# Essays in Telecommunications Policy and Management

Submitted in partial fulfillment of the requirements for

the degree of

Doctor of Philosophy

in

Engineering and Public Policy

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August 2013

*For my wife, my son and for my parents*

## Abstract

This work comprises three independent essays in Telecommunications Policy and Management.

In the first study we focus on the deployment of green field next generation access network infrastructures when the national regulatory authority has the power to define geographical markets at sub-national level for which it can apply differentiated regulatory remedies - Geographically Segmented Regulation (GSR). Using a game theory model that we developed, we confirm the asymmetric business case for the geographic development of these new infrastructures: highly populated areas are likely to develop into competitive telecommunication markets while regions with low household density will only see limited investment and little or no competition. We show that supply side interdependencies among markets make the implementation of GSR non-trivial, namely, we show that changes in the wholesale access price in one market can have undesirable consequences in the competitive conditions of interrelated regions where wholesale prices are unchanged.

In the second study we focus on how individual purchase decisions are influenced by the behavior of others in their social circle. We study the case of the diffusion of the iPhone 3G across a number of communities sampled from a dataset provided by a major mobile carrier in one country. We find that the propensity of adoption increases with the proportion of each indivudal's adopter friends. We estimate that 14% of iPhone 3G adoptions in this carrier were due to peer influence. We provide results from several policy experiments that show that with this level of effect from peer influence the carrier would hardly be able to significantly increase sales by selectively targeting consumers to benefit from viral marketing.

Finally, in the third study, we perform a randomized field experiment to determine the role that likes play on the sales of movies in Video-on-Demand (VoD). We use the VoD system of a large telecommunications provider during half a year in 2012. The system suggests movies to consumers ordered by the number of consumer likes they obtained in previous weeks. We manipulated such natural order by randomly swapping likes across movies. We found that movies promoted (demoted) increased (decreased) sales, but the amount of information publicly available about movies affected the result. Better known movies were less sensitive to manipulations. Finally a movie promoted (demoted) to a fake slot sold 15.9% less (27.7% more) than a true movie placed at that slot, on average across all manipulations. A movie promoted (demoted) to a fake slot received 33.1% fewer (30.1% more) likes than a true movie at that slot. Hence manipulated movies tended to move back to their true slots over time. This means that self-fulfilling prophecies widely discussed in the literature on the effect of ratings on sales are hard to sustain in markets with costly goods that are sufficiently well-known.

## Acknowledgments

I would like to acknowledge the financial support provided by the Portuguese Foundation for Science and Technology through the Carnegie Mellon Portugal Program under Grant SFRH/BD/33772/2009.

I would also like to acknowledge the two industrial partners that allowed me to use their databases without which this work would not have been possible.

I would like to thank Professor Pedro Ferreira, my advisor, for all his support and professional as well as personal guidance during this journey. For the lively discussions, and for all the time he dedicated to my research.

I would like to extend a special thank you to Professor David Krackhardt and to Professor Rahul Telang who had particularly active roles in the co-supervision of my research and to whom I am indebt for the time, expertise, recommendations and constructive criticism.

Finally, I would also like to thank all members of my Ph.D. committee: Professor Pedro Ferreira (chair), Professor Francisco Lima (co-chair), Professor David Krackhardt, Professor Rahul Telang, Professor Marvin Sirbu, Professor Ravi Bapna, and Professor João Paulo Costeira for their interest in my research.

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# Chapter 1

# Introduction

In 2002 8% of the world population was online. Mobile phone subscribers were approximately 1 billion (ITU, 2002). By the end of year 2011, the worldwide penetration of cellular phones reached 85% (approximately 6 billion mobile phone subscriptions), 32% of the world population was using the Internet and 33% (0.6 billion) of worldwide households had a fixed Internet connection(Bank, 2012). ICTs' usage growth has spanned both developed and developing countries and such growth trajectory is expected to continue[1] (ITU, 2012).

The increasing use of ICTs' and its developments are bringing people closer to each other, changing the way individuals interact and shaping new ways to conduct business. At the same time, such developments are creating several challenges for which there are not yet definite regulatory or public policy responses.

The volume of data traffic exchanged over the internet is reaching magnitudes that

[1] A substantial digital divide gap persists. By 2011, the penetration of mobile phones in developed countries was 120% against 85% in the developing world and the penetration of Internet usage in developed countries reached 70% against 24% in developing economies (ITU, 2012)

current infrastructures will not be able deal with, consumers are leaving a digital footprint of their behavior that firms are starting to exploit, and the amount of information and product variety available to consumers in the market place is so vast that it challenges the basic economic notion that increased choice is beneficial for consumers. My thesis deals with these realities in three independent essays.

In the first study we focus on a decision of the European Commission that allowed the introduction of sub-national regulatory regimes across the members of the European Union. The new mechanism allowed geographical segmentation of telecommunication markets - Geographically Segmented Regulation (GSR) - and the application of differentiated remedies in different geographies (Comission and Commission, 2009). The spirit and scope of GSR are broad, but so far, one of the main unanswered questions relates to the potential interactions between GSR and the regulation of wholesale telecommunication markets which on its own has been a core concern of research efforts targeting the telecommunications' industry. We address this issue using a game theory model that we developed and parameterized with publicly available data. We confirm the asymmetric business case for the geographic development of these new infrastructures that was at the origin of GSR: highly populated areas are likely to develop into competitive telecommunication markets while regions with low household density will only see limited investment and little or no competition. However, we show that supply side interdependencies among markets make the implementation of GSR non-trivial, namely, we show that changes in the wholesale access price in one market can have undesirable consequences in the competitive conditions of interrelated regions where wholesale prices are unchanged.

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# Chapter 2

# Wholesale Price Regulation in Telecoms with Endogenous Entry and Simultaneous Markets

**Abstract:** *Geographically Segmented Regulation (GSR) - the application of sub-national regulatory regimes – is a regulatory framework targeting to create incentives and controls for the deployment of NGNs. We study how the price of wholesale together with the enforcement of GSR might impact nationwide deployments of NGNs. We present a game theoretic model that predicts the number of infrastructure providers and virtual firms that will enter green-field regions when a regulator commits à-prior to a price of the wholesale good and to a geographical partition of the country in multiple regulatory regions. Using engineering data from publicly available sources and a simulation software we developed, we parameterize the model to analyze several types of regions where NGNs can be deployed - rural areas, urban areas and downtown areas. We conclude that low wholesale prices can attract a disparate number of virtual providers that erode the profitability of infrastructure providers and their incentives to invest. We also show that high wholesale prices can deter the entry of virtual providers and incentivize investment, but will not necessarily maximize welfare which can be higher in situations where a single provider invests in infrastructure opening his network to virtual providers at reasonable prices. We confirm the asymmetric*

*business case for the development of NGNs which motivated the emergence of GSR in the first place: highly populated areas are likely to develop into competitive telecommunication markets while regions with low household density will only see very limited investment in network infrastructures and little or no competition. Finally show that supply side interdependencies among markets, common to the telecommunications industry, make the implementation of GSR a non-trivial and we show that there are situations in which changes in the wholesale price in one market can have undesirable consequences in competitive condition of interrelated regions where prices are unchanged.*

## 2.1 Introduction

The deployment of Next Generation Networks (NGNs) is technically and socially desirable. From a technical perspective, new network applications such as Remote Managed Backups, Cloud Computing, High-Definition video streaming and Peer-To-Peer file sharing increased significantly the demand for bandwidth. But as (Huigen and Cave, 2008) point out, most telecommunications providers still operate copper and cable networks now believed insufficient to offer such services in the long run. From a social perspective (Czernich et al., 2009; Qiang et al., 2009; Lehr et al., 2006), among others, show that there are strong and positive effects of broadband penetration in GDP growth and (Begonha et al., 2010) associate these positive effects to job creation, new business models and in productivity increases. Recent industry reports from McKinsey and Company bring forward (e.g. (Begonha et al., 2010)) that due to the strong up-front capital cost that NGN infrastructures require, market forces alone seem unable to trigger the socially desirable levels of investment in these new infrastructures .

Figure 2.1 presents the penetration levels of Fiber to the Home (FTTH)/Fiber to the

Building (FTTB) infrastructure in different countries around the world and it shows essentially two aspects: (1) that FTTH/FTTB investments are asymmetric across developed countries and (2) that the US and the EU are lagging behind in the adoption of these technologies when compared to their Asian counterparts.

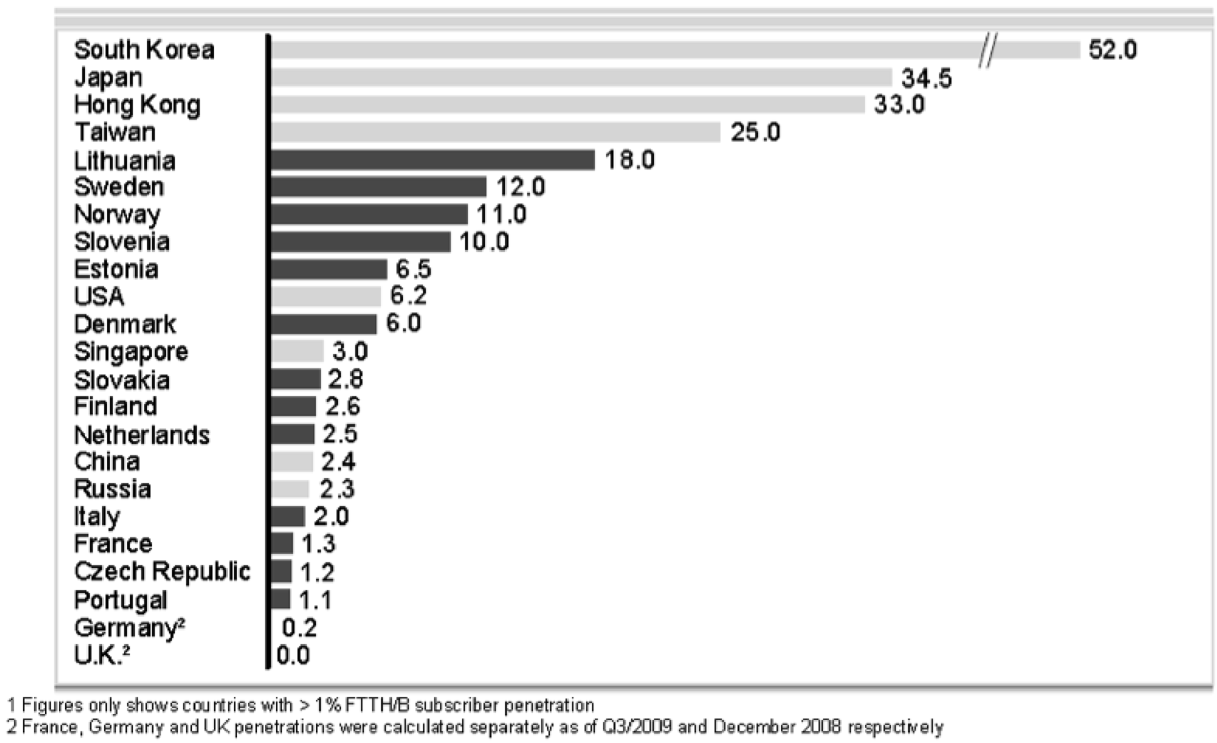



Figure 2.1: 1 % of households subscribing to Fiber-to-the-Home/Building in February 2010. Graphic taken from(Begonha et al., 2010)

As described in (Cave, 2004; ERG, 2008; Commission, 2010), National Regulatory Authorities (NRAs) have adopted different policies to support the deployment of NGNs which fall into three categories: (1) Government led policies as in Asian countries where NGN investments were subsidized and wholesale open-access was adopted; (2) Private led policies such as in the United States (US) where it is up to operators to fund NGN investments and telecommunication firms have exclusivity rights on their own infrastructures; and (3)

Mid way approaches such as in the European Union (EU) where no regulatory holidays are granted to operators who invest in NGNs, but markets are only regulated when there is a risk of firms enjoying Significant Market Power (SMP).

However, as (Valletti, 2003; Huigen and Cave, 2008; Cambini and Jiang, 2009) bring forward, it is still very hard to link the regulatory policies pursued with the observed levels of investment in NGN. This is also evidenced by the vast amount and diversity of research literature existing in this field which (Cambini and Jiang, 2009) and (Brito and Pereira, 2010) categorize according to a set of branches summarized in Figure 2.2 below:

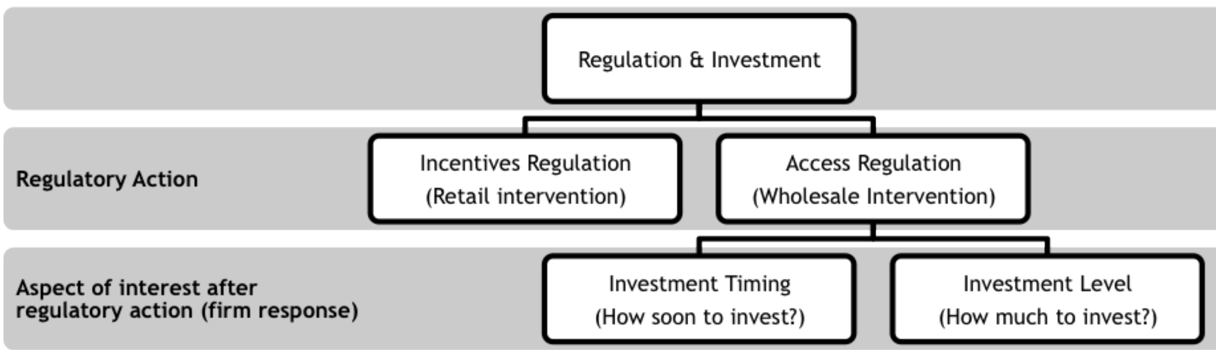



Figure 2.2: Breakdown of the research efforts according to their main concerns in what respects the telecommunications' industry

The Incentives Regulation branch studies the impact of direct intervention in retail markets on infrastructure investment. On the other hand, the Access Regulation branch is concerned with the formation of wholesale prices that firms who unbundle their infrastructure offer to competitors.

In their bibliographic review (Cambini and Jiang, 2009) conclude that within the Incentives Regulation branch, most authors focus on the impact of retail price caps. Such authors agree that price caps at retail level create cost cutting incentives to telecommunication operators, but can deter infrastructure deployments as shown by (Armstrong and Sappington, 2006). Still in terms of regulatory interventions in retail telecom markets, (Foros and Kind, 2003) and (Valletti et al., 2002) study the impact of retail uniform pricing on infrastructure deployments. These authors conclude that policies that force a unique and uniform retail price across multiple country regions can limit infrastructure investment and, consequently, coverage.

Research focused on determining the impact of different access prices on infrastructure investment is complementary to the Incentives Regulation branch. One of the main targets of this research is the search for mechanisms that will create the right incentives for telecommunication providers to make optimal investments over time. Examples of papers targeting the relationship between the wholesale price and the optimal time to invest include (Gans, 2001; Bourreau, 2005; Bourreau and Dogan, 2006; Vareda and Hoernig, 2010). These papers rely on models of Research and Development races inspired, among others, by the seminal work of (Harris and Vickers, 1985) and conclude that low access prices can delay or even deter investment in telecommunications infrastructure while high access prices will have the opposite effect and preempt firm investment.

(Foros, 2004; Nitsche and Wiethaus, 2009) are examples of research which goal is to determine the optimal investment amount rather than its optimal time. The former paper shows that unbundling obligations can reduce investment, lower welfare and that quality differences between products in the retail market, can lead integrated firms to over-invest as a way to foreclose entry from providers who do not own infrastructure. The latter paper establishes a rank of regulatory mechanisms concluding that regulatory holidays and fully distributed cost policies promote higher investment levels than risk-sharing or long-run-incremental cost policies.

Orthogonal to all these concerns, is the topic of regulatory commitment. (Brito et al., 2010) prove that before any telecommunication infrastructure has been deployed, the welfare maximizing regulatory strategy is to set a high access price in order to create the right incentives for infrastructure deployment. However, after the investment has been made, regulatory authorities will find it optimal to revise the access-price downwards due to the sunk cost nature of telecommunications infrastructures. The problem with such scenario is that providers can anticipate this behavior and investment might not occur. Such problem would be solved if regulatory authorities could commit to an à-priori course of action.

Authors researching telecommunications policy have followed different strategies to tackle the dynamic inconsistency of regulatory commitment in their economic models of access regulation. For example, (Foros, 2004) assumes that regulatory commitment is not possible, while (Gans, 2001) and (Hoernig and Vareda 2007) assume otherwise[1]. (Guthrie, 2006) surveyed how this issue is approached in real life, but in real world situations as in theoretical models, the way to enforce regulatory commitment remains an open issue subject to much disagreement.

Amidst all this complexity an in an attempt to promote a common approach for consistent implementation of remedies regarding NGN deployment (ERG, 2008), the European Union proposed the utilization of Geographically Segmented Regulation (GSR) in the as-

[1]Disagreement is often related with the belief or disbelief that a national regulatory authority will/will not be able to maintain their position when faced with significant public pressure. The issue is that investment in network infrastructure is largely irreversible which puts operators in a vulnerable position as soon as they deploy the network. Investment is sunk and after the fact, firms have no choice but to accept opportunistic behavior of regulators if it occurs

sessment of the regulatory needs of each individual European country. GSR consists in the identification of sub-national geographical areas where distinct competitive conditions call for specific regulatory remedies and countries might be better served with different regulatory regimes in each region (ERG, 2008; Ferreira and Regateiro, 2008).

The main principle behind GSR is that one size does not fit all. GSR is persuasive when regional markets are completely independent. In such cases, it is optimal for the regulator to act independently in each market, which may easily result, for example, in a different wholesale price cap for each region. In practice, this is the exception rather than the rule. The telecommunication industry is characterized by economies of scale and scope, as documented in (Faulhaber and Hogendorn, 2000; Valletti et al., 2002; Majumdar et al., 2002; Foros and Kind, 2003) and demand side network effects, as shown by (Majumdar et al., 2002; Foros, 2004; Curien and Economides, 2006). Therefore, interdependencies across adjacent telecommunications markets can seldom be ignored.

When interdependency exists, segmentation is no longer straightforward because regional markets interact. In such cases, changes in a regulatory remedy of one market might trigger unexpected consequences in adjacent regions, which renders the regulator's role extremely complex.

This paper contributes to the debate surrounding the operationalization of GSR in the telecommunications industry by recovering (Faulhaber and Hogendorn, 2000)'s discussion on the market structure of this industry in the absence of regulation and introducing the existence sub-national geographical markets where regulatory policies might differ from market to market.

We build an informative game theoretic model of the possible impacts of access regulation and geographically segmented regulation on infrastructure investment. Our model assumes that firms consider NGN investments in a country that has been split in multiple geographical markets that interrelate through supply side economies of scale and that each market is subject to specific regulatory policies targeting the price of wholesale access. Our model considers endogenous firm entry and assumes that regulatory commitment is possible.

For each market, the model takes as input an access price, a demand curve and the costs to deploy NGN infrastructure. The model predicts the market structure that will emerge, namely the number of infrastructure providers and virtual operators that will compete in each retail market.

Our model is closest in structure to that of (Bourreau et al., 2009), but unlike these authors we focus primarily on endogenous multi-market entry of both infrastructure firms and virtual providers and less on how wholesale prices build up. As in a substantial proportion of the literature, we assume that telecommunications firms compete in quantities in the retail market. We use (Shubik and Levitan, 1980) formulation to account for some degree of product differentiation between the retail goods offered by distinct firms. We model economies of scale through fixed costs as in (Faulhaber and Hogendorn, 2000).

We depart from most works referred before by considering endogenous entry whereas most authors analyze duopoly situations. Exceptions are (Faulhaber and Hogendorn, 2000; Foros and Kind, 2003), but these authors do not look at the relationship between access regulation and investment and do not consider the wholesale market.

Also, to the best of our knowledge, this paper is the first of its kind to explicitly model the problem of multi market interaction in the context of GSR. This paper highlights situations where geographically segmented regulation might yield undesirable consequences and it informs regulators on the access prices that could help generate investment and entry in each particular region.

The paper is organized as follows: Sections 2.2 and 2.3 describe the model and its parameterization. Section 2.4 describes the simulation results for a situation without geographical segmentation of regulation. Section 2.5 expands the analysis to a multi-market situation and section 2.6 summarizes the main findings and concludes.

## 2.2 Model Description

In our model we consider $n_1$ regulated integrated providers ("RIP") that deploy infrastructure (e.g. an optical fiber network) and provide service to end-users and $n_2$ virtual providers ("VP") that lease infrastructure from RIP firms and sell service to end-users.

To capture the fact that not all infrastructure providers are required to unbundle and lease infrastructure in wholesale markets we consider $n_3$ non-regulated integrated provider ("NRIP") that deploy infrastructure just like RIP firms, but unlike RIP firms they do not re-sell their access network to other firms.

These three firm types capture a realist scenario in the U.S. and in Europe where regulators have applied asymmetric remedies to firms selling broadband services. Over time, cable companies and traditional telecom operators have been subject to different regulatory obligations, the same being true for telecom operators with market power (usually the incumbents) and those with smaller market shares (the entrants or market challengers).

We assume that all firms compete "*à-lá*" Cournot at the retail level. Let $q_{mtk}$ $m = 1,...,M,\ t = 1,2,3,\ k = 1,\ldots,n_t$ represent the number of households served by firm $k$ of type $t$ in market $m$. Let $q = (q_{111},...,q_{11n_1},...,q_{M31},...,q_{M3n_3})$ represent the vector of quantities produced by the distinct firms that challenge the market. RIP firms are type 1 whereas VPs are type 2 and NRIPs are type 3. Let $Q_{mt} = \sum_{k=1}^{n_t} q_{mtk}$ represent the aggregate output of all firms of type $t$ in market $m$ and $Q_m = \sum_{t=1}^{3}\sum_{k=1}^{n_t} q_{mtk}$ the aggregate output of all firms of all types in market $m$. Products sold in the retail market can be either homogenous or differentiated depending exclusively on the parameterization of the demand formulation which we detail in section 3.

In the wholesale market all RIP firms rent infrastructure to virtual operators. They charge $w_m$ per connection leased in market $m$. This price is exogenously determined and represents a regulatory commitment. Finally, we assume that the wholesale product is perfectly homogenous across integrated providers and that the retail good is derived one-to-one from the wholesale input [2].

Integrated and virtual providers play a two-stage game. In the first stage they decide which markets to enter (if any). In the second stage they compete in quantities for end-users. All firms face costs $F_{mtk}$ $m = 1,...,M,\ t = 1,2,3$ and $k = 1,...,n_t$ which represent fixed costs. Due to their retail operations firms pay $c_{mtk}$ $t = 1,2,3,\ k = 1,...,n_t$ per connection established. Additionally to retail marginal costs, RIP and NRIP firms pay an additional $cw_{mtk}$ $m = 1,...,M,\ t = 1,3,\ k = 1,...,n_t$ per connection established which

[2] In the telecommunication industry this entails that integrated providers own infrastructure all the way to consumers' premises, thus our model captures a fiber to the home (FTTH) environment

reflects the cost of operating the infrastructure and correspond to the marginal costs of the wholesale business.

Figure 2.3 below depicts the basic building blocks of our model and Table 2.1 provides the payoff functions for both integrated and virtual providers when they decide to enter in the first stage of the game, otherwise their payoff is zero.

To ensure stability and uniqueness of equilibrium in the second stage of the game we assume decreasing price functions of class C2 with $\frac{\partial P_m(q)}{\partial q_{mtk}} + q_{mtk} \frac{\partial^2 P_m(q)}{(\partial q^2_{mtk})} < 0$, that is, marginal revenue must decrease in own quantity[3], which is a reasonable assumption as discussed in (Vives, 2001) and (Kolstad and Mathiesen, 1987).

Due to the multiplicity of game configurations we do not provide a complete and compact characterization of the possible equilibria at the first stage of the game. For $M$ markets, $T$ types of firms and $K$ firms of each type, the first stage of the game yields $2^{MTK}$ possible outcomes. The identification of the subset of outcomes constituting Nash equilibrium of this game requires case-by-case analysis and cannot be generalized. Taking this into consideration we proceed through simulation analysis.

## 2.3 Model Parameterization

We parameterize the model of section 2.2 with the demand formulation developed in (Shubik and Levitan, 1980) which is flexible enough to capture features such as product differentiation and inherent market share asymmetries among firms, but is simple enough to

[3]Another condition is that $c''_{mtk} - P''_m > 0$ but our cost formulation and previous assumptions ensure this directly.

Table 2.1: Payoff functions for integrated providers and virtual providers. $Q_{m2}$ are the number of households served by virtual firms in market $m$. $q_{mtk}$ , $m = 1, ..., M$, $t = 1, 2, 3$ designate the number of households served by firm $k$ of type $t$ in market $m$. $w_m$ is the wholesale price in market $m$, $c_{mtk}$ , $m = 1, ..., M$, $t = 1, 2, 3$ is the marginal costs that firm $k$ of type $t$ must pay to connect each consumer in market $m$ and and $F_{mtk}$, $m = 1, ..., M$, $t = 1, 2, 3$ are the fixed costs that firm $k$ of type $t$ has to pay in order to enter the market $m$. $n_{m1}$ is the number of regulated integrated providers who actually entered market $m$. $q$ is the vector o quantities produced by each firm from every considered type. $\alpha_{tk}$, $t = 1, 2, 3$ is a scale factor and $f_t(.)$ is a function of the fixed costs that together with the scale factor represents the economies of scale that each firm obtains by investing in more than one market at the same time.

| Firm Type | Payoff Functions |
|---|---|
| Regulated Integrated | $\pi_{m1k}(q) = (P_m(q) - c_{m1k} - cw_{m1k})q_{m1k} + (w_m - cw_{m1k})\frac{Q_{m2}}{n_{m1}} - F_{m1k}$ <br> $\Pi_{1k}(q) = (\sum_m \pi_{m1k}(q)) + \alpha_{1k} f_1(F_{11k}, ..., F_{m1k}, ..., F_{M1k})$ |
| Virtual | $\pi_{m2k}(q) = (P_m(q) - c_{m2k} - w_m)q_{m2k} - F_{m2k}$ <br> $\Pi_{2k}(q) = (\sum_m \pi_{m2k}(q)) + \alpha_{2k} f_2(F_{12k}, ..., F_{m2k}, ..., F_{M2k})$ |
| Non-Regulated Integrated | $\pi_{m3k}(q) = (P_m(q) - c_{m3k} - cw_{m3k})q_{m3k} - F_{m3k}$ <br> $\Pi_{3k}(q) = (\sum_m \pi_{m3k}(q)) + \alpha_{3k} f_3(F_{13k}, ..., F_{m3k}, ..., F_{M3k})$ |

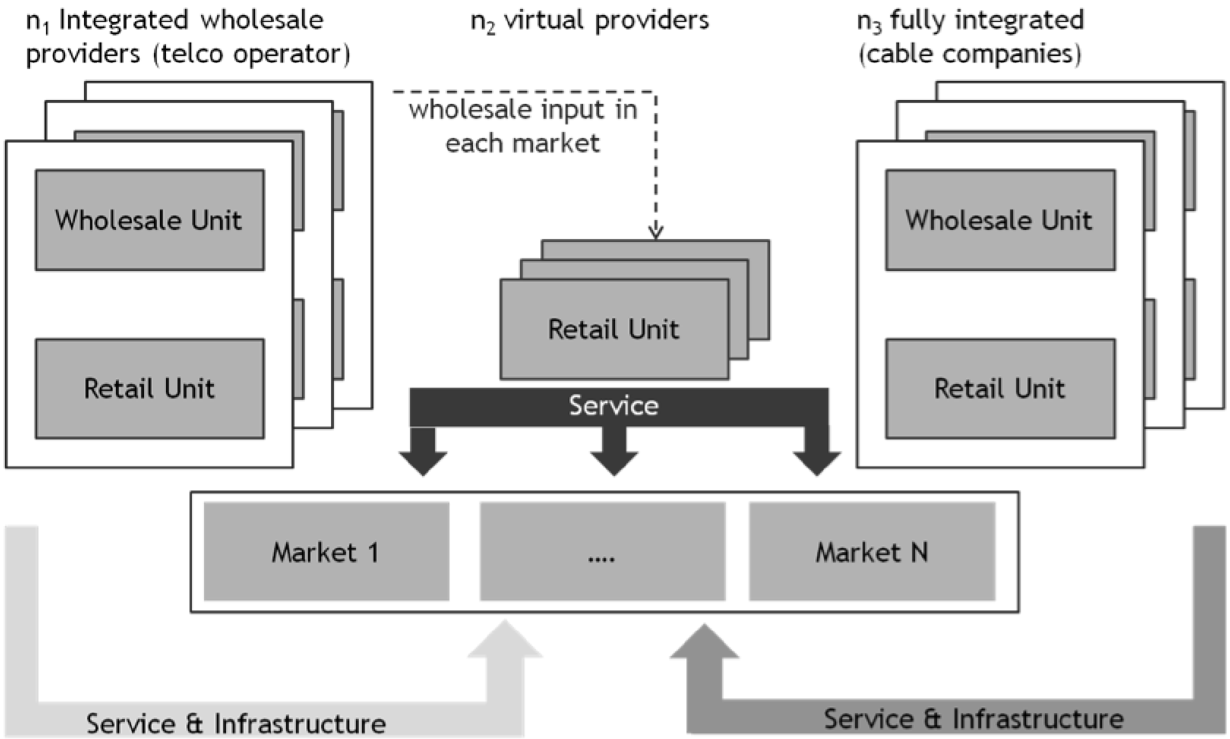



Figure 2.3: Structure of the model

allow for a tractable analysis.

Shubik's demand system is obtained from the optimization problem of a representative consumer with utility function given by:

$$U_m(q,z) = a_m \sum_{t,k} q_{mtk} - \frac{b_m}{2(1+\gamma_m)}[\sum_{t,k} \frac{q_{mtk}^2}{s_{mtk}} + \gamma_m(\sum_{t,k} q_{mtk})^2] + \mu z \tag{2.1}$$

The solution of this optimization yields the demand function:

$$D_{mtk}(p) = \frac{1}{b_m} s_{mtk}(a_m - p_{mtk} - \gamma_m(p_{mtk} - \bar{p}_m)) \tag{2.2}$$

The direct demand function can be inverted into the corresponding inverse demand function:

$$P_{mtk}(q) = a_m - \frac{b_m}{(1+\gamma_m)}(\frac{q_{mtk}}{s_{mtk}} + \gamma_m \sum_{t,k} q_{mtk}) \tag{2.3}$$

In the demand system above, $a_m$ measures the consumer's maximum willingness to pay for a broadband offer of any type in market $m$. This is the price that causes demand to be zero. The substitutability between broadband offers of competing providers is captured by parameter $\gamma_m \in [0; +\infty[$. Products are independent when $\gamma_m = 0$ and they become perfect substitutes when $\gamma_m \to +\infty$. When $\gamma_m \to +\infty$ the indirect demand function converges to $P_m(q) = a_m - b_m \sum_{t,k} q_{mtk}$.

The parameter $\bar{p_m} = \sum_{t,k} s_{mtk} p_{mtk}$ is a weighted average price of all products sold in market m. The weights $s_{mtk}$ are defined a-priori and they allow capturing intrinsic asymmetries in the market shares. An intrinsic asymmetry in the market share means that if all firms charged the same price they would exactly sell their à-priori market shares.

To perform simulations we configure the model parameters described so far with data from (Sigurdsson H., 2006; Banerjee and Sirbu, 2006; Wittig et al., 2006; Consulting, 2008; FTTH.Council, 2010; Rosston et al., 2010; Anacom, 2011).

We simulate multiple types of geographies that we categorize according to their household densities as defined in (Sigurdsson H., 2006). These regions include rural areas (household density $100h/km^2$), urban areas (household density $1,000h/km^2$)) and downtown locations (household density $10,000h/km^2$).

Consistently with our data sources, we assume that firm fixed costs are decreasing in household density in order to capture the economies of scale that characterize the telecommunications industry. We also assume that here are no partial investments, this is, when firms decide to invest in infrastructure they deploy access to all households in the region considered[4].

We report monthly values in all simulations and, for consistency among the different data sources we convert all monetary values to 2006 euros. Furthermore, we assume that firms require a 7.5 year period for project payback as in both (Wittig et al., 2006; FTTH.Council, 2010). The weighted average cost of capital ("WACC") is assumed at 12% as recommended in (FTTH.Council, 2010) for cases where the construction methodology requires deploying new ducts and rights of way can be slow to obtain.

To estimate the $a_m$ and $b_m$ parameters of the demand curve in a market with $N$ households we assume that a representative consumer's willingness to pay for broadband is normally distributed according to data from (Dutz et al., 2009) and (Rosston et al., 2010). We take $N$ draws from the willingness to pay distribution and we order each draw in decreasing order of willingness to pay. Finally we calculate a simple linear regression of the slope and intercept. To configure the perceived demand by each particular firm we set $\gamma_m = 10$ which according to (Ordover and Shaffer, 2007) is a high enough value to represents close to homogenous products and we set the market share expectation parameters $s_{mtk}$ proportionally to the number of firms attempting to enter the market. Additional details on demand estimation simulation procedure are described in Appendix A.

The monthly marginal costs of connecting each client are taken from (Banerjee and Sirbu, 2006; Consulting, 2008). These costs include the installation of the drop, the pro-

[4]We ignore network topology and technology which is assumed the same for every scenario

vision of the central office and the consumer premises equipment as well as the costs of providing the broadband connection, transit and second mile costs, the connection to the point of presence of the backbone internet operator and marketing and other operational costs. Table 2.2 summarizes the base parameterization of the model described in 2.2.

Table 2.2: Parameterization Summary

<table>
<tr><th colspan="2">Model Parameter</th><th>Value</th><th>Units</th><th>Comment / Description</th></tr>
<tr><td rowspan="2">Genera Parameters</td><td>WACC</td><td>12</td><td>%</td><td>Based on (FTTH.Council 2010)</td></tr>
<tr><td>Payback</td><td>7.5</td><td>Years</td><td>Based on (FTTH.Council 2010) and (Wittig, Sinha et al. 2006)</td></tr>
<tr><td rowspan="3">Variable Costs per subscriber</td><td>$c_{m1k}$<br>$c_{m3k}$</td><td>6.5</td><td>€/month</td><td>Corresponds to variable Co in (Banerjee and Sirbu 2006). The value, which was originally in dollars, was converted to euros at the rate 1€-$1.25 as recommended by (IRS 2011).</td></tr>
<tr><td>$c_{m2k}$</td><td>10</td><td>€/month</td><td>Assumed that virtual firms have higher customer setup costs due to the synchronization with the integrated firm and smaller scale</td></tr>
<tr><td>$cw_{m1k}$<br>$cw_{m3k}$</td><td>16</td><td>€/month</td><td>Corresponds to $C_1$ variable in (Banerjee and Sirbu 2006). It includes "the cost of providing data service, the cost of transit, second mile costs of transporting data from the central office to the point of presence of the Internet backbone provider and other operation costs". The value, which was originally in dollars, was converted to euros at the rate 1€-$1.25 as recommended by (IRS 2011).</td></tr>
<tr><td>Rural Geography</td><td>$F_{m1k}$<br>$F_{m3k}$</td><td>4,500</td><td>€/house passed</td><td>Household passing cost for a household density of 100 h/km$^2$ as in (Sigurdsson H. 2006)</td></tr>
<tr><td>Urban Geography</td><td>$F_{m1k}$<br>$F_{m3k}$</td><td>1,500</td><td>€/house passed</td><td>Household passing cost for a household density of 1,000 h/km$^2$ as in (Sigurdsson H. 2006).</td></tr>
<tr><td>Downtown Geography</td><td>$F_{m1k}$<br>$F_{m3k}$</td><td>585</td><td>€/house passed</td><td>Household passing cost for a household density of 10,000 h/km$^2$ as in (Sigurdsson H. 2006).</td></tr>
<tr><td>All Geographie s</td><td>$F_{m2k}$</td><td>10%</td><td>%</td><td>According to the scenarios described in (Consulting 2008) a virtual provider needs to invest less than 20% of the capital invested by infrastructure providers.</td></tr>
<tr><td>Demand</td><td colspan="4">See Appendix A</td></tr>
<tr><td>Markets</td><td colspan="4">The number of markets depends on the specific simulation</td></tr>
<tr><td>Wholesale</td><td colspan="4">The price of the wholesale good which is assumed to be a regulatory commitment depends on the specific simulation</td></tr>
</table>

## 2.4 Single Market Simulation

In this section we study how NGN deployment costs affect firm entry. NGN infrastructure costs are tightly connected with household density through economies of scale. For our simulations we used deployment costs in $[200; 5000]$€/home passed range. This interval allows capturing the three scenarios presented in the Table 2, plus it allows for deployment costs to be below the 585€/household estimate. According to industry reports such as (Consulting, 2008) these low infrastructure deployment costs are possible in non-greenfield situations where the existing ducts are wide enough to accommodate additional fibers minimizing construction costs.

Figure 2.4 below illustrates four different simulations that capture market situations that are common in existing telecommunication's markets.

Scenario 1 illustrates a case in which capital constraints lead only very few providers to enter the market. Such situations are typical in industries where capital expenditures are high and sunk, as in the telecommunications industry. Scenario 2 introduces a situation where unregulated infrastructure firms (usually cable companies) compete head to head with regulated integrated firms in the broadband market. Scenario 3 broadens the scope of the simulation assuming that a large number of RIP and VPs can enter the market. The actual number of firms is limited to 4 RIP and 4 VPs due to algorithmic performance issues, but ceteris paribus, increasing the number of firms further would not significantly change our results. Finally Scenario 4 is included as benchmark and illustrates a situation where there is a single infrastructure provider and retail competition is only realized if virtual firms.

There are combinations of deployment costs and wholesale prices for which multiple equilibria in pure strategies coexist. In such cases we show the equilibrium with lowest social welfare (which coincides with the equilibrium market structure with fewer firms competing). Consequently, our pictures depict worst-case scenarios in terms of market competition that we believe represent the core concern of regulatory authorities.

The multiplicity of equilibria evidences that policies that focus solely on setting the wholesale price might not be sufficient to predict the industry's market structure. Nevertheless, our simulations show that both wholesale prices and network infrastructure passing costs are of paramount importance in determining the industry's market structure.

For low $w$, in all scenarios, there are configurations of the infrastructure costs for which there are no pure strategy equilibrium where NGN investment. Nash equilibrium in pure strategies does not exist because with low $w$, too many virtual providers want to enter the market if at least one regulated integrated firm deploys infrastructure. Therefore, the competitive pressure from the virtual providers is too high and will block profitable entry from the regulated integrated providers. Competitive pressure will depend on the interplay between the number of firms that can attempt entry and the intrinsic characteristics of the market studied. Low consumer demand and high costs (both fixed and variable) imply more competitive pressure. The same is true for the number of firms up to the extent that their entry can be accommodated.

The situation described above occurs in regions with household density high enough to allow profitable entry of at least one RIP and one VP firms. In such situations, the minimum $w$ for which integrated firms invest is increasing in the cost of infrastructure deployment. In low cost locations, the minimum $w$ that triggers at least the entry of one RIP firm is near marginal cost, but for regions with higher deployment costs, the wholesale cost that will trigger investment is much higher.

In all scenarios as $w$ increases (for reasonable levels of per-house deployment cost), integrated firms become potentially more profitable, at the expense of the profitability of virtual providers, to a point beyond which at least one integrated provider deploys infrastructure. If the cost of wholesale increases further, the number of VPs that can profitably compete in the retail market reduces, but the profitability of integrated firms increases. As $w$ becomes higher more RIP firms will enter the market substituting the VPs that choose to leave due to the high cost of access that will prevent them from making business.

Infrastructure competition will only emerge when household passing costs are low which means that such investments will occur in either highly populated regions or locations where the construction costs are small (e.g. regions with pre-existing ducts that do not require change). In these regions, some form of oligopolistic competition can develop, but due to the small number of firms that will ever be active in the market, antitrust law will be needed (ex-post regulation) to deter collusive behavior.

When household passing costs are higher such as in urban locations, at most one provider is likely to deploy NGNs. In these regions retail competition is only possible where virtual provider decide to enter the market. To guarantee that competitive products are available, wholesale access must be reasonably priced: high enough to create incentives for infrastructure providers, but low enough for VPs to compete. Such balance in the price of the wholesale good is likely to require regulatory intervention through unbundling impositions and or wholesale price controls.

Finally, in low-density urban regions or in rural locations, investment in NGNs is not at all likely. For NGNs to reach these sparsely populated regions, significant subsidies must be awarded to cover part of the development costs.

Notice that in all simulations consumers benefit the most when more firms are active in the retail market, which leads to increased coverage and lower prices. Depending on the scenario under analysis, the highest number of active firms in the retail market might occur for wholesale prices far above marginal cost.

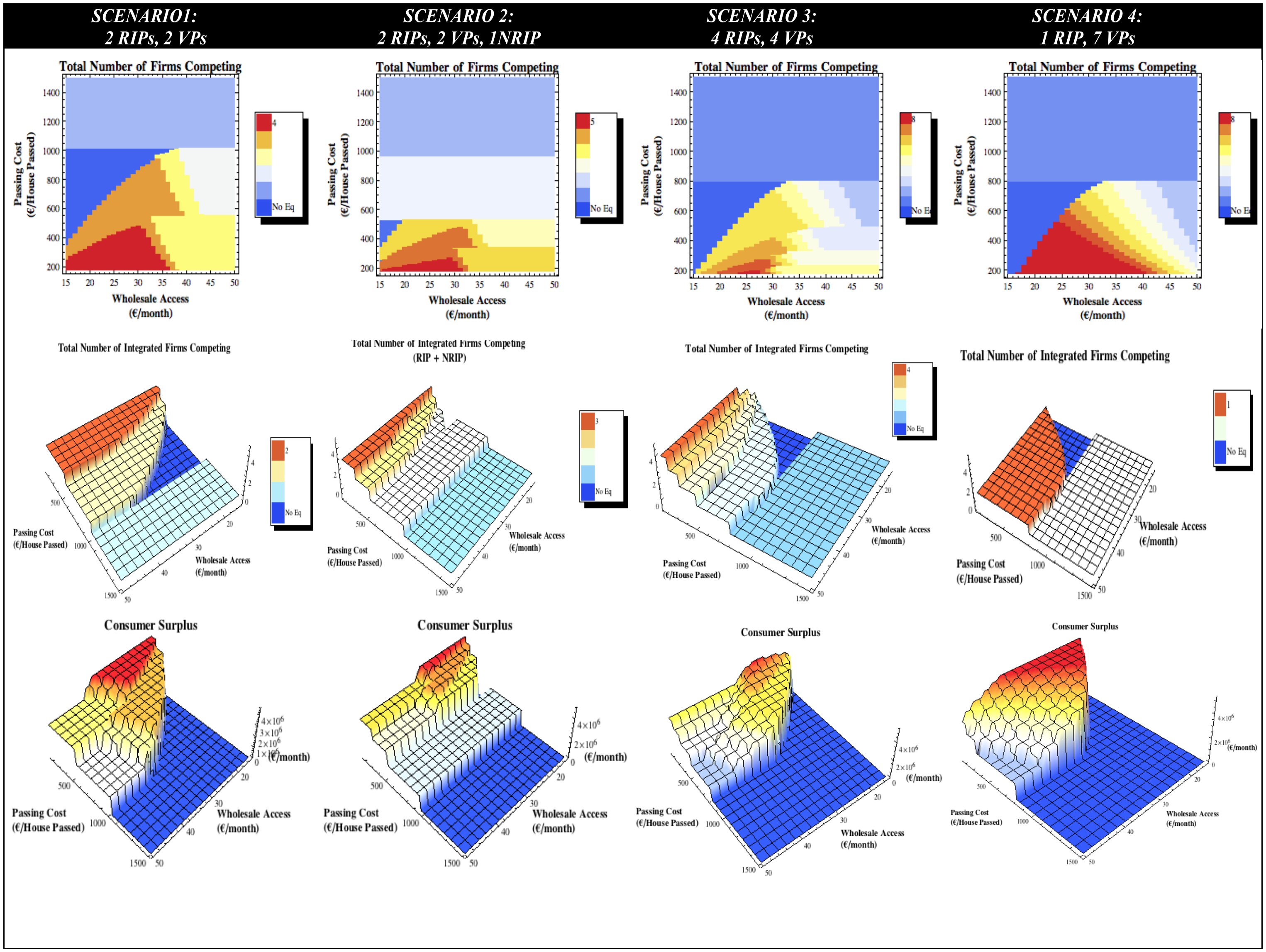
Across all analyzed scenarios, the highest level of consumer surplus occurs when the economies of scale are fully explored and the operator's cost savings are passed on to consumers through price reductions. Economies of scale are maximized if there is no network duplication and price reductions occur if there is effective retail competition. Such scenario requires a $w$ high enough to allow RIP firm entry, but not so high that VP firms will prefer to stay out of the market, so that more firms will be able to compete. Scenario 4 illustrates such a situation.

Notice that as we progress from scenarios 1 to 4, the number of firms considering entry in the market increases, but the maximum deployment costs for which a market develops decreases for all values of the wholesale price. Such response to the increase in the number of market challengers is a consequence of a decrease in the à-priori market share expectation, which makes the market less attractive for all even when its fundamental characteristics remain unchanged (in all simulations we assume that, à-priori, market challengers expect to split the market evenly).

Another takeaway is that in all scenarios, whenever the market structure remains constant, retail prices and coverage are non-decreasing in the price of the wholesale good and the same is true for consumer surplus. However, when the market structure changes as a consequence of an increase in the wholesale price consumer surplus can also increase as is shown in scenario 3.

Finally, scenario 2 shows that in markets where infrastructure competition is possible, NRIP firms can increase the level of retail competition, but in high FTTH cost areas the reverse might happen. In regions with high infrastructure costs, the asymmetries in regulatory interventions that permit the existence of NRIP firms create the possibility of monopoly where retail competition would be possible through infrastructure sharing.

Figure 2.4: Outcome of single market simulations. The first row details the total number of firms that enter the market and the second row specifies which of these are infrastructure providers. The bottom row quantifies the consumer surplus in each scenario. All images are built based on a temperature map where warmer colors indicate higher values. In rows one and two, the coolest color corresponds to combinations of the wholesale price and infrastructure costs for which there is no pure strategies equilibrium.



## 2.5 Multi Market Simulation

We extend our analysis to the case where firms consider investment in multiple regions simultaneously. As put forward in the introduction, modeling multi-market entry allows for testing some consequences of the implementation of GSR for the structure of the telecommunications industry.

Our focus is to study how the implementation of GSR through wholesale price differentiation across geographical regions will influence the number of RIP and VP firms that are likely to enter multiple retail markets of NGN broadband products.

Due to the increased complexity brought forward by multi-market analysis, in this section we will characterize a single scenario. We assume that the NRA has identified two distinct markets where competitive conditions for NGNs differ. There is one region with high household density (and low infrastructure deployment costs) and a second region where population density is lower and infrastructure deployment costs per household are high enough for competition in infrastructure to be economically infeasible. As explained in (Xavier, 2010), in the context of the EU regulatory framework, such market partition would be a reasonable candidate for the application of differentiated regulatory remedies.

Using the above-mentioned scenario, we simulate the "à-priori" de-regulation of the more densely populated market (which we charecterize through an increase in the wholesale price) and study the impact of de-regulation in the structure of the two geographies being studied.

In European countries such as the U.K. and Portugal, and also in other jurisdictions such as Australia and Canada, NRAs used GSR in the following way: (1) they split the market into multiple regions; and (2) they propose to de-regulate a sub-set of these regions based on a “n-plus” rule of thumb (Xavier, 2010) which consisted in counting the number of firms operating in each region and establishing a threshold number below which some particular regulatory remedies remain. In regions where more firms compete, the NRA forebears from regulate. (Xavier, 2010) provides a concise summary of the orientations followed in several cases.

It should be noted that in its essence, GSR was not designed for the purpose of market de-regulation, but rather targeted regulation. In fact, in (ERG, 2008) the European Regulator Group asserts that the application of GSR can increase the severity of the regulatory remedies applied to a given market. Nevertheless, in practice, attempts to de-regulate markets have been the focal point of the application of this regulatory mechanism.

To parameterize the two-market scenario selected we use the results of the simulations of 2.4. Specifically, for $market1$, we select a parameterization of costs that, in the single market case, allows entry of at least three integrated providers in the highly populated region. For $market2$ we select a parameterization of costs that allows only one integrated firm to deploy infrastructure, but that allows concurrent VP firms to enter.

Due to algorithmic performance issues we consider that there are only 2 RIPs and 1 VP attempting to enter both markets simultaneously and to keep the profit functions simple we configure the interaction function as $\alpha_{tk} f_t(F_{1tk}, F_{2tk}) = \alpha_{tk} \sum_m F_{mtk}$ with $0 < \alpha_{tk} < 1$.

For the case of VP firms we select $\alpha_{2k} = 0.5$ such that each firm pays only half of the total fixed costs that they would normally incur if they invested in each market separately. Such decision is consistent with the fact that VP firms do not deploy infrastructure, therefore, their establishment costs will be largely independent from the number of markets where they decide to operate.

For RIP firms $\alpha_{1k} = 0.1$ which creates a small supply side interaction between the two markets. Such interaction is expected due to construction and equipment savings caused by the investment in multiple geographical regions[5].

Figure 2.5 below provides the summary output of our simulation. The first depicted row describes the total number of firms RIP and VP that enter each one of the two markets for every combination of the wholesale prices. The second row describes the average price of the broadband product in each retail market. Finally, the bottom row provides the aggregate consumer and producer surplus which NGN broadband services are estimated to generate in the two markets considered.

The main difference from the analysis of the previous section is that ceteris paribus, changes in the wholesale price of one market can have spillover effects on the other market. This is evident from the two pictures in the first row of the figure.

With $w_2$ low there is no equilibrium in pure strategies where firms invest in either market (dark blue region in the contour plots). This situation is similar to the competitive pressure scenario described in section 2.4, but slightly more complex due to a spillover effect from market 2 to market 1. When $w_2$ is low the VP will want to enter market 2 if at least one RIP firm does, but if VP entry occurs in market 2, overall RIP firm profitability is higher investing solely in in market 1. Nevertheless, it is not an equilibrium strategy for RIP firms to invest in market 1 alone because each RIP firm has an incentive to deviate

[5]We tested different values of this interaction parameter in the $]0; 0.2]$ range and the results did not change our conclusions

and enter market 2 if there is no VP entry, as such equilibrium is not reached.

A less technical and more interesting conclusion occurs when $w_2$ is high enough to dismiss the problem of competitive pressure. When such level of $w2$ is reached and at least one RIP firm invests in both markets, changes in the wholesale price of the more sparsely populated area (market 2) will not cause any changes in the market structure of the downtown location (market 1), but changes in the price of wholesale of the latter will have dramatic impact in the former. In particular, when the price of the wholesale good in market 1 increases beyond a point where VPs can no longer enter in market 1, it is possible that VPs will not enter market 2. In other words, de-regulation of market 1 will cause a monopoly situation in the sparsely populated area (market 2).

The result just described is illustrated in the first row of figure 2.5. In both market 1 and market 2, the dark orange region marks the combinations of $w_1$ and $w_2$ for which the VP enters the market. In market 1 two RIP firms enter the market concurrently with the VP. In market 2, by design, only one RIP firm will enter together with the VP. In market 1, ceteris paribus, as $w_1$ increases the two RIP firms remain active, but there is point beyond which the VP leaves and the total number of firms reduces from three to two ($w_1 \approx 25$€/month). When such value of $w_1$ is reached VP firms also decide to leave market 2 creating a monopoly situation in this sparsely populated region.

The result of this simulation is important because it shows that de-regulation of a highly populated and potentially very competitive (low deployment cost) market can trigger a monopoly situation in an adjacent low populated market (high cost market). An obvious conclusion is the fact that "N-plus" rules of thumb are not sufficient to guarantee that the implementation of GSR is welfare improving.

Formally, considering the notation of 2.2, whenever VP entry in market 1 is profitable for some configuration of the wholesale price ($\exists_{w_1} : \pi_{121}(w_1) \geq 0$) and entry in market 2 alone is unprofitable for all wholesale prices ($\forall_{w_2} : \pi_{122}(w_2) \leq 0$), but entry in both markets is viable for some levels of the wholesale price $\Pi_{21} \geq 0$, then an increase in the wholesale prices in market 1 will prevent VP entry in market 2.

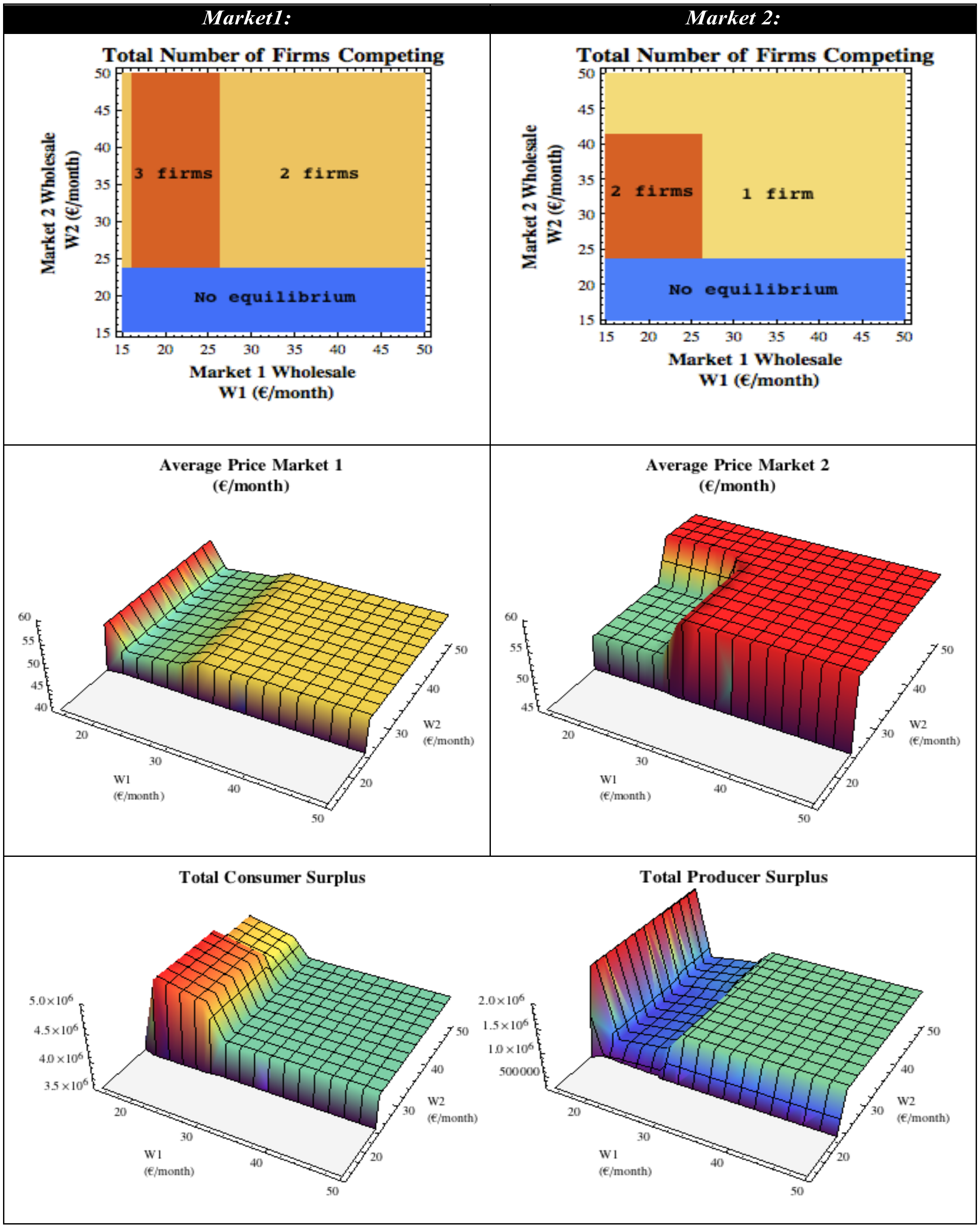
The table below also confirms that consumer surplus is maximized for $w_2 \neq w_1$. This was expected given the market asymmetry of the two regions, but highlights that if applied carefully GSR, can work towards a healthy development of NGN deployment.

## 2.6 Conclusions

This paper analyzes the impact of wholesale access pricing in the structure of telecommunications markets. We provide a game-theoretical model that predicts the number of integrated and virtual providers likely to enter a market characterized by the demand function and deployment costs – both infrastructure and operational. We use this model to analyze multiple types of regions where NGNs can be deployed. These regions include rural, urban and downtown locations and cover most of today's concerns of telecommunications' regulators.

Our paper shows how wholesale access prices determine the competitive nature and structure of telecommunications markets. Our simulations illustrate that even very attractive markets might not see investment when wholesale prices are low. Low wholesale prices attract a disparate number of virtual providers that erode the profitability of infrastructure

Figure 2.5: Summary output of the simulation. The panels illustrate the equilibrium values of the main variables being monitored in each of the two markets considered in this simulation. The simulation considers that 2 RIPs and 1 VP consider entry in both markets simultaneously



providers. The latter anticipate this effect and do not invest in pure strategies equilibrium. Otherwise, consumer surplus is decreasing in the wholesale access price and the same is true for retail prices.

Our simulations show that high wholesale prices reduce the number of virtual firms. This reinforces the idea that high wholesale access prices incentivize infrastructure competition. However, high wholesale prices might not be the optimal strategy from a welfare point of view. In fact, in some parameterizations of the model, welfare is maximized when a single infrastructure provider opens up its network to virtual firms, which only occurs for relatively low levels of the wholesale price and when there are multiple virtual providers challenging the market.

Our simulations show that areas with low household density are likely to see only very limited investment in infrastructures, unless consumers are willing to pay substantially high prices, which is not typically the case in such regions. Subsidies might be used to trigger infrastructure deployment and even attract virtual providers to compete in such regions, but competition in these regions will always be very limited.

We also find that when regulated integrated firms compete with other infrastructure providers that are not subject to regulatory obligations at the wholesale level (e.g. cable companies), a monopoly in retail can arise in urban regions where retail competition would be possible through infrastructure sharing if no such regulatory asymmetries existed.

We also show that supply side interdependencies among markets make the implementation of GSR a non-trivial task. We prove through an example that ceteris paribus, regulation changes in a very competitive market can have negative consequences in interrelated, but less competitive market.

To the best of our knowledge this paper is the first attempt to combine wholesale and retail markets with endogenous entry of RIP, VP, NRIP firms and multi-market analysis. Our model allows regulatory authorities to estimate the type of regulatory commitments needed, at the wholesale level, to allow and promote both investment and competition in green-field telecommunications markets accounting for a variety of complexities that such decisions entail.

Our model also suffers from limitations that we expect to address in future work. Namely, we assume that perfect information is available to all players. A more detailed model could consider uncertainty in both demand and costs. Our model assumes that wholesale markets are homogenous and that wholesale prices are completely determined by regulatory action. In practice, wholesale markets are heterogeneous and virtual firms bargain over the wholesale price even when this is subject to regulatory price caps. We also discard the existence of legacy networks and assume fiber to be a green-field market. We also assume that firms consider entry all at the same time. A more realistic model could take these facts into consideration. Finally, our model assumes that firms consider investment multiple regions, but we only explore the cost side interdependencies among markets. In the real world, markets interact through supply side reasons (e.g. economies of scale), but also demand side arguments (e.g. network effects) and regulatory constraints (e.g. uniform pricing restrictions). Significant extensions need to be made to capture the complexity these underlying multi-market oligopoly problems.

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## 2.A Simulating the linear demand curve

(Rosston et al., 2010) study the demand for broadband in the United States market. They conclude that in 2010 the representative consumer paid on average \$ 39.15 (stdev=\$ 23.17) for a broadband connection. They also conclude that a representative consumer would pay an additional \$ 48.12 (stdev=\$ 0.54) for improving its broadband access from a slow to a very fast Internet connection. Finally they determine that such consumer would value a very reliable high-speed Internet connection with traffic prioritization mechanisms at approximately \$ 98.

With this information, we assume that consumer willingness to pay for next generation Internet follows a normal distribution. We set $Z\ N(39.15, 23.17)$ and $Y\ N(48.12, 0.54)$ and we assume that $WTP = Z + Y$ with $Z$ and $Y$ being independent random variables (which is a simplification).

For each market with $N$ households we take $N$ draws from the WTP distribution and we order each draw in decreasing order of willingness to pay. Finally we use ordinary least squares (OLS) to calculate a simple linear regression of the number of households on the willingness to pay in order to estimate the demand curve.

Figure 4 below illustrates the three steps of the procedure for a region with $200,000$ households. The left panel has the random draw of the willingness to pay distribution for each of the $200,000$ households. The right panel has the households sorted in decreasing order of their willingness to pay (blue line) and the estimate of the linear demand curve (red line).

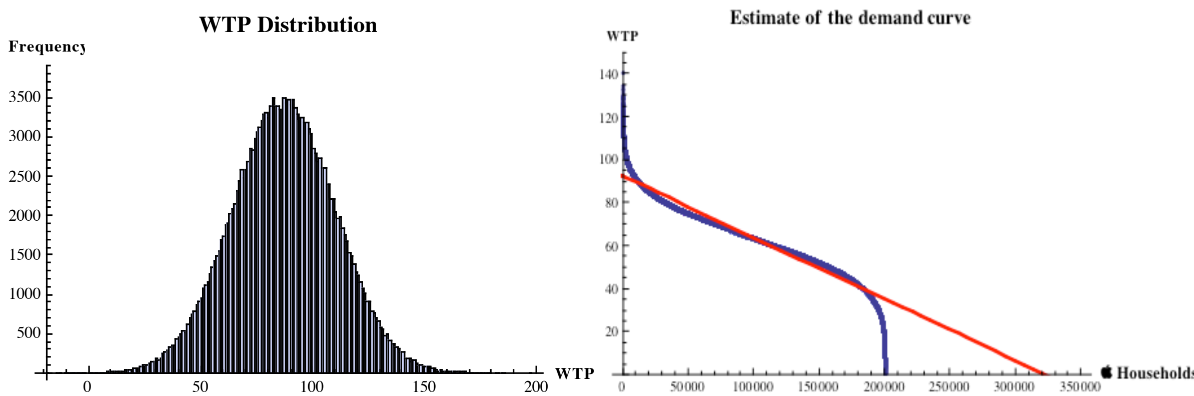



Figure 2.6: The left panel displays the WTP distribution for a region with 200,000 households and the right panel displays the corresponding estimation of the demand curve

# Chapter 3

# Peer Influence in Product Diffusion over Very Large Social Networks

**Abstract:** *This paper studies the effect of peer influence in the diffusion of the iPhone 3G across a number of communities sampled from a large dataset from a major European Mobile carrier in one country. We use instrumental variables to control for potential correlation between unobserved subscriber heterogeneity and peer influence. We provide evidence that the propensity of a subscriber to adopt increases with the percentage of friends who had already adopted. While this result is clearly positive and significant its magnitude is relatively modest. We estimate that 14% of iPhone 3G adoptions in this carrier were due to peer influence, after controlling for social clustering, gender, previous adoption of mobile Internet data plans, ownership of technologically advanced handsets and some heterogeneity in the regions where subscribers move during the day and spend most of their evenings. We provide results from several policy experiments that show that with this level of effect from peer influence this carrier would hardly be able to significantly increase sales by selectively targeting appropriate early adopters to benefit from viral marketing.*

## 3.1 Introduction

The pervasiveness of simple, small and light handsets has changed the way people communicate. According to the International Telecommunication Union the penetration of mobile handsets worldwide grew from 12% in 2000 to 87% in 2011. Smartphones account for a significant part of this growth and their penetration in the third quarter of 2011 was 29% worldwide, 65% in the US and 50% in Europe (Mobile, 2011). The mobile handset market is expected to reach $340 billion in revenues by 2015. Smart-phones are expected to account for 75% of these revenues, which represents an increase of 24% per year from the $85 billion registered in 2010 (marketsandmarkets.com, 2011).

Handsets became like small computers in recent times. Accordingly, their value shifted towards the software and the data services provided (Economist, 2011). As a consequence, manufacturers have been increasingly bundling handsets with applications that generate positive network externalities. Examples of nascent markets for these applications include Apple's App Store and the Android Apps. Applications such as FaceTime for the iOs Apple or Google Talk for the Android allow users to video call over the Internet at no cost, but they require users to own an Apple device or an handset running the Android OS, respectively. Therefore, the utility derived from using these applications, and therefore these handsets, increases with the number of users that do so.

Following the seminal insights provided in (Rohlfs, 1974) and (Katz and Shapiro, 1986) the role that network externalities play on product demand has been widely developed in the literature. The standard perspective is that for products that generate positive network externalities, the overall installed base of users of a certain product increases the expected utility that consumers will derive from a certain purchase decision (Farrell and Saloner, 1985).

For some products, such perspective is realistic. Examples include the case study of automated teller machines (ATMs) in the United States where network effects are the consequence of accessibility (consumers benefit from their bank having a large ATM network and the largest the network the higher the consumer's expected utility) (Saloner and Shepard, 1995), or the case of spreadsheet software where network externalities emerge from the most used software benefiting from a broader range of training materials, compatible products as well as increasing likelihood of vendor accessibility (Brynjolfsson and Kemerer, 1996).

However, for mobile communication products, it is likely that peers rather than the installed base of users will determine the extend of utility changes that each consumer faces when some other member of the social systems adopts the technology. Take the case of mobile carrier choice when the price of calls between subscribers of the same carrier is lower than the price of calls spanning multiple carrier networks. In such contexts users will have incentives to join the provider that the majority of their regular calling parties use, but they will be indifferent to the behavior of a random individual whom they never expect to call (Birke and Swann, 2005, 2007, 2010). A similar situation occurs in the case of consumer churn in mobile carriers where it has been observed that users tend to engage in herd behavior mimicking the actions of those with whom they interact frequently (Dasgupta et al., 2008; Dierkes et al., 2011).

Peer influence has been shown to play a significant role in contexts as varied as student academic performance (Sacerdote, 2001; Carrell et al., 2009; Boucher et al., 2010), smoking and drinking behavior (Case and Katz, 1991; Mercken et al., 2010), on sexual conduct (Romer et al., 1994), in the diffusion of trade unions (Hedström, 1994), on vaccination decisions (Rao et al., 2007), the diffusion of new drugs (Coleman et al., 1966; Burt, 1987; Strang and Tuma, 1993; Valente, 1996a) or physician's adoption of electronic health records (Zheng et al., 2010). Yet, the role that social networks and peer influence play in the diffusion of telecommunication products, and of handsets in particular, is a topic still largely unexplored. Exceptions include the investigation of peer influence in the diffusion of video-conference technology (Tucker, 2008), the diffusion of a mobile application that delivers personalized news (Aral et al., 2009) or the diffusion of call ring back tones (Ma et al., 2010).

However, the data on data on cell phone activity that mobile companies own, can be used to trace the diffusion of handsets across social networks. These datasets allow for understanding which types of handsets benefit more from word of mouth and who are the users that can exert more influence over their friends to purchase new handsets.

In this paper, we use a large dataset from a major European Mobile Carrier (EURMO) in one country to determine the role of peer influence in the diffusion of the iPhone 3G. EURMO is the leader in mobile communications in this country with a market share of roughly 50%. The iPhone 3G is a conspicuous and expensive handset which are product characteristics that are likely to make peer influence a relevant player in the diffusion process(Childers and Rao, 1992).

Such information is valuable for firms because knowing whether the sales of a particular handset can benefit from strong peer influence may be used to design better marketing strategies. While it is clear that reaching a critical mass of early adopters is fundamental to compete with products that exhibit network externalities, when peer influence plays a significant role in the diffusion of such products, companies do not want to target just any early adopters. They want to focus primarily on the early adopters that are more likely to be able to influence their friends to also purchase the product. If, however, peer influence has only a small effect on sales, then companies might be better off with mass marketing campaigns instead of targeted advertising.

To answer such questions we look, ex-post, at the percentage of iPhone 3G sales by EURMO that can be attributed to peer influence and we discuss what the company could have done to further increase sales had it known the impact of peer influence on sales beforehand.

A major difficulty in our study is that individual unobserved heterogeneity can be correlated with the adoption decision of the iPhone 3G. If that is the case, homophily - the tendency that individuals have to be connected to those who are similar to themselves (McPherson et al., 2001) - may trigger correlations between the variables that capture the amount of exposure to the iPhone 3g that each individual obtains from its peers and the unobservables.

To control for correlated effects we use instrumental variables (IV) which we construct using the complete structure of our large communication graph.

Still, because latent homophily may be simultaneously correlated with the behavior of interest and also determine the tie formation/dissolution among the members of the social system, we follow a suggestion by (Shalizi and Thomas, 2011) and identify communities of users within the large communication graph. We then use the information of community membership to explicitly control the latent unobservables that are likely to be shared among the members of the same user group as well as to capture unobserved group effects in the spirit of (Manski, 1993) that can lead to the adoption of this particular handset. Another advantage of extracting community membership information is that it allows us to to adjust the standard errors of the inference procedures for within community correlations rather than falsely assuming independence across the observations in our sample.

We also use Stochastic Actor-Based Models for the Co-evolution of Network Dynamics and Behavior (SAMCNDB) (Snijders et al., 2010) that allow for modeling network formation and behavior as they jointly co-evolve over time to test the robustness of our instrumentation approach. We achieve this by independently fitting SAMCNDB models to each of the communities identified in our sample and computing a summary effect through meta-analysis (Hedges and Olkin, 1985) which we then compare to the results we obtain using IV.

Our contributions are of value for the industry and academia.

In one-hand we develop empirical knowledge on the particular case of handset diffusion over social networks. We show that the propensity of iPhone 3G adoption increases with the number friends that purchase this same handset. Such result is positive and statistically significant, but its economic impact was modest. We estimate that 14% of iPhone 3G adoptions in EURMO were due to peer influence, after controlling for social clustering, gender, previous adoption of mobile internet data plans, ownership of technologically advanced handsets and some heterogeneity in the regions where subscribers move during the day and spend most of their evenings.

Furthermore, we show that considering the impact of the peer influence effect on the diffusion process, the effectiveness of a potential viral marketing intervention would be small. We provide results from several policy experiments and sensitivity analysis that show that traditional degree and betweenness based targeting strategies of viral marketing would hardly be economically viable for EURMO to put in practice.

Finally we also provide an empirical framework for the identification of peer influence in observational studies that can be readily extended and applied to other situations involving large social networks. In particular, to the best of our knowledge, we are the first authors to use community identification algorithms (widely developed in the literature of social networks) to control for latent homophily and correlation among the observations in the sample and we also provide a methodology for applying SAMCNDB models to large networks using tools from the social networks and the clinical trials literature.

This paper has nine sections. Section 3.2 provides a review of relevant literature and positions our paper and contributions in the field. Section 3.3 discusses the introduction and the diffusion of the iPhone 3G in the country studied and describes our dataset. Section 3.5 presents our empirical strategy and section 3.6 provides our results for the impact of peer influence in the diffusion of the iPhone 3G in the country under analysis. Section 3.7 provides several robustness checks of the results. Policy simulations are discussed in section 3.8 and we conclude in section 3.9.

## 3.2 Literature Review

### 3.2.1 Diffusion and Peer Influence

The term diffusion denotes the dissemination of some trait, product or characteristic within a social system (Strang and Soule, 1998). It is generally characterized by four elements which are the ***social system*** comprised of the individuals, the groups and the institutions that are potential adopters, the ***channels of communication*** that are the means through which the members of the social system obtain information and discuss the ***element being diffused*** - which we will refer to loosely as the *innovation* - and ***time*** that relates to the rate at which adoption takes place (Mahajan, 1985, page 7).

Diffusion can be caused by external influence processes, by mechanisms internal to the social system or by a conjugation of both. When diffusion is caused by external sources it is usually because forces such as the mass media broadcast information about the innovation of interest and such information compels the members of the social system to adopt (Valente, 1996a, page 81). Other external mechanisms of diffusion exist and they include policy impositions, or other societal level events that could compel or force the adoption behavior (Mahajan, 1985, page 15)(Valente, 1996a, page 95).

Alternatively, diffusion may be the result of mechanisms internal to the social system that will cause individual adoption behavior to be dependent on the adoption behavior of other members of the same system (Strang, 1991). These are the mechanisms that we are concerned with in this paper.

Peer influence, social influence, influence or contagion, are terms used in this paper interchangeably to denote the dyadic process that takes place when an individuals shapes his own behavior, beliefs or attitudes according to what other actors in the same social system think, express or how they behave (Leenders, 2002).

In the context of diffusion, peer influence is the micro-level manifestation of a broad range of mechanisms internal to the social system which include, but are not limited to product network externalities in the sense provided in the previous section that have been a core concern in the telecommunications' related research thus far.

(Strang and Soule, 1998; Van den Bulte and Lilien, 2001; Leenders, 2002) list the main sociological mechanisms that can drive peer influence.

Such mechanisms include *Information transfer* when members of the social system get to know about the innovation by direct or indirect communication with previous adopters (Katz and Lazarsfeld, 1955), *competition* which occurs when individuals look at their rivals as frames of reference. Rivals are typically defined as those connected to similar others than the ego (structural equivalent actors) (Burt, 1987). *Conformity* that depends on group values and norms and it assumes that individuals comply to the behaviors and attitudes of the groups to which they belong (Menzel, 1960). *Network externalities* when the utility of adopting a particular innovation increases with the *installed-based* of adopters, the members of the social system who decide to adopt will also benefit from further adoptions (Katz and Shapiro, 1994) and *Spatial Proximity* since geographically proximal actors tend to influence each other even if there is no particular explanation for why that is so except that spatial proximity facilitates all types of interactions (Strang and Soule, 1998).

Empirically such differentiation is usually impossible (Van den Bulte and Lilien, 2001), therefore, in this paper, we are concerned with a broad concept of influence in which all the mechanisms laid out above can play a part which we do not attempt separating. Our concern in this research is to quantify the weight of peer influence in the adoption decision of product in a social network inferred from communication links, but we will make no claim as to what mechanism is really driving such influence process.

### 3.2.2 Related Studies

Our paper is part of a vast literature of observational studies that characterize the diffusion of innovations. Early work in this field puts forward that people contemplate the experience of others before deciding whether to adopt a novel product. The idea is that interactions between adopters and non-adopters mitigate the risk and uncertainty associated with novelty (Rogers, 1995). A common theme is the characterization of the diffusion process using a Bass Model (Bass, 1969) or any of its variants surveyed in (Mahajan, 1985; Mahajan et al., 1990) that assume that every individual in the population can influence any other member of the same social system.

In our paper, we look at individual level connections as the source of social influence rather than the installed based of adopters. Like (Granovetter, 1978; Granovetter and Soong, 1983, 1986, 1988) our hypothesis is that the likelihood of adoption is linked to the level of exposure to the innovation, with exposure defined as the proportion of people in one's social circle that have already adopted (Valente, 1996a). However, unlike those authors who are concerned with establishing individual level thresholds of exposure above which individuals decide to adopt, our research is concerned with characterizing the average marginal impact that additional adopters of the iPhone handset in the ego network of each subscriber have in the individual probability of adoption.

How innovations diffuse depends on the actual characteristics of the product of interest (Rogers, 1995), therefore, studies of how social influence affect the diffusion process are situation and context specific. To the best of our knowledge, we are one of few authors characterizing the impact of peer influence in telecom products and we are the first to do so for the case of handsets. A few previous studies have focused on the diffusion of mobile phones, but for the purpose of explaining the penetration of wireless communications and not to characterize how particular handsets spread. Examples of such studies include (Gruber, 2001) for the diffusion of mobile communications in Eastern European, (Botelho and Pinto, 2004; Carvalho, 2006) for the Portuguese case,(Doganoglu and Grzybowski, 2007) for Germany (Singh, 2008) in India, (Chu et al., 2009) for Taiwan and (Park and Ueda, 2011) in Korea and Japan.

Our study is also related with the methodological literature on the identification of peer effects in social networks that was developed following the seminal work of (Manski, 1993). Manski's research highlighted the difficulties of identifying the effect of group behavior on individual choices when (1) it is impossible to identify the reference groups for each individual in the social system; (2) there are unobservables that can cause correlated outcomes as well as influence the formation of links between members of the social system; and (3) there exists simultaneity in the behavior from ego and alters.

The identification of reference groups became possible through data collection strategies that capture the structure of the relations among the members of the social system (the social network). Such data allows determining who influences whom (Wasserman and Faust, 1994; Bramoullé and Fortin, 2009). In several domains, collecting this type of information is costly or even impossible and so far, only a handful of studies have used large real world networks to analyze how peers affect each other in societal level networks (Aral et al., 2009).

In this paper we use a large network from a market leader in mobile telecommunications services in one country whose clients make up for approximately half of the population of that country. In itself, the analysis of large network data is a relevant contribution for the diffusion of innovations literature. This is so because small network data contains only a small sample of the population and most often a non-random sample since due to homophily, social networks tend to clustered in homogeneous groups of individuals (McPherson et al., 2001). Additionally, individuals in small networks are also likely to be part of larger networks and in studies of small networks, such a fact, and its strong implications, are never discussed. (Anagnostopoulos et al., 2008) and (Aral et al., 2009) have analyzed the problem of innovation diffusion in large social networks, but their research focused on the spread of free of charge products in a context completely distinct from ours.

Correlated effects and simultaneity have been tackled in several distinct ways.

The preferred course of action is the use of randomized control trials. (Aral and Walker, 2011) and (Bapna and Umyarov, 2012) are notable examples of studies that do so in large scale networks.

The former uses a Facebook.com application that allows its users to share comments related to the film industry. The application has the ability to send messages to each Facebook.com friend of the adopter individual. The results of the study show that the ability of viral messaging within the application created contagious adoption among the millions of Facebook.com friends of a set of 9,687 individuals that were recruited to participate in the experiment.

The latter uses Last.fm, website for music sharing. The authors test the hypothesis that users connected to others who pay for premium services provided by Last.fm will be influenced to adopt these paid services themselves. By awarding free subscriptions to a randomized set of users, (Bapna and Umyarov, 2012) are able to show that the odds of subscribing the premium service increase by up to 50% due to the influence generated by a friend who adopted the service.

The two above mentioned studies are at the frontier of IS research, however, in markets of physicals goods that are expensive, it is unlikely that similar opportunities for experimentation in large scale networks will emerge frequently. There is the obstacle of deriving the social network of interest of the parties involved and the actual cost that such efforts would entail. While the marginal cost of a Last.Fm subscription is likely to be negligible for the provider, in the case of the iPhone 3g, for example, it would cost hundreds of thousands of dollars to distribute a few thousands of phones in the population. Providers will not engage in such initiatives unless they expect to profit in return.

So far, the knowledge on social influence does not yet permit predicting and controlling the flows of social influence in real world networks (Aral, 2012) and many more experimental and observational investigations will be needed until we reach that far, thus the identification of ways to deal with the problems of simultaneity and correlated effects in social networks are still very much needed.

In observational studies, simultaneity can be solved using instrumental variables in peer effect models (Lee, 2007; Bramoullé et al., 2009; Oestreicher-Singer and Sundararajan, 2010; Lee et al., 2010) or through instrumental variables derived from natural experiments (Sacerdote, 2001; Tucker, 2008). Correlated effects due to unobservables that determine behavior can be controlled using fixed effects methods (Lin, 2010). Alternatively, matching in high resolution panel data settings, can also be used (Rubin, 1973; Hill et al., 2006; Aral et al., 2009) to deal with these problems.

Natural experiments are rare and peer effect models and matching can break in the presence of unobservables that simultaneously determine tie formation and behavior (Shalizi and Thomas, 2011). Instruments derived in peer effect models rely on the structure of the social network so they require that network ties are exogenous to the behavior of interest. Matching estimators assume that treatment assignment is strictly ignorable conditional on a set of observed explanatory variables and they also assume that individuals belong to the treated or the control group with positive probability (A. Smith and E. Todd, 2005).

In this paper we differentiate from the previous approaches by using instrumental variables, but at the same time controlling for community membership of the individuals of our population of interest.

The community membership controls emerge as an attempt to capture part of the unobserved traits that simultaneously determine the adoption behavior and the actual links that that tie individuals together.

Homophily suggests that social networks will tend to be formed of homogeneous clusters of individuals sharing similar values of the unobserved traits (Aral et al., 2009). Therefore, as suggested in (Shalizi and Thomas, 2011) controlling for community structure may help. The assumption is that the communication graph used to infer the social network structure of the subscriber set provides sufficient information to uncover the group membership of each subscriber *conditionally independent* on the observed adoption behavior. In other words, the community membership captures the part of the unobservables that determine the network structure, leaving out only those latent characteristics that influence behavior, but that do not determine the formation of ties among individuals.

Communities, as defined in (Newman, 2004), are clusters of individuals who speak more time amongst each other than to the rest of the network as a whole. They can be identified with community detection algorithms that have been widely developed in the literature and surveyed in great detail by (Fortunato, 2010). We test several community detection algorithms in this paper and report our conclusions regarding to which methods are most promising to the task at hand.

Additionally, because we identify communities in the social network we are also able to go a step further and test the robustness of our results using *Actor Based Models* of network dynamic co-evolution and behavior.

Such methods use agent-based simulation models to describe the dynamics of link formation across members of a social network and the relationships between the emerging social network structure and behavior (Snijders et al., 2010). This class of models separate the contributions of homophily and influence for the diffusion of a certain practice through the social network by estimating network structure and behavior jointly (Steglich et al., 2010). Because of computational complexity, and the assumption that each member of the social system is a suitable candidate to befriend any other member, this approach does not scale well to large networks (Aral, 2010). Furthermore, providing interpretation with economic meaning to the estimate of the parameters of interest is far from straightforward (Ripley and Snijders, 2010). However, due to our community identification strategy we are able to fit these models to small networks within the large communication graph that respect both the theoretical assumptions as well as computational requirements of the algorithm.

Finally our work is also related to the literature on viral that is emerging as a response to consumers' overwhelm with information about new products and services (Hinz et al., 2011) and avoidance of the traditional marketing instruments (Hann et al., 2008). Viral marketing campaigns assume that information about products is generated and spread by consumers among themselves starting from a small set of initial adopters called the seed (Leskovec et al., 2007; Bampo et al., 2008).

Leveraging on the estimates for average partial effect of the peer influence on the individual probability of adoption of the iPhone 3g, we test how different seeding strategies that are frequently considered in the viral marketing literature could have been used by the operator to increase sales. In particular we test whether targeting well connected individuals (Goldenberg et al., 2009), bridges (Granovetter, 1973; Watts, 2004) or well connected individuals that are far apart from each other in the social network (Watts et al., 2007) could have benefited the spread of the iPhone 3g in the population.

Our results show that targeting hubs and bridges in the social network performs better than randomly seeding, however, they also highlight that the marginal benefit of such strategies will be low unless the virulence of the product itself is high. We show that when the cost of seeding is non-trivial, companies may have little incentive to engage in viral marketing unless the content of the product itself favors its own diffusion through the social network.

## 3.3 The iPhone 3G and the EURMO dataset

### 3.3.1 iPhone 3G Release

The iPhone 3G was released in 2008 as the first Apple smartphone commercialized in the country under analysis [1]. People in that country spent on average 20 Euros per month in mobile communications during 2008. The median was 15 Euros per month. NOKIA was the preferred mobile phone brand in that country with a market share above 40%, followed closely by Samsung. LG and SONY had market shares below 10%. Overall, smartphone sales were still incipient in that country accounting for a mere 11% of the yearly handset sales. Figure 3.1 shows that ease of use, price, size and weight were among the most important factors that consumers considered when buying a handset[2].

[1] The country analyzed is not disclosed for protection reasons. All numbers in this section were provided by a major consulting company operating in this country that regularly runs market surveys

[2] The price of the iPhone 3G at launch in this country was 500 (600) Euros for the 8Gb (16Gb) version without a contract with a provider. Alternatively, the iPhone 3G could have been purchased at a reduced price with a contract with one service provider. Prices varied between 130 Euros and 400 Euros depending on the type of contract selected. Contracts lasted at least 24 months and significant penalties applied to terminate a contract before expiry. Both with and without contract, the iPhone 3G was sold with a software lock to the service provider selling the device. The lock could be released at no charge after 24 months. Consumers willing to release the lock before 24 months would need to pay a 200 Euro charge. Communication contracts associated with the iPhone 3G varied slightly across service provider. They ranged between 30 Euros and 65 Euros per month

The iPhone 3G was a conspicuous luxury product. It was expensive, innovative and users could only benefit from its full potential if they subscribed to a data plan. There was a clear mismatch between what the average user expected from a handset and the full set of features offered by the iPhone. All such factors were likely to generate uncertainty and motivate consumers to seek the opinion of others before making a purchase decision (Childers and Rao, 1992).

Our hypothesis is that peer influence was a positive determinant of iPhone 3g sales and that the more of one's friends adopted the handset, the more likely it would be for the ego to adopt as well.

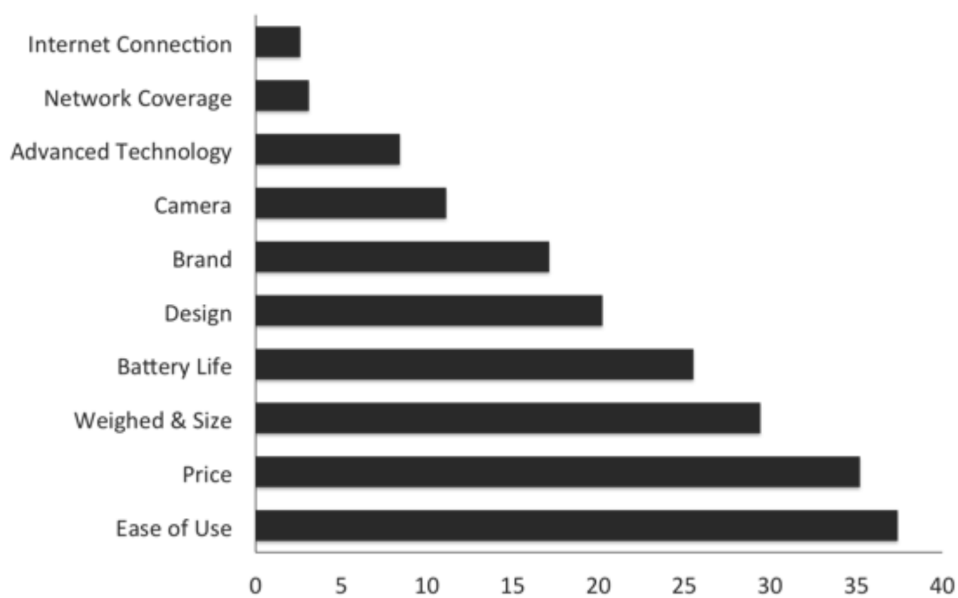



Figure 3.1: Most important characteristics considered when purchasing a new handset (% of total respondents who named each particular characteristic)

### 3.3.2 Raw Dataset

Our dataset includes communication data between August 2008 and June 2009. The iPhone 3G was released in July 2008 by EURMO. For every call originated or received by a EURMO subscriber we have the anonimized phone numbers of the caller and the callee, the cell towers they used to call each other, a timestamp for when the call took place and the duration of the call. We also have the GPS coordinates for all cell towers in EURMO. For every sms sent or received by a EURMO subscriber we have the anonimized phone numbers of the caller and the callee. We also have a set of subscriber characteristics including date of birth, gender, zip code for the account owner, type of contract, tariff plan, add-on services such as ring tones, free weekends, packs of sms, handset and changes over time for all these characteristics. We have 16.5 million phone numbers in our database, 3.7 billion calls and 13 billion of sms.

### 3.3.3 Social Network

We use the dataset described above to define an undirected graph of communications across EURMO subscribers over the entire period of analysis. We trim subscribers from other mobile operators because we do not have their account information and therefore we cannot know, for example, whether they adopted the iPhone 3G.

An edge between two users is added to our graph if one of them called or sent an sms to the other and the latter answered back with a call or an sms within the same calendar month. This procedure disregards communications that are unlikely to proxy social proximity such as those involving message bots, short numbers and call centers as well as non reciprocal communication across regular subscribers.

We also remove from our dataset numbers that at some point in time were owned by multiple subscriber accounts (called recycled phone numbers), as well as numbers whose subscribers switched between pre-paid and post-paid because in both these cases we cannot accurately track their history. These two cases eliminate less than 5% of the EURMO active subscriber base.

Finally, we trimmed from the dataset subscribers whose out-degree was more than 3 standard deviations above the mean. This removes PBX machines and ensures that the size of our graph is computationally manageable. This eliminates less than 1.6% of the subscribers in our graph.

In the subsequent analysis we use the term *friends* to identify people who contact each other and are thus connected with an edge in our communication graph. Our final communications graph includes $4,986,131$ subscribers and $57,069,798$ undirected edges. The undirected graph density is $4.59 * 10^6$ and the mean number of friends (degree) is 22.9 with a standard deviation of 25.5. The median number of friends is 13. Figure 3.2 plots the distribution of the number of friends.

## 3.4 Community Based Sample

Communities are defined as groups of individuals whose members have dense connections within the group and only sparse links to individuals outside the group (Newman, 2004).

Peer influence is a local phenomena. It occurs when alters play a part in the ego's decision process (Leenders, 2002). As mentioned above, the social network that we use

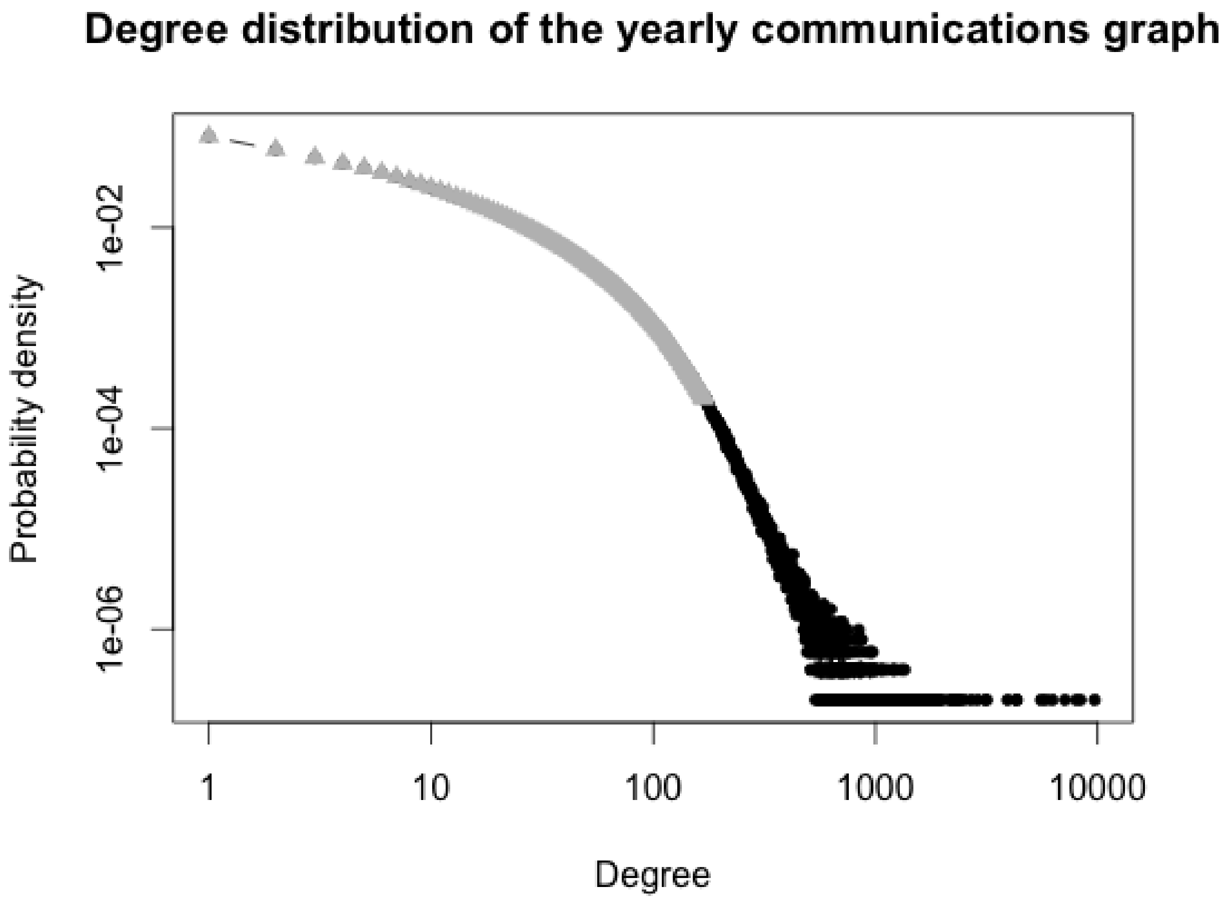



Figure 3.2: Empirical degree distribution of our communications graph. Grey dots represent subscribers whose out-degree is three standard deviations below the mean

in this analysis includes 4.9 million subscribers that are sparsely connected. As such, it is likely that influence flows will occur within local clusters of this large network and not span across the entire population of subscribers.

Homophily suggests that social networks will tend to be formed of homogeneous clusters of individuals sharing similar values of unobserved traits and this is a central concern of most studies of contagion (Aral et al., 2009). To minimize the bias introduced by the confounding effects of latent unobservables we uncover such clusters of users through community identification algorithms as was first suggested in (Shalizi and Thomas, 2011). The underlying assumption is that community membership will tend to capture part of the unobservables that determine the network structure and that could simultaneously derive behavior.

A further advantage of community identification is that it allows to separate user communities with no adoption events, from those where at least one member adopted the iPhone 3g. To understand why such possibility is important consider an example from epidemiology.

Suppose that there is a disease called *pox* and that there are two separate populations of users of he same size. Population $p1$ is completely immune to the disease while population $p2$ is vulnerable. If one tried to estimate the virulence of *pox* within population $p1$ by introducing sick individuals into $p1$, the conclusion would be that *pox* is not contagious. However, if the same experiment was repeated in $p2$ the analysis would allow determining the rate at which the disease spreads. If $p1$ and $p2$ were analyzed as a single population the virulence of *pox* would be underestimated.

In the market place, companies segment clients into different categories and they try to sell different product versions or even distinct products to different consumer segments. Segmentation reflects *the adjustment of products and marketing effort to consumer or user requirements*(Smith, 1956). Therefore, knowing the size of the influence effect in the population of susceptible is more valuable to the firm, than when the effect is averaged over the immune.

Communities in which at least one adoption occurred are more likely to represent clusters of susceptible individuals than communities with no adopters.

Finally, community identification also allows working with a smaller part of the social network by permitting us to use a sample of cohesive groups of users that are independent from each other. If such clusters are identifiable, then they can also be used to correct the standard errors of regression procedures which will also be biased when dealing with social network data. Such fact is usually ignored in most empirical work, which tends to assume independence across sample units which in social networks is impossible by definition.

### 3.4.1 Community Identification Algorithms

The physics and social network literature are rich in community identification algorithms for which excellent and in-depth surveys are provided in (Lancichinetti and Fortunato, 2009; Fortunato, 2010). Table 3.1, which we adapted from (Fortunato, 2010), lists a wide range of algorithms of this kind.

A majority of the community identification algorithms listed in the table have computational complexities that make them impossible to use in networks as large as the one that we use in this investigation. The computational complexity provided in the last column of the table is for the worst case scenario, but (Pons and Latapy, 2006; Lancichinetti et al., 2008; Lancichinetti and Fortunato, 2009) show that the first ten alternatives listed in table 3.1 are not capable of processing a social network with 4.9 million nodes and 57 million edges.

Taking this into consideration we focus on algorithms 11 through 17[3]. We summarize the mechanics of each algorithm in appendix 3.C.

Table 3.1: Community Detection Algorithms and Their Computational Complexities

| # | Authors | Reference | Computational Complexity |
|---|---|---|---|
| 1 | Palla et. al. | (Palla et al., 2005) | $O(exp(n))$ |
| 2 | Newman & Girvan | (Newman and Girvan, 2004) | $O(m^2 n)$ |
| 3 | Girvan & Newman | (Girvan and Newman, 2002) | $O(mn^2)$ |
| 4 | Furtunato et al. | (Fortunato et al., 2004) | $O(n^4)$ |
| 5 | Bragow & Bollt | (Bagrow and Bollt, 2004) | $O(n^3)$ |
| 6 | Donetti & Munoz | (Donetti and Munoz, 2005) | $O(n^3)$ |
| 7 | Zhou & Lipowsky | (Zhou and Lipowsky, 2004) | $O(n^3)$ |
| 8 | Duch & Arenas | (Duch and Arenas, 2005) | $O(n^2 log(n))$ |
| 9 | Radicchi et. al. | (Radicchi et al., 2004) | $O(n^2)$ |
| 10 | Newman | (Newman, 2003) | $O(n^2)$ |
| 11 | Zhang et.al. | (Zhang and Krackhardt, 2011) | $O(n_c^2(n_c + n_b))$ |
| 12 | Latapy & Pons | (Pons and Latapy, 2006) | $O(n^2 log(n))$ |
| 13 | Clauset et.al. | (Clauset et al., 2004) | $O(nlog^2(n))$ |
| 14 | Wu & Huberman | (Wu and Huberman, 2004) | $O(m + n)$ |
| 15 | Raghavan et.al. | (Raghavan et al., 2007) | $O(m + n)$ |
| 16 | Blondel et.al. | (Blondel et al., 2008) | $O(m)$ |
| 17 | Rosvall & Bergstrom | (Rosvall and Bergstrom, 2008) | $O(m)$ |

**Note 1:** Adapted from (Fortunato, 2010) **Note 2:** $n$ denotes the number of nodes in the social network, $m$ denotes the number of edges in the social network, $n_c$ denotes the target number of nodes in the sub-population of interest $n_b$ denotes the number of nodes in the boundary of the sub-population of interest.

The overall adoption rate of the iPhone 3g was less than 1% therefore, if we sample very small communities of users, it is unlikely that we will be able to find clusters within which at least some individuals purchased the phone. Because of this, we aim at identifying groups of individuals with about 100 members, which according to Leskovec et al. (2009) is the size about which clusters tend to start blending into the very large graph from where they are sampled and are unlikely to represent real social clustering.

[3] We ignore algorithms 14 and 15 described in (Wu and Huberman, 2004; Raghavan et al., 2007) because we could not find publicly available software implementations. The authors of (Raghavan et al., 2007) kindly provided us with their implementation in JAVA, but the software would not directly run in our data. For this algorithm, the igraph0 package (Csárdi and Nepusz, 2005) also contains an available implementation. However, the library code has a data structure problem and it takes $O(n^2)$ rather than $O(n + m)$ to run. We actually attempted to use the iGraph0 version of the software, but after 4 months of runtime we stopped the algorithm with no output at all

### 3.4.2 Community Identification

Table 3.2 contains the output of the different algorithms used.

More than 50% of the groups identified by the different algorithms have at most two subscriber members and no adopter individuals. Such communities are irrelevant for our analysis which goal is to find cohesive clusters of individuals that are likely to share the same value of unobservables. Additionally, the proportion of total subscribers assigned to communities with sizes larger than 100 individuals is 63.2% for the Walktrap (Pons and Latapy, 2006), 99.5% for the Louvain's method (Blondel et al., 2008), 99.6% for Infomap (Rosvall and Bergstrom, 2008) and 98.2% for Clauset (Clauset et al., 2004; Clauset, 2005). Therefore, an overwhelming majority of subscribers was placed in communities that due to their large sizes are unlikely to entail social meaning (Leskovec et al., 2009).

Besides TCLAP, (Pons and Latapy, 2006) produces better results than the remaining algorithms, however, as table 3.3 highlights, the number of communities identified by this algorithm that have adopter individuals is quite limited.

With these results for the different community algorithms we choose T-CLAP to proceed our analysis to which we devote further attention in the next section.

Table 3.2: Summary of the community identification algorithms output

| Algorithm | Edge Weights | Execution Time | Number of Communities | Community Size: Min | Median | Max | Mean |
|---|---|---|---|---|---|---|---|
| Latapy & Pons | Yes | 1 week | 977,999 | 1 | 1 | 488,471 | 5.0 |
| Blondel et.al. | No | 3 hours | 8,417 | 2 | 2 | 886,764 | 592.4 |
| Rosvall & Bergstrom | No | 4 hours | 8,113 | 2 | 2 | 1,564,858 | 614.6 |
| Rosvall & Bergstrom | Yes | 4 hours | 8,081 | 2 | 2 | 2,490,201 | 617.6 |
| Clauset et.al. | Yes | 1 month | 25,373 | 2 | 2 | 317,426 | 179.3 |
| Zhang et.al. | Yes | 3 weeks | 2,134 | 2 | 103 | 115 | 96.7 |

**Note 1**: Unlike the other algorithms used T-CLAP does not process the entire social graph. It looks for local community focusing on small parts of the social network at a time.

Table 3.3: Communities identified with $25 \leq communitysize \leq 200$

| Algorithm | Number of Communities | Communities with Adopters | Total Number of of Adopters | Adopters per Community Mean | Min | Median | Max |
|---|---|---|---|---|---|---|---|
| Latapy & Pons | 2,996 | 313 | 447 | 0.149 | 0 | 0 | 8 |
| Blondel et.al. | 47 | 3 | 8 | 0.179 | 0 | 0 | 6 |
| Rosvall & Bergstrom | 24 | 2 | 2 | 0.018 | 0 | 0 | 1 |
| Rosvall & Bergstrom | 14 | 0 | 10 | 0.000 | 0 | 0 | 0 |
| Clauset et.al. | 232 | 27 | 37 | 0.159 | 0 | 0 | 3 |
| Zhang et.al. | 2134 | 1936 | 72,995 | 36.51 | 0 | 16 | 115 |

**Note 1:** Number of T-CLAP communities before discarding overlaps

### 3.4.3 T-CLAP community sample

T-CLAP extracts random communities in three steps: (1) it selects one node at random and collects a sample of nodes and edges through breath first search; (2) applies a clustering procedure to the collected nodes to identify dense regions within the sample; (3) sequentially discards nodes that have more links to outside the community than inside, as measured by the individual Internal External Ratio (IER) until a certain community size is obtained. The IER is an adaption from the E-I index proposed in (Krackhardt and Stern, 1988) and is detailed in equation 3.1:

$$IER = \frac{I - E}{I + E} \tag{3.1}$$

In this case, $I$ denotes the number of calls and sms exchanged across community members and $E$ denotes the number of calls and sms exchanged between community members and individuals outside the community. IER varies in $[-1; 1]$. The lower bound is attained when the community members communicate only with members outside the community. The upper bound is attained when community members do not communicate with members outside the community. A community with a higher IER is more isolated from the rest of the network graph. The higher the IER the more isolate the community. Communities with negative IER imply that its members as a whole interact more often with other individuals outside the community and is an indication of poor grouping.

Because iPhone adoption was a rare event, the chances of any random community of size smaller to 100 identifying adopter members is low. Unlike the other algorithms that we tested, T-CLAP looks for local communities in subgraphs of the complete network, it does not process the entire social graph. This exacerbates the problem of identifying communities with iPhone adopters, since a global partition of the graph is not provided by this algorithm.

To accommodate and overcome this problem, the version of T-CLAP used in this paper was modified from the original algorithm to focus on communities where adoption events occurred. To increase the performance of the algorithm with respect the identification of communities with iPhone 3g adopters, we changed T-CLAP in the following three ways: i) in step (1) we start the snow-ball sample from nodes that adopted the iPhone 3G (we sample 4 waves out); ii) we skip step (2) altogether; iii) in step (3) we prune iPhone 3G adopters with lower probability. If two subscribers have the same IER, but one of them adopted the iPhone, we prune the non adopter first.

Our version of TCLAP takes longer to run than the original code because it skips the clustering phase, but it increases the probability of identifying communities with adopters. We then use the IER index to evaluate the communities obtained by the modified TCLAP algorithm.

Other metrics for community evaluation exist, the most commonly used being modularity (Newman and Girvan, 2004). Modularity is an index of the quality of a graph partition that compares the number of edges within a given group of nodes and the expected number of edges that such group would have if the network ties were randomly determined (Newman and Girvan, 2004). Modularity evaluates a partition of the entire graph into communities. We do not use it in this case because modularity suffers from a resolution limit (Fortunato and Barthelemy, 2007). (Fortunato and Barthelemy, 2007) show that when the size of the social network increases, the expected number of edges between two groups decreases possibly becoming smaller than the unit and the consequence is that for large graphs, the modularity index will tend to overlook the existence of small, but non-trivial communities. This is problematic for large networks as our own.

Unlike modularity,$IER$ is agnostic to network size. Additionally, several other theoretical notions are embedded in the IER which are of interest to the identification of cohesive and homogeneous groups.

$IER$ is a measure of dominance of internal over external connections, it reduces with the decrease of internal communication, but also with the increase of external communication (Zhang and Krackhardt, 2011). The time that individuals can devote to maintain friendship and intimacy through to social interaction is limited and the IER captures the trade-off between the attachment to the group and the relationships that one is able to maintain outside (Krackhardt and Stern, 1988). By comparing internal against external links, the IER also controls for heterogeneity in the amount of time that individuals devote to communication and to the number of connections that they maintain. People who interact with more people and more frequently are likely to do so internally and externally and the reverse is also true for individuals who engage in fewer communication interactions. Because the IER is reported as a ratio, it is not the absolute number of interactions, but rather the balance between internal and external communications that is factored when analyzing the attachment of any individual to a group.

To select our community sample we require that communities have a positive IER index and we exclude from the sample groups of individuals that overlap. From the 2,134 communities that we obtained with the TCLAP algorithm only 263 match these two criteria. These communities have 24,131 subscribers of which 1,758 adopted the iPhone 3G [4].

Table 3.4 extends the calculation of the IER index to the communities generated by the remaining algorithms. It again reinforces the idea that TCLAP is the most appropriate algorithm for the task at hand.

Table 3.4: Non overlapping communities with $25 \leq communitysize \leq 200$ and positive IERs

| Algorithm | Communities with $IER > 0$ | Total Adopters |
|---|---:|---:|
| Latapy & Pons | 70 | 15 |
| Blondel et.al. | 46 | 8 |
| Rosvall & Bergstrom | 20 | 2 |
| Rosvall & Bergstrom | 10 | 0 |
| Clauset et.al. | 21 | 0 |
| Zhang et.al. | 263 | 1,758 |

Besides having positive IERs and being non-overlapping, the 263 communities that we obtained are also very much disconnected from each other in the actual social network. To determine the extent of community separation we perform two distinct tests.

The first separation measure consists in calculating geodesic distances between users who belong to different communities. We select two communities randomly and we se-

[4]We chose the communities in random order and when two communities have overlapping individuals and positive IER we keep the first community that we sampled and discard the latter.

lect one user randomly within each community chosen. Finally we compute the shortest path between the users within the entire communication graph. We repeat this procedure $500,000$ times. We find that the mean distance across random pairs of users in distinct communities is 4.76 edges with a standard deviation of 0.66 and figure 3.3 depicts the empirical distribution of the length of the geodesics between random pairs of users in distinct communities.

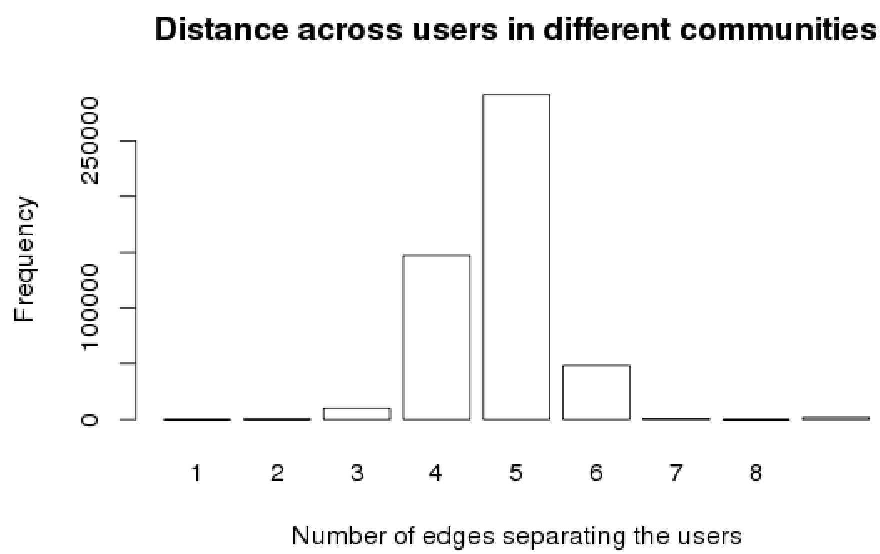



Figure 3.3: Path between subscribers in distinct communities

Additionally we look at the extreme cases. We look for subscribers at the edge of each community that may be linked directly to members of other communities in the sample. To do so, for each community extracted using T-CLAP, we perform a breadth first search of depth one in all members of that community. Such operation allows identifying the friends of the community members that are external to the community itself. Using this information we create an undirected network of the 263 communities with each community representing a node in this network. The community network has a density of 0.07 which means that out of the 34,453 theoretically possible inter-community ties there are only 2,425 connections between communities. 1,827 of these links are of weight one which means that the connected communities share a single tie between them. This shows that communities are not completely isolated from one another, but that they are at most very sparsely connected.

Finally, Figure 3.4 displays the distribution of the adoptions in the community sample over the 12 months that we analyze. Figure 3.5 depicts the relationship between the IER and both community density and community size for the 263 communities analyzed highlighting that there appears to be no particular correlation between any of such measures.

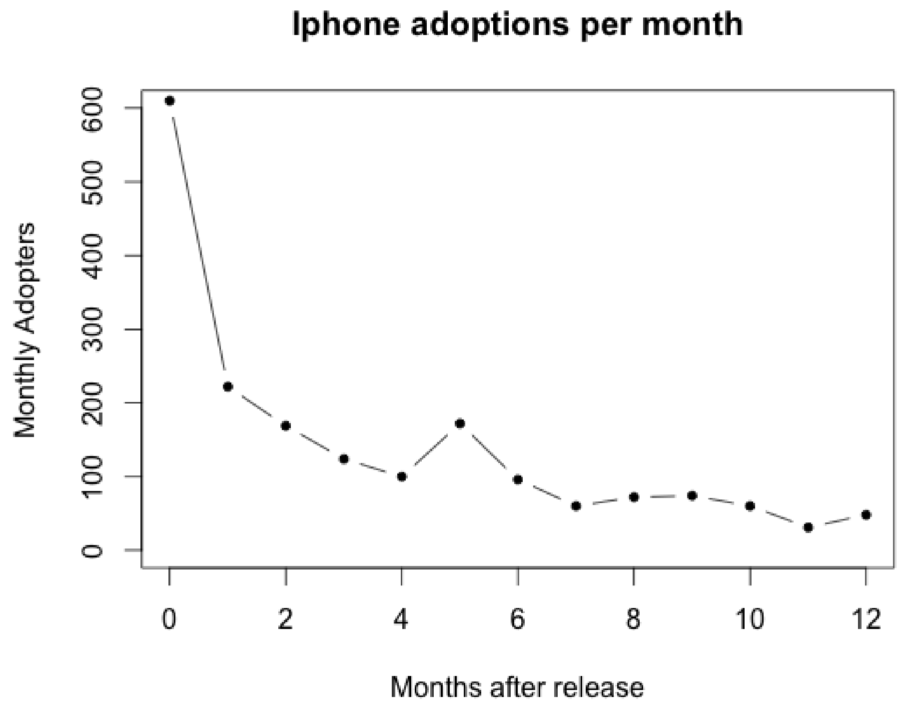



Figure 3.4: Number of adoptions each month for the subscribers in the sample. The 0 in the x-axis indicates the month of July which coincides with the release period of the iPhone 3G handset

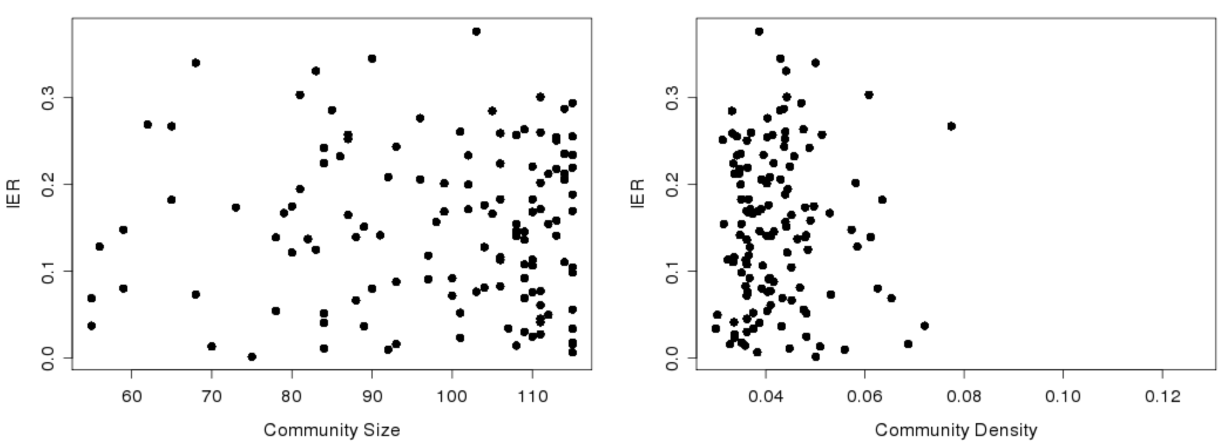



Figure 3.5: Communities extracted with the modified T-CLAP algorithm

## 3.5 Consumer Utility Model

At any point in time users choose to adopt or not the iPhone 3G. Let $U_{it}$ represent the difference in utility for user $i$ from adopting and not adopting the iPhone 3G at time $t$. $U_{it}$ is defined by the following reduced form equation:

$$U_{it} = \alpha + X_i\beta + Z_{it}\gamma + \rho W_i Y_{t-1} + \epsilon_{it} \tag{3.2}$$

$X_i$ is a set of time invariant covariates, which in our case include gender, subscription of mobile data plans and the technological sophistication of the handset owned just prior to the release of the iPhone 3G. Such controls are included because several studies adoption of technology show that past experience with technologies similar to the innovation of interest contribute positively to the perceived usefulness of the innovation (Karahanna et al., 2006) which in turn is known to contribute to adoption (Venkatesh et al., 2003). Gender has also been reported to play an important role in how individuals perceive that a certain technology will perform (Gefen and Straub, 1997; Venkatesh and Morris, 2000; Venkatesh et al., 2003). This set of covariates is summarized in Table 3.5.

$Z_{it}$ is a set of time varying covariates, possibly time lagged. In our case it includes tenure with EURMO, which may relate to the experience and trust that a subscriber has with this carrier and therefore can contribute to the probability of adoption of the new handset from EURMO. Tenure with EURMO is summarized in Table 3.6.

$W$ is an adjacency matrix, $W_i$ is the $i^{th}$ row of such matrix and $Y_{t-1}$ is a column vector that stacks the adoption decisions of all individuals up to time $t-1$. $\epsilon_{it} \sim N(0,1)$ is the

Table 3.5: Descriptive statistics of time invariant covariates

| Variable | Description | Mean | Standard Dev. |
|---|---|---|---|
| $genderM$ | =1 for male | 0.209 | 0.406 |
| $genderF$ | =1 for female | 0.185 | 0.388 |
| $genderU$ | =1 for subscribers who did not report a gender | 0.605 | 0.489 |
| $prepaid$ | =1 if subscriber $i$ had a pre paid tariff on June 30 2008 | 0.606 | 0.489 |
| $mobileNet$ | =1 if subscriber $i$ had a mobile internet on June 30 2008 | 0.023 | 0.150 |
| $phone2.0g$ | =1 for ownership of 2.0g handset on June 30 2008 | 0.157 | 0.363 |
| $phone2.5g$ | =1 for ownership of 2.5g handset on June 30 2008 | 0.478 | 0.499 |
| $phone3.0g$ | =1 for ownership of 3.0g handset on June 30 2008 | 0.331 | 0.470 |
| $phone3.5g$ | =1 for ownership of 3.5g handset on June 30 2008 | 0.028 | 0.166 |
| $phoneOther$ | =1 for ownership a handset with unknown range on June 30 2008 | 0.004 | 0.066 |
| $phoneAge$ | Number of years a subscriber has used the handset it owns on 30th of June of 2008 (before the iPhone 3g release) | 0.790 | 0.716 |

**Note** 1: Mean and standard deviations over the subscribers in the sample

Table 3.6: Descriptive statistics of time varying covariates

| Variable | Description | Mean | Standard Dev. |
|---|---|---|---|
| $tenure$ | Number of months a subscribers is using the EU-RMO provider | 66.393 | 43.832 |

**Note** 1: mean and standard deviation computed over the entire panel

error term. User $i$ will adopt the iPhone 3G at time $t$ if $U_{it} > 0$. Therefore, $y_{it} = 1\{u_{it} > 0\}$. In this model, the terms $\alpha + X_i\beta + Z_i\gamma$ capture the individual intrinsic utility from acquiring the iPhone 3G while parameter $\rho$ measures the contribution of peer influence to adoption. In this model, if peer influence is positive, adoption increases the number of friends that adopt, as well as the number of friends of friends that adopt recursively, which in turn increases the propensity to adopt. In this case, and after a while, the model originates the well known *S-Shaped* diffusion curve. If peer influence is negative or very low and the intrinsic utility to adopt is small, fewer people are likely to adopt and the handset will not spread across the population.

Table 3.7 provides descriptive statistics for variables related with adoption.

Table 3.7: Descriptive statistics for the variables related to adoption

| Variable | Description | Mean | Standard Dev. |
|---|---|---|---|
| $adopted_t$ | =1 if the subscriber $i$ adopts the iPhone 3g ate time $t$. | 0.006 | 0.079 |
| $frd\_adopters_{t-1}$ | % of a subscriber's contacts who adopted the iPhone 3g up to time $t-1$ | 0.013 | 0.033 |
| $N\_frd\_adopters_{t-1}$ | absolute number of contact adopters up to $t-1$ | 0.412 | 0.889 |

**Note** 1: mean and standard deviation computed over the entire panel; **Note** 2**:** Adoption means handset usage for a minimum consecutive period of thirty days

As discussed in (Allison, 1982) and in (Tucker, 2008) the model laid out in equation 3.2 can be empirically estimated with a pooled probit as long as the standard errors are adjusted to account for error correlation (either through *sandwich* estimator (Wooldridge, 2002, page 486) or *block bootstrap* (Efron, 1993, page 3188)) if the data is organized into a panel and observations after the adoption event are removed from the sample.

However, due to unobserved heterogeneity, the error term in equation 3.2 can be correlated with $\rho W_i Y_{t-1}$. We know from the vast literature in social networks that similar people tend to be connected to each other (McPherson et al., 2001). When this happens the unobservables in $\epsilon_{it}$that can influence one's adoption are also likely to influence the adoption of one's friends, $Y_{t-1}$. In the case of the iPhone 3G two individuals who are connected to each other may adopt the iPhone sequentially because of some sales call from a EURMO representative advertising the iPhone (which we are unable to control for). In the opposite direction and given its high price, it is also possible that budget constraints could deter more than one person in the same family to own the iPhone 3G.

We start by adding a significant number of dummy variables to control for heterogeneity that might lead to correlated adoption. We control for three types of heterogeneity, namely across regions, across subscribers and over time.

First, subscribers living in large cities are likely to face lower search costs because the iPhone 3G was mainly available from EURMO franchises located in major shopping malls. Subscribers in large cities might also find it more beneficial to use the iPhone because part of its functionality requires using the Internet and network coverage in cities is likely to be better than in rural areas. We use regional dummy variables to control for these effects. We split regional dummies in two sets. The first set describes the location where individuals live which we infer from the zip code of the account holder. A second set of regional dummies identifies the regions where subscribers spend most of their daytime (8am to 8pm), which we obtain by using the GPS coordinates of the cell towers used to route calls. We then match regions with statistical information on wages using the last Census.

Second, the baseline propensity to adopt the iPhone 3G might be different across subscribers. Factors that may lead to such differences that we control for include gender, the type of contract with EURMO, the characteristics of the handset owned prior to the release of the iPhone 3G and whether the user had already subscribed to data services from EURMO as we already presented in tables 3.6 and 3.5.

In addition, and in the spirit of the work by (Manski, 1993), unobservable groups effects can also drive the adoption of the iPhone 3G and confound our estimates of peer influence. One example is sets of individuals who communicate frequently within the group because they belong to the same company and this company decides to adopt the iPhone 3G (or another competing handset for that matter) as the primary handset for its employees. Alternatively, there could be latent variables determining both the adoption of the iPhone 3g and tie formation as detailed in (Shalizi and Thomas, 2011). To control for these effects we include community dummy variables.

Third, we add time dummies to control for the fact that the net benefit from adopting the iPhone 3G changes over time with seasonal promotions, changes in price and similar policies enacted by EURMO. Table 3.8 summarizes the above mentioned dummy variables.

Table 3.8: Descriptive statistics for the adoption related variables

| Variable | Description | | Mean | Standard Dev. |
|---|---|---|---|---|
| $geoWageVL$ | = 1 if $i$ spends most days in regions 2 standard deviations below the average the national average. Regions are studied at municipal level and daytime is considered to ranged from 8:00 to 20:00 for each day of the 11 month of communications | | 0.001 | 0.065 |
| $geoWageL$ | = 1 if $i$ spends most days in regions were salaries are between 1 and 2 standard deviations below the national average Regions | | 0.009 | 0.095 |
| $geoWageA$ | = 1 if subscriber $i$ spends most days in regions within 1 standard deviation of the national average | | 0.312 | 0.463 |
| $geoWageH$ | = 1 if $i$ spends most days in regions were salaries are between 1 and 2 standard deviations above the national average | | 0.439 | 0.496 |
| $geoWageVH$ | = 1 if $i$ spends most days in regions 2 standard deviations above the national average | | 0.237 | 0.425 |
| | | | Subscriber/Dummy | |
| | | N Dummies | Mean | Standard Dev. |
| $ZIP\_Code\_FE$ | Dummy variables for home zip code | 70 | 342.3 | 521.8 |
| $Community\_FE$ | Dummy variables for community membership | 263 | 91.7 | 17.2 |
| $Month\_FE$ | Dummy variables for each month | 12 | 23,064 | 532.8 |

**Note** 1: Regions are studied at municipal level and daytime is 8am – 8pm

Despite all controls, there might still be unobserved heterogeneity or reverse causality. To account for such possibility we use instrumental variables.

We start by considering three EURMO users. User $j$ is a friend of user $i$ and user $k$ is a friend of user $j$. We want to instrument $j$'s decision to adopt. One potential instrument is the adoption decision of user $k$. The more friends $j$ has that adopted the iPhone 3G the more likely she is to adopt. The adoption decision of user $k$, however, might be correlated with the adoption decision of user $i$. This might be particularly true if user $k$ and user $i$ are also friends.

Therefore, we instrument the adoption decisions of the friends of user $i$ with the adoption decision of the friends of friends of user $i$ that are not friends of user $i$. Call $k$' a friend of user $j$ that is not friend of user $i$.

Still because of well known sociological processes, such as comparison (Burt, 1980, 1987), one could argue that this instrument might still be endogenous due to indirect influence from $k$ on $i$. Therefore, we go a step further to limit that possibility.

We use the GPS coordinates of the cell towers used to route calls to identify the region where each subscriber spends most of her time. With this information we consider only users $k$' whose primary region is different from the primary region of user $i$. This ensures additional separation between user $i$ and the users used to instrument her adoption decision.

Users that spend most of their time in different regions are less likely to influence each other, particular if there is no additional evidence that such individuals are related in any way. Note that geographical proximity is known to facilitate interactions (Strang and Soule, 1998) and that the frequency of face to face and electronic interactions between people tend to decrease as their geographical separation increases (Tillema et al., 2010).

We expect that the instrumental variable just described will perform well to solve the problem of omitted variable bias and reverse causality because for a subscriber $i$, the behavior of the friends of $i$ will likely be correlated with the behavior of the friends of friends of $i$ due to homophily, which is common in social networks (McPherson et al., 2001). We note that we do not assume the existence of influence, but we do assume the existence of correlation in behavior, which is not a strange assumption since such a fact has been widely shown in the previous literature. This is the gist for the intuition behind our instrument. Our instrument correlates well to the endogenous variable, and correlates to the dependent variable only through the endogenous variable.

Additionally, note that even if we ignore that people who are similar tend to be linked, by construction, our instrument and the endogenous variable should be correlated as our instruments is built from a standard method used spatial econometrics and peer effects model (Bramoulle and Rogers, 2009; LeSage, 2008). To illustrate this point consider $A$ as a binary adjacency matrix representing the social network. Then $A^2$ is the matrix that defines the friends of friends. Finally $(ONE – A) * A^2$ is the matrix that defines the friends of friends that are not friends of the ego - ONE is a dense matrix with 1 in all elements except the diagonal which is zero. Correlation is achieved by construction because both the endogenous variable and the instrument depend on $A$.

The restriction to be imposed is that $I$, $A$ and $A^2$ be linearly independent, otherwise it will not be possible to indentify the peer effects Bramoullé et al. (2009). However, in this case the aforementioned matrices are linearly independent.

A problem with this instrument can come from indirect influence through the social network. This is why we seek additional geographical separation between a ego and its instrument. Another problem with this instrument can come from correlation between $A$ (the adjacency matrix) and the error itself. The assumption that we make throughout this paper is that people did not become friends because they both adopted the iPhone 3G or that because they both did not adopt or if they did such fact will be capture when we control for community dummy variables.

Table 3.9 summarizes our instrumental variable named $ffnfdc\_adopters_{t-1}$. The instrumental variable is computed taking into consideration all the ties in the social network and not only those within each community. Appendix 3.B describes in detail how we achieve geographical separation of subscribers and provides additional descriptive statistics. Table 3.10 details the average straight line geographical distance between the ego and the subscribers used instruments for the case of the $ffnf$ and $ffnfdc$ variables.

Table 3.9: Description of the instrumental variable

| Variable | Description | Mean | Standard Dev. |
|---|---|---|---|
| $ffnf\_adopters_{t-1}$ | % of friends not friends who adopted the iPhone 3G | 0.009 | 0.011 |
| $ffnfdc\_adopters_{t-1}$ | % of friends not friends who live in a distinct region who adopted the iPhone 3g during period $t-1$ | 0.010 | 0.009 |
| $N\_frd$ | Number of distinct friends | 33.632 | 22.475 |
| $N\_ff$ | Number of friends of friends | 1333.279 | 1081.448 |
| $N\_ffnf$ | Number of friends of friends not friends | 1311.574 | 1064.555 |
| $N\_ffnfdc$ | Number of friends of friends not friends living in a different | 566.580 | 586.7173 |

**Note** 1: mean and standard deviations for the time varying instruments was calculated considering the entire panel;**Note** 2: mean and standard deviation for time invariant covariates is calculated over the subscribers and not the entire panel of observations

Table 3.10: Average Geographical Distance from ego and the individuals used as instruments

| Instrument | Average Geographical Distance from Ego in Km | Comment |
|---|---|---|
| ffnf | 75.4 | All ffnf |
| ffnfdc | 179.9 | Distinct Nuts ffnf |
| ffnfsc | 3.3 | Same Nuts ffnf |

## 3.6 Peer Influence Estimate

Table 3.11 presents details of the observations that are included in the model detailed in equation 3.2.

From the original 263 communities and 24,131 users in the community sample we discarded 44 adopter individuals and 241 non adopters. Those users were removed from the sample due to missing data for the variables $tenure$, $mobileNet$ as well as the dummies that described the previous handset that they owned. The immediate consequence was the fact that 5 out of the 263 communities identified had also to be removed from the sample. After removing the adopters with missing data, the afore mentioned communities had no more adopters within, therefore they were perfect predictors of non-adoption for the remaining subscribers and this generated a problem of complete separation of the outcome (Albert and Anderson, 1984). Together these two operations eliminated 711 subscribers. Finally there were 269 other subscribers also removed from the sample because they lived in zip codes where no one else adopted the iPhone 3g. Again this created a problem of perfect separation of the outcome that we deal with by removing those observations from the sample.

We estimate our model using 258 communities with a total of $23,151$ subscribers of which $1,714$ adopted the iPhone 3g during the period of analysis.

Table 3.11: Observations used in the estimation of the empirical model

| | Adoption | | |
|---|---|---|---|
| Time | No | Yes | Total |
| 0 | 22,782 | 369 | 23,151 |
| 1 | 22,558 | 224 | 22,782 |
| 2 | 22,403 | 155 | 22,558 |
| 3 | 22,254 | 149 | 22,403 |
| 4 | 22,133 | 121 | 22,254 |
| 5 | 21,945 | 188 | 22,133 |
| 6 | 21,813 | 132 | 21,945 |
| 7 | 21,739 | 74 | 21,813 |
| 8 | 21,642 | 97 | 21,739 |
| 9 | 21,565 | 77 | 21,642 |
| 10 | 21,477 | 88 | 21,565 |
| 11 | 21,437 | 40 | 21,477 |
| Total | 263,748 | 1,714 | 265,462 |

Table 3.12 presents the results from estimating the model in equation 3.2. $frd\_adopters_{it-1}$ is the percentage of one's friends who adopted the iPhone 3G by time $t-1$. We find evidence of positive peer influence in the diffusion of the iPhone 3G both before and after instrumentation. This finding remains unchanged even after controlling for subscriber and community fixed effects as well as for regional heterogeneity. Column (1) in this table shows the results of the probit regression without community and regional fixed effects. Column (2) in this table show the results of the probit regression controlling for regional effects. Column (3) presents the probit regressions that controls for community effects in addition to all other fixed effects. In all cases, the coefficient for the percentage of friends who have already adopted the iPhone 3G is positive and highly significant.

Furthermore we note that in model (3) the inclusion of the community dummy variables reduces the coefficient associated with peer effects which highlights the fact that community dummy variables are capturing some heterogeneity in the adoption behavior.

The parameter estimates for the remaining controls are not the main concern of this paper and as such they are omitted from the table. For completeness we detail and discuss them in the appendix 3.A, but all estimates for the effect of the additional covariates behave as expected and are robust cross models, which increases our confidence in our IV strategy.

Table 3.12: Coefficient estimates for the discrete time hazard model

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Probit | Probit | Probit | IV Probit |
| VARIABLES | $adopted_{it}$ | $adopted_{it}$ | $adopted_{it}$ | $adopted_{it}$ |
| $frd\_adopters_{t-1}$ | 3.241*** | 3.247*** | 2.851*** | 9.935*** |
| | (0.269) | (0.256) | (0.258) | (1.952) |
| | | | | [2.087] |
| Observations | 265,462 | 265,462 | 265,462 | 265,462 |
| Community FE | No | No | Yes | Yes |
| Zip Code FE | No | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Other Covariates | Yes | Yes | Yes | Yes |
| Pseudo R2 | 0.112 | 0.117 | 0.157 | |
| Log Lik | -9192 | -9133 | -8721 | |

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

**Note** 1: Community clusters robust standard errors in () for Probit; **Note** 2: Newey estimator standard errors in () for IV Probit; **Note** 3: Community block-bootstrap standard errors in [] for IV Probit (200 replications) are used to calculate the significance level of the IV probit estimate **Note** 4: 265,462 observations included

Table 3.13 shows the Average Partial Effect (APE) for the effect of peer influence. For the standard probit estimator, the average partial effect is obtained from the partial derivatives of the expected value function $E[\Phi(\alpha+Z\delta)]$. The standard errors are computed through the Delta Method as suggested in (Wooldridge, 2002, p.471).

For the instrumental variable version of the estimator, we obtain the average partial effect using the formulas provided in (Wooldridge, 2002, p. 475) which are derived from the partial derivatives of the following equation:

$$E_v[\Phi(\alpha_p + Z\delta_p + \theta_p v)] \tag{3.3}$$

The subscript $p$ highlights that the two step procedure for the IV Probit estimates the parameters up to a scale factor. The variable $v$ in the expected value equation denotes the residuals from the first stage regression of the instrumental variable setup. For more details on the Newey IV estimator and the calculation of the partial effects refer to (Wooldridge and Imbens, 2007, section 6) where the procedure for averaging out these effects over time is also described in detail.

At any point in time, if all of one's friends adopted the iPhone 3G, the instantaneous probability of adoption would increase by 0.150. Taking into consideration the average number of friends in this sample this means that having one more friend who adopted the iPhone 3G increases the probability of adoption by 0.0045.

Table 3.13: Marginal effects for peer influence

| | (1) Probit $P(adopted_{it})$ | (2) Probit $P(adopted_{it})$ | (3) Probit $P(adopted_{it})$ | (4) IV Probit $P(adopted_{it})$ |
|---|---|---|---|---|
| APE | 0.053*** | 0.053*** | 0.045*** | 0.150*** |
| | (0.005) | (0.005) | (0.004) | [0.032] |
| Community FE | No | No | Yes | Yes |
| Zip Code FE | No | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Other Covariates | Yes | Yes | Yes | Yes |

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

**Note 1:** Community block-bootstrap standard errors in [ ]; **Note 2:** In Probit, cluster robust standard errors in parenthesis; **Note 3:** Partial effects for IV Probit calculated without resorting to the joint normality of the error terms between the first and second stage equations (Wooldridge, 2002, p. 475)

Figure 3.6 shows that with this level of effect peer influence must have been responsible for approximately 14% of all iPhone 3G adoption in the country analyzed during the 12 months after the release of this handset. Table 3.14 details the pseudo-code of the algorithm that we used to obtain such estimate.

Table 3.14: Pseudo-code for estimating peer influence based adoptions

| | |
|---|---|
| **Key variables** | |
| $m$ | Marginal effect of peer influence estimated through the IV probit model |
| $D(t)$ | Function that returns the marginal effect of time dummies |
| $N(t)$ | Function that returns the number of people who did not adopt the iPhone 3G at time $t$. For t=0 it returns the sample size. |
| $AVG\_FRD\_ADP(t)$ | Function that returns the sample average of the $frd\_adopters_{t-1}$ variable at time $t$ |
| $EAI(t)$ | Expected adoptions that occur due to peer influence |
| **Algorithm** | |
| | $m = 0.150$<br>**for** $t = 0 \rightarrow T$ **do**<br>$EAI(t) = N(t) * (m * AVG\_FRD\_ADP(t) + D(t))$<br>$N(t+1) = N(t) - EAI(t)$<br>**end for** |

Table 3.13 shows that the effect of peer influence increases significantly after instrumentation.

We note that budget constraints might explain the increase in the marginal effect of peer influence after instrumentation. For example, in the case of the iPhone 3G it is likely that not all members of the same family can purchase this expensive handset.

Our rational is that people within the same household will tend to call each other. Therefore, they will appear as friends in our social graph. When one household member adopts the iPhone 3G, budget constraints may deter the remaining members from adopting.

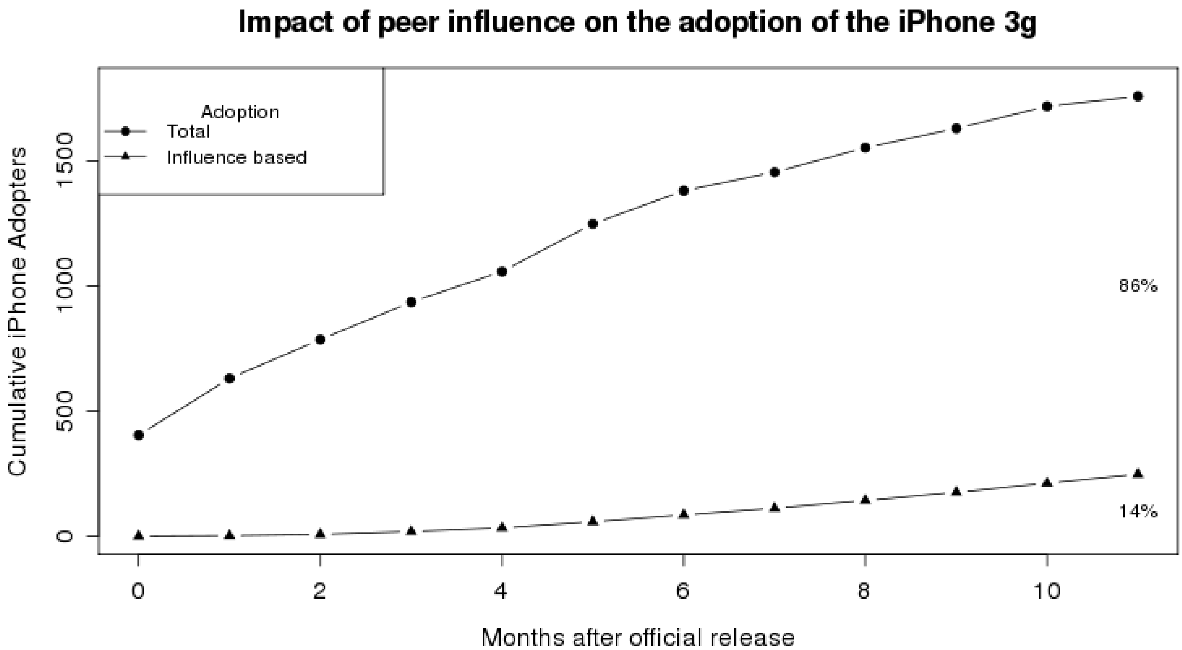



Figure 3.6: The role of peer influence in the adoption of the iPhone 3G

Say that $i$, $j$ and $k$ are members of the same household. Consider further that $i$ adopted the iPhone and that $j$ and $k$ could not adopt because of budget constraints. Then in our social graph, regardless of the number of adopter friends that $j$ and $k$ might have, they will never adopt because $i$ did (even if they wanted to adopt). It is this artifact that may downplay the estimates of peer influence when we do not use instrumental variables.

This type of constraint could cause the error term to be negatively correlated with our endogenous variable, which would explain why the magnitude of peer influence increases after instrumentation.

To shed more light on this issue we assume that all phone numbers in the same billing account belong to either the same person, people in the same family or employees of the same firm. While nothing prevents unrelated individuals to share the same phone bill such cases are certainly exceptions rather than the rule.

Figure 3.7 plots the number of iPhone 3G adopters in billing accounts with more than 1 and less than 6 phone numbers, most likely associated with families. This figure shows that most billing accounts have only one iPhone 3G. A similar picture is obtained when considering billing accounts with more than 5 phone numbers, most likely associated with firms. These facts are consistent with the hypothesis of budget constraints and reveal that firms did not massively adopt the iPhone 3G. Additionally our data also reveals that on average, for individuals in accounts with more than one phone number, about 20% of their friends belong to the same billing account and therefore intra account ties cannot be overlooked.

## 3.7 Robustness Checks

### 3.7.1 Instrument Robustness

To provide tests for the robustness of our instrument we perform four distinct analysis.

First, we compute the LPM version of model (3) in table 3.12 and compare their partial effects. We do so because the use of instrumental variables in the linear probability model is subject to less restrictive assumptions on the error distributions than the probit formulation. Additionally, as highlighted in(Wooldridge, 2002) and in (Allison, 1982), the LPM is often a good approximation to the average partial effect in the population. The result is provided in table 3.15. In this case, the 95% confidence interval for the coefficient of interest is $[0.07; 0.18]$ and thus the estimate obtained with LPM is not statistically

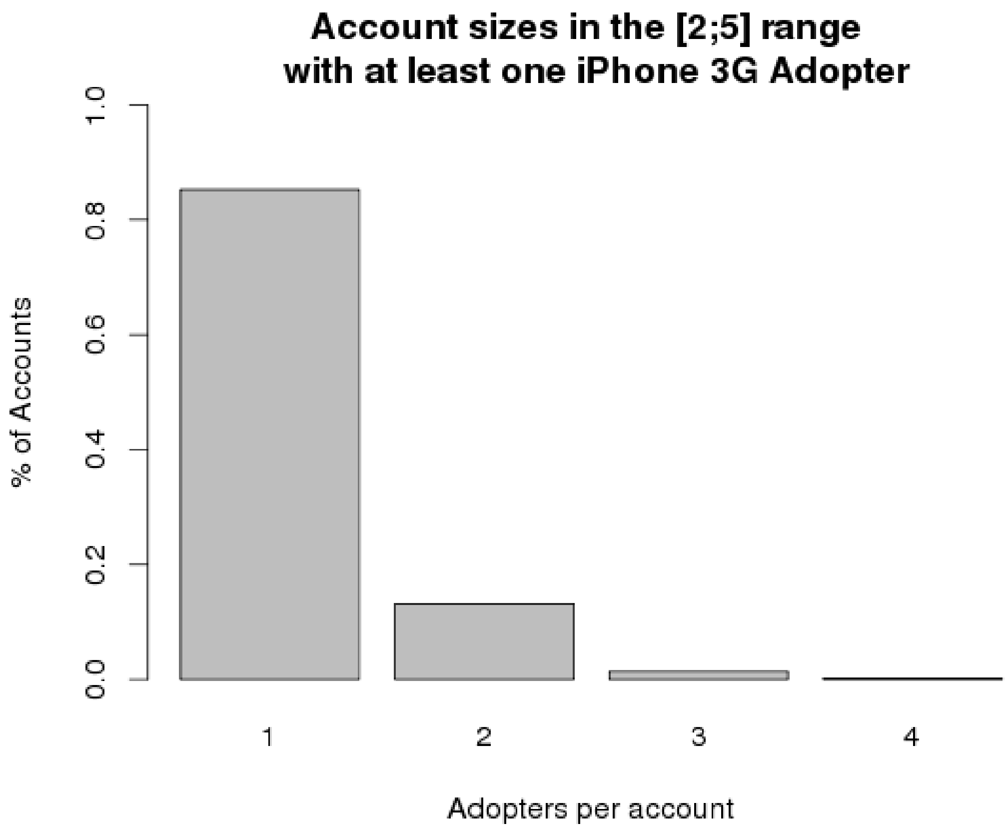



Figure 3.7: Percentage of accounts with less than six members per number of adopters

different from that obtained with IV probit which shows that our results are not exclusively dependent on the functional form assumed for the consumer purchase decision.

Second, in the same spirit of our original instrumental variable, we develop four alternative instruments. Namely $ffnf$, $wfwfnf$, $ffnf\_1path$ and $wfwfnf\_1path$.

$ffnf$ is the simplest version of the instrument described in section 3.5. It measures the proportion of $i$'s friends of friends who are not simultaneously $i$'s friends and who adopted the iPhone 3g. With $i$ as the ego, $wfwfnf$ is obtained by sorting all of her friends $j$ in decreasing order of the number of calls and text messages exchanged between them. $i$'s friends that are in the lower quartile in terms of number of interactions are called the weak

Table 3.15: Coefficient estimates for linear probability formulation

| VARIABLES | (1)<br>OLS<br>$adopted_{it}$ | (2)<br>2SLS<br>$adopted_{it}$ |
|---|---|---|
| $frd\_adopters_{t-1}$ | 0.058*** | 0.128*** |
| | (0.007) | (0.029) |
| Observations | 265,462 | 265,462 |
| Community FE | Yes | Yes |
| Zip Code FE | Yes | Yes |
| Month FE | Yes | Yes |
| Other Covariates | Yes | Yes |
| R2 | 0.015 | 0.015 |

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

**Note** 1: Community clusters robust standard errors in ();

friends. Then if $j$ is a weak friend of $i$ we consider $k$ a weak friend of $j$ that is not friend of $i$ to construct $wfwfnf$. Finally the $\_1path$ version of these instruments is obtained by ensuring that there is a single network path between the ego $i$ and the individual used as instrument $k$.

Table 3.16 details the estimate for the coefficient of interest using the different instrumental variables which in all cases is similar to the one reported in table 3.12. We also report the average partial effects implied by each coefficient which again are similar to our previous estimate.

Third, we use LPM to perform the under-identification and the Stock-Yogo Weak identification (Stock and Yogo, 2002) tests for all the instrumental variables. We report the results in table chp03:tab:first-stage. Due to the possibility of non i.i.d. errors, we follow the recommendation in (Baum et al., 2007) and use the *Kleibergen-Paap rk LM statistic* and the *Kleibergen-Paap rk Wald F statistic*, respectively, to perform these tests. In all cases we reject the null hypothesis. This means that we do not find evidence of under-

Table 3.16: Regression Results for the Alternative Instruments

| INSTRUMENT<br>VARIABLES | (1)<br>IV Probit<br>ffnfdc<br>$adopted_{it}$ | (2)<br>IV Probit<br>ffnf<br>$adopted_{it}$ | (3)<br>IV Probit<br>wfwfnf<br>$adopted_{it}$ | (4)<br>IV Probit<br>ffnf_1path<br>$adopted_{it}$ | (5)<br>IV Probit<br>wfwfnf_1path<br>$adopted_{it}$ |
|---|---|---|---|---|---|
| $frd\_adopters_{t-1}$ | 9.935*** | 7.864*** | 10.347*** | 9.037*** | 10.200*** |
| | (1.952) | (1.171) | (3.183) | (1.350) | (3.211) |
| | [2.087] | [1.185] | [2.761] | [1.228] | [3.116] |
| Observations | 265,462 | 265,462 | 265,462 | 265,462 | 265,462 |
| Community FE | Yes | Yes | Yes | Yes | Yes |
| Zip Code FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Other Covariates | Yes | Yes | Yes | Yes | Yes |
| $\chi^2$ p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| APE | 0.150*** | 0.120*** | 0.160*** | 0.142*** | 0.154*** |
| | [0.032] | [0.018] | [0.041] | [0.018] | [0.046] |

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

**Note** 1: Community clusters robust standard errors in () for Probit; **Note** 2: Newey estimator standard errors in () for IV Probit; **Note** 3: Community block-bootstrap standard errors in [] for IV Probit (200 replications) are used to calculate the significance level of the IV probit estimate

identification and that none of our instruments is weak[5].

Finally with the new instruments that we created, we use the linear probability model to perform a Sargan-Hansen test for over-identifying restrictions when we consider all five instruments at the same time. In such test, a rejection of the null hypothesis would cast doubts on the validity of all our instruments. The robust Hansen J Statistic is 7.451 ($p < 0.12$) which means that we cannot reject the null hypothesis that all our instruments correlate to the adoption decision only through the endogenous variable. This reinforces our confidence in the IV strategy and our instruments.

[5]Stock-Yogo did not tabulate the critical values for non i.i.d. errors, so we follow the recommendations in (Staiger and Stock, 1997) and (Baum et al., 2007) which suggest that for an F-stat above 10 weak identification is not usually a problem.

Table 3.17: First Stage Regression for IV Analysis

| INSTRUMENT VARIABLES | (1) IV Probit ffnfdc $frd\_adopters_{t-1}$ | (2) IV Probit ffnf $frd\_adopters_{t-1}$ | (3) IV Probit wfwfnf $frd\_adopters_{t-1}$ | (4) IV Probit ffnf_1path $frd\_adopters_{t-1}$ | (5) IV Probit wfwfnf_1path $frd\_adopters_{t-1}$ |
|---|---|---|---|---|---|
| $X\_adopters_{t-1}$ | 0.492*** | 1.204*** | 0.184*** | 1.067*** | 0.183*** |
| | (0.049) | (0.076) | (0.028) | (0.0672) | (0.028) |
| Observations | 265,462 | 265,462 | 265,462 | 265,462 | 265,462 |
| Community FE | Yes | Yes | Yes | Yes | Yes |
| Zip Code FE | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes |
| Other Covariates | Yes | Yes | Yes | Yes | Yes |
| Underidentification and Weak Instrument Tests: | | | | | |
| Kleibergen-Paap rK LM $\chi^2$ p-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| Kleibergen-Paap rK Wald F-stat | 99.975 | 252.762 | 42.927 | 252.323 | 42.362 |

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

**Note** 1: Community clusters robust standard errors in ()

### 3.7.2 Alternative Weight Matrices

Additionally to the robustness checks on the instrumental variable we also test several alternative specifications of the adjacency matrix to show that peer influence remains positive and statistically significant even when we change how definition of friendship.

In the model 3.2 we defined W as a row standardized version of the adjacency matrix defining the social network. The construction of the adjacency matrix was described in detail in section 3.3.

However, as discussed in (Leenders, 2002), an adjacency matrix relevant to study peer influence can be defined in different ways. These can yield different estimates for the effect of peer influence. For example, it is possible that each user assigns different weights to the behavior of her friends. To determine whether our estimates of peer influence are robust to alternative specifications of the adjacency matrix, we test alternative definitions of $A$ as below:

- **Number of interactions:** $a_{ij}$ is the total number of calls and text messages exchanged during the entire period of analysis. This would reflect the fact that one can assign more weight to the behavior of friends with whom one communicates more frequently;

- **Duration of interactions:** $a_{ij}$ is the sum of the duration of all calls during the entire period of analysis. This would also reflect the fact that one can assign more weight to the behavior of friends with whom one communicates more;

- **The Degree of the friends:** $a_{ij}$ is the degree of $j$ when $i$ called or sent an sms to $j$ and the latter answered back with a call or an sms within the same calendar month. This specification captures the fact that users may assign more weight to friends that are more connected. This might happen, for example, because communication with people with more friends is likely to provide more information about the new handset and possibly be more valuable.

Table 3.18 presents the results obtained[6].

We use mean centered and standardized versions of $frd\_adopters_{t-1}$ to allow for an easier comparison of the magnitude of peer effect across the different models. Furthermore, we estimate the effect of peer influence with each weight matrix at a time in a separate regression because we do not have enough instruments to include all of them in one fuller

[6] We show only estimates for the effect of peer influence because there are no significant changes in the sign and magnitude of the coefficients for the other covariates

regression.

Our results show that under all specifications the estimate of peer influence is positive and significant which adds to the robustness of our results. Furthermore, the confidence interval for the parameter estimates of models (3), (4), (5) and (6) overlap, the same being true regarding models (1) and (2) and models (2) and (6) thus we can't really interpret the difference in the results as being statistically significant.

Table 3.18: Heterogeneity of influence across alters

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | IV Probit | IV Probit | IV Probit | IV Probit | IV Probit | IV Probit |
| | $adopted_{it}$ | $adopted_{it}$ | $adopted_{it}$ | $adopted_{it}$ | $adopted_{it}$ | $adopted_{it}$ |
| $frd\_adopters_{t-1}$ weighed by ... | | Degree | Calls + SMS | Calls | SMS | Airtime |
| $std\_frd\_adopters_{t-1}$ | 0.327*** | 0.358*** | 0.814*** | 0.798*** | 0.756*** | 0.747*** |
| | (0.0643) | (0.0660) | (0.144) | (0.141) | (0.134) | (0.133) |
| Observations | 265,462 | 265,462 | 265,462 | 265,462 | 265,462 | 265,462 |
| Community FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Zip Code FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Other Covariates | Yes | Yes | Yes | Yes | Yes | Yes |

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

**Note** 1: Network tenure, Previous handset age as well as dummies for gender, previous handset technology, regional wage level, type of contract (pre/post paid) and subscription to mobile internet data plans prior to iPhone release included in all regressions. $std\_frd\_adopters_{t-1}$ is the same as variable $frd\_adopters_{t-1}$ , but mean centered and standardized to facilitate comparison across regressions. The instrument for $std\_frd\_adopters_{t-1}$ is the mean centered and standardized proportion of the subscriber's $i$ friends of friends that are not simultaneously $i$'s friends and that spend most of their time in regions with different NUTS-III code than $i$ himself. **Note** 2:Newey estimator standard errors in parentheses

### 3.7.3 The impact of having a time varying social network

A central hypothesis of our analysis is that social ties inferred from the communication network of the EURMO are stable over the 11 month period that we analyze. To relax this assumption we use SIENA (Snijders et al., 2010). SIENA is an implementation of Stochastic Actor-Based Models for the Co-evolution of Network Dynamics and Behavior (SAMCNDB) (Snijders et al., 2010) that can be used to model the dynamics of link formation across members of a social network and the relationships between the emerging social network structure and behavior (Snijders et al., 2010).

#### The Mechanics of SIENA

SIENA requires two or more snapshots of the social network and of the behavior of interest. Additional individual and network characteristics that may affect tie formation and behavior can be added to the model to increase its explanatory power. Agents play a game that establishes a path from one snapshot to the next. At every discrete point in time, called mini-step, one agent is selected to take action. For each actor, the time between mini-steps is modeled as a Poisson process with a constant rate parameter $\lambda$ common to all actors. Two types of actions can occur. At a network mini-step actors create or eliminate a tie in the social network. They do so to maximize the utility given by a network objective function of the form $f_i(B, x) = \sum_k B_k S_{ki}(x)$, which is a sum over all effects $k$ of the utility associated with each effect, $S_{ki}(x)$, weighted by a scaling factor, $B_k$. The utility associated with an effect depends on the state of the network, $x$. At a behavioral mini-step actors can change their behavior. In the case of the diffusion of the iPhone 3G, at such a mini-step, actors choose whether they want to adopt this handset. They do so to maximize the utility given by a behavioral objective function of the form $f_i^Z(B^Z, x, z) = \sum_{\tilde{k}} B_{\tilde{k}}^Z S_{\tilde{k}i}(x, z)$, which is the sum over all effects $\tilde{k}$ of the behavioral utility associated with each effect, $S_{\tilde{k}i}^Z(x, z)$, weighted by a scaling factor, $B_{\tilde{k}}^Z$. In this case, utility depends not only on the state of the network but also on the current behavior of all other agents, $z$.

Functions $S$ and $S^Z$ represent effects that according to social network theory influence tie formation and behavior, respectively. Examples include transitivity: friends of friends are likely to become friends, and homophily: people who are similar and behave similarly are likely to become friends. Borrowing from the econometric theory of random utility models, SIENA introduces a separable unobservable in the utility function of each actor. Such error term is assumed to follow a type one extreme value distribution with mean 0 and a scale parameter normalized to 1. As a consequence the probability with which an actor chooses an action is characterized by a multinomial logit function. For example, at each network mini-step the probability that action $a$ is selected across all actions in action space $A$ is given by $e^{f_i(B,x(a)))} / \sum_{a \in A} e^{f_i(B,x(a')))}$.

Parameters $B_k$ and $B_k^Z$ together with the rate parameter $\lambda$, which determines the waiting time between actors' actions, form a vector that parameterizes the probability distribution of a Markov process that captures the dynamics of the game described above. The likelihood function of such process is often impossible to determine analytically (Snijders, 1996). For this reason, SIENA estimates the parameters using a method of moments. The solutions for the moment equations are approximated using Monte Carlo simulation (Snijders, 2001).

SIENA requires that both network and behavioral changes between consecutive snapshots embody enough variance to allow for estimating the parameters of interest. However, such changes cannot be so large as to challenge the assumption that snapshots are indeed observations of a network that is gradually changing over time (Snijders et al., 2010). For this reason, below we detail very carefully how we prepare our sample to fit the SIENA model.

### Preparing the sample and choosing the model variables

Let $[t_1; t_2]$ denote a period starting in the first day of month $t1$ and finishing in the last day of month $t2$. For each community in the sample, we break the eleven months of communication data that we have in two distinct and non overlapping periods that we use to parameterize the SIENA. Several time partitions were possible. We choose to focus on partition $[1; 4] - [5; 11]$. This break down of the sample provides a good balance between the time span of each period as well as the number of adoption events in both periods (1058 adoptions in the first snapshot and 700 adoptions in the second snapshot). Several alternative partitions were considered and tested which did not affect the results. Appendix 3.D provides the output for all possible two-snapshot combinations.

For partition $[1; 4] - [5; 11]$, the changes in the social network across time are small, that is, a substantial proportion of the ties linking individuals in each of the communities in the sample remains unchanged from the first to the second period. This is evidence that the social network structure is rather stable and that the communication links captured in the communication network are likely to entail real social meaning rather than sporadic communication interaction.

Still, for these two periods, there are communities in our sample with little variation in the adoption of the iPhone 3G across time. In 30 communities (out of 263) there is no variability in adoption behavior from the first to the second period and for 80 others, there is variation in behavior, but too little change for SIENA to converge to acceptable levels in the behavioral part of the model.

For each community and time period, we create an adjacency matrix $A_{ct}$ with $a_{ctij} > 0$ indicating that user $i$ in community $c$ called or sent an sms to user $j$ during time period $t$. We use a vector $y_{ct}$ to register the behavior of interest. $y_{cti} > 0$ indicates that user $i$ owned the iPhone 3G during the time period $t$[7]. These variables are the main parameterizations of the SIENA model.

Additionally, to explain the evolution of the social network, we include in our SIENA model, the effect of $outdegree = \sum_j a_{ctij}$ that measures the overall tendency to form ties which are costly to establish and to maintain, $reciprocity = \sum_j a_{ij}a_{ji}$ that controls for the fact that people tend to return calls and sms from their friends and $transitivity = \sum_j a_{ij}max_h(a_{ih}, a_{hj})$ to account for triad closure bias, that is, people tend to communicate with the friends of their friends. We also include the effect of $adoptionsimilarity = \sum_j a_{ij}(sim_{ij} - \overline{sim_i})$ with $sim_{ij} = 1\{y_i = y_j\}$ that captures the tendency that individuals may establish links to other individuals that display the same behavior. This effect estimates homophily in the adoption of the iPhone 3g, in other words, the impact that the adoption of the iPhone 3g will have in the structure of the social network. For ease of

[7]No subscriber in our sample adopted the iPhone 3G and then switched to another handset.

comprehension we named this effect $Behavior- > Network$.

To explain behavior we focus on the effect $adoptionaveragesimilarity = \sum_j a_{ij} sim_{ij} / \sum_j a_{ij}$ that controls for influence and is scaled by the size of the social circle. In this case, the effect captures the level of exposure that each user has to the innovation. We identify this effect by $Network- > Behavior$.

SIENA provides several alternative effects that allow controlling for influence and homophily. We chose the ones reported above following the recommendations in (Ripley and Snijders, 2010) and (Snijders et al., 2010). The adoption of the iPhone is coded as binary event and the SIENA manual recommends the utilization of covariate similarity for controlling homophilous attachment in such cases. Finally, we chose the influence effect $adoptionaveragesimilarity$ because it reflects the concept of exposure (Valente, 1996b) and it permits an interpretation that is possible to compare with the marginal effect of peer influence that we estimate in the previous sections of the paper.

**SIENA model output**

We fit SIENA to each community in our sample. For the communities such that SIENA converges, we obtain estimates for the set of parameters described above. We combine the estimation results of the different parameters across the different communities using meta-analysis (Hedges and Olkin, 1985; DerSimonian and Laird, 1986; Viechtbauer, 2010) to obtain a summary effect.

We estimate the summary effect for each variable in our model through a random-effects model to allow the true effect of each parameter to vary across communities rather than impose a true value of the effect shared by all(DerSimonian and Laird, 1986). We use a restricted maximum likelihood estimator to obtain the summary effect (Paule and Mandel, 1982; Rukhin et al., 2000) and we use the standard error bias correction suggested by (Knapp and Hartung, 2003)[8].

For each coefficient summary effect estimate, we perform a $Q$-test of heterogeneity (Huedo-Medina et al., 2006). The null hypothesis of the test assumes that the true value of the parameter is the same across the communities included in the estimation procedure(Higgins and Thompson, 2002; Huedo-Medina et al., 2006). For a given parameter, if the null hypothesis of the $Q$-test is rejected, there is evidence of unobserved heterogeneity explaining the difference in the parameter estimates across communities that is not attributable to sampling error. Such scenario provides an argument against reporting a single summary effect for the set of communities. On the contrary, if the null hypothesis of the $Q$-test is not rejected, we are more confident that differences in the parameter estimates across communities are a consequence of sampling error and the summary effect may be interpreted as an estimator for the true parameter value in the population(Higgins and Thompson, 2002).

To provide a more complete picture of the analysis we also report the $I^2$ index which measures the percentage of the total variation in effect sizes across communities that is caused by between-studies variability (unobserved heterogeneity in our communities)(Huedo-Medina et al., 2006).

Table 3.19 contains the results. We highlight that the effect of peer influence, measured

[8]Nevertheless, using other estimators such as the DerSimonian-Laird estimator, Maximum Likelihood or Empirical Bayes yields similar results in this case

by the parameter $Network- > Behavior$ is positive and statistically significant at the 1% level. We find influence even in the presence of a changing social network over time. For this parameter, we cannot reject the null hypothesis of the $Q$-test, as such the summary effect can be interpreted population wise with respect the communities in our analysis. Furthermore, the $I^2$ index for this effect is essentially zero which implies that the variation in the estimation results that occurs across communities can be attributable to sampling error.

$Behavior- > Network$ is positive, but not statistically significant across the communities. The $Q$-test provides evidence of heterogeneity across communities sampled for this effect. Moreover $I^2$ is large. These results do not provide sufficient proof of the role homophily may have played in the diffusion of the iPhone 3G, that is, we do not find robust evidence that similar behavior in terms of adoption of the iPhone 3g leads to changes in the network ties.

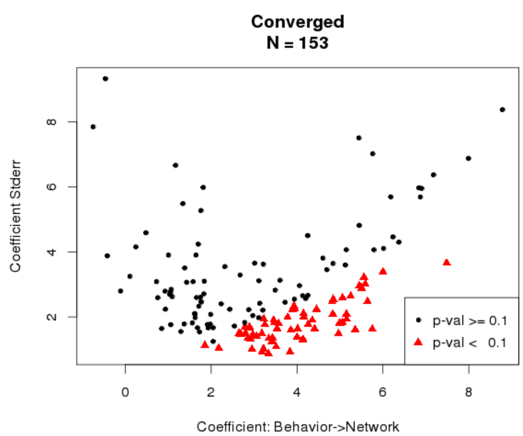
Figure 3.8 is a scatter plot of the 153 estimates of the coefficients of influence (top panel) and homophily (bottom panel) together with their standard errors and statistically significance. The picture shows that the $Behavior- > Network$ coefficient varies significantly across communities. In some cases, the effect of is negative and significant, in other communities it is positive and significant. Still, for a majority of the scenarios, the effect is close to zero and not statistically significant.

We note that for the other variables, the $Q$-test rejects the null hypothesis and the corresponding $I^2$ is large which implies that there are unobservables deriving the variation of those parameters across the communities. Nevertheless, the coefficients obtained from the meta-analysis exhibit the expected signs. This means that, on average, across the communities we sampled, they behave as theory predicts. Random ties are not likely to form and reciprocity and transitivity have a positive impact on tie formation.

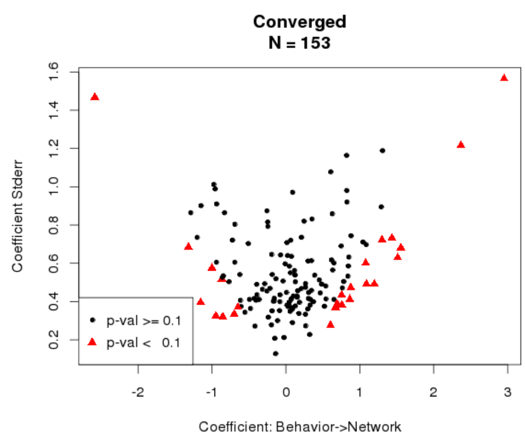
Table 3.19: Results of the meta-analysis for each of the behavioral and network effects included in the SIENA model

| name | coeff | stderr | pval | $I^2$ | $H^2$ | $\tau^2$ | Q-Test | Q-Test (p-val) | N obs |
|---|---|---|---|---|---|---|---|---|---|
| outdegree (density) | -4.414 | 0.043 | 0.000 | 62.851 | 2.692 | 0.182 | 543.708 | 0.000 | 153 |
| reciprocity | 4.398 | 0.067 | 0.000 | 75.399 | 4.065 | 0.448 | 782.592 | 0.000 | 153 |
| transitive ties | 2.174 | 0.034 | 0.000 | 51.141 | 2.047 | 0.086 | 345.009 | 0.000 | 153 |
| $Behavior- > Network$ | 0.043 | 0.044 | 0.334 | 24.219 | 1.320 | 0.061 | 208.778 | 0.002 | 153 |
| $Network- > Behavior$ | 3.168 | 0.102 | 0.000 | 0.000 | 1.000 | 0.000 | 62.002 | 1.000 | 153 |

**Note 1:** variable $Behavior- > Network$ is captured by the $behaviorsimilarity$ SIENA effect; **Note 2:** variable $Network- > Behavior$ is implemented through the $behavioraveragesimiliraty$ SIENA effect; **Note 3:** Meta analysis estimated through Maximum Likelihood assuming a random effects model with Knapp and Hartung standard error correction; **Note 4:** $\tau^2$ is the estimate of total amount of heterogeneity, $I^2$ is the % of total variability due to heterogeneity, $H^2$ is $\frac{totalvariability}{samplingvariability}$.




(a) $Network- > Behavior$




(b) $Behavior- > Network$

Figure 3.8: Scatter plot for the 153 estimates of the $Network- > Behavior$ and $Behavior- > Network$ variables of the SIENA model

**Interpretation of the effect**

In SIENA, for a behavioral mini-step of the simulator, the log-odds ratio of adoption vs. no adoption for the $Network- > Behavior$ is given by $\beta(Ad - NAd)/(Ad + NAd)$. $Ad$ denotes the number of friends that adopted the iPhone 3g, $NAd$ denotes the number of friends that did not adopt the iPhone 3G and $\beta$ denotes the coefficient of the effect[9].

For a subscriber $i$ for whom all friends $j$ have adopted the iPhone 3g ($NAd = 0$), the log-odds simplifies to $\beta$. Therefore, the odds ratio of adoption vs no adoption is $\frac{\frac{p'}{1-p}}{\frac{p}{1-p}} = exp(3.168) = 23.760$ where $p$ denotes the probability of adoption for an individual for whom all his friends adopted and $p'$ denotes the probability of adoption for an individual whom no friend adopted the handset.

A comparable figure can be computed for the probit model presented in section 3.6.

Using the model estimated in section 3.6, we estimated that the average instantaneous probability of adoption of across the individuals that had no prior adopter friends is 0.006. Using instrumental variables, we estimate that for a user whom all friends adopted the iPhone 3g, the instantaneous probability of adopting would increase by 0.150 with a standard error of 0.032. Such information can be used to compute the odds ratios of having all friends adopting the iPhone versus no friend adopting which is comparable to the odds ratio that SIENA estimates.

At the mean of the confidence interval of the marginal effect of peer influence, the odds ratio for the probit formulation is given by $\frac{\frac{p'}{1-p'}}{\frac{p}{1-p}} = \frac{\frac{0.006+0.150}{1-(0.006+0.150)}}{\frac{0.006}{1-0.006}} = 30.6$. At the lower end of the confidence interval for the marginal effect, the odds ratio is $\frac{\frac{p'}{1-p'}}{\frac{p}{1-p}} = \frac{\frac{0.006+0.087}{1-(0.006+0.0087)}}{\frac{0.006}{1-0.006}} = 16.9$.

[9]Additional details can be obtained from (Ripley and Snijders, 2010, page 148)

This shows that magnitude of the influence effect estimated through SIENA is in the same order of magnitude of that reported in the previous sections of the paper.

## 3.8 Policy Experiment

In this section we estimate whether common heuristic marketing strategies, such as those described in (Bampo et al., 2008) and (Hinz et al., 2011) could have helped spread further the adoption of the iPhone 3G at EURMO. For this purpose, we code a simulator that computes the additional expected number of adopters as a function of a particular seeding strategy. Table 3.20 presents the pseudo-code for our simulator. At the outset $n$ seeds are selected to adopt the iPhone 3G. The probability of adoption for each individual evolves over time according to the adjacency matrix $W$ for the set of users considered, $S$, and a fixed exogenous marginal effect for peer influence, $m$. To keep our simulator sufficiently simple we disregard influence across paths through subscribers that do not belong to $S$ and we assume the same marginal effect for all subscribers in $S$. The number of adopters evolves according to this dynamic probability up to time $T$, which we set to 12 months in our simulations. In table 3.20 $A(0) = Policyk(n, m, S)$ instantiates the seeding policy.

Table 3.21 summarizes the seeding strategies that we investigate and figure 3.9 shows the results we obtained. Panel (a) in this figure shows the number of additional adopters as a function of the seeing policy and of the number of iPhone 3G awarded. The random strategy performs the poorest and local degree yields the most additional adopters. Panel (b) in this figure shows the cost/revenue ratio, $C/R$, for which each policy breaks-even. While the random strategy could only break even if the cost to produce the iPhone 3G is

Table 3.20: Pseudo-code for policy simulator

| **Key variables** | |
|---|---|
| $k$ | policy indicator (0 for no policy) |
| $n$ | number of policy seeds |
| $m$ | marginal peer influence effect |
| $S$ | set of subscribers |
| $\hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\rho}$ | parameters from probit estimation |
| $W$, $X_i$, $Z_{it}$ | covariates in equation (6) |
| $AO(i,t)$ | adoptions observed in our dataset |
| $A(i,t)$ | adoptions generated in simulation |
| $BPA(i,t)$ | baseline probability of adoption |
| $PA(i,t)$ | probability of adoption |

**Algorithm**

```
function SIMULATOR(k,n,m,S)
    TotalAA = Σ_{j=1}^{N} (AA(k,n,m,S) − AA(0,0,m,S))
    return TotalAA/N − n
end function

function AA(k,n,m,S) - Additional Adopters
    A(0) =Policyk(n,m,S)
    for t = 0 → T, i ∈ S do
        BPA(i,t) = Φ(α̂ + X_i β̂ + γ̂ Z_it + ρ̂ W AO(t − 1))
    end for
    for t = 0 → T, i ∈ S : A(i,t) == 0 do
        PA(i,t) = BPA(i,t) + mW(A(t − 1) − AO(t − 1))
        A(i,t) = 1{draw U(0,1) > PA(i,t)}
    end for
    return Σ_{i∈S} A(i,T)
end function
```

no more than 20% of the revenue, the local and global degree strategies can break even at higher ratios. Policy $k$ breaks even if $AA(k,n,m,S)(R - C) = nC$. According to iSuppli `http://www.isuppli.com/` the iPhone 3G marginal cost is roughly 50% of the revenue. If this estimate is true panel (b) in Figure 3.9 shows that all the policies tested here can hardly break even.

Table 3.21: Policy Interventions Tested

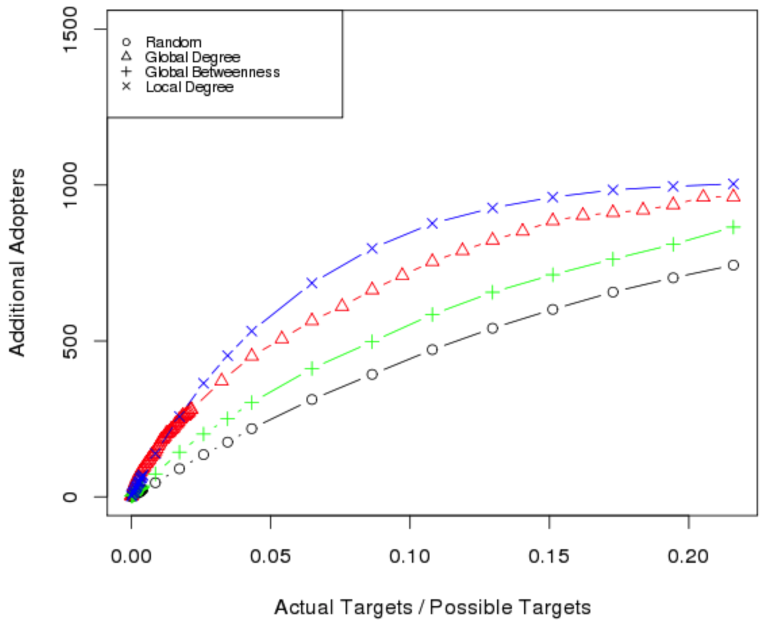
| Policy $t = 0$ | Policy Description |
|---|---|
| Random | Award the iPhone 3G to a random sample of $n$ subscribers in $S$ |
| Global Degree | Award the iPhone 3G to the $n$ subscribers in $S$ with highest degree |
| Global Betweenness | Award the iPhone 3G to the top $n$ subscribers in $S$ with highest betweenness |
| Local Degree | Randomly select $n$ communities with replacement and at each draw award the iPhone 3G to the subscriber with the highest degree in that community still without one |

Figure 3.10 shows a sensitivity analysis on the marginal effect of peer influence for the case of global degree, which is the most popular seeding strategy used by firms to explore viral marketing (Hinz et al., 2011). Panel (a) in this figure shows that this seeding strategy can only break even if the marginal effect of peer influence is substantially higher than our IV probit estimation. Still, panel (b) in this same figure, derived assuming $C = 300$ and $R = 600$, shows that with high levels of peer influence viral marketing strategies can sometimes increase expected profits by as much as 50%.

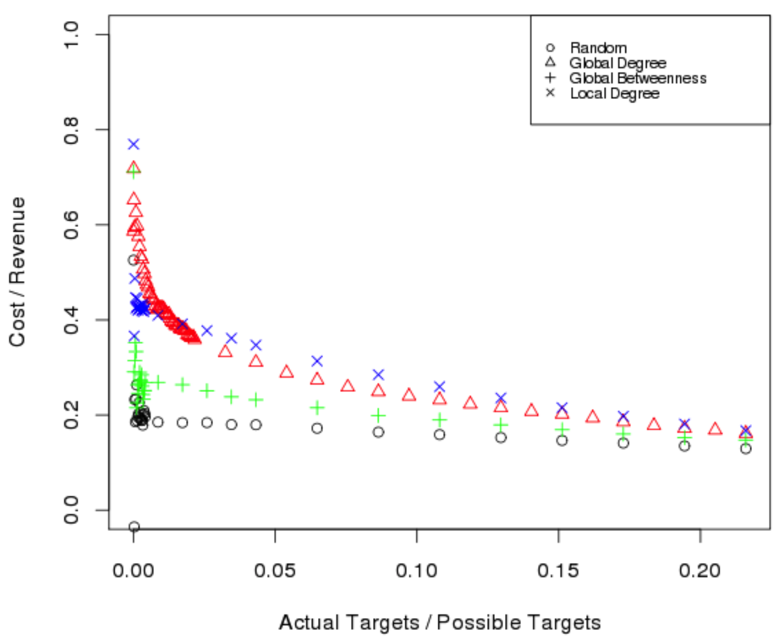
## 3.9 Conclusion

This paper studies the effect of peer influence in the diffusion of the iPhone 3G across a number of communities that were sampled from a large dataset from a major European Mobile (EURMO) carrier in one country.

We use instrumental variables to control for potential correlation between unobserved subscriber heterogeneity and peer influence. Our goal was to show whether there is a relationship between the percentage of friends who adopt the iPhone 3G and one's propensity to do so. We instrument the friend's decision to adopt with the adoption decisions of

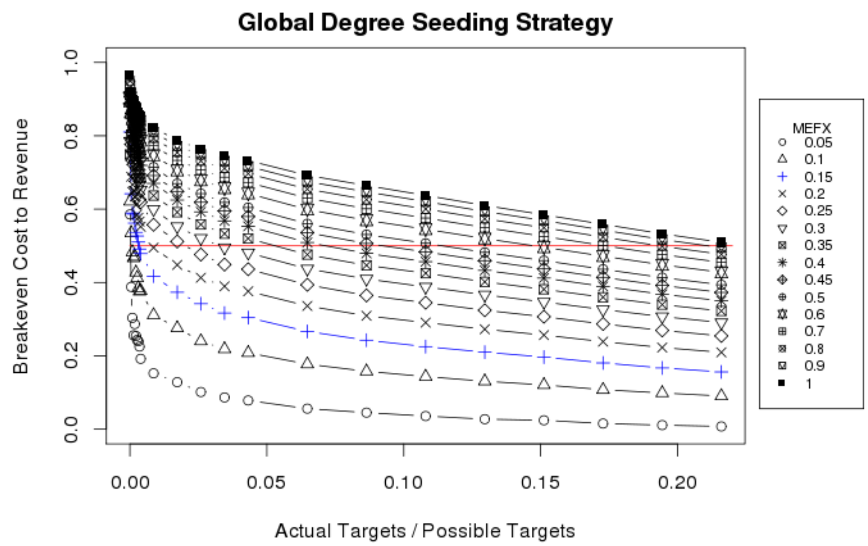



(a) Additional Adopters

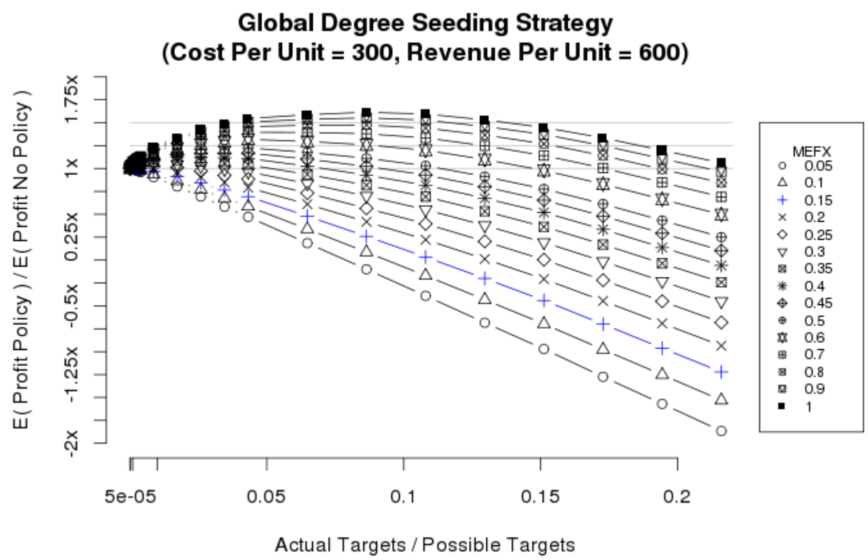



(b) C/R for breakeven

Figure 3.9: Policy outcomes of awarding the iPhone 3G to different numbers of policy targets




(a) C/R for breakeven




(b) Additional profits

Figure 3.10: Potential profits from seeding the iPhone 3G with global degree

the friends of friends that are not friends of the ego that live in a different city from the one where the ego does. This instrument explains well the adoption decisions of friends and provides separation, both geographically and in terms of the call graph, between the instrument and the ego. In fact, we provide several robustness checks that show that our instrument behaves as expected.

We provided evidence that the propensity of a subscriber to adopt increases with the percentage of friends that had already adopted. We estimated that 14% of iPhone 3G adoptions in EURMO were due to peer influence, after controlling for social clustering, gender, previous adoption of mobile internet data plans, ownership of technologically advanced handsets and some heterogeneity in the regions where subscribers move during the day and spend most of their evenings. Our estimate for peer influence without IV is three times lower that the above statistic, which hints that unobserved effects might be negatively correlated with adoption. We provide additional empirical evidence that budget constraints might be at work preventing several family members, or many employees in the same company, from purchasing the iPhone 3G, which was a conspicuous and expensive handset for the average consumer in the country studied.

We also provide results from several policy experiments that show that with an effect of peer influence with this magnitude EURMO would hardly be able to significantly increase sales by selectively targeting appropriate early adopters to benefit from viral marketing. We show that a seeding strategy using local degree yields the largest number of additional adopters among the strategies compared in this paper, but even such policy could only hardly break even for the cost/revenue ratio at which the iPhone 3G might have been commercialized.

Our paper also comes with limitations. On one-hand, our analysis relies on a random sample of clusters of subscribers that call more within the cluster. We used this technique to sample our dataset to control for unobserved con founders that could determine adoption and social network ties. That is particularly important given our IV strategy that relies on the actual structure of the social network. However, this clustering criterion is not unique and multiple runs of our sampling algorithm could also produce slightly different community structures.

We attempted to use other algorithms of community extraction to repeat the analysis, but we show in this paper that the community algorithms that are able to deal with very large networks such as our own, do not provide partitions of the data that would be useful for the type of analysis that we conduct.

On the other hand, we use communication events as a proxy for social proximity, but we only have access to text and voice communications. It is possible that people use other means of communications, such as e-mail and face to face meetings, that can just as equally spread information about the iPhone 3G and trigger or hinder adoption. However, we are not able to control for them in our case.

Finally we only use data from EURMO but other mobile operators in the same country also offered the iPhone 3G. Therefore, it is possible that friends that do not subscribe to EURMO might have also played a role in shaping the diffusion of the iPhone 3G across EURMO subscribers, but we are unable to account for them. Still in the country in question, EURMO is a dominant player with respect to the adoption of the iPhone 3G. Only two operators licensed agreements for this handset from day one of its release (the other major operator in the country launched the iPhone 3G only much latter): EURMO, whose market share is approximately 40%, and another operator, whose market share is about 17%. Therefore, it is likely that most iPhone adoption occurred with EURMO.

Furthermore, the prices at which these two operators offered the iPhone 3G were similar and thus it is hard to believe that there was disproportionately more adoption with the other carrier. Additionally, in the country analyzed, the prices to call someone in other networks are considerably higher than those to call within the same operator (on average the former is 40% more expensive), therefore a majority of one's friends belongs to the same operator. In fact, from the data we have, on average, each month, EURMO subscribers call seven times more other EURMO subscribers than subscribers in any other network. Therefore, it is even more likely that one's friends adopting the iPhone belong to the same carrier.

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## 3.A Full Regression Results

Table 3.22 provides the details for the regression equation presented earlier in table 3.12 and table 3.23 details LPM alternatives that were presented in section 3.7.

Table 3.22: Complete output for the model presented in table 3.12

| Variables | (1) Probit $adopted_t$ | (3) Probit $adopted_t$ | (4) IV Probit $adopted_t$ |
|---|---|---|---|
| $frd\_adopters_{t-1}$ | 3.240*** | 2.851*** | 9.935*** |
| | (0.269) | (0.258) | (1.952) |
| | | | [2.087] |
| $Log(tenure_t + 1)$ | 0.350*** | 0.300*** | 0.329*** |
| | (0.0975) | (0.101) | (0.0955) |
| | | | [0.103] |
| $Log(tenure_t + 1)^2$ | -0.0407*** | -0.0330** | -0.0370*** |
| | (0.0131) | (0.0138) | (0.0127) |
| | | | [0.0139] |
| $prepaidY$ | -0.444*** | -0.549*** | -0.508*** |
| | (0.0250) | (0.0283) | (0.0274) |
| | | | [0.0307] |
| $genderF$ | -0.0427 | -0.0616* | -0.0572 |
| | (0.0339) | (0.0343) | (0.0332) |
| | | | [0.0351] |
| $genderM$ | 0.151*** | 0.144*** | 0.143*** |
| | (0.0250) | (0.0271) | (0.0261) |
| | | | [0.0275] |
| $mobileNetY$ | 0.449*** | 0.425*** | 0.398*** |
| | (0.0434) | (0.0427) | (0.0397) |
| | | | [0.0445] |
| $phone2.5g$ | 0.511*** | 0.484*** | 0.469*** |
| | (0.0525) | (0.0547) | (0.0536) |
| | | | [0.0581] |
| $phone3.0g$ | 0.667*** | 0.637*** | 0.628*** |
| | (0.0516) | (0.0542) | (0.0537) |
| | | | [0.0596] |
| $phone3.5g$ | 0.930*** | 0.917*** | 0.876*** |
| | (0.0631) | (0.0658) | (0.0640) |
| | | | [0.0735] |
| $phoneOther$ | 0.521*** | 0.575*** | 0.503*** |
| | (0.138) | (0.142) | (0.140) |
| | | | [0.162] |
| $phoneAge$ | -0.197*** | -0.143*** | -0.152*** |
| | (0.0527) | (0.0551) | (0.0512) |
| | | | [0.0601] |
| $phoneAge^2$ | 0.0413* | 0.0256 | 0.0279 |
| | (0.0240) | (0.0251) | (0.0240) |
| | | | [0.0273] |
| $geoWageH$ | 0.0940*** | 0.133*** | 0.113*** |
| | (0.0317) | (0.0431) | (0.0381) |
| | | | [0.0420] |
| $geoWageL$ | -0.0259 | -0.146 | -0.111 |
| | (0.126) | (0.142) | (0.150) |
| | | | [0.150] |
| $geoWageVH$ | 0.117*** | 0.198*** | 0.150*** |
| | (0.0397) | (0.0563) | (0.0510) |
| | | | [0.0540] |
| Constant | -3.234*** | -3.602*** | -3.652*** |
| | (0.189) | (0.214) | (0.310) |
| | | | [0.249] |
| Observations | 265,462 | 265,462 | 265,462 |
| Community FE | No | Yes | Yes |
| Zip Code FE | No | Yes | Yes |
| Month FE | Yes | Yes | Yes |
| Pseudo R2 | 0.112 | 0.157 | |
| Log Lik | -9192 | -8721 | |

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

**Note** 1:Community clusters robust standard errors in () for Probit **Note** 2:Newey estimator standard errors in () for IV Probit **Note** 3:Community block-bootstrap standard errors in [] for IV Probit based on 200 replications

The sign of the controls is consistent with what one would expect prior to running the

Table 3.23: Complete output for the model presented in table 3.15

| VARIABLES | (1)<br>OlS<br>$adopted_t$ | (2)<br>OlS<br>$adopted_t$ | (3)<br>OlS<br>$adopted_t$ | (4)<br>2SLS<br>$adopted_t$ |
|---|---|---|---|---|
| $frd\_adopters_{t-1}$ | 0.0713*** | 0.0701*** | 0.0576*** | 0.129*** |
| | (0.00745) | (0.00736) | (0.00687) | (0.0288) |
| $Log(tenure + 1)$ | 0.00609*** | 0.00576*** | 0.00469** | 0.00501*** |
| | (0.00173) | (0.00174) | (0.00182) | (0.00180) |
| $Log(tenure + 1)^2$ | -0.000676*** | -0.000636*** | -0.000468* | -0.000512** |
| | (0.000239) | (0.000241) | (0.000252) | (0.000248) |
| $prepaidY$ | -0.00719*** | -0.00726*** | -0.00857*** | -0.00815*** |
| | (0.000540) | (0.000539) | (0.000618) | (0.000624) |
| $genderF$ | -0.000510 | -0.000528 | -0.000644 | -0.000599 |
| | (0.000381) | (0.000377) | (0.000400) | (0.000396) |
| $genderM$ | 0.00204*** | 0.00200*** | 0.00195*** | 0.00195*** |
| | (0.000464) | (0.000462) | (0.000496) | (0.000493) |
| $mobileNetY$ | 0.0272*** | 0.0271*** | 0.0266*** | 0.0263*** |
| | (0.00404) | (0.00401) | (0.00388) | (0.00387) |
| $phone2.5g$ | 0.00313*** | 0.00313*** | 0.00263*** | 0.00247*** |
| | (0.000313) | (0.000311) | (0.000290) | (0.000310) |
| $phone3.0g$ | 0.00582*** | 0.00578*** | 0.00492*** | 0.00483*** |
| | (0.000404) | (0.000406) | (0.000394) | (0.000406) |
| $phone3.5g$ | 0.0191*** | 0.0191*** | 0.0183*** | 0.0179*** |
| | (0.00211) | (0.00211) | (0.00203) | (0.00201) |
| $phoneOther$ | 0.00256 | 0.00267 | 0.00294 | 0.00221 |
| | (0.00257) | (0.00257) | (0.00256) | (0.00260) |
| $phoneAge$ | -0.00334*** | -0.00326*** | -0.00195** | -0.00206** |
| | (0.000893) | (0.000888) | (0.000907) | (0.000911) |
| $phoneAge^2$ | 0.000850** | 0.000834** | 0.000458 | 0.000486 |
| | (0.000371) | (0.000369) | (0.000375) | (0.000378) |
| $geoWageH$ | 0.00147*** | 0.00144*** | 0.00166*** | 0.00145*** |
| | (0.000442) | (0.000547) | (0.000558) | (0.000558) |
| $geoWageL$ | 7.56e-05 | -0.000554 | -0.00151 | -0.00117 |
| | (0.00120) | (0.00146) | (0.00134) | (0.00129) |
| $geoWageVH$ | 0.00207*** | 0.00228** | 0.00258*** | 0.00211** |
| | (0.000671) | (0.000895) | (0.000855) | (0.000849) |
| Constant | 0.00300 | 0.00782 | 0.00680 | 0.0316** |
| | (0.00302) | (0.00902) | (0.0132) | (0.0134) |
| Observations | 265,462 | 265,462 | 265,462 | 265,462 |
| R-squared | 0.011 | 0.011 | 0.015 | 0.015 |
| Community FE | No | No | Yes | Yes |
| Zip Code FE | No | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |

Community clustered standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

model. This is true both before and after instrumentation.

People with previous plans of mobile internet were more likely to adopt the iPhone 3g and the same was true for subscribers using handsets superior to 2g technology prior to the iPhone release.

EURMO subscribers that spent most of their day time in regions with very high or high average wage levels were more likely to adopt than individuals spending most of their time in regions with wages close to the national average. The opposite was true for subscribers moving in low and very low wage regions, the latter perfectly predicting non-adoption and as such dropped from the binary outcome model.

Users subscribing to prepaid tariff plans before the iPhone release were less likely to adopt which is as expected. The explanation is one of price since in order to buy the iPhone 3g and still remain a prepaid subscriber, consumers needed to pay the full price of the handset upfront. The alternative would be to change their status from prepaid to postpaid, but in this country, consumers have a clear preference towards prepaid plans which is also true in the EURMO operator where approximately 80% of all subscribers are prepaid.

Finally, up to a point, network tenure was a positive contribution to the probability of iPhone adoption even beyond the age of the handset used prior to the iPhone release. This probably implies that subscribers required some experience with the services provided by the EURMO prior to purchasing a phone that would bind them for at least 24 month [10].

[10] As mentioned in 3.3.1 all iPhone 3g handsets were sold locked to a particular the mobile communications provider regardless of the nature of the contract binding the subscriber to the operator

## 3.B Instrumental Variable Details

To construct our instrumental variable $ffnfdc\_adopters_{t-1}$ we use the social network built from the communication graph which we have described in section 3.3, but also information that allows us to track the regions where subscribers spend most of their time.

For each call placed or received, our dataset contains information detailing the cellular towers that were used in the beginning of the call. Additionally, each cellular tower is associated with GPS coordinates.

For every subscriber and for every call placed or received, we use the GPS coordinates of the call to determine a NUTS-III regional identifier for the caller and the callee. We then use the mode of the NUTS-III territories as the primary location of the individual since that is the region where the subscriber was seen most often[11]. On average each subscriber primary NUTS-III was identified through the analysis of 753.2 (median=387) calls.

NUTS codes - "*Nomenclature of territorial units for statistics*" - are statistical divisions of the economic territory of the EU designed for developing consistent regional statistics across EU countries and also to develop socio-economic analyses of the regions `http://epp.eurostat.ec.europa.eu/`. We choose to use NUTS-III as the unit of territorial partitioning because by construction, these regions represent contiguous municipalities that face the same type of economic and development challenges and within which it is likely that people could have substantial mobility.

We only know the location of a subscriber when she performs or receives a call and

[11]Cell tower ranges can cover from 1 up to 30 Km therefore there is some uncertainty associated with the true location of each individual, particular in regions with low population density where there are fewer cell towers with broader ranges.

by using a territorial portioning based on NUTS-III code we attempt to ensure that the region is large enough so that each subscribers moves within rather than between most of the time, but also we try to capture the fact that the socio-economic challenges faced by subscribers within the same territory are similar.

Figure 3.11 depicts the number of NUTS-III codes where each subscriber was seen receiving or placing calls.

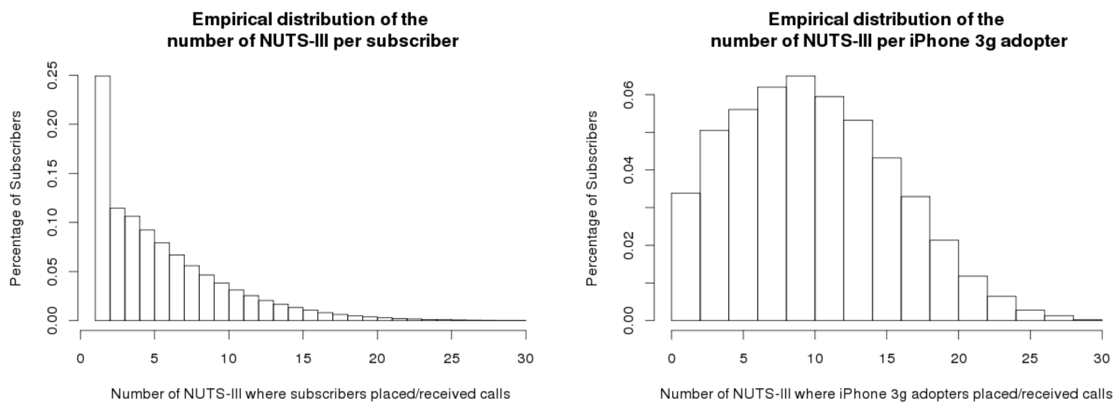



Figure 3.11: Number of NUTS-III codes where subscribers received or placed calls from August 2008 until July 2009

The average number of NUTS-III per subscriber, for the entire population of subscribers, was 5.9 with a standard deviation of 4.5. Still about 25% of the subscribers were seen placing or receiving calls within a single NUTS-III region. iPhone 3g adopters were more mobile than the average user with an average of 10.4 NUTS-III per subscriber and a standard deviation of 5.6. This fact does not affect our separation strategy because looking in detail to the number of calls that allowed identifying each subscriber within each NUTS-III, an overwhelming majority of calls were placed or received within the primary NUTS-III region. This is true both overall and for the iPhone 3g adopters in particular.

Such fact highlights that while people do move around in their daily lives (particularly when considering a large span of time such as 11 months), they tend to stay within their primary region most of the time. Therefore, people with distinct NUTS-III primary regions will clearly be geographically separated almost always. Such fact is shown in figure 3.12 from which we can derive that the average proportion of calls placed within the primary NUTS-III region across subscribers is 83% (median 88%) overall and 78% (median 82%) for iPhone 3g adopters.

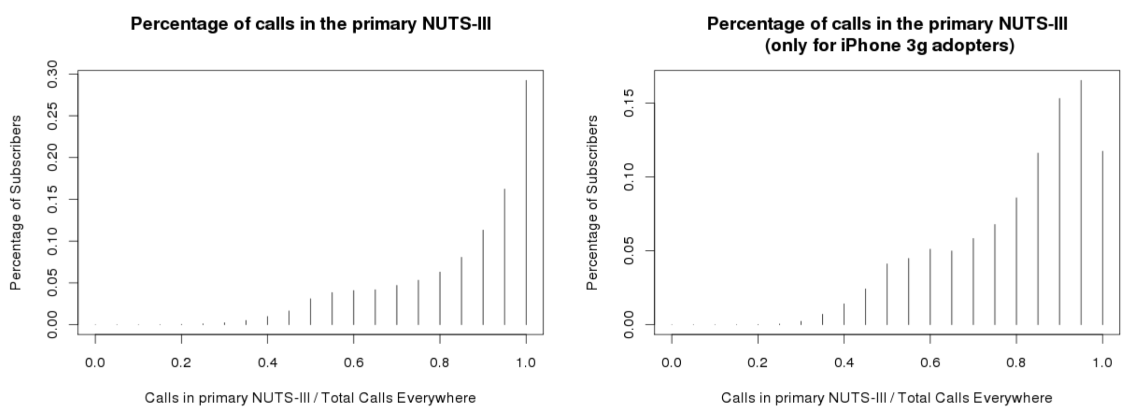



Figure 3.12: Proportion of phone calls within the primary NUTS-III region from August 2008 until July 2009

## 3.C Summary of the community identification algorithms

### 3.C.1 The T-CLAP algorithm (Zhang and Krackhardt, 2011)

T-CLAP looks for local community focusing on small parts of the social network at a time. T-CLAP begins by selecting a random node in the social graph. Then the algorithm proceeds in three steps: i) it collects a sample of nodes and edges through breadth first search (until a stopping criteria is reached); ii) applies a clustering procedure to the collected nodes to identify dense regions within the sample which it calls the core of the group; iii) sequentially discards nodes that have more links to outside the group than to the inside (core vs periphery). The attachment to the group is measured by the IER of each individual. Pruning occurs in increasing order of IER and it stops when a target community size is achieved.

T-CLAP's clustering phase is agnostic and does not allow for focusing on particular types of communities. T-CLAP is ideal to identify random communities with the highest possible IER. However, in our case, we are only interested in communities where the adoption of the iPhone 3G occurs. In our network, the adoption of the iPhone 3G is a rare event with less than 1% probability and therefore it was not surprising that T-CLAP's random identification of communities of size close to 100 members failed to identify communities with adopters.

We changed T-CLAP in the following way: i) in step i) we start the snowball sample from nodes that adopted the iPhone 3G (we sample 4 waves out); ii) we skip step ii altogether; iii) in step iii) we prune iPhone 3G adopters with lower probability such that if two individuals

We also ensure that the communities extracted do not overlap. This new version of TCLAP takes longer to produce high quality communities but reduces largely the probability of identifying communities with no adopters while still returning communities with high IER.

### 3.C.2 The walktrap algorithm (Pons and Latapy, 2006)

The ***walktrap*** algorithm assumes that when a node belongs to a densely connected group, random walks that originate from such node are likely to traverse the members of the group (Pons and Latapy, 2006).

The algorithm starts with every node as separate community and it computes a distance among nodes based on random walks of configurable path length. Once node distances are computed, the algorithm groups the nodes according to Ward's method (Ward, 1963) which is a widely known hierarchical clustering technique.

After each merge, distances among clusters are recalculated based on random walks and the algorithm proceeds iteratively for n-1 steps. Each step of the algorithm generates a partition of the graph into communities that are hierarchically organized. The preferred partition is the one for which the modularity index is highest.

We configured walktrap with a path-length of two for the random walk. We experimented with larger path-lengths, but the amount of RAM required to run the algorithm under such configuration far exceeded the computational capacity that we had readily available. We used the code implementation available in the igraph R library (Csárdi and Nepusz, 2005). The software took 7 days and 50Gb of RAM to process our complete social network data.

### 3.C.3 Label propagation algorithm (Raghavan et al., 2007)

The label propagation algorithm initializes all nodes in the network with their own unique label. Secondly it sorts all nodes randomly. Thirdly for each node $i$ in sorted order, the algorithm determines the most common label among $i$'s and assigns such label to $i$. If there are more than one labels having the same frequency among $i$'s alters, the label that $i$ takes is chose at random from all tied labels.

The algorithm stops when each node $i$ has the label that is most frequent among its neighbors $j$. Otherwise nodes are reordered randomly and the relabeling operation continues.

### 3.C.4 Fast greedy modularity optimization (Clauset et al., 2004)

The fast greedy algorithm for community detection is an efficient implementation of the modularity maximization based algorithm proposed in (Newman, 2003). Optimizing the modularity index requires exploring the complete set of possible node aggregations within a social network. However, because such state space is intractable for large networks, most community detection algorithms use heuristic approximations.

The (Clauset et al., 2004) algorithm starts with each node in a social network considered as an isolated community and it then merges together the nodes that produce the highest increase in the modularity property. The innovation of this algorithm is that it uses an efficient data structure to perform the merges. Such data structure reduces the computational complexity of these operations allowing significant performance improvements over the original version detailed in (Newman, 2003).

### 3.C.5 The Louvain's method (Blondel et al., 2008)

Louvain's method is a community detection algorithm that optimizes modularity in the neighborhood of network nodes (Blondel et al., 2008).

Louvain's method is divided in two phases. It starts with every node as a single community and in phase one, for every node $i$, it determines whether the modularity index would increase if $i$ was merged in a community with with an alter $j$. If modularity increase is possible, $i$ is jointed together with the community where such increase is greatest. The process is repeated iteratively for every node $i$ until no merge operation increases the modularity index further. Note that the outcome of this part of the algorithm is a local maximum of the modularity index because the output of the algorithm depends on the order in which nodes are processed and a single order is considered.

The second phase of the algorithm consists in creating a new network where each community is reinterpreted as a network node.

The two phases are iterated one after the other until it is no longer possible to improve network modularity further.

### 3.C.6 The infomap algorithm (Rosvall and Bergstrom, 2008)

The Infomap is based on the idea that groups of nodes within which *information flows quickly and easily can be aggreagated* to describe a module (Rosvall and Bergstrom, 2008). It is based on principles from information theory and it provides groupings of nodes that when clustered together minimize the *map equation* (Rosvall et al., 2009). The actual details of the algorithm are too complex for us to go over them in the paper, but we refer th reader to both (Rosvall and Bergstrom, 2008; Rosvall et al., 2009) that describe the algorithm in great detail.

## 3.D Further details of the SIENA Analysis

### 3.D.1 Robustness of the $Network- > Behavior$ effect

We assess if the summary effect for $Network- > Behavior$ coefficient is sensitive to changes in the set of communities that are included in the meta-analysis. For that purpose we run a *leave-one-out* test (Viechtbauer and Cheung, 2010). The test is iterative and consists in estimating 152 different models each time excluding a different community from the set of communities included in the analysis. If there are outlier studies biasing the effect, we would expect that the summary estimation to vary substantially when such communities are not included in the estimation procedure. Panel (b) of figure 3.13 highlights that this is not the case.

Additionally to *leave-one-out* test, we run a cumulative meta analysis test (Lau et al., 1992). The cumulative analysis starts with a single community and cumulatively expands the community set one community at the time. In each iteration, the test computes a summary effect for the communities included in the set until that particular iteration. The outcome of this test is displayed in panel (a) of figure 3.13 and it highlights that the cumulative estimate converges very quickly to the value of the of the summary effect that we report.

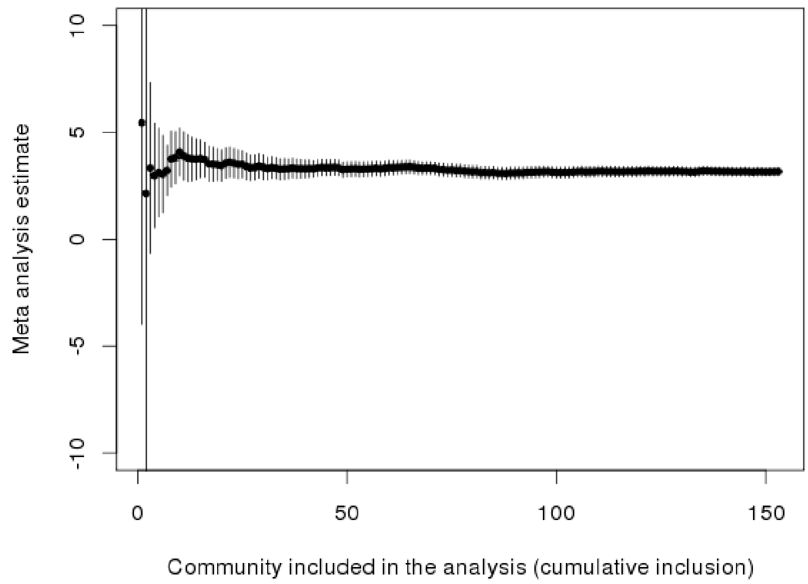
Figure 3.14 provides further details on the meta analysis of the $Network- > Behavior$ coefficient

### 3.D.2 Alternative partitions of the time period

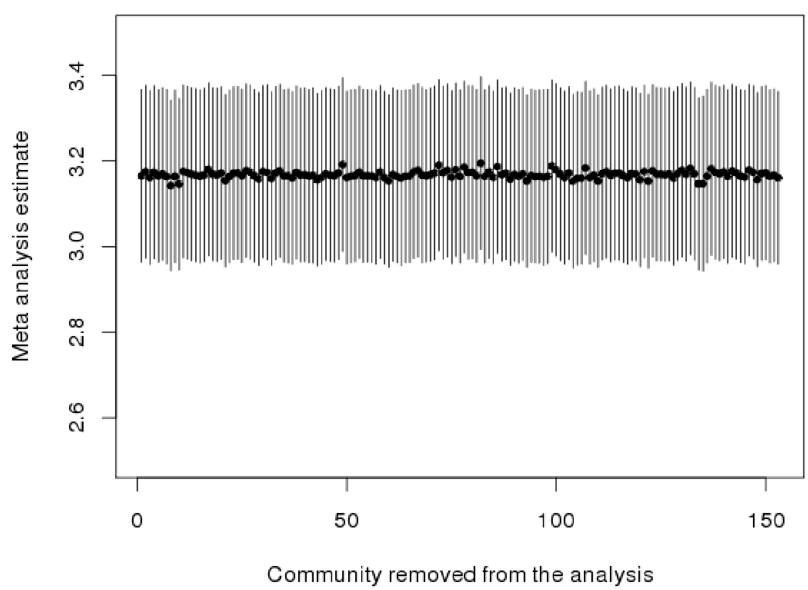
Table 3.24: Mean Jaccard Index Across the 263 Communities in the Sample

<table>
<tr><th>Time Span</th><th>AGO</th><th>SET</th><th>OCT</th><th>NOV</th><th>DEC</th><th>JAN</th><th>FEV</th><th>MAR</th><th>APR</th><th>MAY</th><th>JUN</th></tr>
<tr><td>One Month</td><td></td><td>0.747<br>(0.046)</td><td>0.765<br>(0.041)</td><td>0.762<br>(0.042)</td><td>0.721<br>(0.047)</td><td>0.719<br>(0.051)</td><td>0.761<br>(0.045)</td><td>0.762<br>(0.043)</td><td>0.761<br>(0.044)</td><td>0.761<br>(0.045)</td><td>0.761<br>(0.046)</td></tr>
<tr><td>Two Months</td><td colspan="2"></td><td colspan="2">0.794<br>(0.043)</td><td colspan="2">0.798<br>(0.042)</td><td colspan="2">0.797<br>(0.039)</td><td colspan="2">0.800<br>(0.043)</td><td>0.762<br>(0.049)</td></tr>
<tr><td>Three Months</td><td colspan="3"></td><td colspan="3">0.815<br>(0.046)</td><td colspan="3">0.816<br>(0.041)</td><td colspan="2">0.804<br>(0.043)</td></tr>
<tr><td>$[1;2]-[3;11]$</td><td colspan="2"></td><td colspan="9">0.749<br>(0.056)</td></tr>
<tr><td>$[1;3]-[4;11]$</td><td colspan="3"></td><td colspan="8">0.794<br>(0.052)</td></tr>
<tr><td>$[1;4]-[5;11]$</td><td colspan="4"></td><td colspan="7">0.816<br>(0.050)</td></tr>
<tr><td>$[1;5]-[6;11]$</td><td colspan="5"></td><td colspan="6">0.826<br>(0.046)</td></tr>
<tr><td>$[1;6]-[7;11]$</td><td colspan="6"></td><td colspan="5">0.828<br>(0.045)</td></tr>
<tr><td>$[1;7]-[8;11]$</td><td colspan="7"></td><td colspan="4">0.821<br>(0.045)</td></tr>
<tr><td>$[1;8]-[9;11]$</td><td colspan="8"></td><td colspan="3">0.802<br>(0.048)</td></tr>
<tr><td>$[1;9]-[10;11]$</td><td colspan="9"></td><td colspan="2">0.765<br>(0.051)</td></tr>
<tr><td>$[1;10]-[11;11]$</td><td colspan="10"></td><td>0.681<br>(0.058)</td></tr>
</table>

**Note 1:** Jaccard Index defined as $Jaccard(g0, g1) = \frac{e_{11}}{e_{11}+e_{10}+e_{01}}$ where $e_{11}$ denotes the edges that are present in both graphs $g0$ ad $g1$, $e_{10}$ denotes the edges that are only present in $g0$ and $e_{10}$ the edges that only exist in $g1$.**Note 2:** Standar Errors in ();




(a) Cumulative Inclusion Test




(b) Leave One Out Test

Figure 3.13: Meta-analysis sensitivity plots for the meta analysis for the $Network->$ $Behavior$ variable of the SIENA model

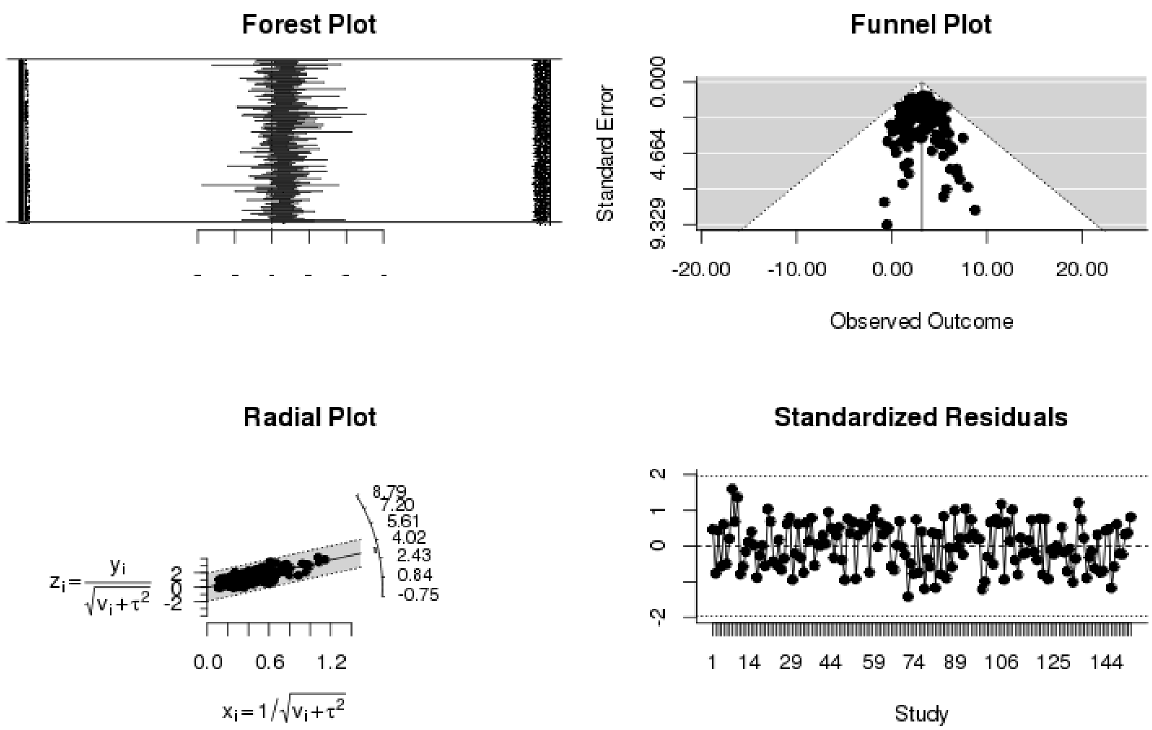



Figure 3.14: Meta-analysis diagnostic plots for the $Network->Behavior$ variable of the SIENA model

Table 3.25: Results of the meta-analysis for each of the behavioral and network effects included in the SIENA model

| Time Part. | name | coeff | stderr | pval | $I^2$ | $H^2$ | $\tau^2$ | Q-Test | Q-Test (p-val) | N obs |
|---|---|---|---|---|---|---|---|---|---|---|
| [1; 2] − [3; 11] | outdegree (density) | -4.214 | 0.052 | 0.000 | 62.458 | 2.664 | 0.169 | 325.644 | 0.000 | 104 |
| | reciprocity | 5.014 | 0.090 | 0.000 | 59.418 | 2.464 | 0.421 | 269.346 | 0.000 | 104 |
| | transitive ties | 2.539 | 0.045 | 0.000 | 56.025 | 2.274 | 0.113 | 263.453 | 0.000 | 104 |
| | $Behavior->Network$ | 0.011 | 0.069 | 0.875 | 34.931 | 1.537 | 0.134 | 164.549 | 0.000 | 104 |
| | $Network->Behavior$ | 3.347 | 0.107 | 0.000 | 0.000 | 1.000 | 0.000 | 43.340 | 1.000 | 104 |
| [1; 3] − [4; 11] | outdegree (density) | -4.393 | 0.043 | 0.000 | 59.972 | 2.498 | 0.167 | 448.472 | 0.000 | 150 |
| | reciprocity | 4.772 | 0.079 | 0.000 | 72.366 | 3.619 | 0.530 | 595.384 | 0.000 | 150 |
| | transitive ties | 2.377 | 0.035 | 0.000 | 52.279 | 2.095 | 0.095 | 351.168 | 0.000 | 150 |
| | $Behavior->Network$ | 0.056 | 0.051 | 0.269 | 26.986 | 1.370 | 0.084 | 213.184 | 0.000 | 150 |
| | $Network->Behavior$ | 3.156 | 0.094 | 0.000 | 0.000 | 1.000 | 0.000 | 58.394 | 1.000 | 150 |
| [1; 5] − [6; 11] | outdegree (density) | -4.370 | 0.053 | 0.000 | 66.291 | 2.967 | 0.204 | 374.884 | 0.000 | 112 |
| | reciprocity | 4.107 | 0.073 | 0.000 | 75.442 | 4.072 | 0.404 | 475.923 | 0.000 | 112 |
| | transitive ties | 1.939 | 0.036 | 0.000 | 47.098 | 1.890 | 0.070 | 230.529 | 0.000 | 112 |
| | $Behavior->Network$ | 0.037 | 0.054 | 0.498 | 29.333 | 1.415 | 0.077 | 167.707 | 0.000 | 112 |
| | $Network->Behavior$ | 2.857 | 0.232 | 0.000 | 27.452 | 1.378 | 2.014 | 121.619 | 0.231 | 112 |
| [1; 6] − [7; 11] | outdegree (density) | -4.443 | 0.057 | 0.000 | 65.275 | 2.880 | 0.214 | 337.356 | 0.000 | 102 |
| | reciprocity | 3.896 | 0.070 | 0.000 | 67.843 | 3.110 | 0.295 | 324.878 | 0.000 | 102 |
| | transitive ties | 1.723 | 0.042 | 0.000 | 53.516 | 2.151 | 0.096 | 228.744 | 0.000 | 102 |
| | $Behavior->Network$ | 0.069 | 0.054 | 0.199 | 26.291 | 1.357 | 0.065 | 144.909 | 0.003 | 102 |
| | $Network->Behavior$ | 3.112 | 0.130 | 0.000 | 0.000 | 1.000 | 0.000 | 24.392 | 1.000 | 102 |
| [1; 7] − [8; 11] | outdegree (density) | -4.504 | 0.061 | 0.000 | 65.212 | 2.875 | 0.226 | 299.468 | 0.000 | 92 |
| | reciprocity | 3.777 | 0.073 | 0.000 | 65.190 | 2.873 | 0.286 | 264.460 | 0.000 | 92 |
| | transitive ties | 1.495 | 0.042 | 0.000 | 48.672 | 1.948 | 0.079 | 186.580 | 0.000 | 92 |
| | $Behavior->Network$ | 0.054 | 0.060 | 0.374 | 26.053 | 1.352 | 0.061 | 147.948 | 0.000 | 92 |
| | $Network->Behavior$ | 3.173 | 0.129 | 0.000 | 0.000 | 1.000 | 0.000 | 16.742 | 1.000 | 92 |
| [1; 8] − [9; 11] | outdegree (density) | -4.845 | 0.077 | 0.000 | 52.680 | 2.113 | 0.189 | 125.514 | 0.000 | 58 |
| | reciprocity | 3.935 | 0.104 | 0.000 | 62.745 | 2.684 | 0.394 | 175.865 | 0.000 | 58 |
| | transitive ties | 1.275 | 0.053 | 0.000 | 35.695 | 1.555 | 0.055 | 90.531 | 0.003 | 58 |
| | $Behavior->Network$ | 0.204 | 0.089 | 0.026 | 32.069 | 1.472 | 0.110 | 94.797 | 0.001 | 58 |
| | $Network->Behavior$ | 3.191 | 0.134 | 0.000 | 0.000 | 1.000 | 0.000 | 5.989 | 1.000 | 58 |
| [1; 9] − [10; 11] | outdegree (density) | -5.118 | 0.133 | 0.000 | 62.162 | 2.643 | 0.339 | 103.864 | 0.000 | 30 |
| | reciprocity | 4.072 | 0.158 | 0.000 | 52.273 | 2.095 | 0.354 | 65.433 | 0.000 | 30 |
| | transitive ties | 1.082 | 0.084 | 0.000 | 51.543 | 2.064 | 0.096 | 64.265 | 0.000 | 30 |
| | $Behavior->Network$ | 0.138 | 0.093 | 0.148 | 0.001 | 1.000 | 0.000 | 29.795 | 0.424 | 30 |
| | $Network->Behavior$ | 2.664 | 0.183 | 0.000 | 0.000 | 1.000 | 0.000 | 2.410 | 1.000 | 30 |
| [1; 10] − 11 | outdegree (density) | -5.539 | 0.259 | 0.000 | 39.885 | 1.663 | 0.222 | 14.597 | 0.067 | 9 |
| | reciprocity | 4.071 | 0.329 | 0.000 | 31.055 | 1.450 | 0.241 | 13.649 | 0.091 | 9 |
| | transitive ties | 0.860 | 0.164 | 0.001 | 36.805 | 1.582 | 0.066 | 15.223 | 0.055 | 9 |
| | $Behavior->Network$ | 0.319 | 0.167 | 0.093 | 0.001 | 1.000 | 0.000 | 7.541 | 0.480 | 9 |
| | $Network->Behavior$ | 2.051 | 0.372 | 0.001 | 0.000 | 1.000 | 0.000 | 0.431 | 1.000 | 9 |

**Note 1:** variable $Behavior->Network$ is captured by the $behaviorsimilarity$ SIENA effect; **Note 2:** variable $Network->Behavior$ is implemented through the $behavioraveragesimiliraty$ SIENA effect; **Note 3:** Meta analysis estimated through Maximum Likelihood assuming a random effects model with Knapp and Hartung standard error correction; **Note 4:** $\tau^2$ is the estimate of total amount of heterogeneity, $I^2$ is the % of total variability due to heterogeneity, $H^2$ is $\frac{totalvariability}{samplingvariability}$.

Table 3.26: Results of the meta-analysis for each of the behavioral and network effects included in the SIENA model

| Time Part. | name | coeff | stderr | pval | $I^2$ | $H^2$ | $\tau^2$ | Q-Test | Q-Test (p-val) | N obs |
|---|---|---|---|---|---|---|---|---|---|---|
| [1; 3] − [4; 6] − [7; 11] | outdegree (density) | -4.195 | 0.038 | 0.000 | 69.841 | 3.316 | 0.107 | 392.527 | 0.000 | 104 |
| | reciprocity | 4.029 | 0.059 | 0.000 | 82.368 | 5.672 | 0.290 | 708.874 | 0.000 | 104 |
| | transitive ties | 1.833 | 0.028 | 0.000 | 57.796 | 2.369 | 0.046 | 265.849 | 0.000 | 104 |
| | $Behavior- > Network$ | 0.012 | 0.037 | 0.748 | 37.558 | 1.601 | 0.052 | 163.277 | 0.000 | 104 |
| | $Network- > Behavior$ | 3.040 | 0.111 | 0.000 | 0.000 | 1.000 | 0.000 | 43.034 | 1.000 | 104 |
| [1; 4] − [5; 8] − [9; 11] | outdegree (density) | -4.320 | 0.051 | 0.000 | 71.312 | 3.486 | 0.129 | 272.047 | 0.000 | 73 |
| | reciprocity | 3.884 | 0.072 | 0.000 | 81.336 | 5.358 | 0.288 | 419.031 | 0.000 | 73 |
| | transitive ties | 1.677 | 0.039 | 0.000 | 64.556 | 2.821 | 0.067 | 211.380 | 0.000 | 73 |
| | $Behavior- > Network$ | 0.067 | 0.042 | 0.113 | 25.463 | 1.342 | 0.031 | 97.622 | 0.024 | 73 |
| | $Network- > Behavior$ | 3.009 | 0.133 | 0.000 | 0.000 | 1.000 | 0.000 | 25.781 | 1.000 | 73 |

**Note 1:** variable $Behavior- > Network$ is captured by the $behaviorsimilarity$ SIENA effect; **Note 2:** variable $Network- > Behavior$ is implemented through the $behavioraveragesimiliraty$ SIENA effect; **Note 3:** Meta analysis estimated through Maximum Likelihood assuming a random effects model with Knapp and Hartung standard error correction; **Note 4:** $\tau^2$ is the estimate of total amount of heterogeneity, $I^2$ is the % of total variability due to heterogeneity, $H^2$ is $\frac{totalvariability}{samplingvariability}$.

# Chapter 4

# The Impact of Likes on the Sales of Movies in Video-on-Demand: a Randomized Experiment

**Abstract:** *We designed and implemented a randomized field experiment to determine the role that likes play on the sales of movies in Video-on-Demand (VoD). We used the VoD system of a large telecommunications provider during half a year in 2012. The VoD system of this provider suggests movies to subscribers when they log in. Suggested movies are displayed on the TV screen under several editorial menus. Under each menu movies are shown from left to right in decreasing order of the number of likes received. During our experiment, movies were primarily placed in their true slots and shown along with their true number of likes. At random moments, some movies were swapped and thus displayed out of order and with a fake number of likes. The movies that were swapped were selected at random. We found that promoting a movie by one slot increased weekly sales by 4% on average. We found that the amount of information publicly available about movies affected this statistic. Better known movies were less sensitive to manipulations. We found that a movie promoted (demoted) to a fake slot sold 15.9% less (27.7% more) than a true movie placed at that slot, on average across all manipulations we introduced. We also found that a movie promoted (demoted) to a fake slot received 33.1% fewer (30.1% more) likes than*

*a true movie at that slot. Therefore, manipulated movies tend to move back to their true slot over time. Hence, we find that the self-fulfilling prophecies widely discussed in the literature on the effect of ratings on sales are hard to sustain in a market in which goods are costly and sufficiently well-known. During this adjustment process, providers are likely to enjoy increased profits while subscribers might lose welfare. This process is likely to converge quickly, which might lead the telecommunications provider to promote different movies over time.*

## 4.1 Introduction

Figure 4.1 shows that home video revenues have increased substantially since the 1970s while theater revenues have remained constant over time. One can still argue that the success of a movie dependents highly on box office sales because exhibition in theaters not only allows for covering a significant part of the cost to produce a movie but also triggers demand in subsequent channels. However, it is clear that digitization is changing the structure of the industry. In particular, the share of Video-on-Demand (VoD) and Pay-Per-View (PPV) in the electronic spending on movie rentals in the US increased roughly 4 times between 2000 and 2009. Brick and mortar's share reduced roughly 50% during the same period of time (Waterman, 2011).

VoD providers such as Amazon, Netflix or Hulu have catalogs with more than 100,000 titles (Rowinski, 2011), whereas traditional brick and mortar stores offer catalogs with no more than 3,000 titles (Anderson, 2006). Economic theory predicts that product variety increases consumer welfare (Hotelling, 1929; Dixit and Stiglitz, 1977; Salop, 1979). However, search costs also increase with the number of products that consumers need to scan.

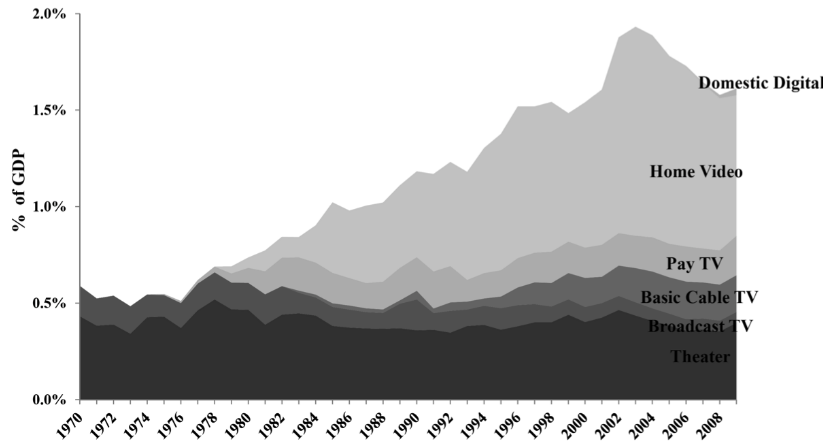



Figure 4.1: Revenues of movie distributors in the US market as a percentage of GDP (excluding merchandising). Source: (Waterman, 2011)

Therefore, consumers may be unable to internalize the benefits of increased variety (Nelson, 1970; Sawhney and Eliashberg, 1996). In fact, a number of studies have reported a negative relationship between product variety and sales. For example, (Iyengar and Lepper, 2000) showed that increasing the variety of flavors of a specific jam product in a supermarket reduced consumer willingness to buy. (Boatwright and Nunes, 2001) showed that reducing the number of stock keeping units in a grocery store had a positive impact on sales. More recently, (Kuksov and Villas-Boas, 2010) developed a theoretical model that shows that excess variety increases consumer search costs and reduces total sales.

Product variety can increase consumer welfare if more efficient search mechanisms become available. This is particularly true in the movie industry. Several surveys in the US show that consumers welcome recommendations on which movies to watch (De Vriendt et al., 2011), probably because movies are an example of an experience good (Nelson, 1970), (Eliashberg and Shugan, 1997): their quality can only be ascertain after consumption. 45% of the people surveyed by Ovum in 9 countries around the world welcomed suggestions from friends when searching for new movies to watch (Little, 2010). Tapping into this opportunity, several companies are now implementing recommender systems to provide suggestions to their clients. Again, Hulu, Netflix and Amazon are widely known examples. These companies incorporate rating mechanisms in their recommender systems whereby consumers are allowed to express whether they liked the content they purchased.

Determining the true impact of rating systems on sales is a challenging empirical question. Observational studies are often subject to the *reflection problem* (Manski, 1993), which hampers the identification of the impact of group behavior on individual decisions. As such, many observational studies offer conflicting perspectives. For example, (Eliashberg and Shugan, 1997) concludes that ratings from movie critics are not good predictors of sales, whereas (Reinstein and Snyder, 2005) concludes otherwise. Several authors used experiments to try to obtain identification. For example, (Salganik et al., 2006) studied the effect of popularity in a market of songs from obscure bands. (Tucker and Zhang, 2011) studied the effect of popularity across wedding service vendors. These studies show that popularity can be, to a certain extent, self-reinforcing. However, they do not explicitly control for the quality of the experience obtained by consumers.

In this paper, we design a randomized experiment to determine the role that social signals play on the sales of VoD products. We use the VoD system of a large telecommunications provider (at which subscribers need to pay to lease movies). Our experiment run live for half a year during 2012. The popularity of a movie in the VoD system of this provider is encoded by the order in which the movie is displayed on the TV screen, hereinafter called the rank, which is a function of the number of likes issued by subscribers. A movie with a higher number of likes is shown farther to the left on the TV screen. During our the experiment, movies were primarily placed in their true rank and shown along with their true number of likes. At random moments, some movies were swapped and thus displayed "our of order" and with a fake number of likes. The movies swapped were randomly selected. These random exogenous shocks allow for disentangling the perceived quality from the true quality of a movie, thus allowing us to obtain unbiased estimates for the effect of popularity on VoD sales.

We find that on average weekly sales increase by 4% when a movie is promoted one rank. We also find that the weekly sales of a movie promoted (demoted) to a better (worse) rank are 15.9% lower (27.7% higher) than those of a movie placed at that rank by the number of likes issued by subscribers, on average across all manipulations we introduced. We show that this asymmetry is related to the amount of information publicly available about the movies manipulated, as measured by number of IMDb votes. Better-known movies are less sensitive to our manipulations. We also find that a movie promoted (demoted) to a better (worse) rank receives 33.1% fewer (30.1% more) likes than a movie placed at that rank by the number of likes issued by subscribers. Therefore, manipulated movies tend to move back to their true rank over time. This means that self-fulfilling prophecies are hard to sustain in a market in which goods are costly and sufficiently well known. Finally, we provide evidence that during this process of adjustment, the provider may enjoy increased profits while subscribers may lose welfare, as measured by the number of likes issued. This process is likely to converge quickly, which might lead the provider to promote different movies over time.

## 4.2 Related Literature

Most papers looking at the impact of quality signals in the movie industry are observational and offer contradictory perspectives. (Litman, 1983) and (Wallace et al., 1993) analyzed 125 and 1687 movies, respectively, released in the US between 1972-78 and 1956-88, respectively. Both report a positive correlation between box office sales and reviews by movie critics. However, (Eliashberg and Shugan, 1997) found that ratings from movie critics are not good predictors of sales during the opening week. They argue that despite being correlated with cumulative movie sales, these ratings do not influence sales in a causal sense.

(Godes and Mayzlin, 2004) studied 44 TV shows released in the US between 1999 and 2000. They found that the dispersion in Word-of-Mouth (WoM) about these shows across distinct groups in Usenet (a news aggregator) was positively correlated to their ratings. However, they were unable to establish a link between WoM, measured by number of conversations about a show, and future rankings, which correlate to sales. (Liu, 2006) studied data from message boards at Yahoo Movies! about 40 movies released between May and September 2002 in the US. They found that the volume of WoM was positively correlated with box office sales but they could not establish a statistically significant relationship between the direction implied in the messages (positive/negative comments) and sales.

A number of previous studies fail to account for the potential correlation between unobserved quality and ratings and therefore are unable to investigate the causal mechanisms that might be at the root of the impact of reviews on sales. Other papers have attempted to overcome this concern. For example, (Reinstein and Snyder, 2005) applied a difference in difference model to a sample of more than 600 movies rated by two influential movie critics to try to identify the marginal impact of reviews on sales. Using the fact that some movie reviews were issued prior to the release of the movie while others were issued after the opening week, they showed that ratings from movie critic were positively correlated with sales and influenced box office sales during the opening week, which again contradicts the findings in (Eliashberg and Shugan, 1997).

(Zhang and Dellarocas, 2006) developed a structural model to study the impact of consumer and movie critic ratings on sales. They showed that good reviews drove movies sales but that the volume and dispersion of the reviews did not. (Dellarocas et al., 2007) developed a predictive model for movie sales that showed that the volume, valence and dispersion of reviews were all positive and statistically significant predictors of box office sales. Finally, (Duan et al., 2008) proposed a model with simultaneous equations to estimate user movie ratings and movie box office sales simultaneously. They concluded that WoM is a strong driver of box office sales, which contradicts the findings in (Zhang and

Dellarocas, 2006). Therefore, there is substantial conflict even across the studies that attempt to control for unobserved quality.

A number of authors used experiments to better overcome the traditional hindrances of observational studies. These studies analyze the impact of popularity on sales in the context of other industries. In a seminal paper, (Salganik et al., 2006) created two virtual markets for songs from unknown bands and recruited a group of subjects on a website for teenager interests. Each subject was randomly assigned to one of these markets. Songs were ordered randomly in one of the markets and ordered according to the number of downloads in the other market. Subjects were asked to chose songs to listen, to rate them and then to download them for free if they so wanted. Their study showed that the best (worst) songs received more (less) downloads. The songs in between tended to receive ever more (less) downloads when shown at a higher (lower) rank. In other words, popularity was self-reinforcing for these songs.

In a follow-up study (Salganik and Watts, 2008) run a similar experiment using similar songs and a similar pool of subjects. In a setup phase they ask participants to listen to the songs and to rate them. Then they order songs according to these ratings so that better songs would come last and thus seem worse. In this setting, they observed that over time all songs (good or bad) tended to converge to their true download rank. Taken together, these studies show that self-fulfilling prophecies in these markets are constrained by the individuals' private preferences.

A similar experiment was developed by (Tucker and Zhang, 2011). They used an online hub for online wedding service vendors to explore the impact of popularity on the number of clicks that each vendor obtained. They displayed vendors in three categories. In one category vendors were sorted in decreasing order of the number of clicks received. In another category vendors were sorted in increasing order of the number of clicks received. In both cases, vendors were listed along with the number of clicks received. In the last category vendors were sorted alphabetically and no information on clicks received was displayed. They compared vendors across different categories, before and during their experiment, to determine the impact of popularity, measured by the number of clicks received, on future clicks. They conclude that popularity is self reinforcing and that vendors that operate in narrower markets benefit the most from this dynamics.

Our paper is different from these studies in some important dimensions. First, the papers by (Salganik et al., 2006) and (Tucker and Zhang, 2011) measure impact of *popularity* on sales. They do not measure the impact of user feedback –*likes* – on sales. One expects *likes* to reflect better the subscribers' taste and assessment of quality. This is especially true for experience goods like music and movies, for which more downloads typically lead to more *popularity* and vice-versa. In our setting, more *likes* may lead to more purchases. However, the decision to provide *likes* in our case is tightly related to the quality of the movies watched. In short, we believe that *likes* are a better and stronger measure of quality than the *popularity* measures used in previous studies. In (Salganik et al., 2006) downloads might proxy whether subjects like songs but in their settings they are only a noisy measure of preferences across songs.

Another important difference in our setting is that the goods are not free. Subscribers, in our setting, have to make explicit decisions that involve financial risks. The price to rent movies in the VoD system of our Industrial Partner (IP varied between \$1.30 and \$5.20. In (Salganik et al., 2006) and (Salganik and Watts, 2008) songs could be downloaded for free. Subjects did not incur any financial risk in either listening or downloading a song. (Tucker and Zhang, 2011) observe click through rates on websites but they know nothing about actual purchase decisions. It is not clear how the results of these studies generalize to goods that are not free. For example, in (Salganik and Watts, 2008) demoted songs eventually recover to their true rank. However, this may be an artifact of the fact that songs were provided for free. Since subjects could easily buy several songs, songs in lower ranks may benefit more than demoted movies in our setting.

Another key distinction is that (Salganik et al., 2006) used mostly obscure songs. Thus, downloads provided almost all the information about these songs to the subjects in the study. In most real settings goods are not as unknown to consumers. Consumers can get some information about the quality of products from many external sources. In such settings, the informativeness of *likes* is unclear. We also note that in our setting subjects are real customers of our IP. Our experiment was conducted live in the real field. While this imposes some challenges to carry it out, it also makes for a unique, general and robust setting.

Finally, our paper goes beyond estimating the effect of rank changes on sales. In particular, we are interested in estimating the social cost of changes in rank. Social cost in our context is measured by the loss in sales, or by the loss in *likes*, when ranks are manipulated. For example, we seek to measure if a movie manipulated into a particular rank sells as much as the correct movie at that rank. Most of the prior work has focused on how rank changes affect sales but not on the social cost associated with these manipulations.

## 4.3 The Context of Our Experiment

### 4.3.1 The Company and its Dataset

Our experiment was performed using a real world VoD system from a major telecommunications provider, hereinafter called Industrial Partner (IP). Our IP offers TV, Internet, telephone and mobile phone service. IP is the market leader of Pay-TV services in the country where it operates. It services approximately 1.5 million households, 69% of which purchase triple play bundles that include TV, Internet and fixed telephony. According to a market report published by Screen Digest, 65% of the households in this country subscribed to Pay-TV services by the end of 2012. The same report shows that 46% of households with Pay-TV obtained service over cable, 23% over IPTV and the remaining 28% over satellite. Our IP offers Pay-TV through both wired connections and satellite.

We had access to our IP's VoD database between February 2009 and December 2012, which includes information on all of its 3,408,995 subscribers, of which 1,479,895 are on average active at any point in time. 623,516 of the active subscribers buy services that include VoD. Overall, 681,036 subscribers watched VoD content at least once and 465,059 subscribers paid for VoD content at least once during this 41-month period. The remaining subscribers with VoD capabilities never used the service. We also had access to all (paid and free of charge) VoD transactions. During this period we observe 89,074,657 transactions, of which 6,293,557 correspond to paid leases.

We have the anonymized identifier of the subscriber requesting each (and every) transaction as well as the anonymized identifier for the MAC address of the specific Set-Top Box (STB) that did so. For each transaction we have a timestamp, the price and the identifier of the movie leased. For each movie in our IP's database we have title, director, studio, play length, synopses, cast, genres, asset type (movie, music, documentary, etc). We also have information on the daily layout of the TV screen that subscribers saw when they logged into the VoD system between 11-2011 and 12-2012. This information includes the tree of menus displayed as well as the order, hereinafter called rank, in which movies were displayed under each menu on the screen from left to right. Menus are associated with different editorial lines as described in the next section. Finally, we also have daily information on all trailer views and on the number of likes issued to each (and every) movie.

### 4.3.2 VoD Service and Interface

Our IP provides service over wired and satellite infrastructure. However, satellite subscribers cannot subscribe to VoD. Wired subscribers can obtain one of three types of services: basic/legacy, standard or premium. All of them can watch TV and subscribe to specific channels such as movies, sports, children's and adults' content, etc. As Figure 4.2 shows, only standard and premium subscribers can use VoD as well as some additional services. For example, both of them can record content if their STB and network connection so allow. Premium subscribers can also restart programs. They can also issue likes for VoD movies and TV programs as well as connect their IP account to Facebook. They are required to also subscribe Internet service. In this paper, we will focus only on standard and premium subscribers. 84% of these subscribers were standard in January 2012. This number reduced to 66% by the end of the year.

| Feature | BASIC/LEGACY | STANDARD | PREMIUM |
|---|---|---|---|
| Watch TV | YES | YES | YES |
| Subscribe to Thematic Channels | YES | YES | YES |
| Video on Demand | NO | YES | YES |
| DVR Capabilities | NO | YES | YES |
| Restart TV Features | NO | NO | YES |
| Like Ability & Facebook Link | NO | NO | YES |
| Mandatory Internet Connection Service | NO | NO | YES |

Figure 4.2: Summary of the main features available to subscribers of our IP.

The look and feel of the VoD screen for standard and premium subscribers is different but the organization of content into menus is hierarchically similar. In fact, our IP does not have the ability to suggest different movies to different subscribers, which has a major impact on the way we designed our experiment, as described in the next section. Both standard and premium subscribers can access the VoD system using a hot-key in their STB remote control. When they press it, the entry screen of the VoD system is displayed. This screen, called the *Highlights Section*, contains a set of menus filled with movies, chosen by an editorial team, which are very easy to access. Movies are organized into menus such as Promotions, Suggestions, Newest Releases, etc. Each menu has a header with a name that clearly identifies the type of movies underneath it. Menus are horizontal lines on the screen. Different menus are stacked vertically. Two menus fit on the screen at each time. A cursor highlights a movie cover at a time. Users can scroll across menus. The natural scrolling direction is down, though premium consumers can also scroll up.

Upon scrolling to a new menu, 8 movie covers are visible under that menu and the cursor highlights the movie farthest to the left. Users can also scroll right and left at their leisure within the same menu. Users can scroll right past the last movie cover on the screen to unveil hidden movies under the same menu. There is no limit for the number of movies under a menu though our IP displays no more than 15 movies per menu. The screen of a standard subscriber is somewhat different. Menus show only 4 movies and only 11 other movies can be accessed by scrolling right.

The title and number of likes of the movie highlighted by the cursor are shown on the screen. Standard subscribers do not see the number of likes. Clicking on the cover of a movie leads to a new screen with the year of release, play length, cast, synopsis and number of likes (the latter only in the case of premium subscribers). A number of actions are then available such as lease the movie, use a promotional coupon to lease the movie or watch the movie trailer (if one is available). Premium subscribers can also signal whether they like the movie.

Finally, subscribers can leave the *Highlights Section* of the VoD interface and search for movies in the complete *Catalog* of titles. The catalog is hierarchically organized into content categories such as movies, music, TV-shows, documentaries, etc. Within each of these category screens are organized as described above with menus for genres. Alternatively to browsing through the entire catalog, subscribers can use a keyword search to look for the content of their interest. They can use words that identify titles, movie directors and actors' names.

We note that the likes feature, visible only for premium subscribers, replicates Facebook's well known like button[1]. The number of likes shown along with movie covers is cumulative since the movie's debut at our IP's VoD. Subscribers do not know who liked a particular movie nor who and how many people leased a particular movie.

[1]Premium subscribers can also notify IP that they dislike a movie but the number of dislikes is not shown.

## 4.4 Experimental Design

A new menu named "The Most Popular During the Past Weeks" was introduced in the highlights Section of IP's VoD system on July 3rd 2012. This menu was available for both standard and premium subscribers and included the 15 movies that obtained the highest number of likes in the last few weeks. These movies were shown under this menu in decreasing order of this number of likes from left to right. The experiment run in 1-month cycles for a period of 6 consecutive months. Each cycle was further split into mini-cycles of 1 week each[2]. Weeks were named true or false. During a true week all movies under this menu were shown in their true rank. The true number of likes they obtained in the recent past was shown to premium consumers. During a false week a carefully devised randomization procedure was used to swap some movies under this menu to separate popularity from unobserved perceived movie quality.

Formally, the experiment ran as follows. Let $t_i$ represent the time at which cycle $i$ began, with $i \in \{1, 2, 3, 4, 5, 6\}$. Let $x$ represent a week's time. At time $t_i$, we sorted all movies in IP's VoD system according to the number of likes they received between $t_i - 2x$ and $t_i$. From this list we erased all movies that IP decided to use in other menus under the highlights section[3]. We kept the 45 movies at the head of the resulting list, which we call list $L$.

[2]Each week started at a time of low VoD usage, namely Tuesdays at around 2pm.

[3]IP decided to list some of these movies under other menus such as Promotions and Suggestions. Cleaning them from our list avoided displaying them under more than one menu in the highlights section, which would notoriously reduce their search cost. Furthermore, IP's log system does not allow for identifying the menu under the highlights section from which a lease originates and thus this cleaning procedure allows also for ensuring that leases of movies under the new menu came only from the new menu.

After the setup phase described above, which took place at the beginning of each cycle, a true week ensued to adjust the subscribers' expectations to the true quality of the movies show under the new menu. We determined the nature of each of the other 3 weeks within every cycle using a coin toss[4]. This allowed us to prevent a static pattern of true/false cycles that subscribers could perceive. Table 4.1 shows the order of true and false cycles used in our experiment.

Table 4.1: Cycles and the nature of sub-cycles during our experiment

| | | | | |
|---|---|---|---|---|
| Cycle 1 | $t_1$: True | $t_1 + x$: True | $t_1 + 2x$: False | $t_1 + 3x$: False |
| Cycle 2 | $t_2$: True | $t_2 + x$: False | $t_2 + 2x$: True | $t_2 + 3x$: False |
| Cycle 3 | $t_3$: True | $t_3 + x$: False | $t_3 + 2x$: False | $t_3 + 3x$: True |
| Cycle 4 | $t_4$: True | $t_4 + x$: False | $t_4 + 2x$: False | $t_4 + 3x$: False |
| Cycle 5 | $t_5$: True | $t_5 + x$: False | $t_5 + 2x$: False | $t_5 + 3x$: False |
| Cycle 6 | $t_6$: True | $t_6 + x$: False | $t_6 + 2x$: True | $t_6 + 3x$: False |

At the beginning of each true week we sorted all movies in $L$ according to the number of likes that they obtain between $t_i - 2x$ and $t_i + nx$ with $n \in \{1, 2, 3\}$ indicating how many weeks elapsed since the start of the current cycle. We displayed under the new menu the first 15 movies in $L$ from left to right on the TV screen. At the beginning of each false week we partitioned $L$ into 3 sub-lists. List $L_1$ comprised the 15 movies at the head of list $L$. List $L_2$ included the movies between ranks 16 and 30 in list $L$. Finally, list $L_3$ contained the movies positioned between ranks 31 and 45 in list $L$. Then, we performed the following swaps:

- *Within Swap:* we selected $y_i$ and $y_j$ randomly from $\{1, ..., 15\}$ such that $y_i \neq y_j$ and we swapped the number of likes associated with the $y_i^{th}$ and $y_j^{th}$ movies in list $L_1$;

[4]The coin used was biased to try to ensure a balance between true and false across the whole experience.

- *Between Swap:* we selected $z_i$ randomly from $\{1, ..., 15\}$ such that $z_i \neq y_i$ and $z_i \neq y_j$ and we selected $z_j$ randomly from $\{1, ..., 15\}$. Then, we swapped the number of likes of the $z_i^{th}$ movie in list $L_1$ with the number of likes of the $z_j^{th}$ movie in either list $L2$ or list $L3$, as determined below.

The movies in list $L_1$ were then displayed under the new menu from left to right on the TV screen. The two types of random swaps introduced with this experiment were aimed at capturing the particular characteristics of the look and feel of IP's VoD interface. *Within Swaps* allow for determining whether changes in ranks across the movies displayed under the new menu have an impact of sales. *Between Swaps* allow for determining the impact of bringing movies from the catalog into the new menu and of removing movies from the new menu into the catalog. A *Within swap* changes the search cost of the swapped movies only slightly but a *Between Swap* reduces substantially the search costs for a movie that is promoted from the catalog to the new menu and increases substantially the search costs for a movie that is demoted from the new menu into the catalog.

We performed two *Within Swaps* and one *Between Swap* at each false week during the first three cycles of our experiment. The latter alternated between lists $L2$ and $L3$. We performed three *Within Swaps* and two *Between Swaps* at each false week, one involving $L2$ and one involving $L3$, during the last three cycles of our experiment. We increased the frequency of swaps in the final three cycles of the experiment to increase the number of treated observations[5].

[5]Whether a week is true or false is still randomly determined and therefore unrelated to sales during our experiment (results are available upon request).

## 4.5 Empirical Model

### 4.5.1 Movie Level Specification

The demand for a movie is given by:

$$y_{it} = \alpha + x_{it}\beta + w_{it}\gamma + z_i\delta + m_i + u_{it}, t = 1, \ldots T \tag{4.1}$$

$y_{it}$ represents the sales of movie $i$ during week $t$, $x_{it}$ includes time varying observed movie characteristics such as age, rank and the number of distinct menus where the movies shows up, $w_{it}$ is the vector of our exogenous random treatments, $z_i$ includes time invariant observed movie characteristics such as genre, cast and price, $m_i$ are time constant unobserved movie fixed effects, such as the quality of the movie's story line, and $u_{it}$ is the idiosyncratic error term. This equation is the classical fixed effects specification, which we can estimate if we eliminate $m_i$. We use first differences with robust standard errors to do so given the potential for serial correlation in $u_{it}$ (Wooldridge, 2010). Therefore, we estimate the following model:

$$\Delta y_{it} = \epsilon + \Delta x_{it}\beta + \Delta w_{it}\gamma + \Delta u_{it}, t = 2, \ldots T \tag{4.2}$$

Note that the time constant movie fixed effects in $z_i$ drop despite being observed. In particular, the retail price drops from our regression. Price includes a fixed margin on the top of the royalty fee and the latter did not change during our experiment. Furthermore, prices do not respond to changes in demand in our setting. IP does not engage in dynamic pricing and the network costs to stream VoD content are essentially negligible.

### 4.5.2 The Magnitude of Treatment

Consider movies $A$ and $B$ under the new menu in ranks $a$ and $b$, respectively, at time $t_i + nx$, with $n < 3$. When these movies are swapped their new ranks in list $L$ are, momentarily, $b$ and $a$, respectively. At time $t_i + (n+1)x$, movies in this list are reordered according to number of likes as described in section 4.4. As a result, assume that the movie at rank $a$ shifts to rank $a'$ and the movie at rank $b$ shifts to rank $b'$. Subscribers see only the cumulative effect of swaps and sorting. Thus, from their perspective, movie $A$ moved from rank $a$ to rank $b'$ (a change of $b' - a$ ranks) and movie $B$ moved from rank $b$ to rank $a'$ (a change of $a' - b$ ranks).

If the swap did not occur then subscribers would have seen that movie $A$ moved from rank $a$ to rank $a'$ and movie $B$ moved from rank $b$ to rank $b'$. Therefore, the effect of the random exogenous swap is given by $(b' - a) - (a' - a) = b' - a'$ for movie $A$ and by $(a' - b) - (b' - b) = a' - b'$ for movie $B$. Note that this difference is zero for control movies. We introduce this difference, which hereinafter we call $rank\_manipulation$, into $\Delta w_{it}$ in equation 4.2. We code it so that it is positive when a movie is promoted and negative when a movie is demoted. Also, $a'$ and $b'$ are the true ranks for movie $A$ and $B$, respectively, which hereinafter we call $rank\_true$. Therefore, we have $rank = rank\_true - rank\_manipulation$.

### 4.5.3 Identification and Exogeneity

Identification is obtained by design in our setting. In equation 4.2, $\Delta w_{it}$ is not correlated to $\Delta u_{it}$ because movie swaps are randomly and exogenously determined. The two movies involved in a swap are randomly selected. Therefore, not only movies are treated at random but also the magnitude of treatment is random. In addition, the moments at which movies are swapped are also randomly selected. Random assignment of treatment also ensures that $\Delta w_{it}$ is uncorrelated to $\Delta x_{it}$. In fact, Table 4.2 shows that the descriptive statistics for the covariates in $x_{it}$ are similar for control and treated movies. Therefore, our estimates for $\gamma$ in Equation 4.2 are unbias

### 4.5.4 Rank Level Specification

Movies are reordered according to the number of likes at the beginning of each week. This establishes a truthful relationship between rank and perceived quality for control movies at the eyes of IP subscribers. Therefore, we can compare the sales obtained by control and treated movies at each rank and determine whether promoted and demoted movies sell differently than true movies placed at that rank. A true movie at a rank is a movie that was placed at this rank as a result of the number of likes obtained from subscribers and not as a result of one of our manipulations. If they do not then rank alone determines movie sales. To test this hypothesis we use the following model:

$$y_{rt} = \alpha + x_{rt}\beta + w_{rt}\gamma + m_r + u_{rt}, t = 1, \ldots T \tag{4.3}$$

$y_{rt}$ represents the sales of the movie at rank $r$ during week $t$, $x_{rt}$ includes observed characteristics of the movie at rank $r$ in week $t$ such as age, price, IMDb rating and the number of distinct menus where the movie shows up, $m_r$ is the intrinsic perceived quality of rank $r$ and $u_{rt}$ is the idiosyncratic error term. $w_{rt}$ is a vector of exogenous random treatments indicating whether the movie at rank $r$ in week $t$ was promoted, demoted or neither. A promoted movie should have, on average, lower quality than the movie it displaces and possibly sell less. Conversely, a demoted movie should have, on average, higher quality than the movie it displaces and possible sell more. We estimate Equation 4.3 using a dummy variable for each rank.

## 4.6 Results and Discussion

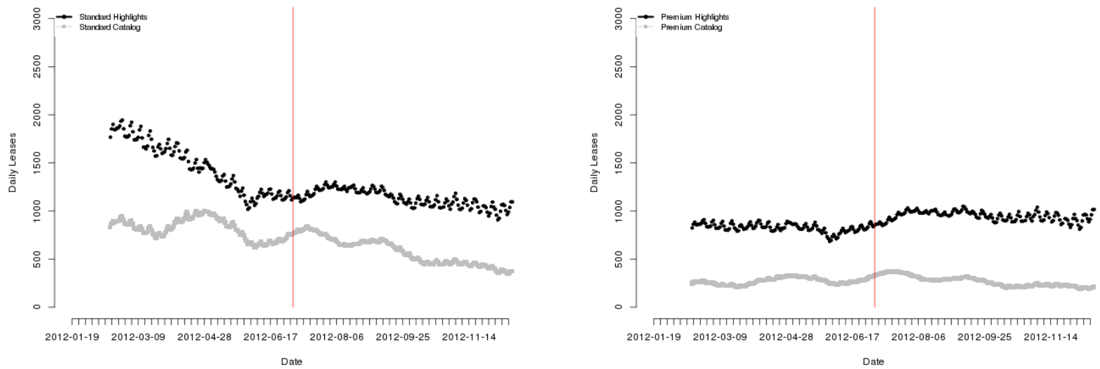
### 4.6.1 Descriptive Statistics

The stock of VoD enabled subscribers at IP grew from 607 thousand in January 2012 to 633 thousand in December 2012. The share of VoD-enabled premium subscribers increased from 16% to 34% during the same period. In the first half of 2012 premium users leased an average of 1.1 thousand movies per day. This increased to 1.2 thousand during the second half of the year. These statistics were 2.3 thousand and 1.7 thousand, respectively, for standard users. Yet, the average number of leases per subscriber decreased from 3.2 to 1.1 from the first to the second half of the year for premium subscribers. These statistics were 1.8 and 1.5 for standard subscribers, respectively. During the first half of 2012, 75% of the leases from premium users originated in the highlights section. This statistic increased to

79% in the second half of the year. These statistics were 64% and 68% for standard users, respectively.

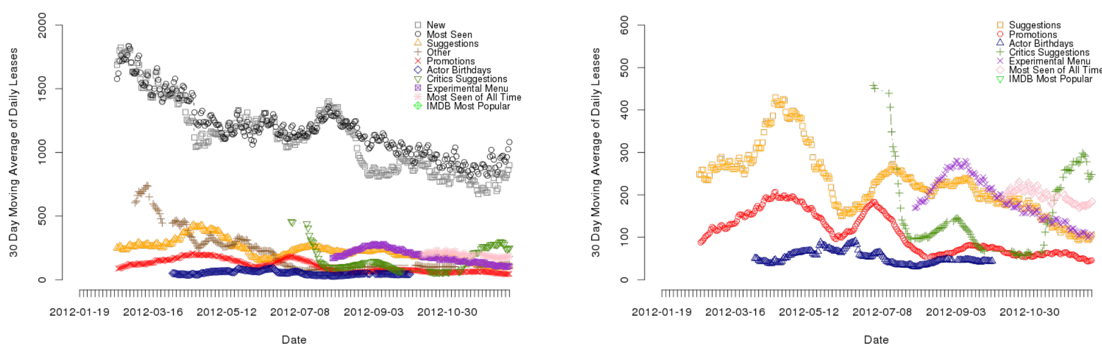
Figure 4.3 shows the 30-day moving average of daily sales in the highlights section and in the catalog for premium and standard subscribers. Most sales came from standard subscribers though this gap reduces significantly in the highlights section towards the end of the year. Sales increased both in the highlights section and in the catalog around the time the experiment started. The latter, however, declined significantly a few weeks into the experiment. Panel (a) of Figure 4.4 shows the 30-day moving average of daily sales for menus under the highlights section. This figure shows that the new menu was well received by consumers and started selling well though not as much as the menus "The Most Seen" and "New". Sales in the new menu increased significantly during the first 10 weeks of the experiment as consumers became aware of it. Panel (b) provides more details. After week 10 sales decreased in most menus. At week 10 IP introduced two new menus into the highlights section, called "The Most Seen of All Time" and "IMDb's Most Popular". These menus competed with the menu used for the experiment both in terms of consumer attention and movies. In fact, when a movie under "The most popular during the past weeks" was also among "The most seen of all times" or "The most voted on IMDb" it would be pulled into the latter two menus and deleted from the former to avoid duplication.

Figure 4.5 shows the weekly sales in the new menu over time. Unlike overall VoD consumption, the majority of sales under this menu came from premium subscribers. Recall




(a) Leases from Standard Subscribers (b) Leases from Premium Subscribers

Figure 4.3: 30-Day Moving Average of Daily Leases in Highlights and Catalog in IP's VoD.




(a) All Lines in Highlights (b) Zoom In the Experimental Line

Figure 4.4: 30-Day Moving Average of Daily Leases in Highlights per Menu in IP's VoD.

that this menu was visible in the entry screen of the VoD system for premium subscribers and reachable with 1 click up, whereas standard subscribers did not see this menu right when they entered the highlights section and needed to click 10 times down to reach it. In addition, standard subscribers do not see the number of likes, which might have rendered this menu less meaningful to them.

Figure 4.6 shows the number of likes per rank in the beginning of each week. This

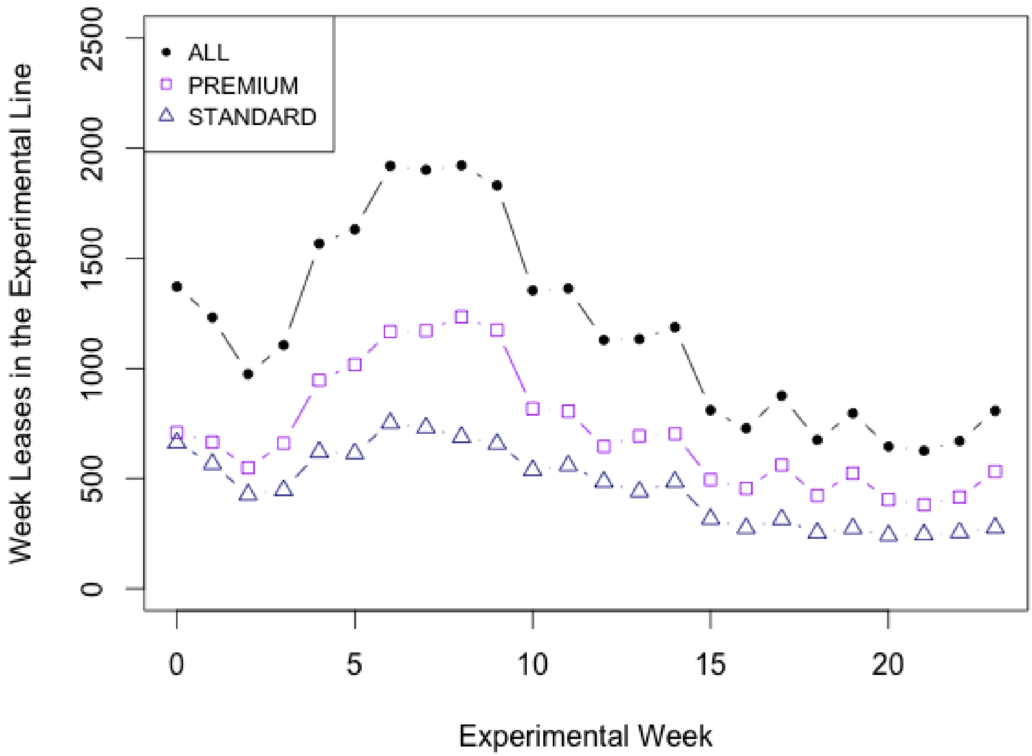



Figure 4.5: Sales in the New Menu During Our Experiment.

is a decreasing function by design. Yet, we observe a clear exponential decay. The most liked movies seem to open a gap relative to the other ones. Figure 4.7 shows the number of leases during the week per rank. This function, however, is far from monotone, which might suggest that subscribers use more information besides rank and number of likes to decide which movies to watch. Figure 4.8 shows the number of likes obtained during the week as a function of rank. Panel (a) shows that the movies in the visible part of the new menu tend to receive more likes than the movies in the hidden part of the menu. Panel (b) shows that, on average, promoted (demoted) movies tend to receive fewer (more) likes than untreated movies. This provides preliminary evidence that manipulated movies might return to their true ranks as they are re-ordered in subsequent weeks according to the number of likes.

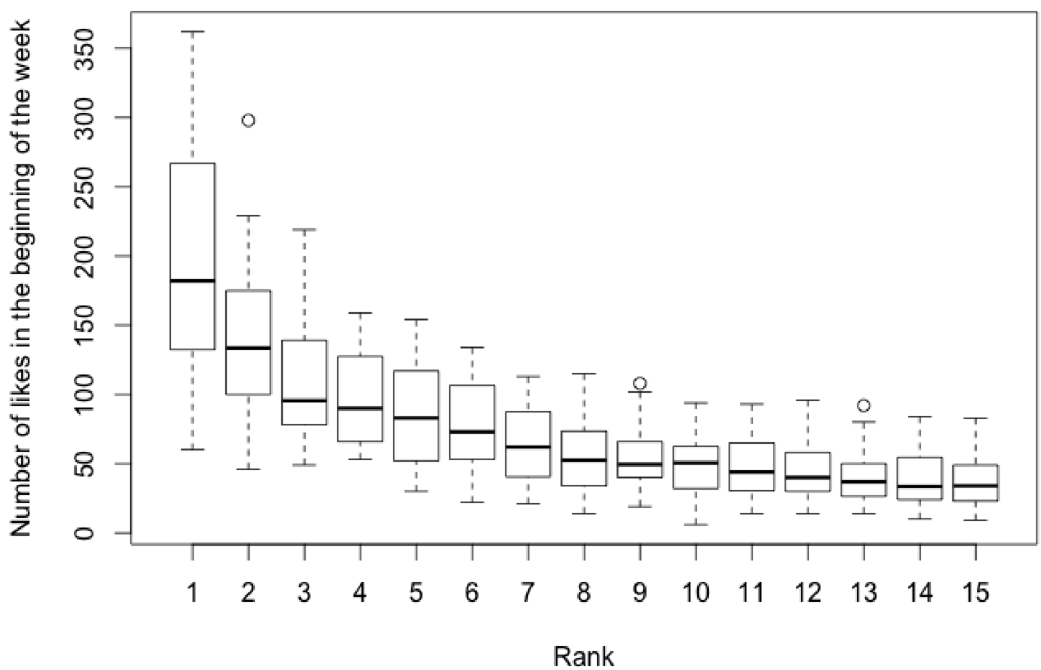



Figure 4.6: Number of Likes per Rank at the New Menu in the Beginning of the Week.

22,034 subscribers leased movies from the new menu. Figure 4.9 shows that roughly 77% of the subscribers leasing movies from the new menu did so only once during the experiment. Figure 4.13 in the appendix provides additional information about the intensity of VoD usage per subscriber. In particular, there is significant heterogeneity across subscribers. 50% of the subscribers lease less than 1 movie per quarter. Roughly 20% of them lease more than 1 movie per month. Panel (a) in Figure 4.10 shows that subscribers lease

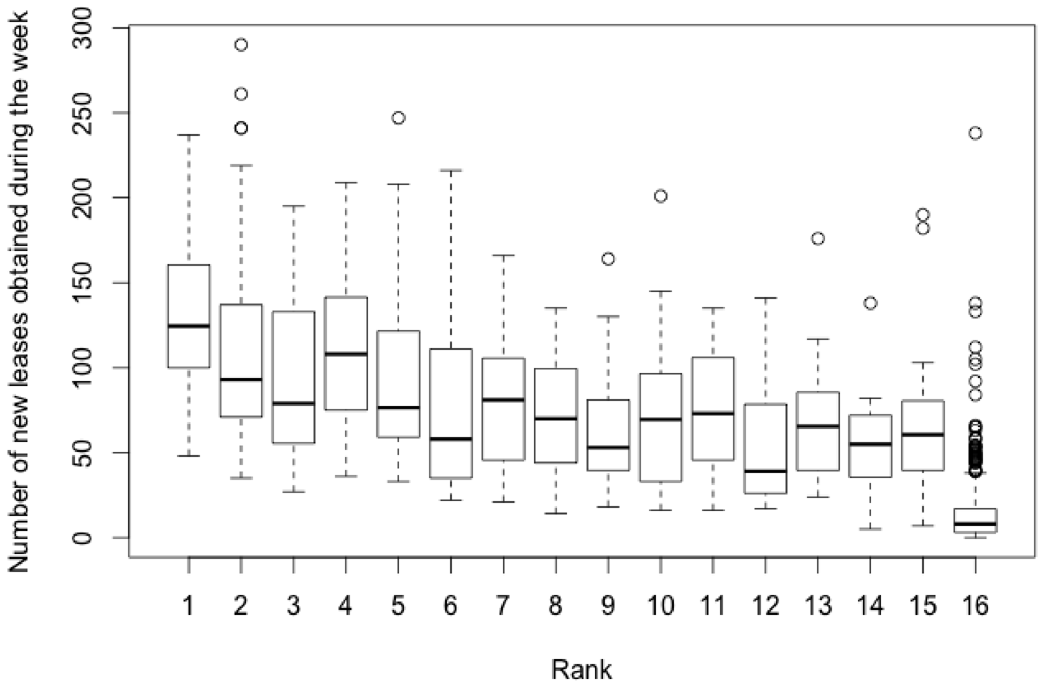
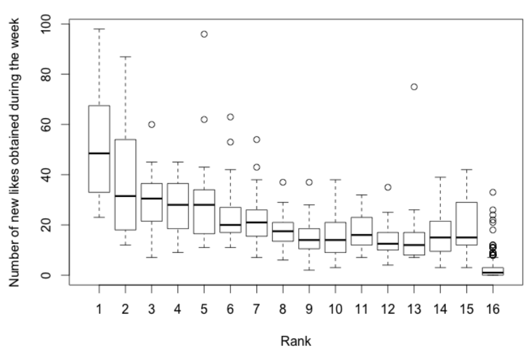
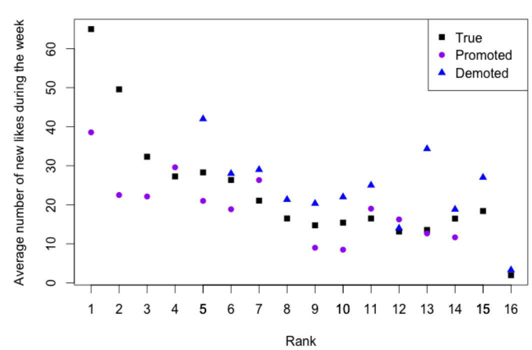



Figure 4.7: Leases per Week as Function of Rank at the New Menu.




(a) Likes per Week as a Function of Rank




(b) Breakdown for Control vs. Treated Movies

Figure 4.8: Likes per Week as a Function of Rank for All, Control and Treated Movies at the New Menu.

more movies after lunch and after dinner. Panel (b) in this Figure shows that subscribers essentially lease movies during the weekend.

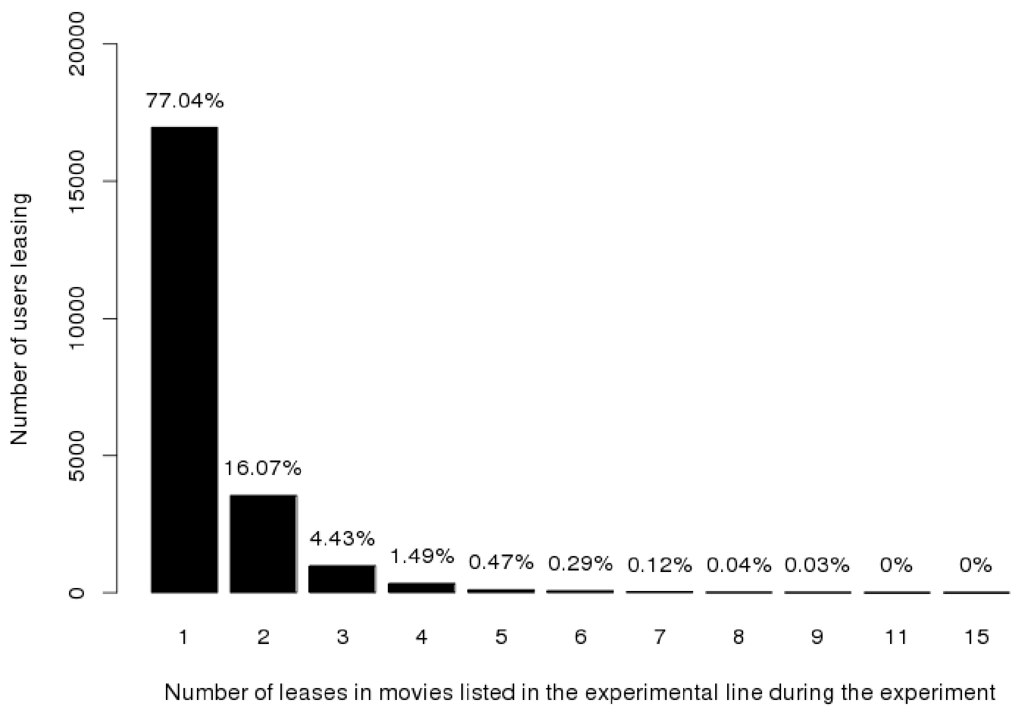
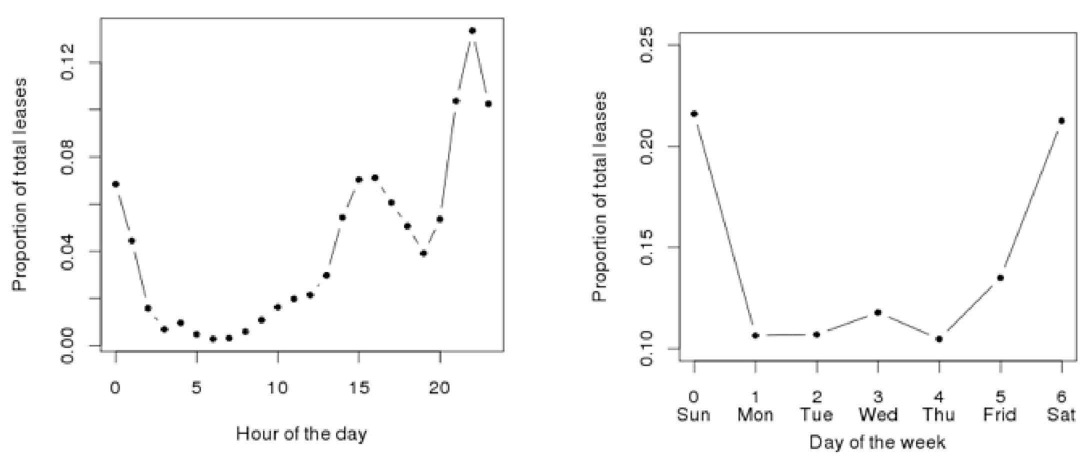



Figure 4.9: Statistics on VoD Consumption per Subscriber.




(a) Sales during the day

(b) Sales over the week

Figure 4.10: VoD usage habits

Finally, Table 4.2 shows descriptive statistics for the covariates used in this paper separately for all movies and for control and treated movies in the catalog and in the highlights section. Essentially, control and treated movies are similar, as expected given our random treatment assignment. T-tests to compare means between control and treated movies show they are similar in all the covariates.

Table 4.2: Descriptive Statistics for Covariates used in this Paper.

| | | | Catalog | | Highlights | |
|---|---|---|---|---|---|---|
| Vars | Stats | All | Control | Treated | Control | Treated |
| n_lease | | | | | | |
| | mean | 36.341 | 12.85 | 19.05 | 80.461 | 82.29 |
| | sd | 45.788 | 18.201 | 18.735 | 50.758 | 45.904 |
| n_lease_premium | | | | | | |
| | mean | 19.648 | 4.174 | 6.9 | 48.23 | 51.527 |
| | sd | 29.136 | 6.124 | 7.247 | 33.785 | 30.23 |
| n_lease_standard | | | | | | |
| | mean | 16.693 | 8.676 | 12.15 | 32.23 | 30.763 |
| | sd | 19.262 | 12.644 | 12.123 | 20.839 | 20.25 |
| rank | | | | | | |
| | mean | 13.311 | 16 | 16 | 8.531 | 7.151 |
| | sd | 4.487 | 0 | 0 | 4.197 | 4.369 |
| rank_true | | | | | | |
| | mean | 13.348 | 16 | 8 | 8.531 | 9.28 |
| | sd | 4.438 | 0 | 4.472 | 4.197 | 5.247 |
| rank_manipulation | | | | | | |
| | mean | 0.037 | 0 | -8 | 0 | 2.129 |
| | sd | 2.5 | 0 | 4.472 | 0 | 6.811 |
| n_menus | | | | | | |
| | mean | 1.984 | 1.708 | 1.65 | 2.609 | 2.258 |
| | sd | 1.058 | 0.932 | 0.813 | 1.193 | 0.674 |
| price | | | | | | |
| | mean | 287.741 | 260.883 | 324 | 331.617 | 346.312 |
| | sd | 92.662 | 84.763 | 96.655 | 90.21 | 74.951 |
| imdbrating | | | | | | |
| | mean | 6.328 | 6.31 | 5.98 | 6.427 | 6.253 |
| | sd | 1.242 | 1.215 | 1.485 | 1.261 | 1.304 |
| imdbvotes | | | | | | |
| | mean | 82434.666 | 87387.516 | 73270.75 | 80008.728 | 58978.022 |
| | sd | 114271.836 | 117701.293 | 168947.22 | 111504.825 | 76944.554 |
| movie_age | | | | | | |
| | mean | 250.257 | 291.779 | 266.294 | 166.844 | 187.112 |
| | sd | 380.553 | 415.368 | 429.838 | 277.441 | 314.458 |
| Observations | | 1017 | 648 | 20 | 256 | 93 |

### 4.6.2 The Effect of Swaps and the Role of Rank

We estimate equation 4.4, which resembles equation 4.1, to learn the effect of rank on leases. In this regression, $treated\_within * rank\_manipulation$ denotes the size of a rank manipulation within the top 15 ranks. $promoted\_to\_line$ and $demoted\_from\_line$ denote the size of rank manipulations that lead a movie to go from the catalog into the new menu or to move from the new menu into the catalog, respectively. These 3 types of manipulations constitute a partition of the space of possible manipulations and therefore their coefficients must be interpreted relative to our control movies. $treated$ indicates whether a movie has been treated.

$$\begin{aligned} leases_{it} = \lambda + \beta_1 log(movie\_age_{it}) + \beta_2 n\_menus_{it} + \beta_3 treated_{it} + \\ \beta_4 rank\_true_{it} + \beta_5 treated\_within * rank\_manipulation_{it} + \\ \beta_6 promoted\_to\_line_{it} + \beta_7 demoted\_from\_line_{it} + \\ + week\_dummies + m_i + \epsilon_{it} \end{aligned} \tag{4.4}$$

Table 4.3 shows the results obtained with first-differences for all subscribers and separately for standard and premium subscribers. The coefficient on $treated\_within*rank\_manipulation$ shows that a promoted (demoted) movie receives more (fewer) leases. This result is statistically significant for both standard and premium subscribers, although less for the former. On average, a manipulation that increases rank by 1 leads to 2.313 (0.509) more leases from premium (standard) subscribers. This corresponds to a 4.7% (1.6%) increase in the number of leases. Promoting a movie to the new menu increases 7.2 (2.1) times the number of leases from premium (standard) subscribers, on average. This significant jump is associated to the difference in search costs between the catalog and the highlights section. Demoting movies from the new menu yields the opposite effect for premium subscribers. The number of leases reduces by 37%. The effect of demotions from the new menu is not statistically significant for standard subscribers. The new menu was much harder to reach for standard subscribers and thus standard subscribers that use this menu might already be more willing to search for good movies. Finally, the coefficient on *treated* is not statistically significant as expected given the random assignment of treatments in our experiment.

During our experiment, movies were primarily shown in their true rank. However, sometimes, they were also exogenously and randomly swapped and thus shown in a fake rank. This variability allows us to study whether a movie placed in a fake rank sells differently from a true movie placed at that rank. To do so, we estimate equation 4.5, which resembles closely equation 4.3:

$$\begin{aligned}
leases_{rt} = \lambda + \beta_1 log(movie_age_{rt}) + \beta_2 n_menus_{rt} + \beta_3 price_{rt} + \beta_4 imdbrating_{rt} + \\
\beta_5 promoted * treated_within_{rt} + \beta_6 demoted * treated_within_{rt} + \\
\beta_7 promoted * treated_between_{rt} + \beta_7 demoted * treated_between_{rt} + \\
+ week_dummies + rank_dummies + genre_dummies + year_release_dummies + \epsilon_{rt}
\end{aligned} \quad (4.5)$$

Table 4.3: The Effect of Swaps Within the New Menu and Between the Menu and the Catalog on Sales.

| Subscribers | All | Standard | Premium |
|---|---|---|---|
| Model | FD | FD | FD |
| Variables | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ |
| (Intercept) | -5.621* | -2.693 | -2.928 |
| | (2.892) | (1.479) | (1.89) |
| | [3.083] | [1.637] | [1.805] |
| log(movie_age) | -11.852** | -11.775*** | -0.076 |
| | (6.389) | (3.268) | (4.176) |
| | [5.617] | [3.657] | [2.788] |
| n_menus | 12.3*** | 5.731*** | 6.569*** |
| | (1.883) | (0.963) | (1.231) |
| | [3.253] | [1.678] | [1.824] |
| treated | 1.356 | 0.387 | 0.969 |
| | (1.857) | (0.95) | (1.214) |
| | [3.039] | [1.039] | [2.571] |
| rank_true | -0.62 | 0.137 | -0.756** |
| | (0.362) | (0.185) | (0.236) |
| | [0.752] | [0.555] | [0.321] |
| treated_within * rank_manipulation | 2.821*** | 0.509* | 2.313*** |
| | (0.28) | (0.143) | (0.183) |
| | [0.488] | [0.278] | [0.333] |
| promoted_to_line | 36.31*** | 9.366*** | 26.945*** |
| | (3.472) | (1.776) | (2.269) |
| | [6.091] | [2.084] | [4.579] |
| demoted_from_line | -23.039*** | -4.848 | -18.191*** |
| | (3.786) | (1.936) | (2.474) |
| | [7.091] | [3.131] | [4.646] |
| $WeekDummies$ | Yes | Yes | Yes |
| N | 817 | 817 | 817 |
| R-Squared | 0.448 | 0.264 | 0.478 |
| R-Squared Adj | 0.431 | 0.254 | 0.461 |
| F-Stat (p-value) | 0 | 0 | 0 |

**Note 1:** Robust standard errors in [ ];
**Note 2:** *** p<0.01, ** p<0.05, * p<0.1
**Note 3:** First Differences Estimator

This regression allows us to compare the number of leases obtained by treated and control movies at each rank. *promoted* (*demoted*) indicates a movie that was promoted (demoted) to a fake rank. *treated_between* indicates whether a rank manipulation entails moving a movie from the catalog to the new menu or vice-versa. Therefore, the 4 types of manipulations included in this regression constitute a partition of the space of possible manipulations and thus their coefficients must be interpreted relative to our control movies.

Table 4.4 shows the results obtained. The first three columns in this table show the effect of rank manipulations on the number of leases whereas the last column shows the effect of rank manipulations on the number of likes. A movie that is demoted to a fake rank within the new menu sells 27.7% more than a true movie at that rank. Consumers are still able to spot high quality movies even if they have been shifted to the right on the TV screen under the new menu. This is true for both standard and premium subscribers though less statistically significant for the former. These results suggest that subscribers use more information besides rank to decide which movies to watch. We will provide more details on this hypothesis later in this paper. Conversely, a movie that is promoted to a fake rank within the new menu sells 15.9% less than a true movie at that rank. However, this result is weaker than the effect of demotions within the new menu. Both its magnitude and its statistical significance are lower. In fact, this effect is only statistically significant for premium subscribers.

The last column in Table 4.4 shows the effect of promotions and demotions on the number of likes obtained. A movie promoted (demoted) to a fake rank receives 33.1% fewer (30.1% more) likes than a true movie at that rank. This result entails that over time, manipulated movies are likely to come back to their true ranks. We will explore this hypothesis in more detail later in this paper. In addition, note that the coefficients for the effects of manipulations interacted with *treated_between* are essentially statistically

Table 4.4: The Effect of Promotions and Demotions on Sales Relative to Movies at True Ranks.

| | Leases | | | Likes |
|---|---|---|---|---|
| Subscribers | All | Standard | Premium | Premium |
| Variables | $leases_{rt}$ | $leases_{rt}$ | $leases_{rt}$ | $likes_{rt}$ |
| (Intercept) | 63.134*** | 0.986 | 62.148*** | 45.615*** |
| | (21.573) | (11.187) | (13.157) | (6.587) |
| | [18.904] | [10.935] | [10.906] | [5.808] |
| promoted * treated_within | -12.184* | -2.789 | -9.396* | -7.614*** |
| | (4.773) | (2.475) | (2.911) | (1.458) |
| | [7.308] | [3.221] | [5.108] | [2.584] |
| demoted * treated_within | 22.348*** | 7.756* | 14.592*** | 6.955*** |
| | (4.749) | (2.463) | (2.896) | (1.45) |
| | [7.034] | [4.501] | [4.21] | [2.511] |
| promoted * treated_between | -4.331 | 1.09 | -5.421 | -7.853** |
| | (5.67) | (2.94) | (3.458) | (1.731) |
| | [8.566] | [3.391] | [5.832] | [3.156] |
| demoted * treated_between | 5.686 | 4.35* | 1.336 | 1.241 |
| | (5.718) | (2.965) | (3.487) | (1.746) |
| | [4.448] | [2.451] | [2.524] | [1.051] |
| log(movie_age) | -3.103*** | -1.814*** | -1.289** | -0.305 |
| | (0.727) | (0.377) | (0.443) | (0.222) |
| | [1.178] | [0.689] | [0.633] | [0.275] |
| n_menus | 4.000* | 3.891*** | 0.109 | 1.276** |
| | (1.115) | (0.578) | (0.68) | (0.34) |
| | [2.106] | [1.207] | [1.063] | [0.531] |
| price | -0.005 | -0.006 | 0.002 | 0.01* |
| | (0.016) | (0.008) | (0.01) | (0.005) |
| | [0.026] | [0.016] | [0.013] | [0.006] |
| imdbrating | 3.541** | 1.005 | 2.536** | 1.112* |
| | (0.759) | (0.394) | (0.463) | (0.232) |
| | [1.429] | [0.717] | [1.096] | [0.576] |
| Week Dummies | Yes | Yes | Yes | Yes |
| Rank Dummies | Yes | Yes | Yes | Yes |
| Genre Dummies | Yes | Yes | Yes | Yes |
| Year Release Dummies | Yes | Yes | Yes | Yes |
| N | 1001 | 1001 | 1001 | 1001 |
| R-Squared | 0.759 | 0.631 | 0.775 | 0.777 |
| R-Squared Adj | 0.697 | 0.58 | 0.713 | 0.714 |
| F-Stat (p-value) | 0 | 0 | 0 | 0 |

**Note 1:** Robust standard errors in [ ]; **Note 2:** *** p<0.01, ** p<0.05, * p<0.1

insignificant, which means that search costs dominate the effect of manipulations. If anything, standard subscribers lease demoted movies more than true movies, which provides suggests that standard subscribers are more willing to search for movies to watch.

### 4.6.3 The Role of Outside Information

We test whether outside information about the movies shown at IP's VoD system mediates the effect of promoting and demoting movies. We use the number of IMDb votes as a proxy for how well movies are known to consumers in general. The number of IMDb votes indicates how may people evaluated a movie irrespective of the rating provided. Figure 4.11 shows that there is significant variation in the number of IMDb votes across movies in our sample. This is not surprising given the well established super star effect in the movie industry whereby popular movies concentrate a disproportionate amount of attention and therefore are more widely known (Elberse and Oberholzer-Gee, 2006). In addition, both IMDb votes and IMDb ratings are similar between control and treated movies. We hypothesize that the movies in IP's VoD system that have more outside information are less sensitive to our exogenous random manipulations. This would be consistent in spirit with the findings in (Tucker and Zhang, 2011) that show that products with broader appeal are less likely to benefit from the popularity they obtain at the specific platforms where they are sold[6].

We classify each movie in our sample according to the number of IMDb votes received until December of 2012. We define a dummy variable called $top25\_imdbvotes$ to indicate whether a movie is in the top quartile of the distribution of IMDb votes in our sample.

[6](Salganik and Watts, 2008) report a similar result but their measure of appeal is endogenous to the population of subjects used in their experiment.

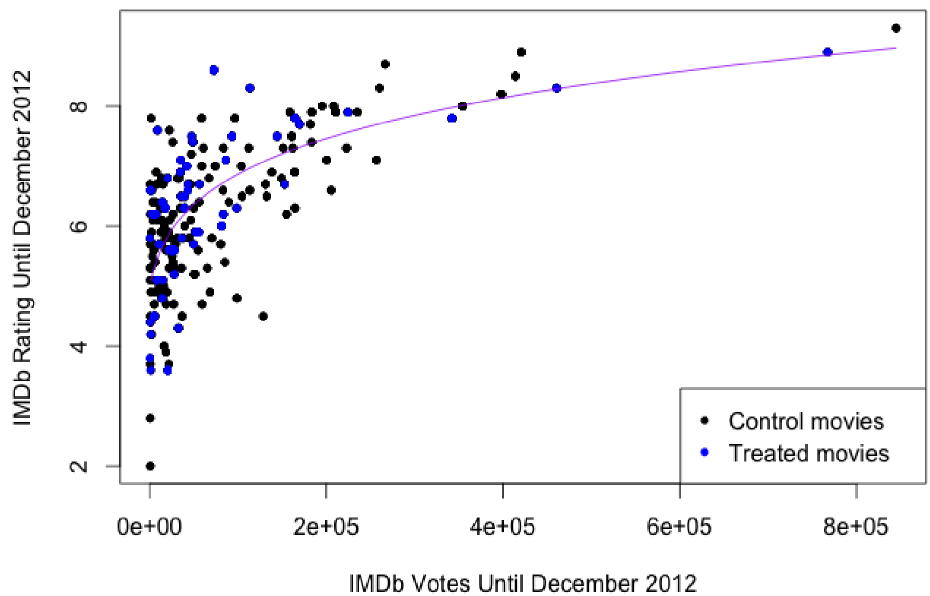



Figure 4.11: IMDb votes and ratings across movies in our sample.

We estimate equation 4.1 adding an interaction term between $rank\_manipulation$ and this dummy variable. In this regression, this interaction term captures the difference in the effect of our rank manipulations for movies in the top quartile of the distribution of IMDb votes relative to the effect on all the other movies in our sample that were also manipulated. Table 4.5 presents the results obtained. The effect of the interaction between $rank\_manipulation$ and $top25\_imbdvotes$ is negative and statistically significant, which confirms our hypothesis.

### 4.6.4 Converge to True Ranks

Figure 4.12 illustrates how manipulated movies converge to their true ranks over time. The horizontal axes represent time relative to the moment of treatment. The vertical axes

Table 4.5: The role of IMDb Votes on the Effect of Rank manipulations on Leases.

| Subscribers | All | Standard | Premium |
|---|---|---|---|
| Model | FD | FD | FD |
| Variables | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ |
| (Intercept) | -5.698* | -2.723* | -2.975* |
| | (2.883) | (1.477) | (1.885) |
| | [3.092] | [1.647] | [1.802] |
| log(movie_age) | -11.932** | -11.807*** | -0.125 |
| | (6.369) | (3.263) | (4.165) |
| | [5.624] | [3.665] | [2.78] |
| n_menus | 12.346*** | 5.749*** | 6.597*** |
| | (1.877) | (0.962) | (1.228) |
| | [3.268] | [1.682] | [1.833] |
| treated | 1.193 | 0.323 | 0.87 |
| | (1.852) | (0.949) | (1.211) |
| | [2.901] | [1.037] | [2.479] |
| rank_true | -0.674 | 0.115 | -0.789** |
| | (0.361) | (0.185) | (0.236) |
| | [0.756] | [0.559] | [0.322] |
| treated_within * rank_manipulation | 3.031*** | 0.591* | 2.44*** |
| | (0.292) | (0.149) | (0.191) |
| | [0.51] | [0.304] | [0.345] |
| treated_within * rank_manipulation * top25imdbvotes | -2.547** | -1.001* | -1.546** |
| | (1.037) | (0.531) | (0.678) |
| | [1.133] | [0.552] | [0.678] |
| promoted_to_line | 36.439*** | 9.416*** | 27.023*** |
| | (3.462) | (1.773) | (2.264) |
| | [6.031] | [2.087] | [4.532] |
| demoted_from_line | -23.461*** | -5.014* | -18.447*** |
| | (3.778) | (1.935) | (2.47) |
| | [6.736] | [3.025] | [4.439] |
| $WeekDummies$ | Yes | Yes | Yes |
| N | 817 | 817 | 817 |
| R-Squared | 0.452 | 0.267 | 0.482 |
| R-Squared Adj | 0.435 | 0.257 | 0.463 |
| F-Stat (p-value) | 0 | 0 | 0 |

**Note 1:** Robust standard errors in [ ];
**Note 2:** *** p<0.01, ** p<0.05, * p<0.1;
**Note 3:** First Differences Estimator

represent, for a particular time $t$ in the horizontal axis, the average number of weekly leases across all movies in our sample that were $t$ weeks away from their treatment date. On the top of each panel we indicate over how many movies each average is computed. Movies tend to sell less over time before treatment mostly due to aging. Promoted (demoted) movies sell significantly more (less) right after treatment. Within slightly more than 3 weeks promoted movies sell as much as they used to sell before treatment. For Demoted movies the same is true, they need slightly more than 3 weeks to sell as much as they used to sell before treatment.

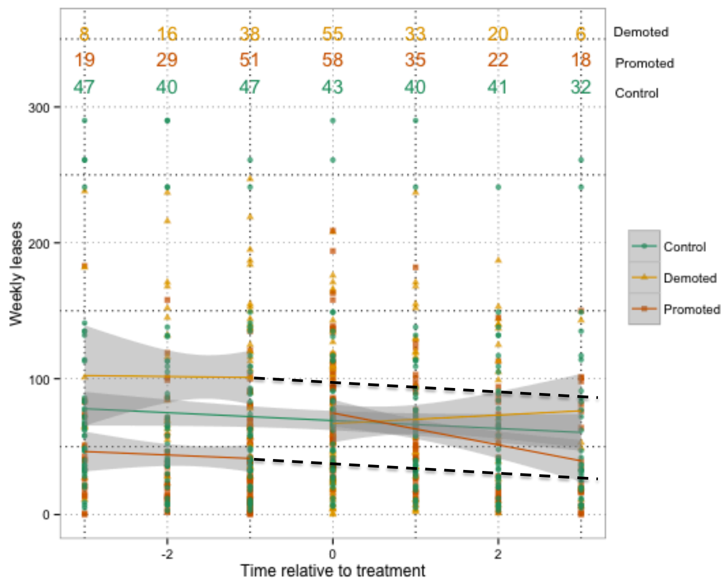



Figure 4.12: Sales per Week for Promoted and Demoted Movies Before and After Treatment.

Manipulated movies may introduce changes in welfare, both for the profits of IP as well as for consumers, though they converge relatively quickly to their true ranks. We compare outcomes in false and true weeks to understand these changes.

Table 4.4 shows that sales during the week after a swap within the new menu increased by 10.2. The average price of the movies in this menu during our experiment was \$3.54 and the average profit margin was 27% per movie. Therefore, IP enjoyed an additional profit of \$9.7 per within swap during the week after the swap. The additional profit associated with premium subscribers is \$4.99. Additionally, after a within swap premium subscribers issued fewer 0.66 likes per week than before the swap. This is evidence that there are changes in consumer surplus as a consequence of movie manipulations although we cannot establish a monetary value for them with the data that we have available. Still our results raise concerns about the effectiveness of recommender systems. While at the outset these systems might be put in place to help consumers navigate large catalogs of options, in the end the way firms manipulate them might be prejudicial for consumers. A recommender system that uses likes from consumer to order the way alternatives are provided to them seems to adjust quickly to extraneous disturbances and thus might help mitigate strategic behavior.

## 4.7 Conclusions

In this paper, we design and implement a randomized experiment to determine the role that *likes* play on the sales of movies over VoD. We use the VoD system of a large telecommunications provider during half a year in 2012. A new menu in the *Highlights Section* of this VoD system was introduced showing the most liked movies in the past few weeks. Movies with more *likes* were shown farthest to the left on the TV screen. During our the experiment, movies were primarily placed in their true rank and shown along with their true number of *likes*. At random moments, some movies were swapped and thus displayed our of order and with a fake number of *likes*. The movies that were swapped were selected at random. Randomization allows us to disentangle *likes* from unobserved perceived quality and thus estimate the effect of the former on sales.

We found that search costs play a major role on sales. A movie brought from the catalog into the new menu sells about 7 times more, on average. We found that promoting a movie by one rank increases weekly sales by 4% on average. We found that a movie promoted (demoted) to a fake slot sells 15.9% less (27.7% more) than a true movie placed at that slot, on average across all manipulations we introduced. We showed that this asymmetry is related to the amount of information publicly available about the movies manipulated. Better-known movies are less sensitive to manipulations.

We also found that a movie promoted (demoted) to a fake slot receives 33.1% fewer (30.1% more) likes than a true movie at that slot. Therefore, manipulated movies tend to move back to their true slot over time. During this adjustment process, the provider enjoys increased profits while subscribers may lose welfare. This process is likely to converge quickly, in a matter of 2 to 3 weeks time, which might lead the provider to promote different movies over time to sustain its profit margin. However, it is not clear whether in the long run subscribers will believe in the number of *likes* exhibited at this VoD system if movies are manipulated often. Another way for the provider to attract attention to, and possibly increase the sales of, specific movies without manipulating their rank is to strategically show and hide movies between the *Highlights Section* and the catalog.

We have measured the impact of *likes* in a real VoD system of a large telecommunications provider. We believe that number of *likes* is a more truthful measure of the quality experienced by subscribers than several popularity measures previously used in the literature. This is specially true in our setting, in which subscribers need to explicitly make decisions that entail financial risks because movies are not free. Because movies are not free in this setting, demoted movies could be unable to climb back to their true rank. We showed they do at a slower pace than promoted movies fall back to their true rank. The fact that movies are well known in our setting reduces the risk associated with choosing a good but demoted movie. Certainly, trailers also allow subscribers to better perceive the quality of a movie before they pay to watch it, which could benefit demoted movies as long as subscribers are willing to search beyond the first ranked movies.

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## 4.A High and Low Intensity VoD Users

We study how High and Low intensity VoD users reacted to the manipulations that we introduced during the experiment. We use leases from January 2012 until December 2012 to classify subscribers according to their overall usage intensity. Figure 4.13 details how we classified usage intensity. We assume that high intensity users are those in the top 50% deciles of usage distribution. These are consumers who leased more than three movies over the year. Low intensity users are part of the bottom 50% deciles of the usage intensity distribution.

We replicate the regressions shown in the main paper using leases by high and low intensity consumers in our experimental line as dependent variables. Table 4.6 presents the results of the analysis.

We find that both high and low intensity were sensitive to within and between swaps. However, more frequent users of the VoD system were less sensitive to manipulation than low intensity consumers. Overall movies promoted by 1 rank position within the experimental line increased sales by 3.5% (2.3%) for low (high) intensity users. On average, promoting movies from the catalog to the experimental lines increased sales by 291.3% (188.1%) for low (high) intensity users.

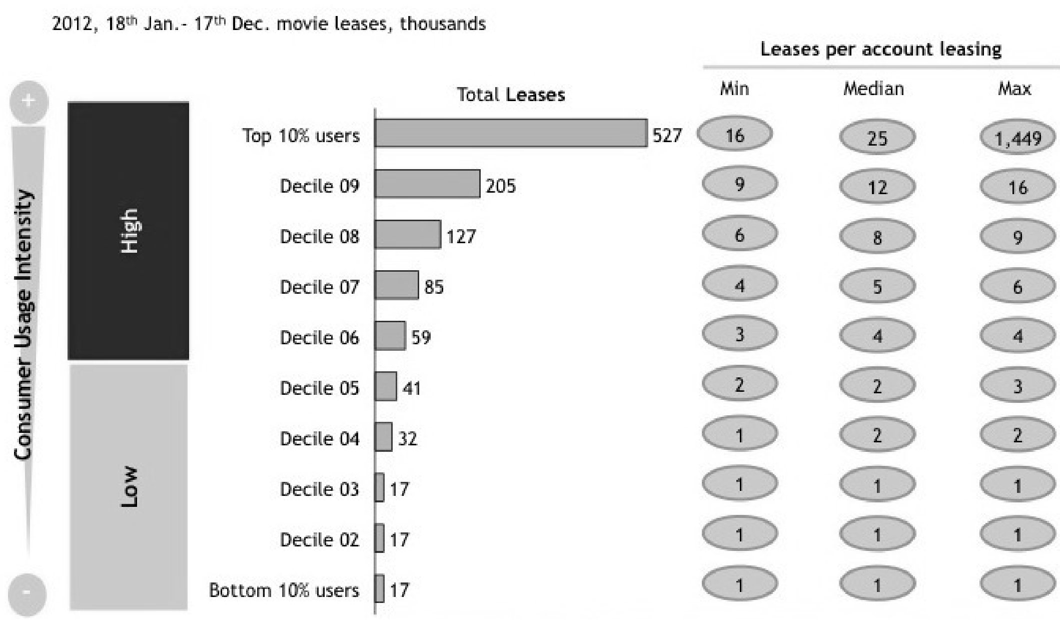


Figure 4.13: Deciles of user VoD usage intensity

Table 4.6: Treatment effect on different consumer categories

| User Type | All | | Standard | | Premium | |
|---|---|---|---|---|---|---|
| Usage Intensity | High | Low | High | Low | High | Low |
| Variables | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ |
| (Intercept) | -0.286 | -5.367* | 0.118 | -2.764* | -0.404 | -2.603 |
| | (0.58) | (2.559) | (0.335) | (1.363) | (0.434) | (1.624) |
| | [0.562] | [2.834] | [0.323] | [1.544] | [0.397] | [1.611] |
| log(asset_age) | 1.381* | -13.181** | 0.086 | -12.21*** | 1.296*** | -0.971 |
| | (1.282) | (5.653) | (0.739) | (3.011) | (0.959) | (3.588) |
| | [0.726] | [5.207] | [0.429] | [3.469] | [0.464] | [2.54] |
| n_menus | 1.655*** | 10.619*** | 0.705** | 5.03*** | 0.95** | 5.589*** |
| | (0.378) | (1.666) | (0.218) | (0.888) | (0.283) | (1.058) |
| | [0.592] | [3.013] | [0.31] | [1.55] | [0.375] | [1.668] |
| treated | -0.576 | 2.188 | -0.52** | 0.699 | -0.056 | 1.489 |
| | (0.372) | (1.643) | (0.215) | (0.875) | (0.279) | (1.043) |
| | [0.432] | [2.254] | [0.233] | [0.935] | [0.406] | [1.869] |
| rank_true | -0.112 | -0.502 | -0.029 | 0.192 | -0.083 | -0.694** |
| | (0.073) | (0.32) | (0.042) | (0.171) | (0.054) | (0.203) |
| | [0.082] | [0.742] | [0.046] | [0.543] | [0.054] | [0.299] |
| treatedwithin * rank_manipulation | 0.218*** | 2.5*** | 0.009 | 0.501** | 0.209*** | 1.998*** |
| | (0.056) | (0.248) | (0.032) | (0.132) | (0.042) | (0.157) |
| | [0.082] | [0.412] | [0.04] | [0.251] | [0.063] | [0.262] |
| promoted_to_line | 2.382** | 33.507*** | 0.804* | 8.771*** | 1.578* | 24.736*** |
| | (0.696) | (3.072) | (0.402) | (1.636) | (0.521) | (1.95) |
| | [0.998] | [5.26] | [0.444] | [1.943] | [0.913] | [3.808] |
| demoted_from_line | -1.857* | -21.313*** | -0.756* | -3.95 | -1.1 | -17.363*** |
| | (0.759) | (3.349) | (0.438) | (1.784) | (0.568) | (2.126) |
| Week Dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 817 | 817 | 817 | 817 | 817 | 817 |
| R-Squared | 0.133 | 0.465 | 0.087 | 0.276 | 0.117 | 0.505 |
| R-Squared Adj | 0.128 | 0.448 | 0.084 | 0.266 | 0.113 | 0.486 |
| F-Stat (p-value) | 0 | 0 | 0 | 0 | 0 | 0 |

**Note 1:** Robust standard errors in [ ];
**Note 2:** *** p<0.01, ** p<0.05, * p<0.1
**Note 3:** First Differences Estimator

## 4.B Impact of Rank on Trailer Views

We replicate the regressions shown in the main paper using trailer views as our dependent variable. In this case, we want to learn whether manipulating the rank of a movie has an effect on the number of trailers watched. Table 4.7 shows the results obtained, which are qualitatively similar to the ones obtained before for the case of leases[7]. However, both the statistical significance and the magnitude of the impact of manipulations are higher than before. Watching trailers is free of charge (the only resource that consumers commit when watching a trailer is time). It seems that the number of likes attracts consumers to watch trailers and thus likes can be a productive tool to attract consumers to particular movies. This, however, does not necessarily translate into more leases as subscribers do use trailers to form a more certain opinion about the quality of the movies.

[7] Which could be expected since the correlation between leases and trailer views is around 0.71 ($p-value < 0.01$)

Table 4.7: Effect of rank on trailer views.

| Subscribers | All | Standard | Premium |
|---|---|---|---|
| Model | FD | FD | FD |
| Variables | $trailerviews_{it}$ | $trailerviews_{it}$ | $trailerviews_{it}$ |
| (Intercept) | -12.071 | -8.692 | -3.379 |
| | (23.021) | (8.895) | (15.748) |
| | [13.891] | [7.152] | [9.061] |
| log(movie_age) | -37.535 | -55.774** | 18.239 |
| | (50.85) | (19.647) | (34.785) |
| | [35.526] | [24.004] | [20.677] |
| n_menus | 96.048*** | 52.873*** | 43.176*** |
| | (14.988) | (5.791) | (10.253) |
| | [20.33] | [10.431] | [11.656] |
| treated | 31.349 | 5.628 | 25.721 |
| | (14.778) | (5.71) | (10.109) |
| | [25.156] | [7.693] | [18.486] |
| rank_true | -6.514 | 1.189 | -7.703*** |
| | (2.88) | (1.113) | (1.97) |
| | [4.613] | [2.511] | [2.58] |
| treatedwithin * rank_manipulation | 32.313*** | 5.979*** | 26.334*** |
| | (2.227) | (0.861) | (1.524) |
| | [5.275] | [1.29] | [4.123] |
| promoted_to_line | 367.434*** | 104.716*** | 262.718*** |
| | (27.635) | (10.678) | (18.904) |
| | [93.576] | [30.849] | [64.49] |
| demoted_from_line | -264.445*** | -71.819** | -192.626*** |
| | (30.13) | (11.641) | (20.611) |
| | [76.292] | [27.873] | [50.342] |
| $WeekDummies$ | Yes | Yes | Yes |
| N | 817 | 817 | 817 |
| R-Squared | 0.554 | 0.472 | 0.562 |
| R-Squared Adj | 0.534 | 0.454 | 0.542 |
| F-Stat (p-value) | 0 | 0 | 0 |

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in []
First Differences Estimator

## 4.C Eliminating Sequences of Treatments

A potential problem with our experiment is the fact that the same movies can be subject to different treatments in consecutive weeks. In this case the effect of the first treatment might contaminate the effect of the second treatment. To assess the impact that such potential contamination might have on our experiment we perform the regressions presented in the main paper but discard all observations of a movie within the same cycle beyond (and including) the second treatment. Because treatment assignment is random, eliminating these observations is equivalent to random attrition in the sample. For each movie that we trim we include a dummy variable indicating whether that movie was trimmed. This dummy variable should not be statistically significant if our assumption of random attrition holds. The trimming operation discards 42 observations (34 treated and 8 after the first treatment).

Table 4.8 shows the results obtained, which reinforce our previous findings. Manipulating the rank, promoting and demoting movies to and from the new menu affect sales as before. As expected, trimmed is not statistically significant, as well as treated.

Table 4.8: Results eliminating sequences of treatments within the same cycle.

| Subscribers | All | Standard | Premium |
|---|---|---|---|
| Model | FD | FD | FD |
| Variables | $leases_{it}$ | $leases_{it}$ | $leases_{it}$ |
| (Intercept) | -5.68* | -2.752* | -2.928* |
| | (2.683) | (1.418) | (1.738) |
| | [3.027] | [1.663] | [1.729] |
| log(movie_age) | -12.366** | -11.933*** | -0.433 |
| | (6.003) | (3.172) | (3.889) |
| | [5.909] | [3.79] | [2.993] |
| n_menus | 11.103*** | 5.499*** | 5.605*** |
| | (1.819) | (0.961) | (1.179) |
| | [3.187] | [1.677] | [1.771] |
| treated | 2.692 | 1.078 | 1.615 |
| | (1.981) | (1.047) | (1.284) |
| | [3.29] | [1.532] | [2.482] |
| rank_true | -0.708 | 0.141 | -0.849** |
| | (0.355) | (0.188) | (0.23) |
| | [0.843] | [0.621] | [0.352] |
| treatedwithin * rank_manipulation | 2.914*** | 0.365 | 2.549*** |
| | (0.323) | (0.171) | (0.21) |
| | [0.581] | [0.271] | [0.429] |
| promoted_to_line | 39.786*** | 10.188*** | 29.598*** |
| | (3.721) | (1.966) | (2.411) |
| | [6.676] | [2.55] | [4.855] |
| demoted_from_line | -31.377*** | -6.851 | -24.526*** |
| | (4.719) | (2.494) | (3.058) |
| | [8.177] | [4.326] | [4.998] |
| trimmed | -0.405 | 0.184 | -0.589 |
| | (4.856) | (2.566) | (3.146) |
| | [4.934] | [2.371] | [3.712] |
| Week Dummies | Yes | Yes | Yes |
| N | 762 | 762 | 762 |
| R-Squared | 0.456 | 0.265 | 0.49 |
| R-Squared Adj | 0.437 | 0.254 | 0.47 |
| F-Stat (p-value) | 0 | 0 | 0 |

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

Robust standard errors in [ ]

First Differences Estimator

## 4.D Berry, Levinsohn, Pakes model (BLP)

Through the paper we assume that the decision of purchasing a particular movie is independent of the choice of any other movie available in the VoD system. To relax this assumption and assess its impact on the results that we report, we use a BLP model (Berry et al., 1995).

In this model, the benefit index that consumer $i$ enjoys by consuming alternative $j$ is defined by:

$$V_{ij} = \alpha_j + \beta x_{ij} + \lambda_j z_i + \delta_j w_{ij} \tag{4.6}$$

$x_{ij}$ are alternative specific and may vary per individual $i$, but have a generic coefficient $\beta$. $w_{ij}$ are specific to each alternative and have alternative specific coefficients $\delta_j$, $z_i$ are individual specific alternatives and have alternative specific coefficients $\lambda_j$. The utility that consumer $i$ derives from good $j$ is determined by:

$$U_{ij} = V_{ij} + \epsilon_j \tag{4.7}$$

Consumer $i$ chooses the alternative that brings him the highest benefit. $i$ chooses $j$ if and only if $U_{ij} > U_{ik} \forall j \neq k$. To determine his choice, the consumer evaluates $J - 1$ conditions:

$$U_{ij} - U_{ik} > 0 \forall j \neq k \tag{4.8}$$

For a particular $j$ and $k$:

$$U_{ij} - U_{ik} = (\alpha_j - \alpha_k) + \beta(x_{ij} - x_{ik}) - (\lambda_j - \lambda_k)z_i + (\delta_j w_{ij} - \delta_k w_{ik}) + (\epsilon_j - \epsilon_k) \quad (4.9)$$

Then, the model is solved based on the general expression for the probability of choosing $j$:

$$P(j|\epsilon_j) = P(U_j > U_1, ..., U_j > U_J) \quad (4.10)$$

As the number of consumers increases towards infinity, $P_j$ can be assumed to be the true market share $S_j$ of product $j$. Following (Berry, 1994) we apply logarithms to the probability function:

$$Log(S_j) = Log(P_j) = V_j - Log(\sum_j e^{V_j}) \quad (4.11)$$

Then we standardize the utility of the outside good to zero such that $P_o = \frac{1}{\sum_j e^{V_j}}$ and we get $Log(S_o) = Log(P_o) = -\sum_j e^{V_j}$. Replacing this term in the equation above we get the simplified reduce form that we estimate using our data on weekly movie leases:

$$Log(S_j) - Log(S_o) = V_j \quad (4.12)$$

In this formulation the elasticity of demand with respect to a covariate $x_j$ is given by:

$$\beta * x_j * (1 - S_j) \tag{4.13}$$

The cross elasticity of product $j$ demand with respect to any covariate of product $k$ is given by:

$$\beta * x_k * S_k \tag{4.14}$$

Table 4.9 provides the average market share of all the movies listed at each rank of the experimental line over the six months of the experiment. It also provides the market share of the outside option which includes leasing movies not listed in the experimental line or opting for not leasing at all.

Table 4.9: Average Market Shares for Movies Positioned at Each Rank

| rank | All | Standard | Premium |
|---|---|---|---|
| 1 | 0.021 | 0.008 | 0.050 |
| 2 | 0.019 | 0.010 | 0.042 |
| 3 | 0.015 | 0.009 | 0.032 |
| 4 | 0.017 | 0.010 | 0.035 |
| 5 | 0.015 | 0.008 | 0.033 |
| 6 | 0.012 | 0.007 | 0.026 |
| 7 | 0.013 | 0.007 | 0.026 |
| 8 | 0.012 | 0.007 | 0.023 |
| 9 | 0.010 | 0.007 | 0.018 |
| 10 | 0.011 | 0.007 | 0.022 |
| 11 | 0.012 | 0.007 | 0.023 |
| 12 | 0.009 | 0.006 | 0.018 |
| 13 | 0.011 | 0.006 | 0.022 |
| 14 | 0.009 | 0.005 | 0.017 |
| 15 | 0.011 | 0.006 | 0.021 |
| 16 | 0.002 | 0.002 | 0.002 |
| Outside Good | 99.753 | 99.839 | 99.547 |
| Market Size | 624,980 | 440,597 | 184,383 |

The results of the BLP model regression are provided in table 4.10 and the study of the elasticity of demand with respect to the rank position is detailed in tables 4.11 and 4.12. For the market share of each individual movie the cross price elasticities are essentially zero which strengthens the legitimacy of the approach that we followed in the paper. Additionally the results reported for the BLP model are the same as those reported for the linear version presented in the paper.

Table 4.10: BLP model regression results

| Consumer Type<br>Variables | All<br>$log(s_j) - log(s_o)$ | Standard<br>$log(s_j) - log(s_o)$ | Premium<br>$log(s_j) - log(s_o)$ |
|---|---|---|---|
| (Intercept) | -0.179** | -0.128 | -0.168** |
| | (0.09) | (0.103) | (0.105) |
| | [0.082] | [0.091] | [0.084] |
| log(asset_age) | -0.369** | -0.597*** | -0.182 |
| | (0.202) | (0.233) | (0.245) |
| | [0.182] | [0.195] | [0.186] |
| n_menus | 0.088 | 0.089 | 0.027 |
| | (0.064) | (0.073) | (0.074) |
| | [0.059] | [0.063] | [0.064] |
| rank | -0.024*** | -0.014** | -0.03*** |
| | (0.006) | (0.007) | (0.007) |
| | [0.005] | [0.006] | [0.006] |
| ishighlight | 1.346*** | 0.975*** | 1.687*** |
| | (0.103) | (0.116) | (0.118) |
| | [0.129] | [0.148] | [0.129] |
| Week Dummies | Yes | Yes | Yes |
| N | 750 | 726 | 663 |
| R-Squared | 0.494 | 0.315 | 0.541 |
| R-Squared Adj | 0.476 | 0.304 | 0.519 |
| F-Stat (p-value) | 0 | 0 | 0 |

**Note 1:** Models estimated using first differences estimator; **Note 2:** Robust standard errors in []; **Note 3:** Decline in the number of observation across models due to movies with zero leases over the period

Table 4.11: Percentage change in sales due to the change in rank by 1 position for the average movie positioned at each rank for Premium consumers.

| Rank Coefficient | Rank Variable | Average Market Share | % Change in Rank Variable if Rank increases +1 | % Change in in Sales due change of 1 rank $\beta * rank * (1 - S_{rank}) * \%change$ |
|---|---|---|---|---|
| -0.030272 | 1.000000 | 0.000496 | 100.000000 | -3.025699 |
| -0.030272 | 2.000000 | 0.000415 | 50.000000 | -3.025943 |
| -0.030272 | 3.000000 | 0.000317 | 33.333333 | -3.026242 |
| -0.030272 | 4.000000 | 0.000348 | 25.000000 | -3.026148 |
| -0.030272 | 5.000000 | 0.000335 | 20.000000 | -3.026187 |
| -0.030272 | 6.000000 | 0.000261 | 16.666667 | -3.026411 |
| -0.030272 | 7.000000 | 0.000263 | 14.285714 | -3.026405 |
| -0.030272 | 8.000000 | 0.000229 | 12.500000 | -3.026508 |
| -0.030272 | 9.000000 | 0.000184 | 11.111111 | -3.026642 |
| -0.030272 | 10.000000 | 0.000218 | 10.000000 | -3.026541 |
| -0.030272 | 11.000000 | 0.000225 | 9.090909 | -3.026518 |
| -0.030272 | 12.000000 | 0.000175 | 8.333333 | -3.026669 |
| -0.030272 | 13.000000 | 0.000223 | 7.692308 | -3.026526 |
| -0.030272 | 14.000000 | 0.000165 | 7.142857 | -3.026700 |
| -0.030272 | 15.000000 | 0.000206 | 6.666667 | -3.026577 |
| -0.030272 | 16.000000 | 0.000023 | 6.250000 | -3.027130 |

Table 4.12: Own rank elasticity of demand ($\beta * x_j * (1 - S_j)$) and cross rank elasticities of demand ($\beta * x_k * S_k$) for Premium consumers. Assuming the market share of the average movie at that rank during our experiment

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.03026 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 2 | 0.00002 | -0.06052 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 3 | 0.00002 | 0.00003 | -0.09079 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 4 | 0.00002 | 0.00003 | 0.00003 | -0.12105 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 5 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | -0.15131 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 6 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | -0.18158 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 7 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | -0.21185 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 8 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | -0.24212 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 9 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | -0.27240 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 10 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | -0.30265 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 11 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | -0.33292 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 12 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | -0.36320 | 0.00009 | 0.00007 | 0.00009 | 0.00001 |
| 13 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | -0.39345 | 0.00007 | 0.00009 | 0.00001 |
| 14 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | -0.42374 | 0.00009 | 0.00001 |
| 15 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | -0.45399 | 0.00001 |
| 16 | 0.00002 | 0.00003 | 0.00003 | 0.00004 | 0.00005 | 0.00005 | 0.00006 | 0.00006 | 0.00005 | 0.00007 | 0.00008 | 0.00006 | 0.00009 | 0.00007 | 0.00009 | -0.48434 |

# Chapter 5

# Conclusion

This thesis covers a theoretical model, an observational study and an experimental study in the telecommunications and media industries.

In the second chapter of this manuscript we developed a game theoretic model that predicts the number of infrastructure providers and virtual firms (companies leasing access from infrastructure providers) that will enter green-field regions. In our model, firm entry occurs in multiple markets characterized by the demand for a general telecommunication service and the costs to deploy the appropriate infrastructure to meet demand. The latter are largely determined by household density.

Using engineering data from publicly available sources and simulation software we developed, we parameterize the model to analyze several types of regions where NGNs can be deployed - rural areas, urban areas and downtown areas. We explore how different wholesale prices can determine the competitive nature and structure of telecommunications markets and by predicting how many firms are likely to enter each market, our model provides fundamental information for regulators to decide the best type of policy a region might require to ensure availability of telecommunications service.

We conclude that low wholesale prices can attract a disparate number of virtual providers to enter the market. The excess competition will reduce the profitability of infrastructure providers and their incentives to invest. High wholesale prices can deter the entry of virtual providers and trigger investment. Yet such scenario does not necessarily maximize welfare which in our simulations can be highest in situations where a single provider invests in infrastructure opening the network to virtual providers at reasonable prices.

We also confirm the asymmetric business case for the development of NGNs which motivated the emergence of GSR in the first place: highly populated areas are likely to develop into competitive telecommunication markets while regions with low household density will only see very limited investment in network infrastructures and little or no competition.

Finally, we show that supply side interdependencies among markets, common to the telecommunications' industry, make the implementation of GSR non-trivial. We show that changes in the wholesale price in one market can have undesirable consequences in the competitive conditions of interrelated regions. Namely we provide an example where our model predicts that wholesale price changes in a competitive market can have negative consequences in an interrelated, but less competitive market where the wholesale price was not changed.

In the third chapter we study the effect of peer influence in the diffusion of the iPhone 3G across a number of communities that were sampled from a large dataset provided by a major European Mobile (EURMO) carrier in one country.

We use community dummies and instrumental variables to control for potential correlation between unobserved subscriber heterogeneity and peer influence. We provided evidence that the propensity of a subscriber to adopt increases with the percentage of friends that had already adopted. We estimated that 14% of iPhone 3G adoptions in EURMO were due to peer influence, after controlling for social clustering, gender, previous adoption of mobile internet data plans, ownership of technologically advanced handsets and some heterogeneity in the regions where subscribers move during the day and spend most of their evenings. Our estimate for peer influence without IV is three times lower that the above statistic, which hints at the fact unobserved effects might be negatively correlated with adoption. We provide additional empirical evidence that budget constraints might be at work and might prevent several family members, or many employees in the same company, from purchasing the iPhone 3G, which was a conspicuous and expensive handset for the average consumer in the country studied.

We also provide results from several policy experiments that show that with an effect of peer influence with this magnitude EURMO would hardly be able to significantly increase sales by selectively targeting appropriate early adopters to benefit from viral marketing. We show that a seeding strategy using local degree yields the largest number of additional adopters among the strategies compared in this paper, but even such a policy could only hardly break even for the cost/revenue ratio at which the iPhone 3G might have been commercialized.

In the fourth chapter we design and implement a randomized experiment to determine the role that *likes* play on the sales of movies over VoD. We use the VoD system of a large telecommunications provider during half a year in 2012. A new menu in the *Highlights Section* of this VoD system was introduced showing the most liked movies in the past few weeks. Movies with more *likes* were shown farthest to the left on the TV screen. During our the experiment, movies were primarily placed in their true rank and shown along with their true number of *likes*. At random moments, some movies were swapped and thus displayed our of order and with a fake number of *likes*. The movies that were swapped were selected at random. Randomization allows us to disentangle *likes* from unobserved perceived quality and thus estimate the effect of the former on sales.

We found that search costs play a major role on sales. A movie brought from the catalog into the new menu sells about 7 times more, on average. We found that promoting a movie by one rank increases weekly sales by 4% on average. We found that a movie promoted (demoted) to a fake slot sells 15.9% less (27.7% more) than a true movie placed at that slot, on average across all manipulations we introduced. We showed that this asymmetry is related to the amount of information publicly available about the movies manipulated. Better-known movies are less sensitive to manipulations.

We also found that a movie promoted (demoted) to a fake slot receives 33.1% fewer (30.1% more) likes than a true movie at that slot. Therefore, manipulated movies tend to move back to their true slot over time This adjustment process is likely to converge quickly, in a matter of 2 to 3 weeks time, which might lead the provider to promote different movies over time to obtain increased sales. However, it is not clear whether in the long run subscribers will believe in the number of *likes* exhibited at this VoD system if movies are manipulated often. Another way for the provider to attract attention to, and possibly increase the sales of, specific movies without manipulating their rank is to strategically show and hide movies between the *Highlights Section* and the catalog.