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REGULAR ARTICLE

Peer influence in network markets: a theoretical and empirical analysis

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Abstract Network externalities spur the growth of networks and the adoption of network goods in two ways. First, they make it more attractive to join a network the larger its installed base. Second, they create incentives for network members to actively recruit new members. Despite indications that the latter "peer effect" can be more important for network growth than the installed-base effect, it has so far been largely ignored in the literature. We address this gap using game-theoretical models. When all early adopters can band together to exert peer influence—an assumption that fits, e.g., the case of firms supporting a technical standard—we find that the peer effect induces additional growth of the network by a factor. When, in contrast, individuals exert peer influence in small groups of size n, the increase in network size is by an additive constant—which, for small networks, can amount to a large relative increase. The difference between small, local, personal networks and large, global, anonymous networks arises endogenously from our analysis. Fundamentally, the first

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type of networks is "tie-reinforcing," the other, "tie-creating". We use survey data from users of the Internet services, Skype and eBay, to illustrate the main logic of our theoretical results. As predicted by the model, we find that the peer effect matters strongly for the network of Skype users—which effectively consists of numerous small sub-networks—but not for that of eBay users. Since many network goods give rise to small, local networks, our findings bear relevance to the economics of network goods and related social networks in general.

Keywords Network markets · Peer influence · Diffusion · Technology adoption · Social networks

JEL Classification L10 · D62 · O32

1 Introduction

For many products a user's utility depends on the number of other users of the good (Farrell and Saloner 1985; Katz and Shapiro 1985). Such network externalities have become ubiquitous with the information economy, in particular with the rise of virtual communities and web 2.0 applications. For the diffusion of new goods, network externalities have two rather different implications. First, the more users a good has, the more attractive the good becomes for potential further adopters. We call this phenomenon the *installed-base effect*, since it is caused by the attractiveness of the current user base to outsiders. Second, growth of the installed base is beneficial also to those users who are already part of it, who thus have an incentive to support its growth by exerting influence on not-yet adopters. We refer to this second mechanism as the *peer effect*. Since current users are more likely to exert influence on those outsiders to which they already maintain social ties, the peer effect relates social networks to the diffusion of network goods (with two slightly differing meanings of the term "network"). In the following, we refer to the installed base of the network good as the *network* under consideration, in contrast to a social network. While the installed-base effect has been treated extensively in the literature (e.g., Katz and Shapiro 1986, 1992), the peer effect has received very little attention.[1] The purpose of this paper is to fill this gap by providing a theoretical analysis and empirical evidence of the peer effect.

As an illustration consider the case of Skype, a proprietary peer-to-peer Internet telephony (VoiP) network.[2] The first public version of Skype was released in August

[1] The studies by Domingos and Richardson (2001) and Subramani and Rajagopalan (2003) are two exceptions published in the field of computing and information systems. The latter article in particular addresses, in a conceptual model, the motives of network members to recruit further adopters.

[2] With some simplification, Skype works in the following way. After registering with the Skype service, a user builds her personal contact list by sending contact requests to other users, or receiving and accepting requests herself. She can then call each person on her personal contact list via Skype. Calls are transmitted over the internet, and are free of charge for both parties. The Skype software also include other features such as conference calls, calls to fixed-line phones (SkypeOut), sending SMS or Instant Messaging. In September 2005, Skype was acquired by the Internet auction provider eBay.

2003. In October 2004, the peak number of subscribers simultaneously logged on to Skype reached 1 million; by June 2011, this number has grown beyond 30 million.[3] The firm reported to the SEC that its total number of registered users had reached 663 million by December 2010, and that its users made 207 billion minutes of voice and video calls using Skype in 2010.[4]

It seems safe to assume that peer influence—Skype users trying to enlist their friends and colleagues for the service—played an important role in enabling this strong growth. The marketing department at Skype is aware of the power of this effect, and supports this particular peer-based way of diffusion by offering its users a pre-formulated e-mail message: "Hey there! Come join me on Skype so we can make free Skype-to-Skype video and voice calls. Simply download Skype—it's totally free [...]".[5] In principle, such activity is well known as viral or word-of-mouth marketing. The distinctive feature of peer influence, however, is that the focal person is motivated by her own benefit deriving from network externalities. The quality and level of this motivation distinguishes the peer effect from other drivers of viral marketing.

The fact that most users would try to enlist a *specific* group for Skype—typically their friends and colleagues—highlights yet another point central to our study. The value of Skype for a particular user strongly depends on how many of those persons she regularly communicates with have adopted the service. In contrast, most of the other millions of Skype users are irrelevant to her. That is, the Skype network that actually matters for her is a replication of an existing—small and local—social network, not the universe of all Skype users. This observation implies, in particular, that the strength of the network externality varies strongly between dyads of users: "local" network externalities, between individuals in close (social) proximity to each other, are stronger than externalities between distant individuals. Such local network externalities have been analyzed, among others, by An and Kiefer (1995), Cowan and Miller (1998), Jonard and Yildizoglu (1998), Tomochi et al. (2005), and Lee et al. (2006).

The type of local network externality described above is in stark contrast to that present, e.g., in marketplaces. Consider the case of the online auction service, eBay. For someone intending to sell a good to a friend there would be little need to conduct the transaction over eBay. The value of eBay, flee markets, and similar marketplaces lies precisely in the fact that they match strangers with corresponding desires to sell and to buy. Unlike Skype, such marketplaces do not rely on existing ties, but aim at creating new ones. They tend to be (socially) non-local, non-personal, and typically large. Thus, while an eBay user may talk her friends into adopting the service because she is fond of it, she would not derive any network benefits from them joining the network.

[3] See http://about.skype.com/ (accessed June 9, 2011).

[4] See http://www.sec.gov/Archives/edgar/data/1498209/000119312511056174/ds1a.htm#rom83085_9 (accessed June 9, 2011).

[5] See http://www.skype.com/intl/en-us/tell-a-friend/ (accessed June 9, 2011).

We analyze the peer effect described above using game-theoretical models and a survey. Building upon Hotelling's (1929) classical approach and employing the concept of fulfilled expectation equilibria, we analyze how introducing the peer effect affects the equilibrium size of a network, and how a seller of a network good leverages the peer effect in its pricing decisions and by supporting users in recruiting new network members. In our model, all user dyads are homogeneous with respect to network externalities. Thus, the network in our model can be interpreted either as a global network (e.g., all eBay users) or as a local (sub-)network characterized by strong network externalities between its members but weak externalities between members and non-members (e.g., a group of Skype users who are part of a class of students). In the latter case, results for the overall set of users obtain by adding up the effects on each sub-network.

We present and discuss three ways of modeling peer influence. The first serves as a benchmark, modeling the maximum additional network growth through peer influence which is incentive compatible. In the second model we assume that all early adopters coordinate to influence new adopters to such an extent that the resulting network size maximizes their utility gains. This model is applicable to firms that, as early adopters of, e.g., a technology standard commit contractually to expand effort to grow the network further. The third model applies to individuals adopting network goods such as Skype and eBay. We assume that individuals who already adopted the good band together in small groups of size n, where $n = 1$ is particularly important, to convince the respective marginal non-consumer to join the network.

Influencing may take the form of advice or technical support, in which case one unit of cost (or effort) expanded by those on the giving side—"influencers"—translates into several (κ) units of benefit for the receiver. We refer to κ as the cost leveraging factor.

We find that introducing peer influence leads to an increase in equilibrium network size which depends positively on the cost leveraging factor κ, the relative strength of the network externality, and in the third model on the group size n. When the provider charges for the network good, equilibrium prices are higher than in the base case absent peer influence; that is, the seller partly skims off the increased attractiveness of her good. For the first and the second model, we find that the increase in network size resulting from the peer effect is by a factor; for the third model, in contrast, growth is by an additive constant. Here, an important distinction arises between "tie-creating" networks such as eBay, and "tie-reinforcing" networks such as Skype. In the latter case, the user base effectively consists of numerous small sub-networks, and the correct unit of analysis for our model is one such sub-network. In that case, additive growth translates to a considerable *relative* growth—both for each sub-network and, by adding up, for the overall user base.

The difference between the two types of networks sketched above thus arises endogenously from our third model: the effective personal network of most Skype users is small, and growing one's personal network by exerting peer influence makes sense. In contrast, all eBay users—in sufficient geographical proximity—are potential buyers of the good a person offers. Growing this already huge network by exerting peer influence makes little sense.

We illustrate the main logic of our theoretical analysis by a survey on the adoption of Skype and eBay. Very clearly, the data support the main logic that drives the results of our theoretical model. Asking participants about the relative importance of the peer effect, the local installed base, and the global installed base of the respective service for their adoption decision, we find that for the adoption of Skype the *peer effect* and the *local* installed base effect (i.e., the effect of the installed base among the members of the potential adopter's pre-existing social network) predominate. For eBay, in contrast, both of these effects are of little relevance, while the *global* installed base effect drives adoption. These findings are fully confirmed by ordered Logit regression analysis with a matched sample design, using observations from those survey participants that had adopted both services. With "intensity of peer influence" as the dependent variable and controlling, amongst others, for age, gender, and level of computer expertise, we find the coefficient of the dummy variable indicating "Skype" positive and highly significant for both experienced and exerted peer influence.

The remainder of the paper is organized as follows. We discuss the related literature in Section 2. Sections 3 and 4 present the model analysis from the adopters' and the seller's perspective, respectively. We present our empirical study in Section 5 and, in Section 6, discuss our findings and point out open questions.

2 Related literature

The analysis of the diffusion of network products dates back to works by Katz and Shapiro (1985, 1986) and Farrell and Saloner (1985, 1986). A large strand of literature has built on these early contributions. Particularly relevant in our context are publications on local network externalities as well as a number of empirical studies.

Models of local network externalities assume that positive externalities from adoption of a network do not benefit each individual in the population, but only a small subset (An and Kiefer 1995; Cowan and Miller 1998; Jonard and Yildizoglu 1998; Tomochi et al. 2005). "Local" in this context denotes social rather than geographical proximity: local network externalities are present between individuals who interact more frequently or more intensively with each other than with persons outside the local network (Koski and Kretschmer 2004). Cowan and Miller (1998) as well as Jonard and Yildizoglu (1998) show that these local externalities are a reason for non-standardization: winner-take-all outcomes do prevail within each local network, but different goods may win in different local networks.

On a global scale, thus, standardization may not arise. The existence of languages and local dialects is an illustrative example: there still exist languages or local dialects that are only spoken by a few people. As Church and King (1993) show, this outcome cannot prevail under the assumption of global network externalities. Abrahamson and Rosenkopf (1997) analyze the effect of social network structure on the extent of innovation diffusion, assuming that information about the innovation is channeled by social networks. In a similar vein, Deroïan (2002) develops a model of innovation diffusion with interacting agents, who influence each other in their effort to evaluate the innovation. Using simulation analysis, Lee et al. (2006) show that the winner-take-all outcome in network markets depends on the structural characteristics of a customer network, that is how good individuals in the network tend to know one another and how many linkages exist between distant local networks. In an empirical study, Tucker (2008) can show that individuals in boundary spanner positions have a strong impact on the adoption decisions of other network members.

Our approach differs from earlier work on local, or social network-based, network effects by explicitly modeling peer influence—that is, the possibility that adopters can influence, or even subsidize, those having not yet adopted in order to increase their own utility derived from network externalities. This mechanism has largely been ignored in the literature, the studies by Subramani and Rajagopalan (2003) and Domingos and Richardson (2001) being notable exceptions. Subramani and Rajagopalan (2003) describe the peer effect as "motivated evangelism" in a conceptual, qualitative model. Domingos and Richardson (2001) analyze, theoretically and empirically, the "network value" of a customer, which arises from her influencing others to buy. However, with "network value" referring to the underlying social network rather than to network externalities, they do not focus on the influencer's motivation that arises from network externalities. Our analysis goes beyond these studies by addressing this source of motivation explicitly in both model and empirical analysis. Furthermore, the distinction between small (and thus local) and large (and thus global) networks is not built into our assumptions, but arises endogenously from our model.

On the empirical side, there is quite some extant work on the installed-base effect, but very little on the peer effect. The installed-base effect is found to exist in industries as diverse as PC and software (e.g., Brynjolfsson and Kemerer 1996; Gandal 1994; Koski 1999), fax machines (Economides and Himmelberg 1995), automated teller machines (Saloner and Shepard 1995), telecommunications (Birke and Swann 2006; Majumdar and Venkataraman 1998), consumer electronics (Shankar and Bayus 2003), and yellow pages (Rysman 2004). To our knowledge, only one empirical study analyzes the peer effect (Block and Köllinger 2007), finding that it has a strong impact on the adoption of Internet-based Instant Messaging services.

The peer effect must be distinguished from word-of-mouth communication.[6] Word-of-mouth describes a communication channel, without specifying the motive of the person exerting interpersonal influence. For example, a person might tell a friend about a recently acquired gadget out of pure enthusiasm. She might derive some utility from speaking to an intrigued listener, and possibly from the fact that her addressee copies her behavior by purchasing the same good. Her utility gain would then be linked either to the act of persuading itself or to a confirmation of her own

[6]Word-of-mouth communication is a much researched topic in marketing and communication research. For an early work in the field of communication research see Lazarsfeld et al. (1944), who introduce the distinction between word-of-mouth communication and mass media influence in the context of voter behavior. For an early contribution in the field of marketing see Arndt (1967), who analyzes the effect of word-of-mouth communication on the diffusion of a new product in an experimental setting.

behavior. It thus can be present for all types of goods, irrespective of network externalities. In contrast, the peer effect, as it is defined in this paper, implies that by recruiting a new user a network member realizes a continuous flow of utility which is directly linked to her and the adopter's use of the good. Peer influence may happen by means of word-of-mouth communication, but other means (e.g., technical support) are conceivable as well. Conversely, word-of-mouth communication may have the purpose of exerting peer influence, but this need not be the case.

Finally, we note analogies between the adoption of network goods and diffusion processes as observed in biology and physics. From these disciplines, epidemiological models (e.g., Bettencourt et al. 2006) and percolation models (Solomon et al. 2000) have been borrowed to describe the spread of ideas, new products, and new processes in social systems. Epidemiological models mostly assume homogeneous populations in which ideas propagate "like viruses infecting new people on the occasion of random binary encounters [...]" (Solomon et al. 2000: 240). Percolation models, in contrast, "take into account the fact that possible adoption of new ideas, products, or technologies concern agents, whose tastes and interests vary across the population and whose mutual influence is a priori pre-determined in a sparse network of social interactions" (Solomon et al. 2000: 240). Considering the applicability of these models to the diffusion of network goods, percolation models appear well suited to model diffusion based on peer influence, while epidemiological models fit best to describe diffusion driven by the installed-base effect.

3 Adopters' perspective

3.1 How peer influence and installed base interact

The goal of our analysis is to show what share of network growth can be attributed to peer influence and to the installed base effect, respectively. To address this question, we first note that whenever a network can grow through the installed-base effect (i.e., if the marginal non-adopter obtains a positive utility from adopting), then it can also grow through the peer effect (i.e., network members find it attractive to recruit the marginal non-adopter for the network). The reverse does not hold, though: situations exist in which growth through peer influence is possible, but growth through the installed-base effect is not. To see why, consider that a consumer will join the network on her own accord, due to the installed-base effect, if she derives a positive utility from doing so. But this consumer can just as well be pulled into the network by earlier adopters.[7] In contrast, a consumer with a negative utility from adopting would not join on account of the installed-base effect alone, but might be recruited

[7] To model this situation, one would have to determine how exactly peer influence is exerted on a person who would take the same action out of her own account. For the purpose of the current analysis, however, this question can remain unanswered. What matters is that up to a certain network size both effects can work concurrently, while beyond this size only the peer effect is relevant.

for the network by existing members—who "subsidize" her—if her disutility from joining is not too large.

Thus, there exists a network size beyond which the network cannot grow further through the installed-base effect. How this size is reached—if through the installed-base effect or through peer influence—is irrelevant for the purpose of our analysis.[8] What matters is that this size (the equilibrium size y_0^* to be introduce below) allows a clear-cut identification of the share of network growth that can be attributed solely to the peer effect.

In the following subsections, we develop three models of network growth through peer influence. In each case, we compare the resulting network size to the benchmark case of y_0^*, i.e., to the maximum network size that can be attained through the installed-base effect alone. In the first two models, we explicitly assume a first stage of network growth only through the installed-base effect, followed by a second stage in which peer influence drives further growth. In the third model, we assume network growth through peer influence alone. As we have explained above, though, it is irrelevant through which mechanism the limiting size y_0^* is reached, and so this distinction does not affect our results.

The three models are related in that they model the market and the network externality in the same manner. They differ, and complement each other, by what insights we can glean from them with respect to peer influence. The first model serves as a benchmark, exploring the maximum additional network growth through peer influence which is incentive compatible (i.e., Pareto neutral). The second model applies best to the case of firms where, subsequent to an initial phase of network growth through the installed base effect, early adopters then contract to exert coordinated peer influence to grow the network further. The third model applies best to individuals. It is motivated by network goods such as Skype and eBay, where individuals who already adopted the good band together in small groups, or act individually, to convince the respective marginal non-consumer to join the network. Before turning to these models of peer influence, we introduce the model setup and study the base case of purely installed-base-driven network growth.

3.2 Base case: adoption without peer influence

Following Hotelling's (1929) classical model, we consider a market of heterogeneous consumers who are distributed on the positive real axis $[0; \infty[$ with density one.[9] There is one good, offered by a monopolist at price p. If the consumer located at

[8] In real life, it is a plausible situation that a network starts out as an insider tip among friends with growth largely through peer influence, while later it becomes popular and further adopters join because of the installed-base effect. However, this scenario is characterized by various overlaying effects, not all of which are captured in our models: the peer effect, the installed-base effect, and the effect of popularity. Popularity of a network good implies that information about it becomes more readily available and may even be impossible to ignore, which increases the perceived benefits and reduces the cost of adoption for all not-yet-adopters. This "popularity" effect is not captured in our models, though.

[9] We use the term "consumer" to keep the presentation simple. However, the potential adopters of the focal good may also be firms or other institutions.

x was the only adopter of the good, she would derive a stand-alone utility of $u(x)$ from it, where $u(x)$ is twice continuously differentiable and $u'(x) \leq 0$.[10] The standalone utility $u(y)$ comprises the gross benefits of use as well as the non-monetary costs of adoption and use. In addition to $u(y)$, a consumer's utility depends on the number of other adopters. With a network size of y her utility, and hence willingness to pay, is $u(x) + v(y)$. The network externality function $v(y)$ is non-negative, twice continuously differentiable, increasing in y, and weakly concave: $v(y) \geq 0$, $v'(y) > 0$, $v''(y) \leq 0$. When all consumers expect the future network size to be y^{exp} and base their adoption decision on this expectation, then the resulting network size y (equal to the position of the marginal adopter) is given by $u(y) + v(y^{\text{exp}}) - p = 0$. A fulfilled expectations equilibrium (FEE) y_0^* then is a solution to the following equation:

$$u\left(y_0^*\right) + v\left(y_0^*\right) - p = 0. \tag{1}$$

The consumers in $[0; y_0^*]$ adopt because they are attracted by the (expected) size of the installed base. That is, their adoption is driven by the *installed base effect*. We will refer to this outcome as the base case. Note that, depending on the shape of the functions u and v there may be multiple FEEs.

Under certain conditions, adoption by the entire market may be an equilibrium. As an example, consider the native language of a country as the network good. However, if the installed base effect alone already leads to complete market penetration, analyzing the peer effect becomes pointless. Thus, in order to focus on analytically interesting cases we assume in the following that $\lim_{y\to\infty}(u(y) + v(y)) < 0$. This condition implies existence of some y_{limit} such that $u(y) + v(y)) < 0$ for all $y > y_{\text{limit}}$. Thus, no FEE y_0^* can exist that is larger than y_{limit}.

Since the network externality $v(y)$ is non-negative, $u(y) + v(y) < 0$ requires that the standalone utility $u(y)$ becomes negative. Such negative values are perfectly plausible since $u(y)$ comprises also the cost of adoption and use. For instance, adopting a new ERP system entails costs for the adopting firms for, e.g., training employees and transferring existing data to the new system. Also, individuals who are not computer users may perceive a high cost of adopting Skype or eBay due to the learning required and due to necessary investments into complementary hardware. Furthermore, the gross standalone benefit (i.e., the benefit ignoring the cost of adoption and use) may be zero for some consumers, such that even minor adoption costs make the net benefit of the good negative for them. Empirically, the fact that neither Skype nor eBay are adopted by the entire population suggests that a considerable share of consumers would face non-zero costs of adoption and little or no gross benefit.

[10] In fact, monotonicity of $u(x)$ need not be assumed. Since each consumer is characterized only by the standalone utility she derives from the good, we are free to assign values of x in such a way to the consumers that their standalone utility decreases with x. Thus, we obtain $u'(x) \leq 0$ by definition rather than by assumption.

The assumption that $\lim_{y\to\infty}(u(y)+v(y)) < 0$ implies that, for each non-negative price p, the set of solutions to Eq. 1 has an upper bound. Existence of at least one FEE follows from the fact that $u(y)+v(y)-p$ is continuous and negative for sufficiently large y. So, either it is negative for all $y \geq 0$, in which case $y_0^* = 0$ is the only equilibrium, or it is positive for some y.[11] In the latter case, $u(y)+v(y)-p$ must change its sign from positive to negative somewhere, which implies existence of a stable equilibrium.[12] In addition to the general model, we will use a linear functional form for u and v in order to simplify the analysis and to arrive at more concrete results:

$$u(x) = u_0 - \lambda x\ , \quad v(y) = \alpha y. \tag{2}$$

The condition that $\lim_{y\to\infty}(u(y)+v(y)) < 0$ requires that $\alpha < \lambda$, which we thus assume in the following. The reverse case is trivial from an analytical point of view, and hence we leave it out. We note, however, that it may well be realistic, leading to adoption of the network good by the entire market. In this linear case, the solution to Eq. 1 becomes

$$y_0^* = \frac{u_0 - p}{\lambda - \alpha}\ . \tag{3}$$

The denominator reflects the relative strength of the network effect (α) compared to the utility loss from not having one's optimal product (λ). When the network externality becomes large ($\alpha \to \lambda$), y_0^* diverges and the outcome approaches adoption by the entire market.

3.3 Benchmark: maximum adoption by surplus redistribution

The marginal buyer in the base case, located at y_0^*, has by definition a utility of zero when all agents in $[0; y_0^*]$ adopt. Hence, any additional adopter at $x > y_0^*$ would experience a negative net benefit. However, her adoption would increase the network size, benefitting all other adopters. If the network externality is strong enough and the additional adopter's disutility not too large, the overall effect of her adoption on consumer welfare will be positive. Thus, with a suitable redistribution of surplus between adopters a Pareto improvement compared to the base case can be achieved. As we have said, we refer to individuals on the giving end of this redistribution as influencers. If an agent at $x > y_0^*$ adopts due to such influencing, then the adoption was based on the peer effect. While the adopter—like all users—also takes the size of the installed base into account, it is the peer effect which triggers her adoption decision.

[11] A third possibility would be that the function equals zero at one or more points and is negative otherwise. These roots would constitute equilibria which are unstable against deviations to lower values of y. We refrain from pursuing this case further since we focus on stable equilibria.

[12] A solution y to Eq. 1 at which the sign changes from negative to positive would mean that, after a small deviation to $y - \epsilon < y$, the marginal consumer would experience a negative net utility and would hence not join the network, reducing its size further. In contrast, a positive deviation of the network size to $y + \epsilon$ would imply that the marginal non-consumer would derive a positive utility from joining the network. She would consequently do so and increase the network size further.

In real life, peer influence may take the form of side payments. This is particularly plausible when the constituents of the network are firms. In this case, one unit of utility provided by an influencer (i.e., cost) corresponds to one unit of utility received by the new adopter. However, peer influence may also be exerted in a non-monetary way. In fact, in networks of individuals this will be the norm rather than the exception. For example, a user of a certain software package may assist her friend in installing the software and learning how to use it. This instance of peer influence differs in two respects from that of side-payments between firms. First, the influencer incurs a *non-monetary* cost, due to the time and effort spent on assisting the friend. Even if this effort is small (e.g., just writing one email) it is non-negative, and influencing many potential adopters may become a real burden on the influencer's time. The second difference is that a high benefit for the new adopter can be generated with relatively little effort on the influencer's side. For example, experienced advice in troubleshooting may take the influencer a minute but may save the adopter one hour. For that reason, we introduce a "cost leveraging" parameter κ: one unit of effort exerted by an influencer translates into κ units of benefit for the receiver. Our argument implies that κ will in general be larger than unity.

Following the above consideration, we ask the following question. What is the maximum y_1^* such that, if all agents in $[0; y_1^*]$ adopt, each of them is at least as well off as in the benchmark case without peer influence? Such Pareto neutrality is arguably the minimum condition that should be stipulated from a peer-influence mechanism, and should thus yield an upper limit for the additional network growth attainable by peer influence.

When $y_1 > y_0^*$ consumers adopt, then the net benefit of adoption (before redistribution) is positive for all $x < \hat{y}_1$, where

$$\hat{y}_1 = u^{-1}\left(p - v(y_1)\right) \ . \tag{4}$$

Obviously, when $y_1 > y_0^*$ and the FEE is unique, then $y_0^* < \hat{y}_1 < y_1$. The sought-for value y_1^* is then given by the following equation:

$$\begin{aligned} y_0^*\left(v\left(y_1^*\right) - v\left(y_0^*\right)\right) &+ \int_{y_0^*}^{\hat{y}_1} \left(u(x) + v\left(y_1^*\right) - p\right) dx \\ &+ \frac{1}{\kappa}\int_{\hat{y}_1}^{y_1^*} \left(u(x) + v\left(y_1^*\right) - p\right) dx = 0. \end{aligned} \tag{5}$$

The first two terms in this expression are positive. The first one describes the utility gains, due to the growth of the network from y_0^* to y_1^*, of those consumers who also adopt in the base case. Figure 1 illustrates the argument for the case of $\kappa = 1$, with the area A_1 corresponding to the first term in Eq. 5. The second term, corresponding to area A_2, captures the positive utility of those "new" adopters who are positioned below $\hat{y}_1$ and who thus have a positive net benefit of adoption without receiving any transfers. The last one, finally, is negative, and corresponds to area A_3. In order to capture the leveraging effect discussed above it carries the inverse of κ as a factor. Introducing $\omega \equiv \alpha/\lambda$, which measures the relative strength of the network externality

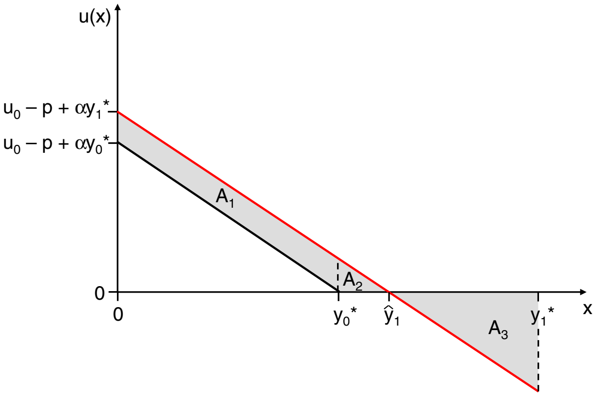

Fig. 1 Network growth by peer influence through surplus redistribution

compared to the decrease in consumers' stand-alone utility when x increases, we can state the following proposition.

Proposition 1

(a) *In the linear case, $\hat{y}_1$ obtains as $\hat{y}_1 = (u_0 - p + \alpha y_1^*)/\lambda$. The solution y_1^* to Eq. 5 is given by*

$$y_1^* = y_0^* \left(1 + \frac{2\omega\kappa}{1 - 2\omega - \omega^2(\kappa - 1)}\right) . \tag{6}$$

(b) *For the general case, the following results can be shown. If $y_0^* > 0$ exists then either a finite solution $(\hat{y}_1, y_1^*)$ to Eq. 4 (with $y = y_1^*$) and Eq. 5 exists, or the left-hand side of Eq. 5 is positive for all pairs $(\hat{y}_1, y_1^*)$, implying adoption by the entire population. As to the number of equilibria, even if y_0^* is unique there may be multiple solutions to Eq. 5.*

Part (a) of the proposition is proved by straight-forward calculation (like all other propositions, unless stated otherwise); part (b) holds because the left-hand side of Eq. 5 is continuous in y_1^* and positive for values of y_1^* incrementally larger than y_0^*.

The proposition says that, as in the base case, the network size diverges when the relative strength of the network effect exceeds a certain limit: for $\omega \to (\sqrt{\kappa} + 1)^{-1}$, y_1^* goes to infinity. Due to the peer effect, much lower values of the relative network externality strength suffice to achieve adoption by the entire market. Even if the cost leveraging factor κ only equals unity, $\omega = 0.5$ is sufficient, compared to $\omega = 1$ in the base case. Larger values of κ imply a hundred percent adoption rate at even lower values of ω. In order to further illustrate Eq. 6, Fig. 2 depicts y_1^*/y_0^* as a function of ω, for various values of the leveraging parameter κ. The figure shows that even for modest values of the relative strength ω of the network externality and

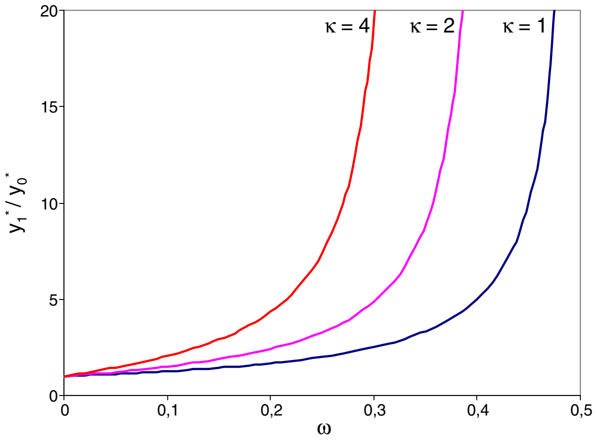

Fig. 2 Relative network growth y_1^*/y_0^* due to peer effect, see Eq. 6

the cost leveraging factor κ, a considerable growth of the network is achieved. For example, with $\omega = 0.3$ and $\kappa = 2$, the network size y_1^* is 4.9 times as large as in the base case.

3.4 Contract-based coordinated peer influence

So far, we have analyzed a Pareto-neutral redistribution that leads to maximum adoption, a benchmark scenario that illustrates the power of the peer effect. We now develop a model in which influencers contract to exert peer influence in a coordinated fashion, with the aim of maximizing their utility. This second model is applicable to a consortium of firms that have joined a certain network (e.g., have adopted a new technology standard) and that, after the initial phase of adoption, contract to expand effort to make further firms join the network.

There are two stages. In stage one, agents decide about adopting the good without taking possible peer effects into account.[13] They thus arrive at the base case described in Section 3.2. In stage two, these early adopters coordinate to influence new adopters. They do so in such a way as to maximize their own utility.

Let the marginal adopter after the second stage be denoted by y_2. Then, as in Eq. 5, we have a range of agents $[y_0^*, \hat{y}_2]$ that do not require any influencing because their net benefit of adoption is positive just due to the increase in network size from y_0^* to y_2. In contrast to the analysis in Section 3.3 (maximum adoption) we assume here that they keep their surplus (instead of having it re-distributed to some other

[13]That is, they have realistic expectations concerning the adoption that will take place in stage one, but are myopic with regard to peer effects coming into play in stage two. Without this assumption, some agents who do adopt in the base case would refrain from doing so, because they do better by deferring their adoption until the second stage, thus not being an influencer. We will relax the assumption later on that each early adopter becomes an influencer in stage two.

adopters at larger values of y).[14] Thus, utility redistribution takes place only between influencers and those new adopters who are situated in $[\hat{y}_2, y_2]$. Assuming that the influencers increase each new adopter's utility to the threshold level of zero, their aggregate utility increase ΔU_s is given by the following equation:

$$\Delta U_s = y_0^* \left(v(y_2) - v\left(y_0^*\right)\right) + \frac{1}{\kappa} \int_{\hat{y}_2}^{y_2} (u(x) + v(y_2) - p)\, dx \quad . \tag{7}$$

In this equation, $\hat{y}_2$ as a function of y_2 is given by an equation analogous to Eq. 4. As in Eq. 5, κ takes account of the leveraging effect of the influencers' effort.

Before continuing we note that the general model, with utility function $u(.)$ and network externality function $v(.)$, would require intricate distinctions between the cases of one and several equilibria in order to clearly formulate our results. Given that the linear model is simpler in this respect and that it makes the effect of each parameter more transparent, we restrict our analysis in the following to the linear model. For this specification, the influencers' aggregate utility increase ΔU_s obtains as

$$\Delta U_s = \alpha y_0^* \left(y_2 - y_0^*\right) - \frac{(\lambda - \alpha)^2}{2\kappa\lambda} \left(y_2 - y_0^*\right)^2 \quad . \tag{8}$$

Maximizing Eq. 8 with respect to y_2 yields the following result.

Proposition 2 *When the base-case adopters coordinate to influence additional adoption in such a way as to maximize their own utility, the resulting network size in an FEE of the linear model is given by*

$$y_2^* = y_0^* \left(1 + \frac{\omega\kappa}{(1-\omega)^2}\right) \quad . \tag{9}$$

Interestingly, this more conservative model of peer influence predicts adoption by the entire market only at $\omega = 1$, as in the base case. The reason for this difference to y_1^* derived in the preceding section is that, in the present model, consumers in $[y_0^*; \hat{y}_2]$ do not act as influencers, while in the earlier model those in $[y_0^*; \hat{y}_1]$ do. Furthermore, influencers do not content themselves with maintaining their base-case utility levels, but maximize their utility and thus refrain from influencing agents that are too hard to convince. However, while the peer effect in this model does not reduce the threshold level of ω for market penetration, it does lead to market growth (Eq. 9). In particular, when $\omega \to 1$ not only the equilibrium market size y_2^* diverges, but—due to the fact that the singularity of y_2^* is of higher order than that of y_0^*—also the relative market size increase compared to the base case, y_2^*/y_0^*.

[14] After they have gone through the adoption process they might, in a third stage, act as influencers themselves. However, we restrict our analysis here to two stages. An extension to three or more stages would of course be feasible. However, if one aims at making the temporal structure more realistic, then a more suitable choice would be to introduce continuous time instead of three or more stages. We refrain from pursuing this approach in order to keep the model tractable.

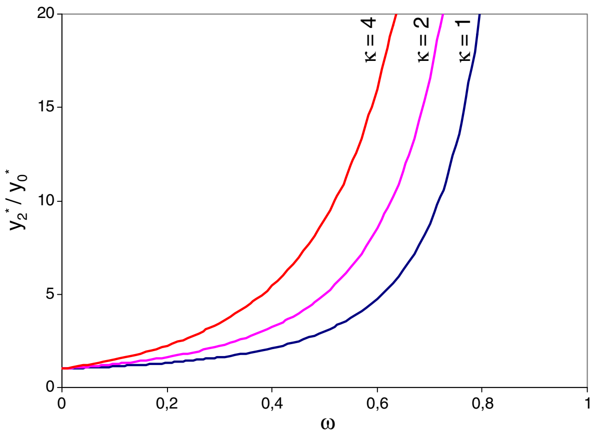

Fig. 3 Relative network growth y_2^*/y_0^* due to peer effect, see Eq. 9

Figure 3 illustrates Eq. 9. Also under the assumptions made here a considerable network growth can be attained. For example, with $\omega = 0.45$ and $\kappa = 2$, the network grows by a factor of 4 compared to the base case.

3.5 Informal coordination within small groups of influencers

The assumption of coordination between all early adopters is realistic if contracts can be closed and enforced. If this is not possible, influencers must resort to informal mechanisms of coordination. Since under these conditions the problem of free-riding arises and becomes more difficult with the size of the influencer group, we assume in the following that *small groups* of size n coordinate to recruit new adopters. The limiting case of $n = 1$ is particularly relevant. This model fits, for example, the peer effect between individuals who grow their (local) network of friends within some social networking platform. Note that, in this case, the real axis models a coherent social group of which a subset adopts the focal network good. Every member of this group exerts, by adopting the network good, the same network externality on each other member. The rest of the world is assumed to have zero network externalities with the social group under consideration—a simplification that we will discuss in the concluding section.

In line with the above assumptions we do not consider the aggregate utility of certain new adopter segments (as we did in the preceding sections), but focus on *single new adopters* each of whom is influenced by a small group. The logic behind the assumption of a small group is that, absent the possibility of contracting, its members can coordinate their joint influencing effort more easily than the early adopter segment as a whole. In addition, monitoring to prevent shirking is easier in small groups. While free riding by those outside the respective small group is still an issue (since all network members benefit equally when a certain group manages to recruit a new adopter), the group's action is rewarding for the group independent of what other adopters do.

Since we consider *individual* processes of recruitment, we also model the temporal structure of network growth differently. We assume that, given the size y of the network, influencing efforts are directed toward the marginal non-adopter since this agent requires the lowest influencing effort. Recruiting of new network members then continues until, for a group of size n, cost and benefit of alluring one additional adopter offset each other.

The utility change $\Delta U(n)$ that a group of network members of size n attains when convincing one additional agent to join the network (currently of size $y-1$) is given by

$$\Delta U(n) = n\,(v(y) - v(y-1)) + \frac{1}{\kappa}\,(u(y) + v(y) - p)\ . \tag{10}$$

In the linear case, Eq. 10 becomes

$$\Delta U(n) = n\alpha + \frac{1}{\kappa}\,(u_0 - (\lambda - \alpha)y - p)\ . \tag{11}$$

Proposition 3 *A group of size n will keep influencing further adopters as long as* $\Delta U(n)$ *is positive. The marginal adopter, and thus the resulting network size, is then given by* $\Delta U(n) = 0$*, which in the linear case yields*

$$y_3^* = \frac{u_0 - p + n\alpha\kappa}{\lambda - \alpha} \equiv y_0^* + \frac{n\omega\kappa}{1-\omega}. \tag{12}$$

Equation 12 shows that, under the mechanism of peer influence assumed here, the network growth compared to the base case is not by a *factor* (as in the cases of y_1^* and y_2^* analyzed above), but by a *fixed number* of new participants. This fact has an important implication: A sizeable *relative* expansion of the network induced by the peer effect (as modeled here) is only possible for small networks. For example, with $\omega = 0.5$ and $\kappa = 3$, network participants banding together in groups of two can attain an overall growth of the network by six members. For a network with a base case equilibrium size of, e.g., ten thousand this increase is negligible. In contrast, for a network with a base case equilibrium size of 10 an increase by six makes for a quite impressive growth of 60 %. And even if coordination in small groups is not feasible (i.e., $n = 1$), still a growth by 30 % can be achieved.

Given the examples of eBay and Skype mentioned earlier, a base case network size of 10 may appear absurdly small. However, even though both services have been adopted by many millions of users, the effective network size in the case of Skype is much smaller. While we are lacking precise data, it seems safe to assume that Skype's user base consists of a large number of small (sub-)networks, each of which is characterized by a high communication intensity among its members and a low communication intensity between its members and non-members.[15] While it is true that also eBay's user base will be divided into sub-networks, e.g., of individuals

[15] Of course, our model is a simplification of this scenario by allowing only two levels of communication intensity: either two individuals belong to the same network or they do not. We also abstract from the fact that some individuals will belong to more than one sub-network.

trading diving equipment, these sub-networks will in general be much larger than in the case of Skype and will create new linkages rather than be based on existing ones.

In applying our model to these real-world examples, it is important to emphasize that the equilibrium network size y_i^* refers *to the relevant sub-network* that is part of some coherent group (e.g., a sports team), not to the entirety of all users of the respective service. For instance, consider a sports team of 20 people. This team corresponds to the real axis in our model (the real axis is of course infinite, but this does not affect the analysis: any equilibrium size larger than 20 would amount to adoption by the entire team). Let us assume that 10 team members adopt Skype without being influenced by their peers, so that $y_0^* = 10$. Now, if two team members join forces to enlist the rest of the team, then a network growth to $y_3^* = 20$—i.e., the entire team—will be achieved, e.g., with $\omega = 0.8$ and $\kappa = 3$. Note that the overall population of Skype users does not figure in our model, due to the simplifying assumption—to be discussed below—that the sub-networks of users are disjoint.

3.6 Comparison of models

From the first to the third of the models presented in this section, our assumptions have become more conservative. The model presented in Section 3.3 led, in the linear case, to a network size of y_1^* (Eq. 5). It serves as a benchmark case, illustrating the implications of peer influence. However, this model made the strong assumption of an adoption-maximizing redistribution of the surplus generated by the network growth from the base case size y_0^* (Eq. 3) to y_1^*.

The second model introduced a more realistic, two-stage timing structure. It assumed that only early adopters act as influencers of later adopters, and that influencers maximize their utility (as opposed to network size). For example, a consortium of firms that are base case members of a certain network might contractually commit to jointly expand effort to grow the network. They would grow it to a size that maximizes their utility gains, having overcome the inherent public good problem of joint influencing by a contractual solution.

The final model is even more conservative in assuming that the public good problem is overcome by coordination within small influencer groups of size n. In addition, it considers the individual acts of influencing as consecutive. Hence, it makes both the influencing mechanism and its timing structure more realistic for a situation such as the adoption of some new communication software by individuals (who are unlikely to set up a contract for this purpose). Due to the fixed size of the influencing group also the network growth achieved, from y_0^* in the base case to y_3^*, is by a fixed number of adopters, not (as for y_1^* and y_2^*) by a factor.

Comparing the equilibrium network size between the three models we find y_1^* larger than y_2^* and, unless the base case network size y_0^* is rather small, y_2^* larger than y_3^*. Given that the additional assumptions introduced in the second and the third model restrict the peer effect mechanism, this finding comes as no surprise. More interesting is the qualitative difference that the first and the second model lead to an increase in network size by a multiplicative factor, while the third model leads to an increase by an additive constant.

4 The seller's perspective

From a seller's perspective, the peer effect is clearly advantageous. The question arises if and how the seller of the network good should take the peer effect into account when setting its price and, potentially, rewarding influencers. Since our first model of peer influence (Pareto-neutral redistribution of surplus) served only as a benchmark, we focus in the following on the second and third model.

4.1 Price setting

Consider, as above, a monopolistic seller of a network good facing a peer effect as modeled in Section 3.5. The seller has to bear a variable cost of c per unit. Without restriction of generality, fixed costs are set to zero. In the base case, the seller's profit $\Pi_0(p)$ obtains as $\Pi_0(p) = (p-c)y_0^*$, which in the linear model becomes

$$\Pi_0(p) = (p-c)\frac{u_0 - p}{\lambda - \alpha} \,. \tag{13}$$

For the profit-maximizing price and the resulting equilibrium profits and market size we obtain:

$$p_0^* = \frac{1}{2}(u_0 + c), \quad \Pi_0^* = \frac{(u_0 - c)^2}{4(\lambda - \alpha)}, \quad y_0^{*e} = \frac{u_0 - c}{2(\lambda - \alpha)}. \tag{14}$$

Taking the peer effect into account, an equilibrium network size of y_2^* (Eq. 9) or y_3^* (Eq. 12) obtains depending on the nature of the peer influence mechanism. The seller's profit is given by $\Pi_{2/3}(p) = (p-c)y_{2/3}^*$, and straight-forward maximization leads to the following results:

Proposition 4

(i) *When pricing is endogenous and all stage-one adopters coordinate to grow the network such as to maximize their own utility (see Section 3.4), then equilibrium price, profit, and network size are as follows:*

$$p_2^* = p_0^*, \quad \Pi_2^* = \Pi_0^* \left(1 + \frac{\omega\kappa}{\left(1-\omega^2\right)^2}\right), \quad y_2^{*e} = y_0^{*e}\left(1 + \frac{\omega\kappa}{\left(1-\omega^2\right)^2}\right). \tag{15}$$

(ii) *With endogenous pricing and peer influence exerted by influencer groups of size n (see Section 3.5), we obtain the following equilibrium outcomes:*

$$p_3^* = p_0^* + n\alpha\kappa/2, \quad \Pi_3^* = \Pi_0^* \left(1 + \frac{n\alpha\kappa}{u_0 - c}\right)^2, \quad y_3^{*e} = y_0^{*e} + \frac{n\omega\kappa}{2(1-\omega)}. \tag{16}$$

As expected, also with endogenous pricing equilibrium profits and market size increase due to the peer effect, irrespective of what mechanism one assumes. Both profits and market size increase in the strength of the network externality α (or its relative strength, $\omega \equiv \alpha/\lambda$), the cost leveraging factor κ, and (if applicable) the group size n. Interestingly, however, also the equilibrium price is increased in the third model (ii), but not in the second (i). That is, when peer influence is exerted by small groups of influencers, then the seller skims off part of the adopters' increased utility. This skimming is reflected in an additive increase in network size ($y_3^{*e} - y_0^{*e}$) which is only half of that obtained under an exogenous, fixed price (see Eq. 12).

4.2 Rewards by the network provider

By recruiting further adopters, influencers exert a positive externality not only on other network members, but also on the seller of the network good. Thus, an additional route to overcoming the public good problem inherent in joint influencing, apart from contracting between influencers and informal coordination within small groups, consists in internalizing the positive externality exerted on the seller. From a management perspective, it seems a natural question to ask if and how the network provider can leverage the peer effect in order to reap even more benefits from it.

As an example consider XING, the professional network. XING offers a free one month premium membership to any member who successfully invites seven friends to join the XING network. In addition to offering this reward, XING reduces influencers' cost of recruiting new members by suggesting a pre-formulated invitation e-mail. The online game, World of Warcraft, uses a recruit-a-friend referral system. Similar to XING, World of Warcraft has pre-formulated an invitation e-mail. In case the invitee accepts the invitation, the account of the invitee and the inviter become linked and both enjoy advantages in the online game itself such as increased experience, character summoning, and promotion to higher levels.

We explore this approach in the following by allowing for the seller to reward influencers. Doing so, the seller benefits from an influencer's own (but possibly insufficient) motivation to exert peer influence, and additionally—in case the cost leveraging factor κ is larger than the seller's corresponding leveraging factor (which we assume equals unity)—from her means to perform recruiting more efficiently than the network provider.

We conservatively restrict our analysis here to the case of influencing by single agents, since coordination within a larger group plus receiving and distributing the reward seems a rather complex procedure. Thus, in the subsequent model extension we focus on the third model with $n = 1$. In terms of timing, we assume that the seller waits until (a) adoption as in the base case has taken place and (b) individual influencers have recruited further network members until their marginal utility from doing so vanishes. The seller then grows the resulting network of size y_3^* (Eq. 12) further by offering a monetary reward of r to each user who recruits a new adopter. In analogy to Eq. 10, the utility change for an influencer receiving the reward for growing the network from $y - 1$ to y equals

$$\Delta U_r = v(y) - v(y-1) + r + \frac{1}{\kappa}\left(u(y) + v(y) - p\right) \ . \tag{17}$$

In the linear case, Eq. 17 becomes

$$\Delta U_r = \alpha + r + \frac{1}{\kappa}(u_0 - (\lambda - \alpha)y - p) \; . \tag{18}$$

Network members will keep recruiting new adopters as long as their gain ΔU_r from doing so is positive. The resulting network size is then defined by $\Delta U_r = 0$, which in the linear case yields

$$y_4^* = \frac{u_0 - p + (\alpha + r)\kappa}{\lambda - \alpha} \equiv y_0^* + \frac{(\omega + r/\lambda)\kappa}{1 - \omega} \; . \tag{19}$$

The seller's profit function obtains in an obvious fashion, and maximizing it with respect to both p and r yields the following results:

Proposition 5 *When the seller pays early adopters to recruit additional network members, the profit-maximizing price, the corresponding reward, the equilibrium network size, and the seller's profits are as follows:*

$$p_4^* = 2\frac{u_0 + \kappa\alpha - c}{4 - \kappa} + c \tag{20}$$

$$r^* = \frac{u_0 + \kappa\alpha - c}{4 - \kappa} \tag{21}$$

$$y_4^{*e} = 2\frac{u_0 + \kappa\alpha - c}{(\lambda - \alpha)(4 - \kappa)} \equiv \frac{4}{4 - \kappa} y_3^{*e} \tag{22}$$

$$\Pi_4^* = \frac{(u_0 + \kappa\alpha - c)^2}{(\lambda - \alpha)(4 - \kappa)} \equiv \frac{4}{4 - \kappa}\Pi_3^* \tag{23}$$

The seller would thus offer a reward which decreases in the variable cost c per unit and increases in the good's gross utility u_0, in the strength α of the network externality, and in the cost leveraging parameter κ. The fact that all of the above values diverge at $\kappa \to 4$ is due to the concrete linear specification of the model, but the general result that higher leverage makes it more attractive to reward influencers clearly makes sense.

An important implication of this analysis concerns the role of the leveraging factor. Our assumption that the seller's own leveraging factor (which we have not explicitly modeled) equals unity may be restrictive. Still, it is plausible that it is smaller than the adopters' leveraging factor, κ, due to an adopter's closer proximity to potential new network members and to his or her higher credibility. At a value of, for example, $\kappa = 2$ we find that rewarding influencers actually doubles the seller's profit. Despite the simplicity of the linear model, this result points to a very effective lever for the network seller.

5 Empirical study

To illustrate the underlying logic of our theoretical model, we conducted an online survey with 373 participants. We asked participants for the relative importance of the local installed base, the global installed base, and peer influence for their decision to adopt eBay and Skype, respectively. The survey took place between August 2nd and September 24th, 2007. Most participants were students, with an average age of 26.6 years (median 25 years). 241 (65 %) were male. 277 (74 %) had adopted Skype, 291 (78 %) had used eBay (as a buyer, a seller, or both).

To find out about the relative importance of the three potential drivers of adoption, we compare each with the other two by means of a semantic differential. Figure 4 shows the exact statements and the corresponding scales. The results shown in Table 1 are clear-cut: for the adoption of Skype, peer influence is considered the most important trigger, closely followed by local network effects. The relevance of global network effects is nearly negligible. For the adoption of eBay the picture is completely reversed: global network effects are the most important trigger, with local network effects and peer influence both far behind and roughly equally unimportant. Figure 5 illustrates and summarizes our results graphically. The figure also shows

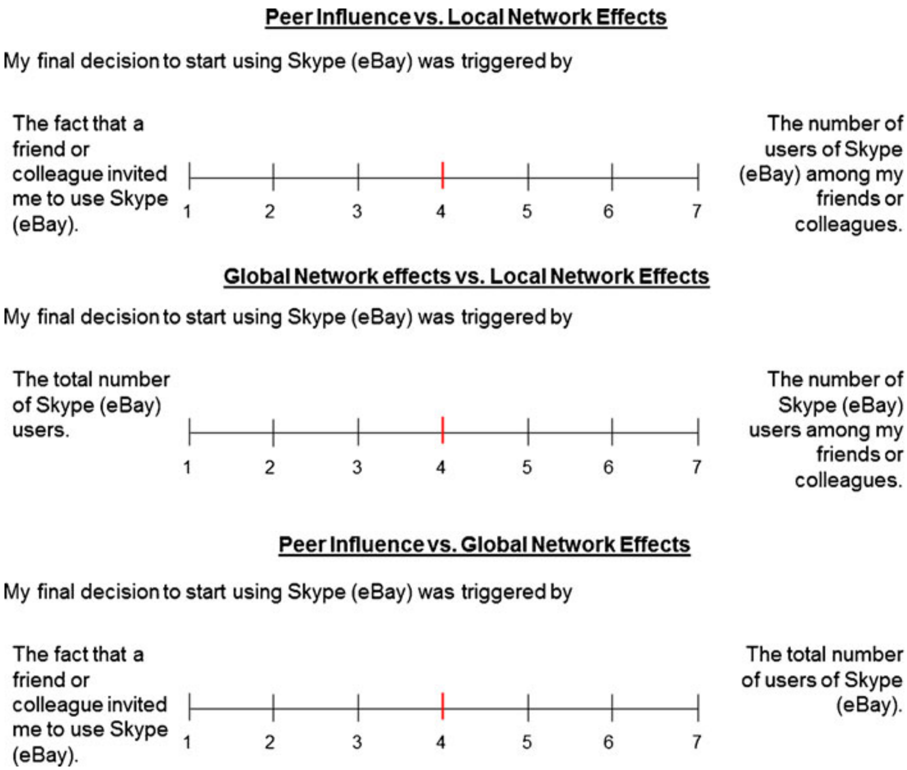

Fig. 4 Semantic differentials as presented to respondents

Table 1 Responses to semantic differential questions regarding triggers of adoption

	N	Min.	Max	Mean	Std. dev.	t-test on equality of means
Peer influence vs. Local network effect						
Skype	277	1	7	3.41	1.89	$p < 0.001$
eBay	291	1	7	4.26	1.54	
Global vs. Local network effect						
Skype	277	1	7	5.81	1.56	$p < 0.001$
eBay	291	1	7	2.67	1.74	
Peer influence vs. Global network effect						
Skype	277	1	7	2.14	1.45	$p < 0.001$
eBay	291	1	7	5.17	1.79	

consistency of the ratings: connecting, for each service, the respective point on the scale between two drivers with the opposite corner of the triangle yields three lines that, to a good approximation, intersect in a single point.[16]

In a further step, we estimate two ordered logit regressions regarding the intensity of peer influence. We employ a matched sample design by using data from those respondents who had adopted both services (resulting in 432 observations from 216 respondents). That is, for each respondent we have one observation relating to his or her adoption of Skype, and the other, to the adoption of eBay. Dependent variables are the levels, measured on 5-point Likert scales, of peer influence experienced by the respondent,[17] and the level of peer influence that the respondent has exerted on others.[18] Asked about Skype, 41 respondents indicated that they had "invited" one or more friends or colleagues to adopt the service; 36 ticked "tried to persuade," and 6 ticked "pressed," totalling 83. The corresponding numbers for eBay are much

[16]The high degree of consistency of the three intersection points for each of the two services can be quantified using vector algebra. Consider, for the case of eBay, the line ending at the upper corner, denoted line P for "peer influence." Normalizing the length of line P to unity, its intersection with line L is at 0.241 while that with line G is at 0.190. The difference thus equals 0.051, or 5.1 % of the length of line P. In an analogous way, the normalized differences between the two intersections obtains as $0.266-0.211 = 0.055$ for line L, and as $0.585 - 0.510 = 0.075$ for line G. For the case of Skype, the normalized differences are 0.086 (P), 0.082 (L), and 0.033 (G).

[17]This variable is operationalized as follows. 1: None of my friends or colleagues had told me about Skype (Ebay) and its features; 2: One or more of my friends or colleagues had told me about Skype (eBay) and its features; 3: One or more of my friends or colleagues had invited me to register with Skype (eBay); 4: One or more of my friends or colleagues had tried to persuade me to register with Skype (eBay); and 5: One or more of my friends or colleagues had pressed me to register with Skype (eBay).

[18]This variable is operationalized as follows. 1: I have not told any of my friends or colleagues about Skype (eBay) and its features; 2: I have told one or more of my friends or colleagues about Skype (eBay) and its features; 3: I have invited one or more of my friends or colleagues to register with Skype (eBay); 4: I have tried to persuade one or more of my friends or colleagues to register with Skype (eBay); 5: I have pressed one or more of my friends or colleagues to register with Skype (eBay).

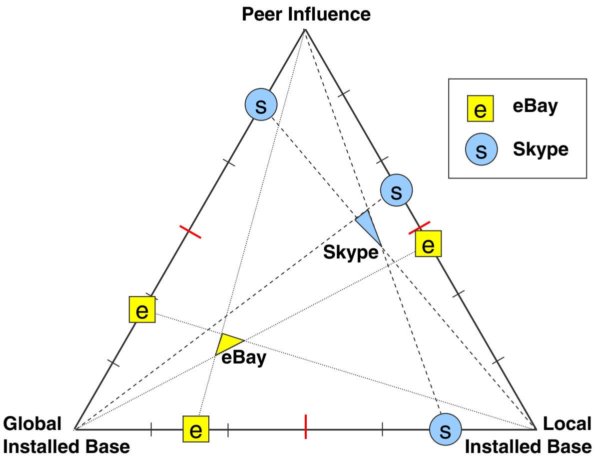

Fig. 5 Relative importance of peer effect, local installed base, and global installed base for the adoption of Skype and eBay, respectively

lower, as expected: 13 had "invited," 6 "tried to persuade," and 2 "pressed" friends or colleagues to join eBay, a total of only 21. Results are similar for experienced peer influence. For the adoption of Skype/eBay, 46/12 respondents had been "invited" by a friend or colleague, 26/5 "persuaded," and 3/1 "pressed".

These descriptive results are confirmed by ordered logit regressions regarding the extent of experienced and exerted peer influence (see Table 2). Our focal independent variable is a dummy variable indicating whether the observation refers to Skype or eBay. We control for several factors that might influence the extent of experienced and exerted peer influence. Prior research by Hallinan and Williams (1990), Sinan and Walker (2012), and Venkatesh and Morris (2000) shows that socioeconomic variables such as gender, age, occupation, and level of education influence the degree and type of peer influence. Moreover, marketing and communication research suggests that opinion leadership, expert status, and an individual's level of communicativeness determine how innovation adopters influence others in their respective innovation adoption decisions (Arndt 1967; Baumgarten 1975; Sinan and Walker 2012; Turnbull and Meenaghan 1980).

Results are clearcut. The coefficient of the dummy variable indicating "Skype" is positive and highly significant ($p < 0.001$) both for experienced and for exerted peer influence. In each specification, only one further variable has a significant influence. For experienced peer influence, "male" is negative and significant ($p < 0.01$). For exerted peer influence, the respondents level of computer expertise (measured on a 5-point Likert scale) has a positive and highly significant ($p < 0.001$) effect.

The empirical findings both from the semantic differential and from the regression analysis illustrate and support an important implication of our theoretical analysis. As we have said, our third model (Section 3.5) is most appropriate for describing peer influence for network goods, such as Skype and eBay, which are adopted by

Table 2 Ordered probit regressions of level of experienced and exerted peer influence

	Experienced peer influence (1 = low, 5 = high)	Exerted peer influence (1 = low, 5 = high)
Independent variables	Coefficients (robust s.e.)	Coefficient (robust s.e.)
Skype versus eBay (Skype=1, eBay=0)	1.93 (0.22)***	1.38 (0.20)***
Male	−0.60 (0.23)**	−0.31 (0.24)
Age (in years)	0.01 (0.03)	0.01 (0.04)
Education (in years)	0.02 (0.03)	0.003 (0.030)
Computer expertise (1 = beginner, 5 = expert)	−0.11 (0.14)	0.55 (0.15)***
Communicative person (1 = strongly disagree, 5 = strongly agree)	−0.26 (0.14)	0.07 (0.13)
Occupation type variables (8 dummy variables)	Included	Included
N observations (individuals)	432 (216)	432 (216)
Wald χ^2	200.89***	86.38***
Pseudo R^2	0.11	0.07

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

individuals. The corresponding Proposition 3 states that, in this case, the additional network growth caused by the peer effect is by an additive constant. Such growth can be large in *relative* terms only if the basic network size, reached by the installed-base effect alone, is small. This is the case, as we have argued, for Skype: the relevant population within which a (sub-)network of Skype users grows is typically limited to a person's friends or colleagues. A large relative growth of each sub-network of course entails the same relative growth for the overall Skype user base, and so we expected the peer effect to be relevant for Skype. In contrast, the basic network size for eBay is large, and so we expected the peer effect to have little relevance. Our empirical findings clearly support this prediction and, thus, the main logic of our theoretical model.

6 Discussion and conclusion

Network effects have two implications. First, the larger a network, the more attractive it becomes for outsiders to join it. This *installed base effect* has been treated extensively in the literature (e.g., Katz and Shapiro 1985, 1986, 1992). Second, growing the network is beneficial for network members, who can thus be expected to engage in exerting peer influence on not-yet-adopters. On this *peer effect*, the extant literature is largely silent, with Domingos and Richardson (2001), Subramani and

Rajagopalan (2003) and Block and Köllinger (2007) as notable exceptions. In particular, there exists no theoretical model describing and analyzing the peer effect. While peer influence will often be exerted by word of mouth, the peer effect clearly stands out from common instances of word of mouth marketing by the type of motivation that drives the acting person—namely, long-term benefits due to internalization of a network externality.

The results of our game-theoretical analysis depend on how peer influence is modeled. If the entire group of early adopters (i.e., agents who adopt the good absent peer influence) can contract to jointly influence outsiders—a plausible assumption, e.g., for firms that have adopted a new technology standard and try to enlist further adopters—then introducing peer influence makes the network grow by a factor which increases in the relative strength of the network externality and the cost leveraging factor. In contrast, if adopters can only coordinate within small groups of size n to recruit new network members—a plausible assumption for networks of individuals—then the peer effect leads to a growth of the network by an additive constant. Since such growth may be very relevant for small networks but negligible for large ones, the distinction between two types of networks arises endogenously.

The first are local, personal, and small networks that exist and grow within a limited population (e.g., a sports team or a class at university). This type of network good builds upon and strengthens existing ties; it is tie-reinforcing. For a small network within such a limited population, growth by an additive constant may imply a considerable *relative* growth. Thus, adding up the additive growth of each small sub-network over all these sub-networks can translate to a large relative growth of the overall user base (of Skype, e.g.). The second type are global, anonymous, and large networks, exemplified by the users of eBay. This services helps to establish new ties, and is thus tie-creating. For such networks, growth by an additive constant amounts only to a small relative growth. The peer effect thus has a negligible influence.

We furthermore find that, by lowering network members' cost of exerting peer influence or by offering rewards to them, a network provider can leverage the peer effect to grow its network. Through price setting, it is able to skim off part of the adopters' increased utility and achieve higher profits as compared to a situation without peer effect.

Our empirical study provides clear support for the main logic underlying our model findings. For Skype—the adoption of which largely replicates existing social ties—peer influence and the size of the local installed base drive adoption. Local, small, and personal networks result (which are, of course, linked among each other to some extent by weak ties). For eBay, a service that users adopt with the purpose of creating new ties, the global installed base effect dominates, leading to a global, large, and anonymous network.

Local network externalities are modeled by heterogeneity between dyads of users of the network good (e.g., Cowan and Miller 1998). This heterogeneity leads to clusters of individuals who value their common membership in the local network highly, but put a lower value on being linked to others. This local network corresponds to our (entire) network when its size is small. A global network of loosely connected local networks then corresponds, in our model, to a patchwork of many independent small networks. This interpretation explains the seeming contradiction that, as we have shown, the peer effect favors winner-take-all outcomes (in local sub-networks), while local network externalities tend to produce non-standardized results (on the level of the overall network) (Cowan and Miller 1998; Jonard and Yildizoglu 1998; Lee et al. 2006). It seems an interesting question, though, in how far the peer effect in the presence of weak ties between local networks can indeed also favor winner-take-all outcomes spanning more than one local network.

Our study has several implications for firms. First, it is important to understand that peer influence may be a far more important driver of network growth than the (global) installed base. For a particular network good, it needs to be checked if and to what extent it inspires its users to exert peer influence. If it does, then firms may leverage the peer effect to grow the size of their network. For example, a provider of a social networking platform such as Facebook can encourage its registered network members to send out invitation e-mails to not-yet-network members, and may facilitate such activity by pre-formulating invitation e-mails or by awarding a premium once a new member has been recruited.[19]

Second, a network provider may also use the peer influence mechanism to inspire new layers of networking among its members. For example, Facebook provides the tool RockYou Live that facilitates the sharing of videos and pictures in local Facebook groups. By using such a tool, the members of a Facebook group superimpose an additional network (of linkages related to file sharing) to their existing one, thus increasing the value of the group to each member as well as the lock-in (and thus the value of the members) to Facebook.

Third, understanding of the peer effect helps network providers to prevent members from leaving the network. As an example that we learned from an industry expert, consider mobile operators. Calling rates are typically cheaper to subscribers of the same operator than to those of other operators. Hence, subscribers derive a network benefit from convincing persons they frequently call to sign up with the same operator. Thus, when a person switches to a different operator, she has an incentive to exert peer influence on her frequent interlocutors to do the same. Anticipating such lobbying, operators specifically target frequent contacts of a person who terminates her contract with marketing measures to keep them loyal.

Finally, our analysis shows that the peer influence mechanism is stronger with local networks than it is with global networks. For example, the peer influence mechanism is unlikely to have an effect with eBay or with online dating websites such as true.com or match.com. Members of such networks have only little incentive to persuade outsiders to join, since no intermediary is needed for selling goods to a person one already knows, nor for dating such a person. In contrast, network

[19] We caution the reader that a platform such as Facebook is far more complex than the relatively simple network services of Skype and eBay that we used as illustrations. Thus, one has to be careful in applying our result to this case. Still, despite many differences the three services share fundamental characteristics, and our theoretical analysis is kept in general terms. We thus think that the underlying mechanisms at work are robust.

goods or services that build on and deepen existing ties do grow based on the peer effect. Providers of network goods should thus carefully analyze whether their particular good implies peer effects or not, and should adjust their network growth and marketing strategy accordingly.

Our study has several limitations. First, we modeled individuals as heterogeneous with respect to the good's stand-alone utility, but as homogeneous with respect to the network benefit that each derives from the participation of any other individual. Implicitly, we assumed that there are other individuals—the "rest of the world"—who do not exert any network externality on those individuals we model nor receive any externality from them. That is, we assume that the network externality can only take on two values: λ within the group we model, and zero for any dyad that involves one individual from outside this group (individuals who are both outside this group may exert a positive externality on each other, but this is beyond the scope of our model). In reality, however, dyads of individuals differ continuously in terms of network benefits. In particular, individuals in the group we model will in general be linked by (weaker) network externalities to persons outside this group. It would thus be an interesting, though rather complex, generalization of our approach to combine peer influence and heterogeneous network externalities into one model. Second, our empirical study was designed to highlight the difference between network goods that give rise to peer influence and those that do not. While it serves well to illustrate and support an important implication of our theoretical analysis, it falls short of testing all implications.

We perceive various other opportunities for further research. First, it would be insightful for scholars as for firms to learn more about the relative effectiveness of different ways to promote peer influence. In particular, what is the role of monetary incentives in this regard? Do they increase an individual's motivation to exert influence on her peers to join the network, or do they possibly crowd out this motivation? Second, it might be possible to alter the character of a network good to some extent. That is, the provider might add an element of the peer effect to a good such as eBay, the network of which mainly grows through the installed base effect. Under what conditions and to what extent the character of a network good can be modified to allow for peer influence is up for research. Third, further empirical studies should attempt to test predictions of our theoretical analysis that are not covered by the empirical work in this paper. Finally, it appears highly relevant to study what implications the peer effect has for competition between network providers. We would conjecture that it tends to increase competition, which would, ceteris paribus, imply a higher degree of industry concentration for goods that exhibit a strong peer effect. The overwhelming success of the social networking service Facebook points in this direction, though more detailed research is needed.

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Appendix

Symbols

c	Variable cost of providing the network good
n	Size of small sub-network which coordinates to recruit a new adopter
r	reward paid by seller to a network member recruiting a new adopter
u_0	Constant in the linear model of $u(x)$: $u(x) = u_0 - \lambda x$
$u(x)$	Stand-alone utility (i.e., excluding network externalities) which consumer x derives from the good
$v(y)$	Utility that each adopter derives due to the network effect when the network size equals y
y_i^*	Marginal adopter in equilibrium, in model i
α	Slope parameter in the linear model of $v(y)$: $v(y) = \alpha y$
κ	Cost leveraging factor: When a user exerts peer influence on some not-yet-adopter, the resulting benefit for the wooed individual equals κ times the cost that the influencer incurs
λ	Slope parameter in the linear model of $u(x)$: $u(x) = u_0 - \lambda x$
ω	$\omega \equiv \alpha/\lambda$ measures the relative strength of the network externality

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