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REGULAR ARTICLE

The interaction between direct and indirect network externalities in the early diffusion of mobile social networking

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Abstract

The early diffusion of mobile social networking (MSN) reflected the interplay of different factors: the affordability of better Internet connectivity and the diffusion of Smartphones suitable for Social Networking Applications. These key technology and cost drivers facilitated both the direct and indirect network externalities, which are necessary to overtake critical adoption barriers and facilitate users' decisions. However, a key challenge in modeling MSN diffusion is in distinguishing among the impact of these two types of network externalities. This paper addresses such a challenge by adopting a two-stage estimation strategy. In the first stage, we focus on direct network externalities by estimating a set of country-specific adoptions peaks that allow differentiating between early and late adopters. In the second stage, we estimate the impact of indirect network externalities on MSN diffusion while also considering the role of pricing strategies. Our results provide significant evidence that indirect network externalities can exert opposite effects on adoption between early adopters and followers, depending on whether they adopt before or after a country's MSN diffusion peak.

Keywords Diffusion · Interaction models · Early adopters · Indirect network externalities · Mobile social networking

JEL classification O33 · O35 · C22 · M31

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1 Introduction

At the time of writing, 2021, there are more than 3.5 billion worldwide users of at least one of Facebook's owned Social Networks (Facebook, WhatsApp, Instagram, or Messenger).[1] Founded in 2004, by 2008, Facebook had reached 100 million users of its platform, rising tenfold to one billion users by 2012. Many other large Social Network platforms are operating worldwide. Table 1 displays the 2021 distribution of users for the seventeen largest Social Networks.

While having key country-specific features, this rapid worldwide diffusion of Social Networks was linked to the availability of Smartphones. By January 2021, 98.9% of the 4.2 billion users accessed them through mobile devices (Kemp, 2021a).

In the noughties, when the early stages of this diffusion process were taking shape, the combined effects of market liberalization policies, technological change and Internet penetration produced radical transformations of the information and communication technologies (ICT) industry and its business models. These transformations, together with the developments and adoption of a multiplicity of Internet-based applications, led to a significant shift of profitability from the traditional voice services (West & Mace, 2010) towards innovative companies supplying new services and applications relying on internet protocol (IP)-based Internet connection, such as mobile social networking (MSN).[2] The provision of new multimedia social networking services through smartphones over IP proliferated, between 2004 and 2012, with the launch and diffusion of platforms such as Skype,[3] Facebook,[4] Twitter,[5] WhatsApp,[6] Spotify[7] and Snapchat.[8]

During the early stages of their development, most platforms introduced disruptive new business models, based on zero-pricing strategies, aimed at reaching a critical mass of early users, necessary to kickstart a process of increasing returns due to

[1] Facebook measures monthly active users as users that have logged in during the past 30 days (https://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide/).

[2] Mobile social networking is intended as a service that enables individuals to connect to their social communities with a mobile device where members share experiences, interests, opinions, presence information and personal content through their mobile devices. Mobile adds new capabilities to social networking, such as location-related services and new visualization mechanisms (Gartner IT glossary 2021, http://www.gartner.com/it-glossary/mobile-social-networks).

[3] Skype Inc. incorporated in 2004 and based in Palo Alto, California, provides social networking via free video and voice calls, instant messaging, and file-sharing services also through smartphones.

[4] Facebook, the online social media and social networking service based in Menlo Park, California was founded in 2004.

[5] Twitter Inc. founded in 2006 and based in San Francisco, California, introduced an online social networking service that enables users to send and read short 140-character messages called "tweets" through smartphones.

[6] WhatsApp Inc. founded in 2009 and based in Santa Clara, California, operates as a cross-platform mobile messaging company that allows social networking through the exchange of unlimited text and multimedia messages, such as audio, video, and photo messages through smartphones.

[7] Spotify USA Inc. founded in 2011 and based in New York, New York, operates a platform that enables social networking for users to find and share music and playlists also on their smartphones.

[8] Snapchat, Inc. founded in 2012 and based in Venice, California, developed a text and photo-based social messaging application for smartphones.

adoptions externalities (Arthur, 1989). Indeed, as MSN rely on sharing users' generated content, their subscribers' utility increases with the number of existing users, not only as this expands the set of possible people with whom to connect, but also because of the additional contents they generate. These are typical features illustrating the role of direct network externalities (Katz & Shapiro, 1985, 1986) in the diffusion processes of MSN. Hence, higher MSN penetration rates, indicating the ability for an adopter to interact and share content with more users directly, are likely to have played a critical role in the speed of MSN adoption, particularly in the initial years of their diffusion. The combination of zero-pricing strategies, to attract more users, and direct network externalities played a critical role in displacing established communication technologies (Church et al., 2008).

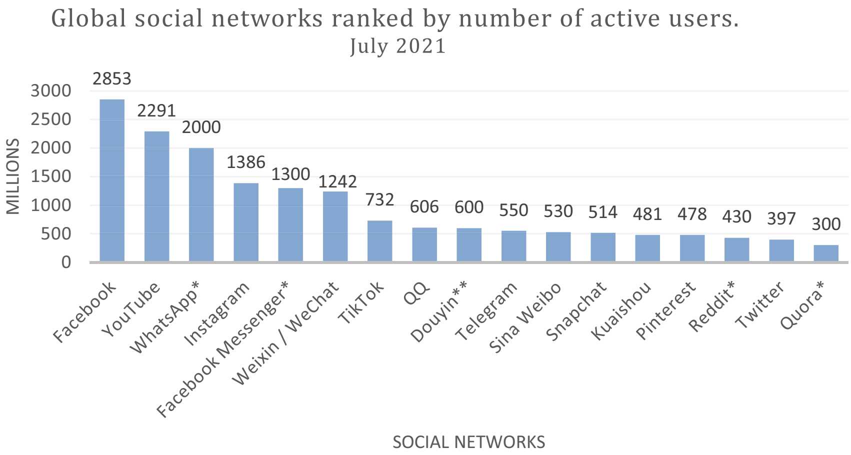
The economic literature has also identified the relevance of assessing the impact of indirect network externalities (Katz & Shapiro, 1985, 1986). These arise when users gain utility from the joint consumption of two complementary goods in combination with another. The main focus of this paper is on understanding the temporal profile of the impact of these indirect network externalities for the diffusion of MSN. This objective is addressed by exploring the complementarity between MSN and Smartphones, as they represent the main hardware component required to access MSN.

While Social Networks' contents are globally accessible at no extra costs, the utility of MSN benefits from location-relevant and language-specific content (Unwin and Unwin, 2009). Hence, the impact of direct network externalities on MSN diffusion is likely to display country-specific dynamics. Given the highly path-dependent (David, 1985; Dosi & Nelson, 2013) nature of the MSN diffusion process, it is essential to understand whether also the impact of the indirect network externalities, captured by the diffusion of the Smartphones, depends on the country-specific path followed by the MSN diffusion process. Hence, in this paper, we focus on the (possibly changing) role of indirect network externalities through a two-stage strategy: first, estimating the impact of the direct network externalities on the diffusion process of MSNs, to determine a set of country-specific dates for the peaks of adoption, and second, differentiating the impacts of the indirect network externalities depending on the adoption stage, i.e., whether adoption is taking place before or after the country-specific peaks.

Our analysis's first stage consists of estimating a set of country-specific logistic curves (Hosmer & Lemeshow, 1989), typically used to capture non-linear, S-shaped, aggregate diffusion curves (Davies, 1979). This stage, driven by direct network externalities, allows estimating each country's peak of MSN adoptions and differentiating between early and late adopters (Rogers, 2003).

With the main contribution of this paper, the second stage focuses on how the indirect network externalities, captured by the diffusion of Smartphones, might exert different, and even opposite, effects between early or late adopters. In this second stage, the country-specific peak dates, estimated in the first stage, are used to differentiate between early adopters, pre-peak, and followers, adopting after the peak. After considering additional covariates and controls, we interact these estimated peaks with country levels of Smartphone penetration, showing that the impact of

Table 1 Global social networks ranked by the number of active users



July 2021. Figures for TikTok do not include Douyin. Author's graph, based on data from Kemp (2021b) © Statista 2021. *Platforms had not published updated user figures in the past 12 months, figures may be out of date and less reliable **Figure uses daily active users, so monthly active user number is likely higher

these indirect network externalities on MSN diffusion is path-dependent, as it differs significantly between early and late adopters.

After this introduction, Sect. 2 contains a brief review of the relevant literature. Section 3 discusses the methodology, including the estimation strategy, the research questions and the data. Section 4 presents the estimation results and discusses the interpretation of the indirect network effects separately between early and late adopters. Finally, Sect. 5 concludes the paper.

2 Related literature

Early contributions on the diffusions of new technologies (Griliches, 1957; Mansfield, 1968) indicated how these processes might take longer to unfold and, more relevantly, how they vary across countries and technologies (Rosenberg, 1976). This evidence is often linked to adoption externalities, whereby the probability of adopting an innovation increases with adoptions.[9]

Models, rooted in an equilibrium perspective, explained these asymmetric paces of adoptions by focusing on heterogeneity in firms' technology and size (Davies,

[9] See, for example, Antonelli, (1990) for the adoption of Fax Machines, Colombo and Mosconi (1995) for that of Flexible Automation technologies and more recently, for the adoption of Fast Ethernet, see Corrocher and Fontana, (2008) and Casagrande-Seretti et al. (2019) for a wide range of radical innovations.

1979). This approach led to rank models of staggered adoption, whereby the reduction in the adoption costs make adoptions progressively more profitable for an increasing number of firms (Stoneman & Battisti, 2010). For consumers, instead, heterogeneity might arise from an underlying distribution of preferences for patience or risk (Stoneman, 2002). These may derive from asymmetric income distribution, leading to different affordability thresholds (Russell, 1980) or different word-of-mouth effects intensities (Chandrashekaran et al., 2010).

Game-Theoretic approaches modeled heterogeneity in adoption behaviors as arising from the strategic consideration of competing firms' adoptions (Reinganum, 1981), as a sequence of waiting games, due to information lags about the perception of the technology (Kapur, 1995), or solely from the interplay between the intensity of localized competition, the relevance of the innovation and adoption costs (Giovannetti, 2000, 2013).

From an evolutionary perspective (Dosi & Nelson, 2013), adoption heterogeneity might emerge from the path-dependence (David, 1985) of learning processes, leading to initial, random events determining the diffusion processes' pace, selection, and features.

Most of these sources of heterogeneity: market equilibrium, game-theoretic, or evolutionary, lead, under simple assumptions, to S-shaped aggregated diffusion curves.[10] These features are well captured by the logistic model,[11] displaying inflection points of the cumulative adoption distribution that identify the timings of the peak of adoptions. Such adoption peaks discriminate between early and late adopters (Rogers, 2003) or as the trade-off between the forces of legitimation period for establishing the new technology and the subsequent competition one (Hannan & McDowell, 1984; Gerosky, 2000, for an excellent survey).

The marketing literature also focused on analyzing pre-and post-peak adoption to capture how direct network externalities shape the take-off, growth and decline of products (Hauser et al., 2006) and to model the chilling effects of network externalities followed by surges of adoptions (Goldenberg et al., 2010).

This paper starts by modeling the direct network externalities impact on MSN diffusion, estimating country-specific logistic models and identifying the qualitative changes occurring around the adoption peaks when the convex portion of the MSN diffusion curves turns concave.[12] Differences across countries in the diffusion of 3G mobile phones were investigated using non-linear mixed modeling with pooled multi-country data to estimate a generalized Bass (1969) diffusion model by Islam and Meade (2012). Also, in a multi-country framework, Scaglione et al. (2015) explored alternative functional specifications to capture network externalities in the diffusion of MSNs, without explicitly modeling the indirect network externalities (Katz & Shapiro, 1985, 1986) impact of the diffusion of system complements.

[10] For applications in mobile telephony, see Frank (2004) and Gruber and Verboven (2001a; 2001b).

[11] For a fascinating historical account of the logistic models, see Cramer (2003)

[12] Our focus on the discontinuity of the network externalities during the diffusion process also connects to the general framework on diffusion and discontinuity due to externalities discussed in Antonelli (1995).

Indirect network externalities affect diffusion processes through the effect on adopters' utility of the combined use of two complementary goods, such as MSN and Smartphones. Early studies identified the relevance of indirect network externalities[13] on systems such as application software and operating systems (Church & Gandal, 1992) and video players and DVDs (Dranove & Gandal, 2003). This paper focuses on indirect network externalities due to the systems composed by MSN and Smartphones. Our crucial question will focus on understanding the interaction between direct and indirect network externalities, focussing on how the impact of the indirect ones might change depending on the stage of the MSN adoption process.

Our analysis of the path-dependent impact of indirect network externalities utilizes a two-stage estimation, the usefulness of which was advocated by Dekimpe et al. (1998) in modeling and forecasting the diffusion of cellular phones in a multi-country context. Different estimation strategies for pre-and post-adoption peaks were implemented by Chu et al. (2009) for the diffusion of mobile telephony in Taiwan.[14] Along similar lines, the work by Grajek and Kretschmer (2009) on the diffusion of multiple generations of mobile telephony adopts a multistage approach, estimating, first, the diffusion of mobile telephony and using the resulting estimates as an input for a second stage estimation of mobile users. Moreover, by introducing interaction variables, these authors capture the role of the time-varying coefficients driving usage intensity. Unlike these authors, in our model, the predicted levels of MSN users, estimated in the first stage, provide the dependent variable for the second stage of the model. In contrast, we use the estimates of the country peaks obtained in the first stage to create the relevant interaction variables for the second stage.

3 Methodology

3.1 Objective and research questions

Our main objective is to capture the path-dependent impact of indirect network externalities on the adoption process of MSN. We address this objective by asking whether the indirect network externalities display significantly different effects between the early and late stages of the MSN adoption process. The critical variable of interest, capturing the complementary technology for MSN diffusion, is the country level of Smartphones adoptions since, as discussed above, MSN and Smartphones form complementary systems (Church et al., 2008).

Following the definition of early adopters (Rogers, 2003), as those adopting before the peak and late adopters as those adopting after it, we assess two research

[13] For applications in the marketing literature see Stremersch et al. (2007) and Stremersch and Binken (2009).

[14] These authors found that a Gompertz functional form for the diffusion process (Islam et al., 2002) would lead to better forecasting accuracy in the pre-take-off stage, while the logistic form, would perform better for the post-take-off stage, hence suggesting that the appropriate choice of functional form to estimate the diffusion model should be stage-dependent (Meade and Islam, 2006; 2015).

questions. The first focuses on the path-dependency of the effects of the indirect network externalities:

> RQ.1 "Do indirect network externalities, captured by Smartphones adoptions, affect MSN adoption differently between early and late adopters?"

Suppose indirect network externalities are time-varying, depending on the country-specific diffusion stage. In that case, their estimation becomes of crucial relevance for the timing of many other time-sensitive managerial decisions, such as, for example, penetration pricing strategies (Dean, 1976). Lower prices[15] have been identified as key drivers of adoption (Stoneman, 2002) as they determine a firm's profitability of adopting new technology or, for consumers, as they extend their budget sets. Expectations about lower prices play the opposite role, as they increase the incentives to postpone adoption choices (Balcer & Lippman, 1984).

The critical aspect of the MSN business models, particularly during the early years of their diffusion, was zero pricing, providing MSN services at no cost while exploiting customers' data extraction for third-party monetization (Summers, 2020). However, zero pricing does not imply that MSN access is cost-free. What still matters for adoption are the prices charged by the mobile operators for other complementary system components required for data access. These prices are often bundled in data, minutes, and handset monthly price packages. To assess the impact of these access prices on the process of adoption of MSN, we use the country's Mobile operators blended average revenue per user (ARPU) divided by minutes of use per connection. Our focus is, again, on the possibly path-dependent nature of this price effect. Hence our second research question asks:

> RQ.2 "Does the price of mobile usage affect MSN adoption differently between early and late adopters?"

3.2 Estimation strategy

As briefly discussed in the introduction, this paper uses a multistage estimation approach to address our research questions:

- In the first stage, we estimate a separate logistic model for the MSN diffusion for seven countries (US, UK, France, Brazil, Germany, Italy and Spain).

  This allows us to obtain the temporal profile of the predicted diffusion of MSN for each country, solely based on the effects of direct network externalities captured through the level of past MSN adoptions in the country. This first stage also leads to the identification of each country's specific peak-time of adoptions and the estimation of the relevant diffusion parameters for adoptions speed and the country's market potential.

[15] For the impact of prices on the diffusion of mobile telephony see Madden and Coble-Neal (2004).

- Once these predicted adoption levels and countries' peaks are estimated in the second stage, the paper focuses on the potentially time-varying impact of the indirect network externalities on MSN adoptions.

In this second stage, we consider all the countries' data within a panel data model to estimate the signs and significance of the interaction variables capturing the differences between the pre-and post-peak adoption impact on the predicted levels of MSN adoption.

This two-stage approach, non-linear logistic regression in the first stage, followed by panel data fixed effects estimates with adoptions' peak-interacted covariates in the second, allows us to address the paper's key objective and establish the path-dependent nature of the indirect network externalities affecting MSN adoption.

3.3 Data

In the first estimation stage, we use time series of quarterly MSN adoptions estimating seven logistic models for the US, UK, France, Brazil, Germany, Italy, and Spain. MSN adoption data were provided by comScore[16] for the period starting in the fourth quarter of 2007 to the second quarter of 2014, for the seven countries analyzed. The MSN Active users[17] are individuals who have registered with at least one MSN, such as Facebook or LinkedIn, etc., to which they log in at least once a month.[18] This metric differs from the number of registrations to social networks since some subscribers might not have accessed their services via their mobile phones in the relevant month.

The second stage of estimations uses quarterly data, obtained from GSMA intelligence,[19] for the following covariates of interest:

(i.) *Smartphone additions:* as the quarterly increase in Smartphone penetration,[20] capturing the key system component for the indirect network externalities.
(ii.) *Effective prices*: the blended average revenue per user (ARPU) divided by minutes of use per connection, capturing the impact of the costs of accessing MSN via mobile access.

[16] https://www.comscore.com/About-comScore.

[17] Hence the number of unique and active MSN users will always be smaller than the total number of registrations for these services.

[18] The original monthly data were then used at quarterly intervals to be integrated with the second quarterly dataset.

[19] http://www.gsma.com/aboutus/.

[20] Penetration is calculated as the Smartphones percentage share of total connections. A smartphone is defined as a mobile handset enabling advanced access to Internet-based services with computer-like functions. Smartphone platforms, such as Android, iOS, Windows phone, and BlackBerry, support native applications created by third-party developers, whereas feature phones used closed platforms that do not support native development, although downloadable applications are often supported using Java.

(iii.) *Mobile market penetration*, given by the total number of country mobile subscribers as a percentage share of the total market population. And finally, we control for

(iv.) *Minutes per connection per month: e*xpressed as the number of total minutes, including incoming, outgoing, and roaming calls, transferred over the mobile network, per connection per month in the period. This variable is of interest as it captures possible behavioral changes in usage patterns of MSN.

Table 2 provides the summary statistics and correlations.

4 Model estimation and discussion of the results

4.1 Estimation: the first stage

The first stage consists of estimating seven separated country-specific logistic diffusion models[21] capturing the impact of *direct network externalities* on the processes of MSN adoptions. The diffusion generated by a logistic process is the solution of the differential Eq. (1)

$$\frac{dN(t)}{dt} = r\frac{N(t)}{m}(m - N(t)) \tag{1}$$

The parameter m estimates the ceiling, the maximum potential number of MSN adopters, and the parameter r captures the speed of adoption. The solution of the differential Eq. (1), given by Eq. (2) below, provides the number of MSN adopters at time t.

$$N(t) = \frac{m}{1 + e^{-r(t-b)}} \tag{2}$$

The parameter b estimates the time of the inflexion's point of the logistic curve, the timing necessary for half of the potential population, to adopt MSN. By substituting Eq. (2) into Eq. (1), one obtains the time-varying growth rate of MSN adopters at time t, as:

$$\frac{dN(t)}{dt} = rm\frac{e^{-r(t-b)}}{\left(1 + e^{-r(t-b)}\right)^2} \tag{3}$$

The empirical logistic specification for the number of MSN adopters in country i at time t is, therefore, given by:

[21] The logistic specification (Hosmer and Lemeshow, 1989) is chosen as this functional form captures the initial growing adoption rate as a function of previous adopters, and the subsequently decreasing rate of diffusion as penetration nears the full potential population of adopters.

$$N_i(t) = \frac{m}{1 + e^{-r(t-b)}} + \varepsilon_{i,t} \tag{4}$$

Given the symmetry of the logistic curve, parameter b of Eq. (4) also estimates the period of the peak of adoptions.

Table 3 reports the first stage estimates for the empirical logistic specifications (4) from the fourth quarter of 2007 to the second quarter of 2014 for the seven countries analyzed.[22]

4.1.1 Discussion of the first stage results

The first stage results display interesting differences in the adoption patterns of MSN among the seven analyzed countries. The effects of the direct network externalities appear at the inflection point, b, expressing the change in the speed of adoption between early and late adopters, in the S-shape for aggregate MSN adoptions (See Appendix 1 for the individual country graphs).

These estimates provide the country-specific quarters of the inflection point, b, indicating the timing of the peak of adoptions. The UK reached its peak in the fourth quarter of 2011. France followed, with a peak reached in the first quarter of 2012, while the US and Italy peaks of MSN adoptions were in the second quarter of 2012. Brazil peaked in the third quarter of 2012, Germany in the fourth quarter of 2012, and, finally, Spain was the last country to reach the MSN adoption peak in the second quarter of 2013.

4.2 Second stage of estimation: indirect network externalities and predicted period MSN adoptions

In this second step of the estimation strategy, the predicted values of MSN adoptions, estimated in the individual logistic regressions for each country in the first stage, are used as the new dependent variables. This *purification* of the dependent variables implies that unobserved components of the country-specific models are excluded from the dependent variable of the second stage. Hence, reducing the risk of endogeneity they might otherwise introduce in the second stage.[23] In this second estimation stage, we focus on the impact of Smartphones additions and mobile pricing on MSN diffusion, assessing whether these effects are significantly different between early and late adopters.

[22] Brazil's estimation started form the first 1st Quarter of 2008, hence we have 26 observations for Brazil. See Appendix 1 for the graphs of the actual and estimated MSN diffusion curves in each country.

[23] This strategy is useful in purging the identification strategy from the presence of endogeneity potentially arising from simultaneity since these variables are estimated from lagged cumulated adoptions, that were not affected by the current values of the covariates, used in this second stage (Giovannetti and Piga, 2017).

Table 2 Descriptive statistics and correlations matrix

Descriptive statistics	Obs	Mean	Std dev	Min	Max
Variables					
Effective prices	182	0.11	0.04	0.03	0.18
Mobile market penetration	182	0.74	0.13	0.37	0.89
Minutes per connection per month	169	213.46	178.85	76	850
Smartphones additions	175	0.02	0.01	−0.01	0.07
MSN users	181	19,982,449	24,415,069	562,127	1.182e+08
Matrix of Correlations	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Variables					
Effective prices	1.00				
Mobile market penetration	0.39	1.00			
Minutes per connection per month	−0.50	−0.06	1.00		
Smartphones additions	−0.14	0.24	0.04	1.00	
MSN users	−0.81	−0.36	0.30	0.25	1.00

4.2.1 The second stage dependent variable

In this second stage, the dependent variable, $y_{i,t}$ is given by the predicted values of MSN adoptions[24] estimated from the first stage logistic models, presented in Table 3.

4.2.2 Second stage covariates

The covariates considered in this second stage, presented in the data section, are Smartphones additions level, Effective prices, Minutes per connection per month, and Mobile market penetration.

4.2.3 Second stage panel data model

The second stage compares two alternative nested panel data model specifications to capture the possibly different impact of the key covariates between early and late adopters:

1. The first panel data specification only includes the direct effects of the selected covariates.
2. The second panel data specification includes the interaction terms between the original covariates and a country-specific dummy variable activated (assuming value equal to one) only after reaching the country's adoptions' peak. This speci-

[24] In Table 4, the dependent variable predicted values of MSN adoptions is rescaled in per million units.

Table 3 Logistic specification for the MSN adoptions. Seven countries

Parameters	Italy	Spain	Germany	UK	France	US	Brazil
Ceiling (m)	1.87e+07***	2.33e+07***	2.49e+07 ***	2.62e+07***	1.79e+07***	1.31e+08***	7.51e+07 ***
Speed of adoption (r)	0.1783***	0.1934***	0.2151***	0.1992***	0.1981***	0.1703***	0.1754***
Quarter and year of the peak (b)	Q2 2012***	Q2 2013***	Q4 2012***	Q4 2011***	Q1 2012***	Q2 2012***	Q3 2012***
Adj R-squared	0.9976	0.9988	0.9996	0.9996	0.9972	0.9984	0.9996
RMSE	503,369	357,689	245,891	339,672	537,257	2,868,940	749,243
Observations	27	27	27	27	27	27	26

Significance level: ***=0.01

fication allows for testing whether there is a significant change of the covariates' signs and intensity after a country-specific adoptions inflection point.

The general panel data structure is given by:

$$y_{i,t} = \alpha_i + x'_{i,t}\beta + \varepsilon_{i,t} \tag{5}$$

where the dependent variable, $y_{i,t}$, is, as discussed above, given by the estimated MSN period adoptions for the country, *i,* at time *t,* derived from the first estimation stage and rescaled in per million units; the α_i are the country-specific effects, typical of panel data models, used to take into account possible sources of endogeneity derived by unobservable country-specific factors; $x_{i,t}$ is the vector of covariates, β the vector of parameters capturing the ceteris paribus effects of the different covariates on the estimated period adoption rates, $y_{i,t}$, and $\varepsilon_{i,t}$ is the country-date idiosyncratic error.

To deal with possible additional sources of endogeneity arising from the potential correlation between the unobserved country-specific, time-invariant component of the error, α_i, and the covariates, $x_{i,t}$ the model specifications are estimated using a fixed effect[25] (FE) method, using time demeaned data, to eliminate the country-specific effect α_i.[26]

The second stage results, panel data Fixed Effects estimations, are reported in Table 4.

The following section focuses on the signs and magnitudes of the pre-and post-peak effects of the different covariates on MSN adoptions. This allows addressing the paper's primary objective to explore the impact of the indirect network externalities and their possible changes depending on the stage of the diffusion process.

4.3 Discussion of the results

Before considering the analysis of the single predictors, it is helpful to compare the two model specifications with and without interaction variables. As the restricted model without interaction with the country's peak is nested within the unrestricted interacted model, we use Model 2, from Table 4, to test the null hypothesis that all the coefficients of the interaction variables are jointly equal to zero.

H_0 ($\beta_{\text{interactions}}$): $\beta_{\text{Mobile market Penetration after peak}} = \beta_{\text{Smartphones additions after peak}} = \beta_{\text{Effective Prices per minute after peak}} = 0$

[25] Pooled regression and random effects estimates were also performed. The results were confirmed in these different estimation strategies, but the fixed effect only was reported as it emerged as most suitable to the estimation problem.

[26] This implies that the conditional expectation for the MSN period adoptions given the country-specific unobserved components, α_i, and the regressors, $x_{i,t}$, is equal to the population regression function, so that the OLS estimates of the effects of the covariates on MSN period adoptions, β_j, are consistent, as long as $\varepsilon_{i,t}$, the country-date idiosyncratic error, remains uncorrelated with each $x_{i,t}$, for all time periods. This condition of *strict exogeneity*, is addressed by the two-stage modeling strategy and using the predicted level of MSN adoptions from the first stage that were estimated based on past values of adoptions.

Table 4 Second stage estimation results

Fixed effects estimates	Model 1-Restricted no peak interaction	Model 2-Unrestricted with peak interaction
Dependent variable: 1st stage predicted MSN period adoptions		
Covariates		
Mobile market penetration	11.26***	11.94***
Mobile market penetration after peak	–	−2.06***
Smartphones additions	3.28	7.16**
Smartphones additions after peak	–	−14.50***
Minutes per connection	−0.02***	−0.16***
Effective price per minute	−12.90***	−17.62***
Effective price per minute after peak	–	13.35***
Constant	−1.36	−2.16
Observations	162	162
Significance levels *** = 0.01 ** = 0.05 * = 0.10		
F	F (4,151) = 45.63 Prob > F = 0	F (7,148) = 49.66 Prob > F = 0
R^2 overall	0.42	0.39
R^2 between Countries	0.75	0.75
R^2 within Countries	0.55	0.70
σ_α	6.13	4.89
σ_e	0.35	0.29
Rho (fraction of variance due to $\alpha_{i)}$	0.99	0.99
Akaike crit. (AIC)	4593.13	4531.71
Bayesian crit. (BIC)	4608.57	4556.41

Data for: Mobile market penetration and Effective price per minute as well their peak -interacted variables, [Effective price per minute after peak and Mobile market penetration after peak] for Italy, Spain, UK, France, Germany, Brazil and US covered 26 quarters [from 4th quarter 2007 to the 1st quarter 2014]. Since we moved to use quarterly differences in Smartphone penetration, as explained above, we lost the observation for the first quarter of the Smartphones additions variable for each country, having 25 quarters for Smartphone penetration [and Smartphones additions after peak]. Finally, for the US, data for the variable minutes for connection was only available for the first 13 quarters [from 4th quarter 2007 to the 4th quarter 2010]

Based on the unrestricted Model 2, the null hypothesis H_0 ($\beta_{interactions}$), that all the interaction parameters are jointly equal to zero, can be rejected.[27] This provides supporting evidence for the alternative hypothesis that: "The impact of the indirect externalities and other relevant predictors for MSN adoption differ significantly between early and late adopters".

[27] As the value of the relevant F(3, 148) test equals 25.46, which has near-zero probability under H_0 (β $_{interactions}$).

Next, we discuss the specific pre- and post-peak effects of the indirect network externalities and the other covariates on MSN adoptions.

4.3.1 The impact of effective prices on MSN adoptions

The first column of Table 4, with the estimates for the restricted model without the interaction variables, shows that effective prices have a negative and significant impact on the predicted MSN period adoptions. However, by disentangling the pre- and post-adoption peak effects, as reported in column two of Table 4 for the unrestricted Model 2 with peak interaction, one sees that effective prices exert a significantly different influence between early and late adopters. In detail, while the effective prices' effect is significantly negative for early adopters, after the peak, column two in Table 4, the two coefficients are negative for the base case (Effective prices per minute) and positive for the additional slope component (Effective prices per minute after peak). These combined effects significantly reduce the initial negative influence on MSN adoptions for the late adopters. Hence, while lowering effective prices leads to higher MSN adoptions before the peak, the impact of this strategy becomes weaker after it. This difference shows that later adopters may be benefiting from the direct network externalities generated by the early adopters and are, therefore, less responsive than early adopters to changes in usage prices. This result provides compelling evidence of a lock-in effect. Low penetration pricing strategies, adopted in the early stage of MSN diffusion (Dean, 1976), can be softened after MSN diffusion has peaked.

4.3.2 Smartphones additions

In the restricted model specification without the interaction term, the level of Smartphones additions, column one of Table 4, displays a non-significant positive effect on MSN adoptions. However, by introducing the interaction terms, in the second unrestricted model specification, the estimates, in column two Table 4, show that the impact of Smartphones additions on predicted MSN adoptions is highly path-dependent. This effect is positive and significant ($p = 0.017$) before the countries' peak, confirming the relevance of the systems complementarities for the early adopters. The impact changes sign, becoming negative after the MSN adoption peaked since MSN late adopters now benefit from the additional indirect network externalities brought out by a more significant smartphone user base.

This result provides evidence that, before reaching a critical mass of MSN adoptions, Smartphones additions and the MSN adoption processes complement each other. However, after reaching the MSN adoptions' peak, this effect reverses, as higher levels of Smartphone penetration have already been achieved.

4.3.3 Mobile phones penetration

Moving to the role of Mobile phones penetration, one can see that the panel data model without interaction captures an overall significant positive effect of the Mobile phone penetration level on period MSN adoptions. After introducing the interaction effect, the estimates of Table 4, column two, retain the positive sign and the significance of both the pre-and post-peak level of mobile penetration on predicted MSN period adoptions. Hence, mobile penetration levels effects on adoption are stronger for late adopters.

4.3.4 Minutes per connection

MSN allow multiple multimedia communication, a substitute for traditional voice communication. In the restricted model specification, without the interaction terms, Minutes per connection has a significantly negative effect on MSN adoptions, indicating the substitute-component relation between usage time and MSN, likely to show a trade-off between voice and non-voice communication. This effect remains unchanged in the unrestricted Model 2 with peak interaction. This empirical evidence confirms the relevance of substitution between the usage time and MSN adoption.

5 Conclusions and managerial implications

Given the interactive nature of MSN contents' generation, users' adoption choices are driven by positive direct network externalities. However, other factors are also critical in predicting MSN adoptions. This paper considered the additional impact on MSN diffusion played by indirect network externalities captured by Smartphones and the costs of accessing MSN due to the non-zero priced components charged by the mobile operators.

Our results indicate that these effects can differ significantly between the early adopters, pre-peak and the late ones, post-peak. These significant changes are linked to country-specific dates of the adoption's peaks of MSN diffusion and provide additional evidence on the role of path-dependence (David, 1985; Dosi & Nelson, 2013) in the impact of the indirect network externalities due to complementary system components (Church, et al., 2008).

The evidence that low penetration pricing strategies (Dean, 1976) are associated with early stages of MSN diffusion, while their effect lessens after the diffusion had peaked, should be of interest for Mobile operators' managerial practice.

Moreover, the analysis of the parallel processes of MSN and Smartphones adoptions reveals some new details and differences between early and late adopters: in the early MSN adoption phase, MSN and smartphones behave as complements, while post-peak, a more significant Smartphones users' base, reverses this pre-peak complementarity.

As a result of these complex path-dependent processes, any policy strategy aiming at supporting the diffusion and usage of MSN for access to information, education activities, and broader societal participation, needs to consider the presence of these time-varying and country-specific effects, together with the direct and indirect network externalities modulating the process MSN diffusion across countries.

5.1 Limitations and extensions

The critical contribution of this paper emerges from the second estimation stage. By introducing a set of interaction variables capturing the time-varying impact of different covariates, the model identifies their potentially different effects between early and late adopters. These results emerge from the analysis of the early years of MSN adoptions in seven countries. They do not include data on least developed countries, where the process of Smartphones and MSN adoptions are still taking shape. Qualitative differences may be at work in different countries, and the impact of Covid-19 has spread the usage of both Smartphones and MSN, given the relevance of online social interaction, as a response to the widespread adoption of public health policies focussing on working from home and social distancing.

On the other hand, low affordability can be a critical factor in hampering the adoption of both Smartphones and hence MSN in the least developed countries. Moreover, due to the pandemic's macroeconomic impact, the economic impoverishment witnessed in 2020 might interact with the otherwise more predictable changes occurring in MSN adoption processes. Critically, since only circa half of the world population had access to Internet connectivity in 2020 (International Telecommunication Union, 2020), the drivers of MSN adoption might work differently depending on the degree of digital inclusion of different countries and communities.

In conclusion, while based on a limited set of dates and countries, the results presented in this paper remain helpful because of their contribution in modeling the presence of pre- and post- adoptions peaks behavioral differences. Moreover, they confirm the significant path-dependence of direct and indirect network externalities for the processes of technological adoption.

Appendix

Appendix 1: Individual countries diffusion graphs and summary statistics

Brazil

See Fig. 1 and Table 5

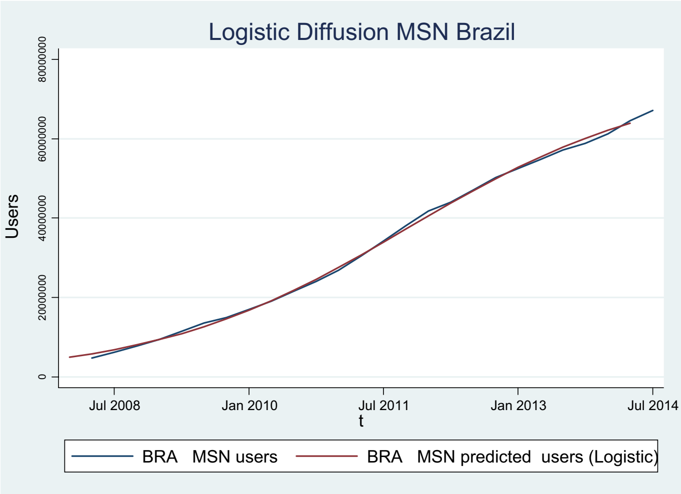


Fig. 1 Logistic diffusion of mobile social networking in Brazil, 2007–2014

Table 5 Summary statistics, Brazil

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.08	0.02	0.05	0.11
Mobile market penetration	26	0.49	0.06	0.37	0.56
Minutes per connection per month	26	110.15	17.46	76	140
Smartphones additions	25	0.01	0.01	0.00	0.03
MSN users	25	3.25E+07	1.96E+07	4,779,000	6.45E+07

Italy

See Fig. 2 and Table 6

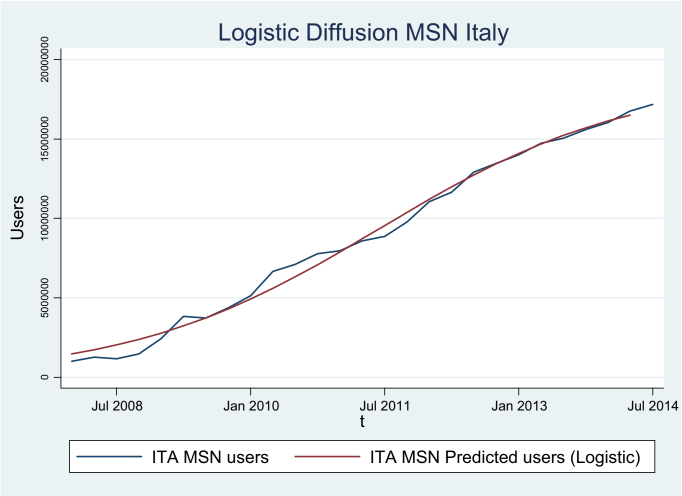


Fig. 2 Logistic diffusion of mobile social networking in Italy, 2007–2014

Table 6 Summary statistics, Italy

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.12	0.03	0.07	0.18
Mobile market penetration	26	0.80	0.01	0.78	0.80
Minutes per connection per month	26	165.46	27.72	124	218
Smartphones additions	25	0.01	0.01	0.00	0.05
MSN users	26	8,555,843	5,200,003	1,022,246	1.68E+07

France

See Fig. 3 and Table 7

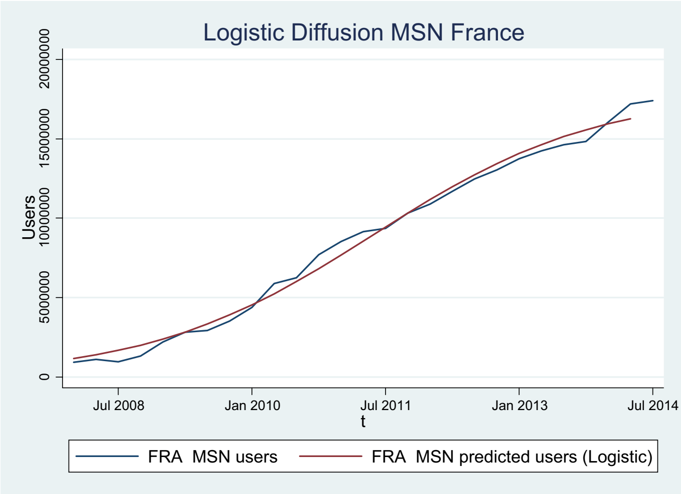


Fig. 3 Logistic diffusion of mobile social networking in France, 2007–2014

Table 7 Summary statistics, France

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.14	0.03	0.09	0.17
Mobile market penetration	26	0.71	0.02	0.68	0.74
Minutes per connection per month	26	232.88	24.51	212	289
Smartphones additions	25	0.02	0.02	0.00	0.07
MSN users	26	8,316,525	5,309,722	942,239	1.72E+07

Germany

See Fig. 4 and Table 8

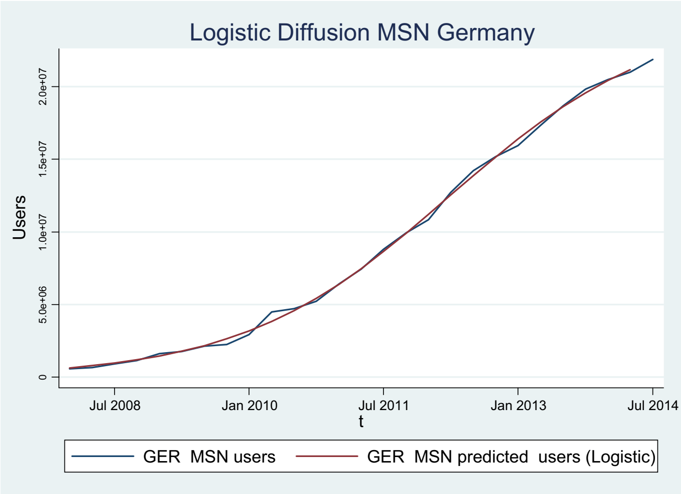


Fig. 4 Logistic diffusion of mobile social networking in Germany, 2007–2014

Table 8 Summary statistics, Germany

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.14	0.01	0.12	0.16
Mobile market penetration	26	0.86	0.02	0.81	0.89
Minutes per connection per month	26	113.81	8.00	100	125
Smartphones additions	25	0.01	0.01	0.00	0.03
MSN users	26	8,720,233	7,064,532	562,127	2.10E+07

Spain

See Fig. 5 and Table 9

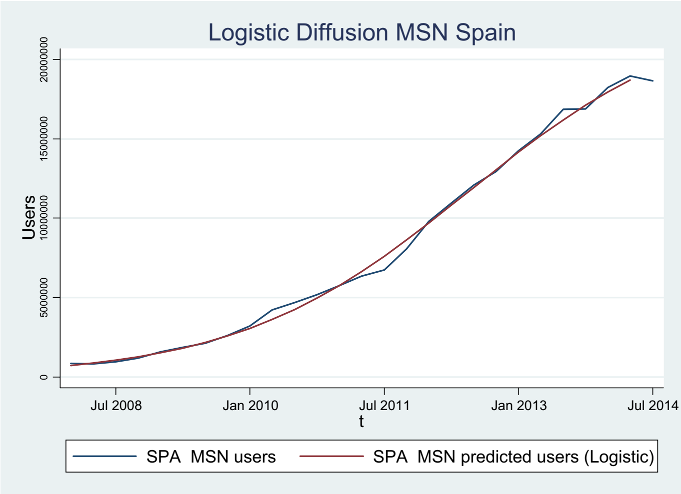


Fig. 5 Logistic diffusion of mobile social networking in Spain, 2007–2014

Table 9 Summary statistics, Spain

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.15	0.02	0.11	0.18
Mobile market penetration	26	0.72	0.00	0.72	0.73
Minutes per connection per month	26	165.88	6.77	155	182
Smartphones additions	25	0.02	0.01	0.01	0.04
MSN users	26	7,789,807	6,108,251	839,069	1.90E+07

UK

See Fig. 6 and Table 10

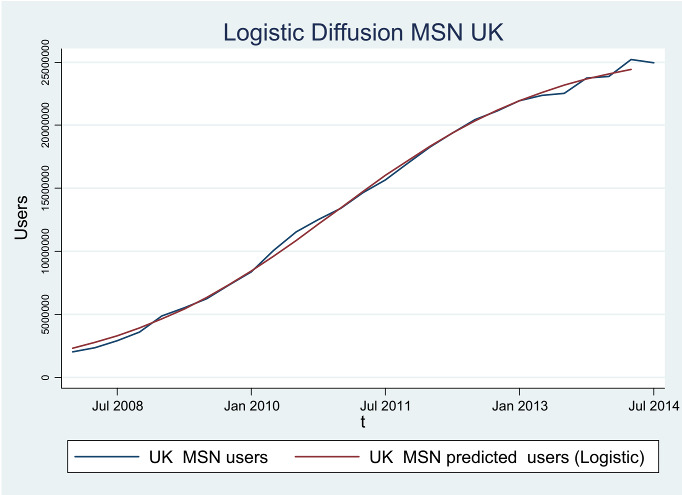


Fig. 6 Logistic diffusion of mobile social networking in UK, 2007–2014

Table 10 Summary statistics, UK

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.13	0.01	0.11	0.16
Mobile market penetration	26	0.89	0.01	0.87	0.89
Minutes per connection per month	26	193.62	6.72	176	207
Smartphones additions	25	0.02	0.01	0.00	0.04
MSN users	26	1.37E+07	7,746,772	2,010,008	2.52E+07

US

See Fig. 7 and Table 11

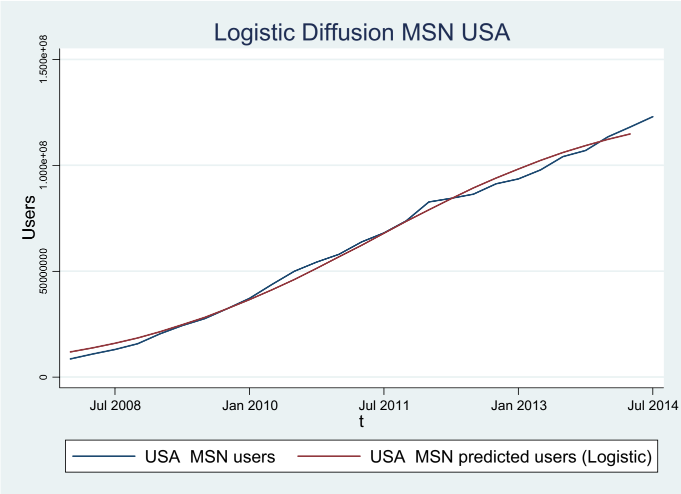


Fig. 7 Logistic diffusion of mobile social networking in the US, 2007–2014

Table 11 Summary statistics, USA

Variable	Obs	Mean	Std. Dev	Min	Max
Effective prices	26	0.04	0.01	0.03	0.05
Mobile market penetration	26	0.70	0.03	0.63	0.72
Minutes per connection per month	13	811.31	23.97	773	850
Smartphones additions	25	0.02	0.01	0.00	0.04
MSN users	26	6.08E+07	3.51E+07	8,632,751	1.18E+08

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