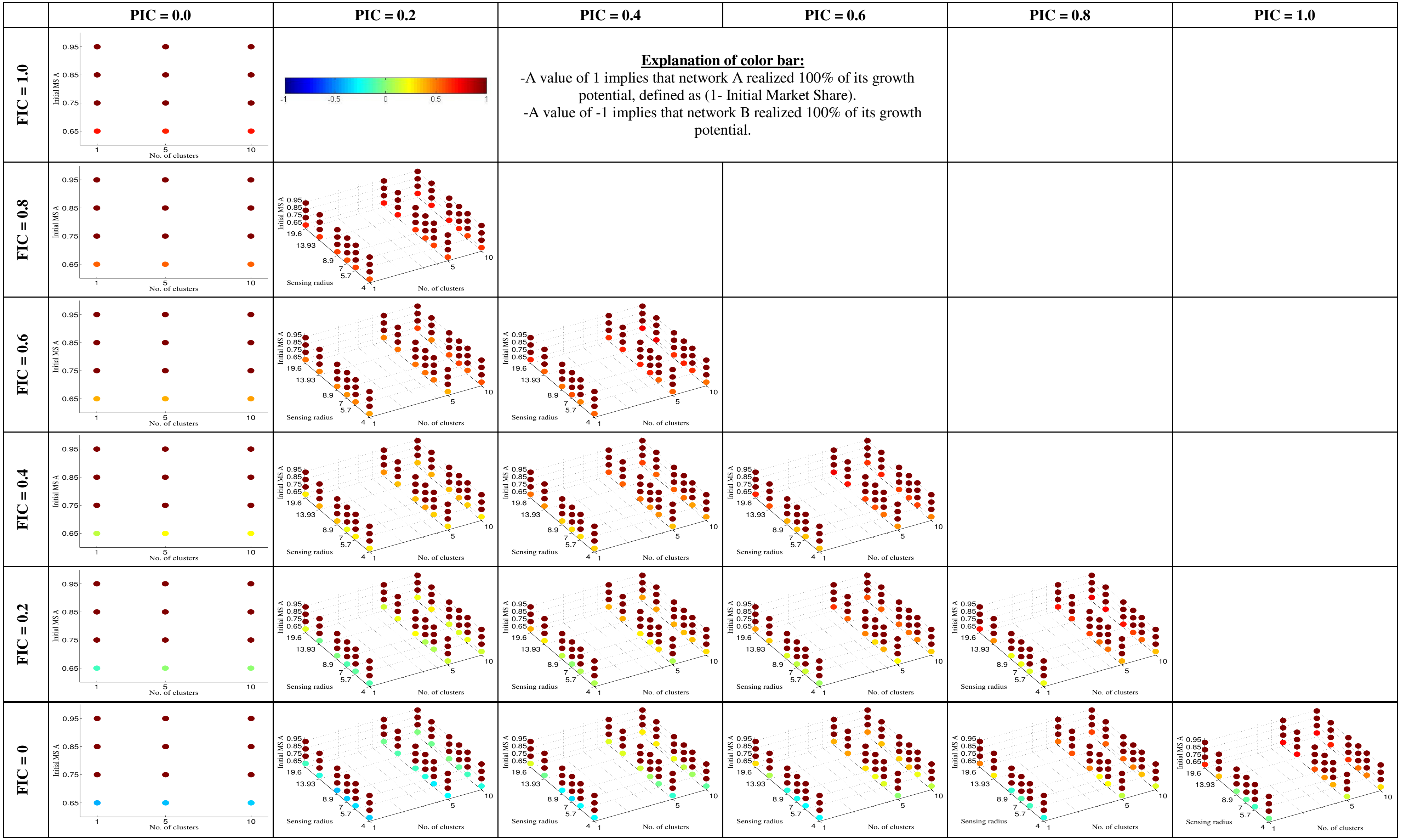


**Figure 12: Graphical visualization of simulation results of model with calling clubs (friends = 5, weight = 75%)**

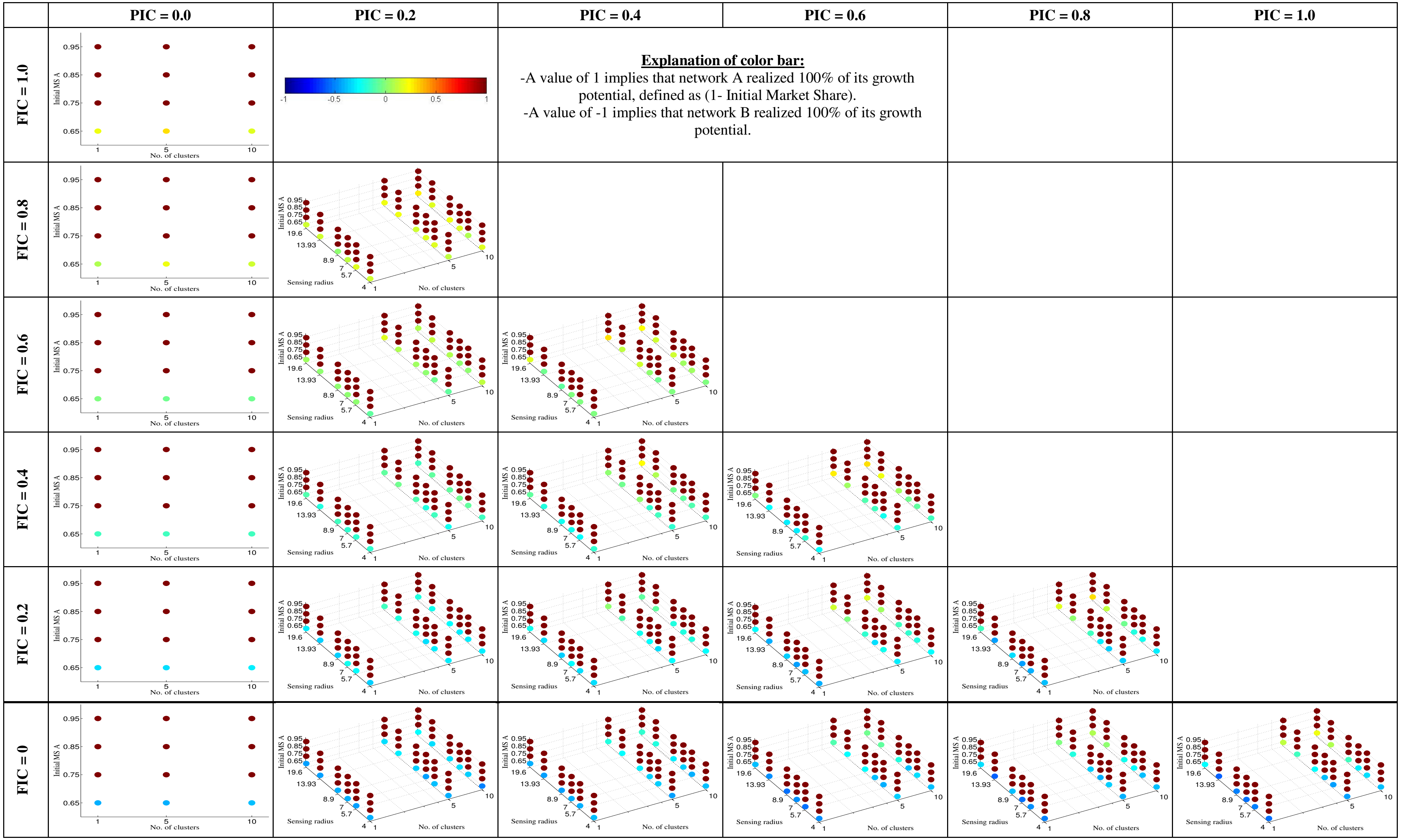


**Figure 13: Graphical visualization of simulation results of model with calling clubs (friends = 5, weight = 95%)**

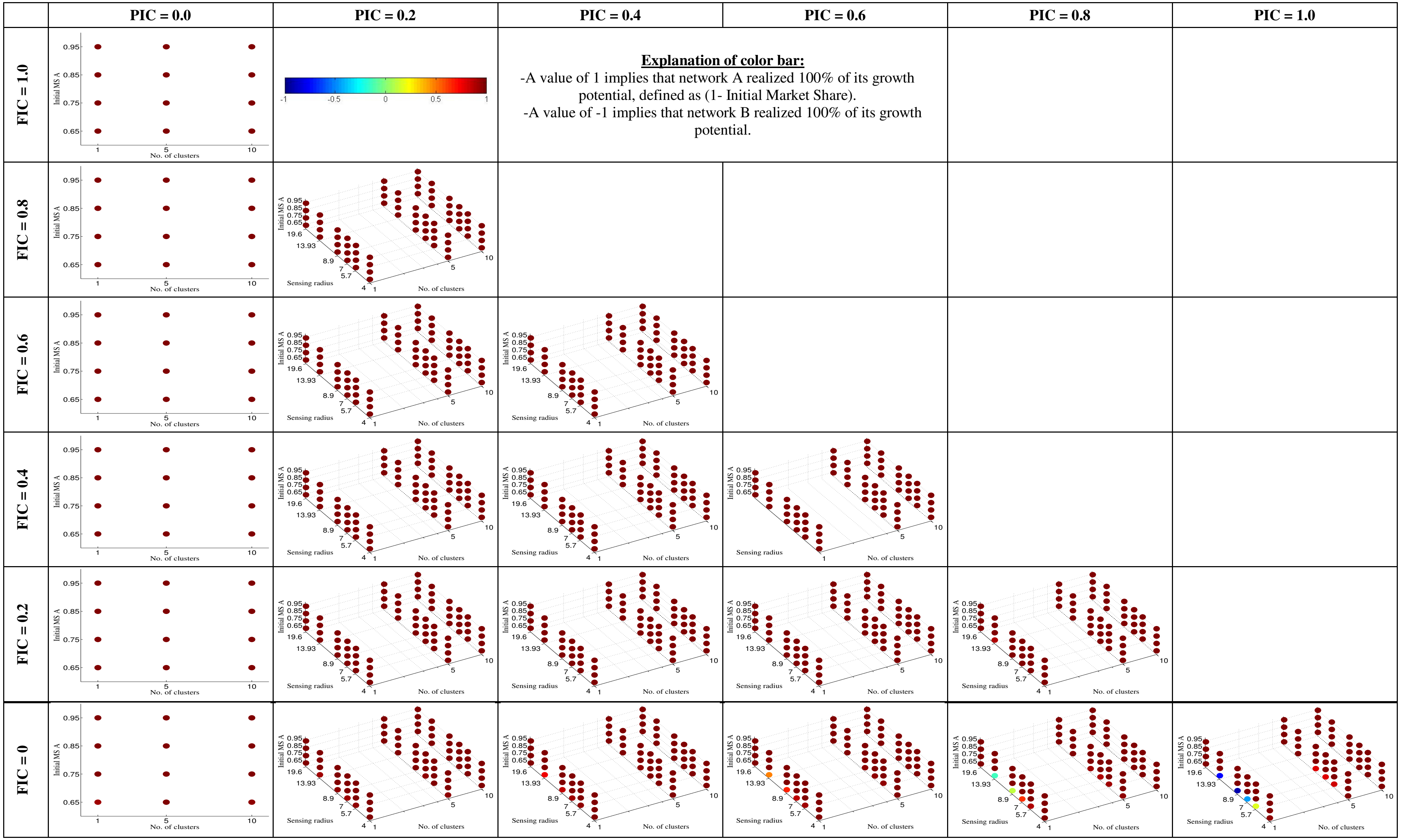


**Figure 14: Graphical visualization of simulation results of model with calling clubs (friends = 10, weight = 50%)**

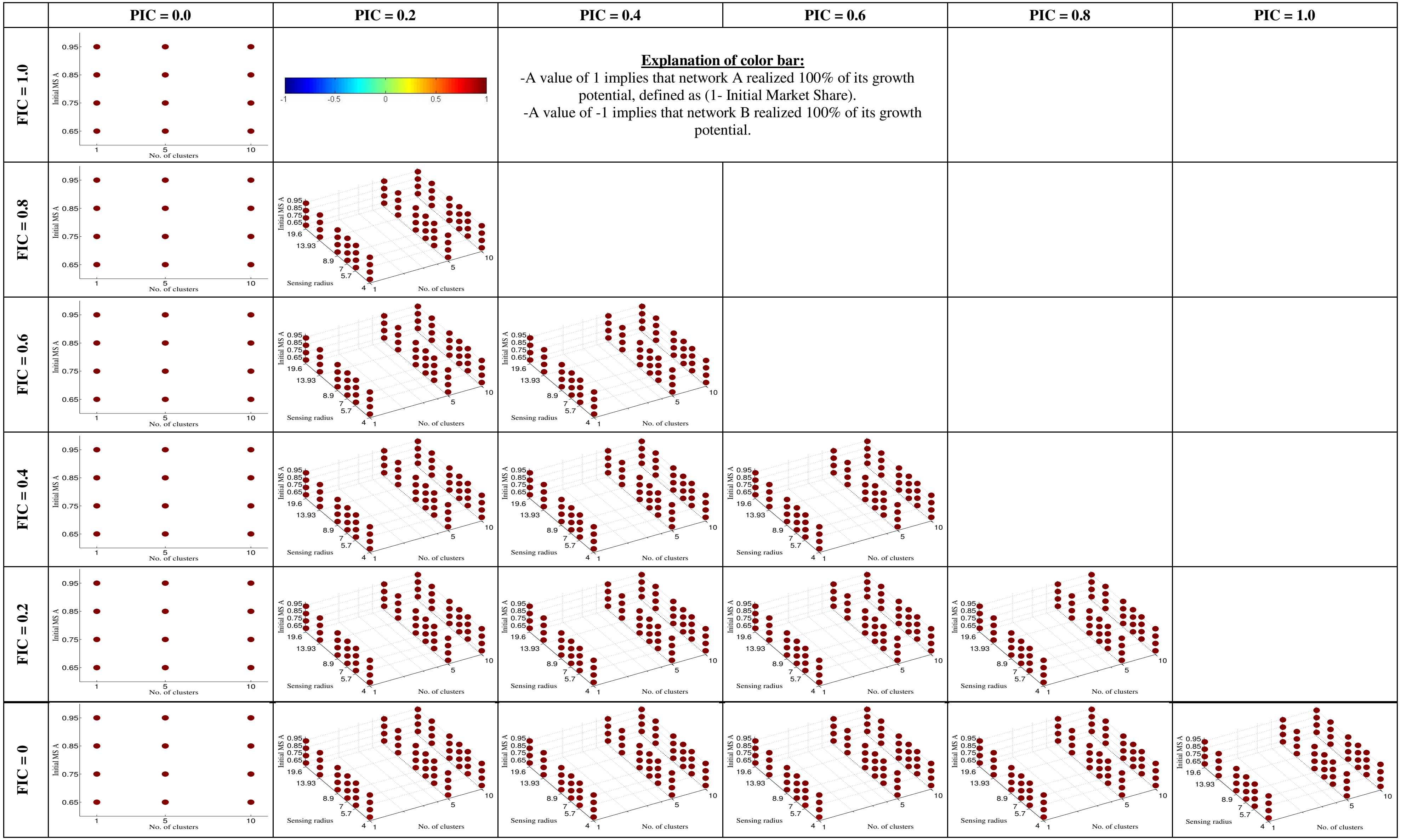


**Figure 15: Graphical visualization of simulation results of model with calling clubs (friends = 10, weight = 75%)**

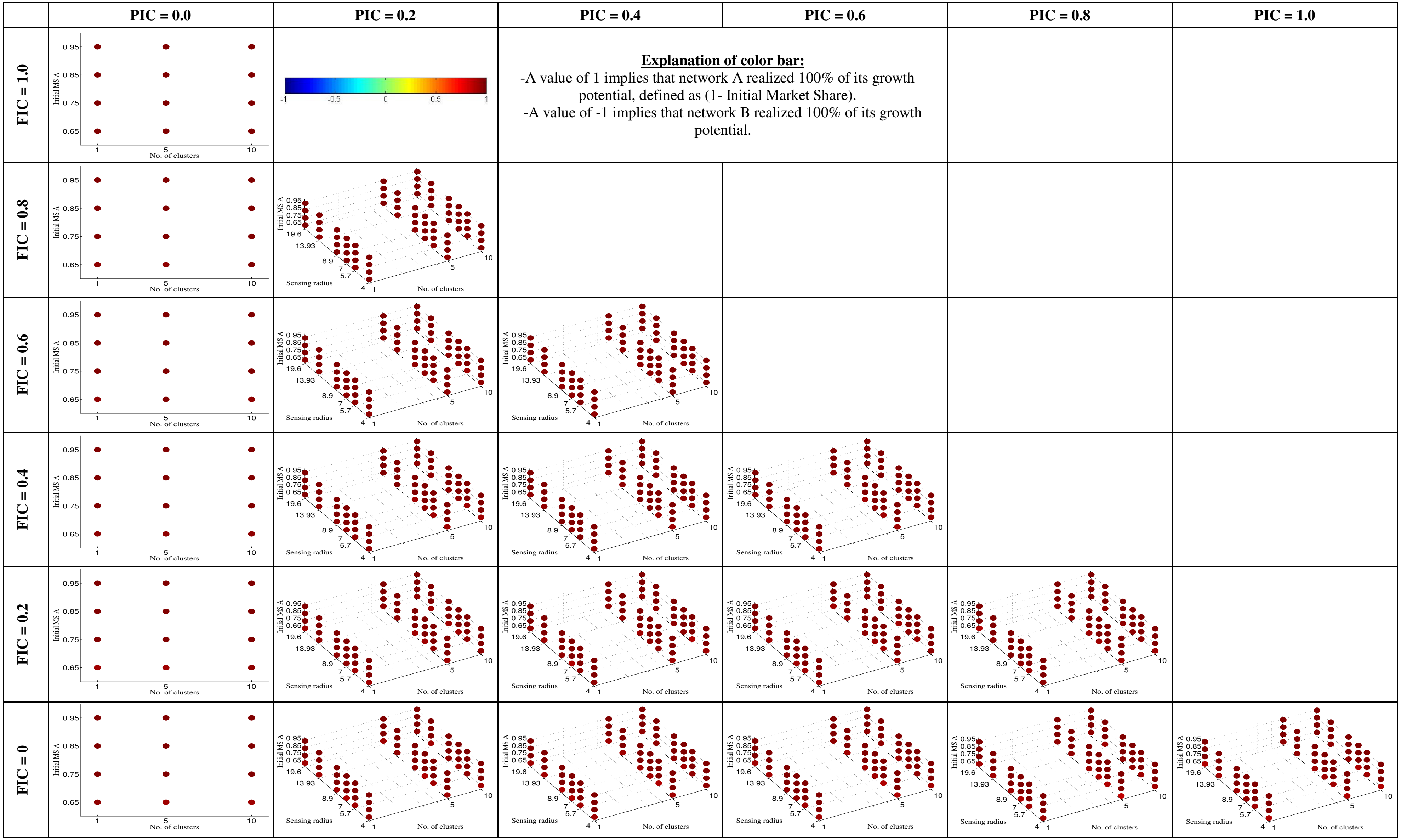


**Figure 16: Graphical visualization of simulation results of model with calling clubs (friends = 10, weight = 95%)**

## APPENDIX D: GRAPHICAL VISUALIZATION OF THE SIMULATION RESULTS OF THE MODEL WITH ENDOGENOUS PRICE SETTING

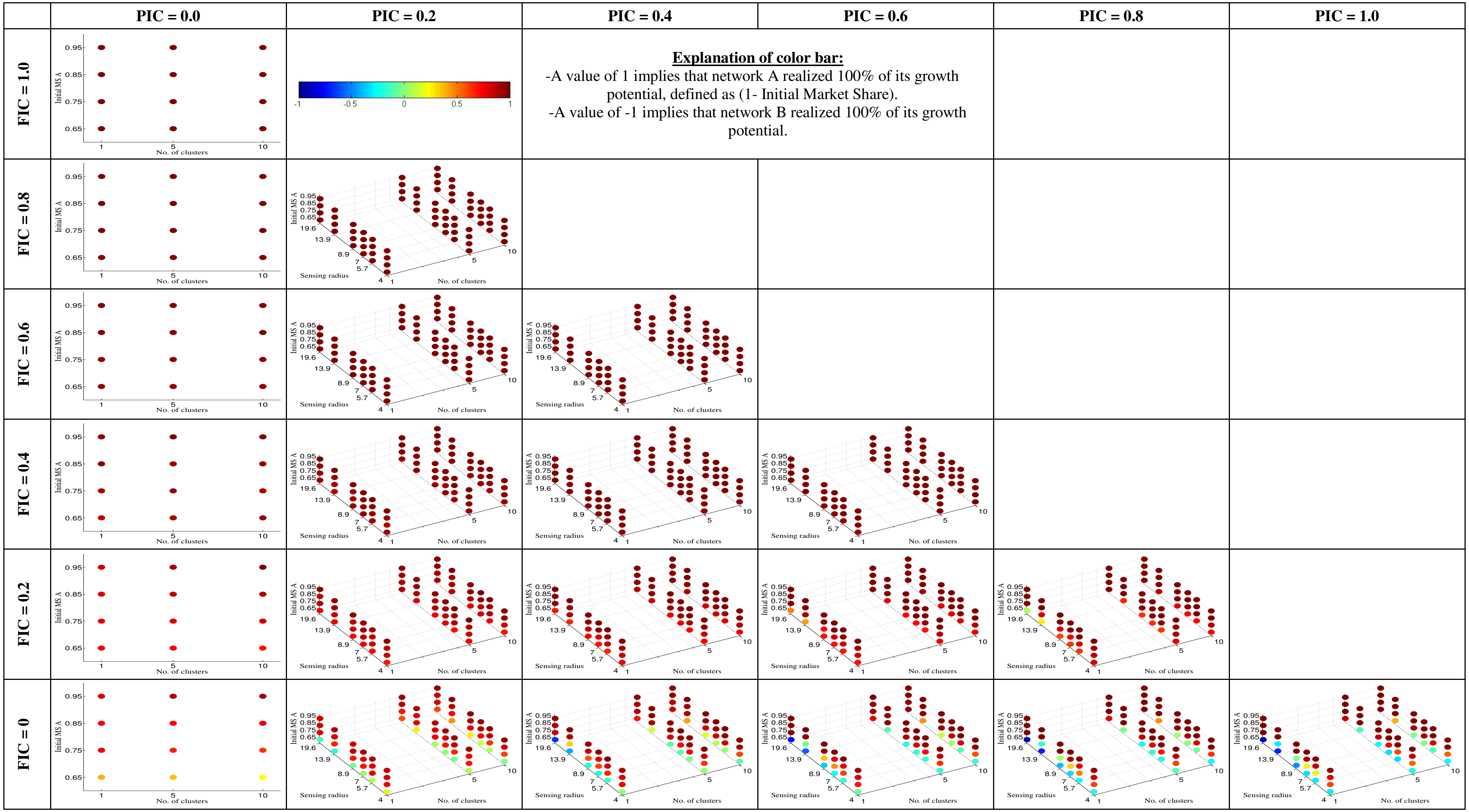


**Figure 17: Graphical visualization of simulation results of model with endogenous price setting (friends = 0)**

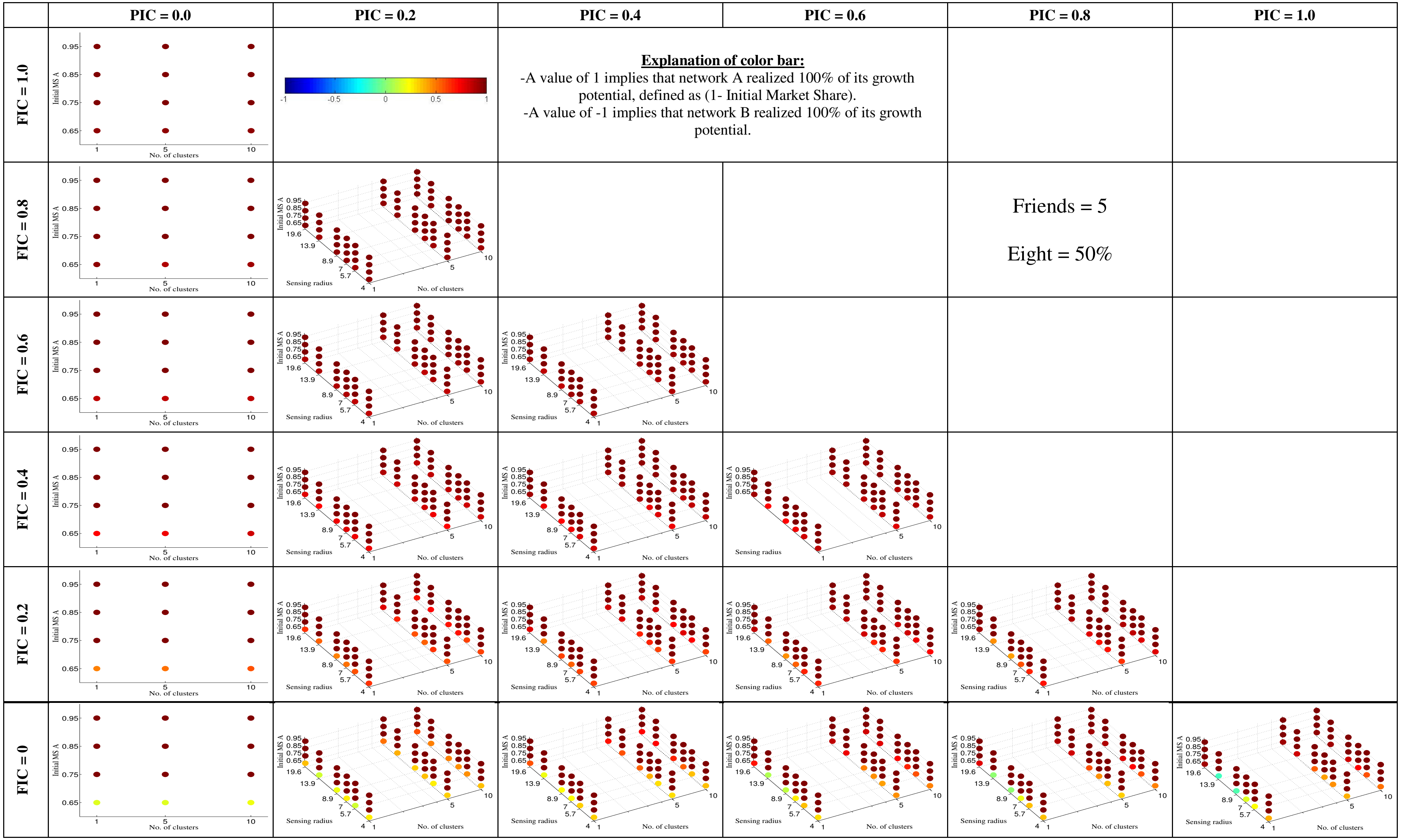


**Figure 18: Graphical visualization of simulation results of model with endogenous price setting (friends = 5, weight = 50%)**

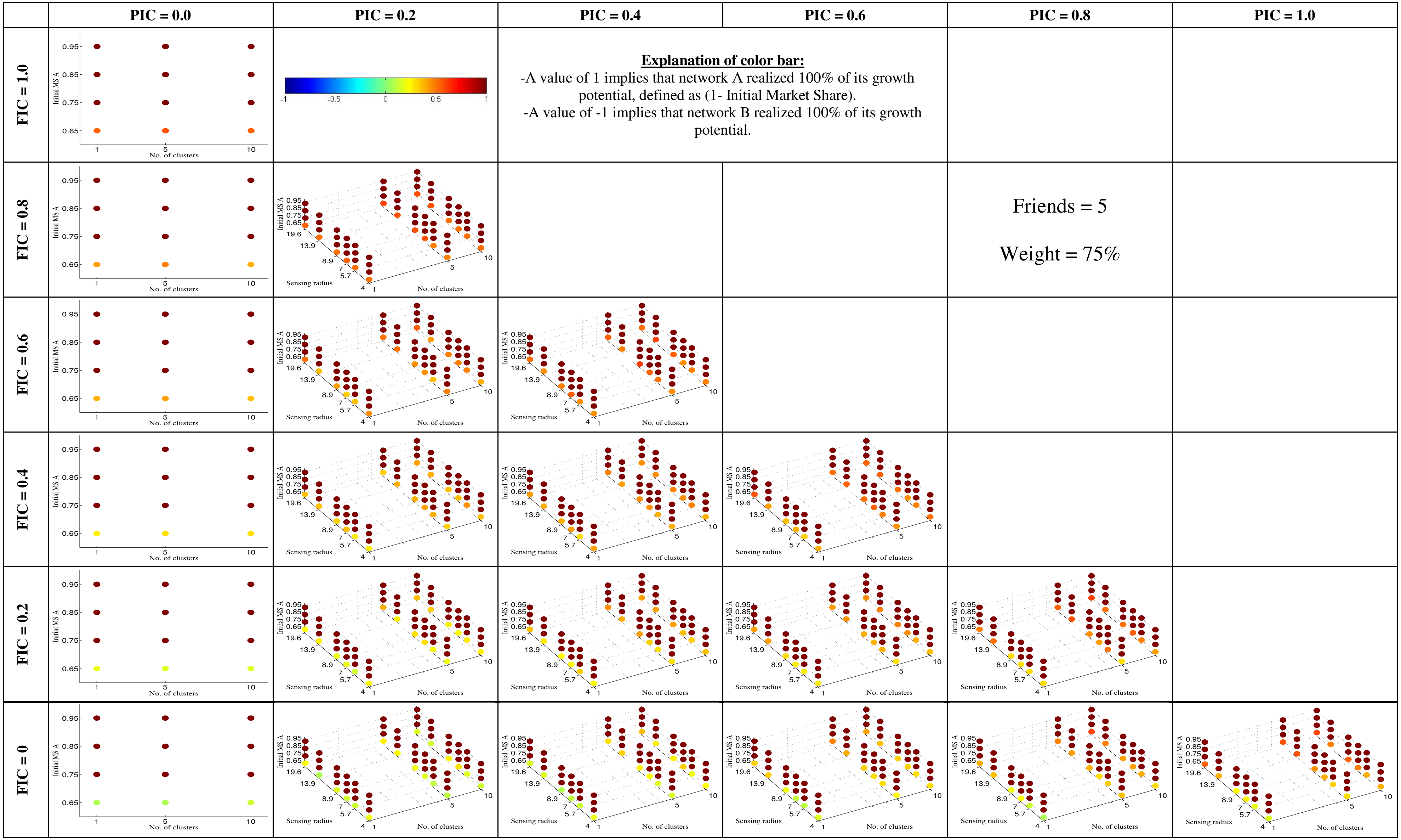


**Figure 19: Graphical visualization of simulation results of model with endogenous price setting (friends = 5, weight = 75%)**

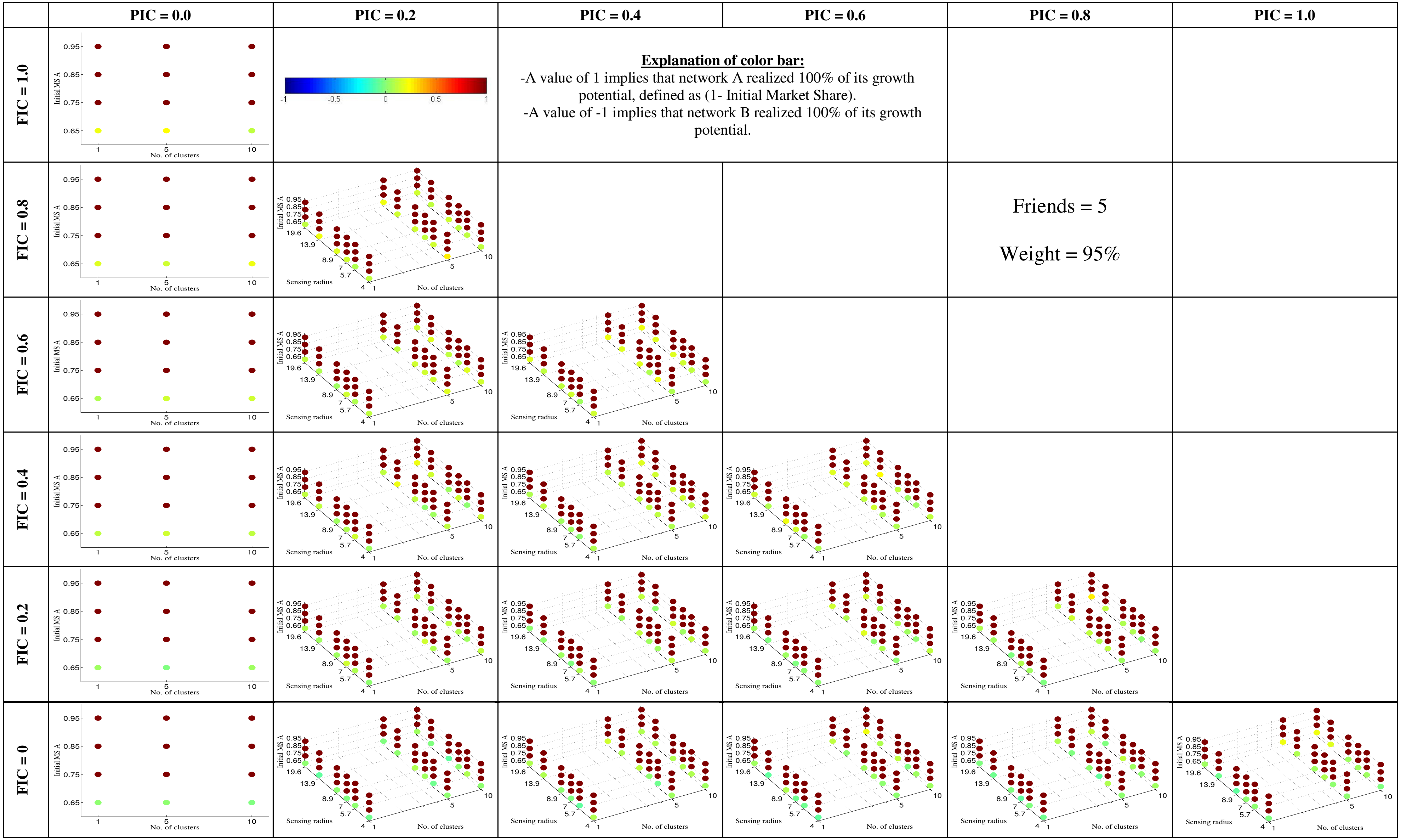


**Figure 20: Graphical visualization of simulation results of model with endogenous price setting (friends = 5, weight = 95%)**

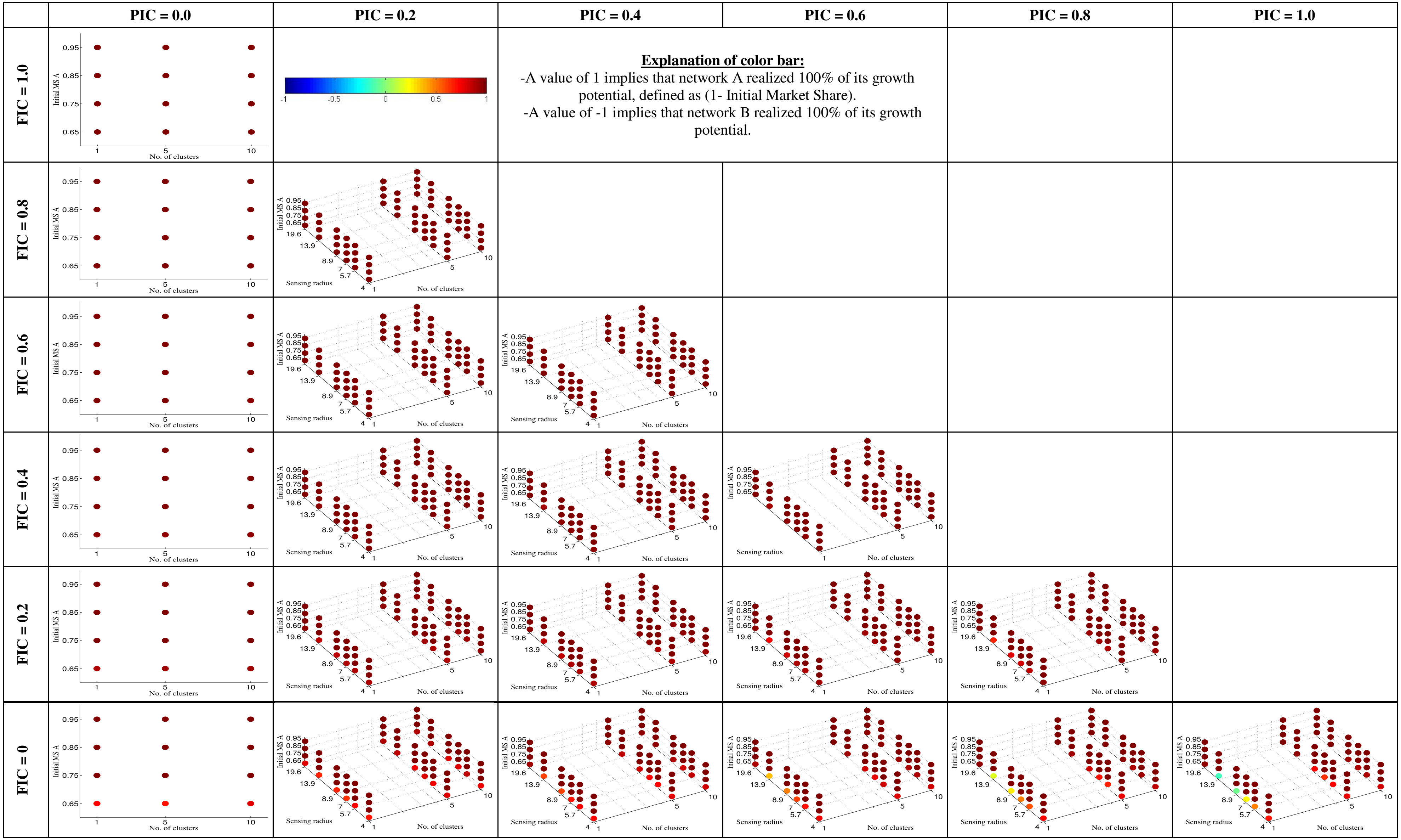


**Figure 21: Graphical visualization of simulation results of model with endogenous price setting (friends = 10. Weight = 50%)**

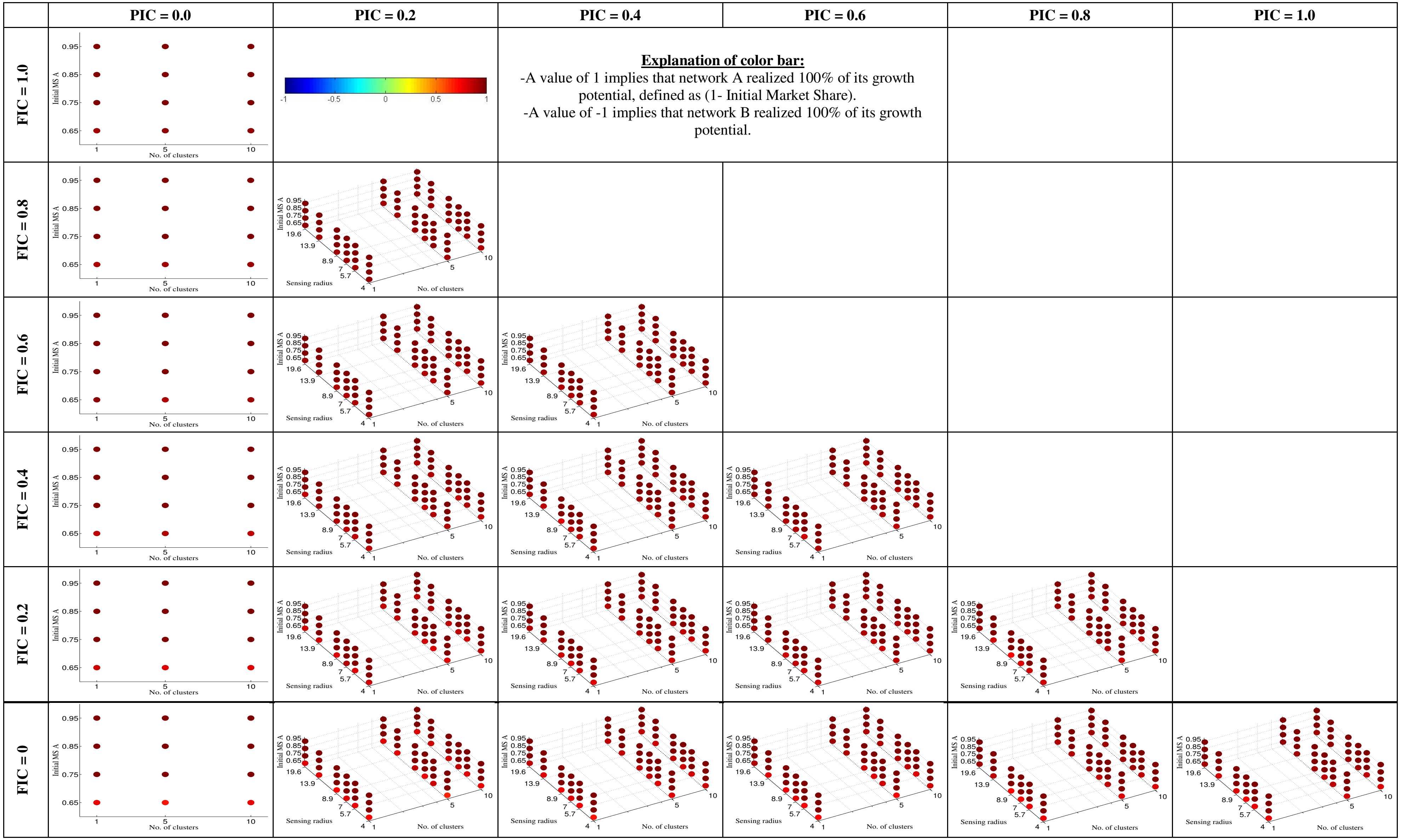


**Figure 22: Graphical visualization of simulation results of model with endogenous price setting (friends = 10, weight = 75%)**

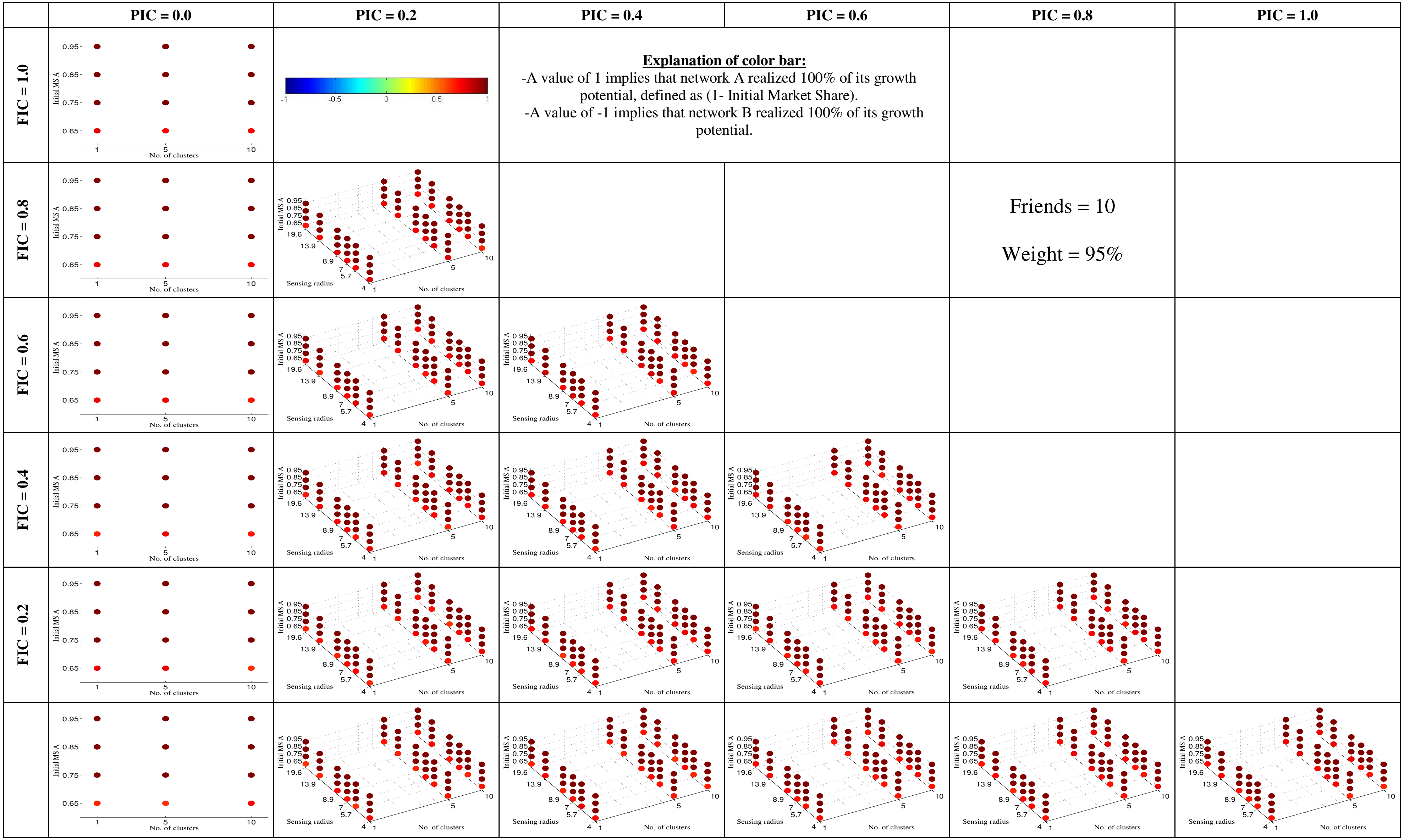


**Figure 23: Graphical visualization of simulation results of model with endogenous price setting (friends = 10, weight = 95%)**

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