Usage and Diffusion of Cellular Telephony, 1998-2004[†]

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Abstract: In this paper, we study the dynamics of usage intensity of second-generation cellular telephony over the diffusion curve. We address two specific questions: First, does information about usage intensity over time allow us to draw conclusions about the underlying drivers of technology diffusion? Second, what effect does the existence and penetration of previous generations and other networks in the same generation on network usage intensity? Using an operator-level panel covering 41 countries with quarterly data over 6 years, we find that heterogeneity among adopters dominates network effects and that different technological generations are complements in terms of usage, but substitutes in terms of subscription.

Keywords: Cellular telephony, diffusion, usage intensity, network effects, consumer heterogeneity, fixed-mobile substitutability.

JEL Codes: L1, L52, O38.

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I Introduction

In this paper, we study the dynamics of usage intensity in the context of second-generation cellular telephony. This is fairly unique as most other studies on the success of new products or technologies look only at diffusion speed (i.e. the slope of an s-shaped diffusion curve) and maximum market size (i.e. the asymptotic value of adopters) as key indicators for technological success. One can think of many reasons why technologies should diffuse in an s-shape, and researchers have developed a large number of diffusion models that generate the same s-shaped outcome. In cellular telephony, diffusion in various geographical markets has been widely documented and analysed. In particular, many papers emphasize the importance of network effects in cellular telephony (Doganoglu and Grzybowski, 2005; Grajek, 2003, Liikanen et al., 2004, Koski and Kretschmer, 2005). The main purpose of these papers is to identify a set of variables that will help explain diffusion speed and shape in a particular country or set of countries and thus, implicitly, uncover levers that policymakers or firms can use in order to ensure the success of a new technology. This approach is well-suited to non-durable goods where the purchase decision takes place at a single point in time.

However, in the case of durable goods for which consumption is divided into an initial (hardware) purchase and follow-up (service) purchases, simply looking at the number of adopters of a new technology may be an inadequate measure of technological success. This is because users make consumption decisions over several periods, and the initial adoption decision is only part of the cumulative expenditure on a durable technology. Therefore, a small number of intensive users may generate higher expected profits or welfare than a large number of nominal users. A better (or at the very least complementary) measure of technological success may therefore be the overall (or average) usage at a given point in time.

Further, since many (if not all) diffusion theories generate s-shaped diffusion curves (often with conflicting assumptions) studying usage intensity may enable us to discriminate between different diffusion models since their implications on usage intensity over time may be different.

We answer two specific questions in our paper:

(i) Can we use information about usage intensity over time to draw conclusions about the underlying drivers of technology diffusion?

(ii) What is the effect of the existence and market penetration of previous generations and other networks in the same generation on a particular network's usage intensity?

The first question is aimed at uncovering a number of effects potentially at play along a technology's diffusion path; the **heterogeneity**, **epidemic**, and **network** effects (Geroski, 2000), which have different implications for the usage intensity of a durable good over time (Cabral, 2006). The second question recognizes that new technologies have to be studied in the context of the technology they may be replacing and/or competing with. Therefore, we are interested if technologies delivering similar services are necessarily **substitutes** or if there is a degree of **complementarity** through **network effects**. We study this question both across and within generations.

Our first major result is that consumer heterogeneity plays a much more important role than network effects in determining the usage intensity for an individual operator. Second, we find that network effects do not seem to operate across different operator networks. Third, we find that fixed-line telephony acts as a complement in the usage intensity of cellular telephony, as evidenced by cross-price effects. Finally, we find evidence of fixed-mobile platform substitution, as lower fixed-line market penetration implies more cellphone usage. These findings are both novel and illuminating for those eager to find more complete measures of technological success.[1]

To our knowledge, our paper is one of the first to consider usage intensity as a measure of success for an emerging technology.[2] By contrasting our results on usage dynamics with results on diffusion speed, we can see if our measures of technological success are correlated with those of the conventional diffusion literature. Our paper is also (to our knowledge) the first to use aggregate usage data to draw conclusions on the preference distribution of users. Our study, especially the analysis of complementarity and substitutability across different technological generations, offers new insights on usage dynamics for new technologies in the presence of an installed base of imperfectly compatible technologies (Grajek, 2003). Further, by taking an explicitly dynamic approach in our analysis, we allow some effects to vary over time to see if fixed lines will eventually be replaced by cellular lines after helping to solve the start-up problem.

The paper is structured as follows: We describe the global cellular telecommunications industry in Section II and discuss potential determinants of usage intensity in Section III. We then describe our data and give descriptive statistics in Section IV. Our empirical results are presented in Section V and a discussion follows in Section VI. Section VII concludes.

II The global cellular telecommunications industry

The general features and recent history of the cellular telecommunications industry are discussed in detail in Grajek (2003), Koski and Kretschmer (2005) and Gruber and Verboven

[1] Comin et al. (2006) develop a framework of technological diffusion in which extensive (adoption) and intensive (usage intensity) dimensions of technology diffusion are separated. Their results suggest that the existing preconception of s-shaped diffusion holds only if we look at the extensive margin, i.e. first adoption, while looking at the intensive margin, i.e. usage intensity, may generate quite different dynamics.

[2] Exceptions include Ward and Woroch, 2004, and Cabral, 2006.

(2001). Therefore, we provide only a brief history of the technological improvements and corresponding generation changes in cellular telephony over time.

In most countries, cellular phones were first available to end consumers in the 1980s. The technology initially used was based on analogue signal transmission, which was relatively inefficient and unreliable. In some countries, first-generation (1G) cellular networks reached their capacity relatively quickly, leading to lower service quality and congestion for initiating calls in particular. As soon as digital technology (second generation, 2G) had matured enough to present a credible alternative to analogue cellular, it was introduced gradually across the world (Dekimpe et al, 2000). Several different technological standards were in existence in different countries – for example, GSM in Europe, PDCS in Japan – and some countries – most notably the US – even introduced several standards in one country. Technological competition between standards within countries has been suggested to have slowed down overall diffusion (Koski and Kretschmer, 2005), but may have had the long-term effect of fostering technological progress for future generations (Cabral and Kretschmer, 2007). In addition to 2G's improved reliability and network capacity, 2G phones also had SMS functionality, which enabled users to send short text messages to each other and was a huge success among younger users, especially in Asia and Europe.[3] Following the success of 2G, a third generation with more advanced data transmission facilities was developed and is currently being rolled out.

For our sample period 1998-2004, 2G cellular was dominant. Second generation telephony itself displayed significant technological progress, with handsets becoming smaller and containing an increasing number of additional functions (Koski and Kretschmer, 2007). In addition to ongoing technological innovations on the product side, pricing and services

[3] In the US, text messaging had not caught on and the average user was sending 203 text messages a year compared to 651 in China in 2004, the end of our study period. (http://www.newsmax.com/archives/articles/2005/8/11/135257.shtml).

became increasingly sophisticated. First-generation cellular phones were mainly targeted at business consumers for several reasons: First, most handsets were rather heavy and thus used predominantly in cars,[4] which, combined with very high tariffs, appealed mainly to business users. With the introduction of digital cellular telephony, however, operators focused on capturing the mass market in order to make the technology succeed commercially.

Penetration pricing: Early attempts by second-generation cellphone operators were targeted at gaining a critical mass of consumers. Since later adopters would be basing their adoption decisions on those of early adopters, operators were willing to take a loss, or at least price aggressively to grow their installed base. With lock-in contracts over one, sometimes two years, this strategy was profitable (Farrell and Klemperer, forthcoming).

Handset subsidies: Most cellular handsets were, and still are, heavily subsidized. This was a strategy to get consumers to adopt in the first place, as handsets were typically the most expensive part of getting a cellphone connected.[5] Quite frequently then, basic handsets are given away "for free"[6] if the consumer signed up for a long-term contract. This is a particular form of product cross-subsidization to overcome the installed-base problem (Barros, 2006).

Prepaid contracts (Pay-as-you-go): Possibly the most successful strategy of moving cellular telephony into the mass market was the introduction of pay-as-you-go contracts. These contracts involve no monthly fee, but a higher per-minute cost. Such contracts are especially attractive for low-frequency users for whom a monthly fee would be too high to warrant the few calls they make or who do not have access to a bank account to set up a monthly debit.

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[4] One of the largest cellphone stores in the UK, founded in 1989, is still called "Carphone Warehouse".
[5] Initially, operators charged a connection fee similar to the fixed-line market, but competition among operators forces and an unwillingness of consumers to pay for the privilege of going to a shop and having a shop assistant "activate" the connection by clicking a button put paid to this practice.
[6] Most commonly, operators would charge £/$/€ 1 for a handset that typically cost about $100 to produce. There are even instances however of "paying" consumers to buy a handset: In France, a Siemens S35 was sold in connection with a contract for FFR190 and contained a voucher for a FFR200 reimbursement if sent to the mobile operator.

The introduction of pay-as-you-go tariffs coincided with a rapid increase in diffusion speed, and most of the growth in later stages of diffusion came from prepaid users.[7]

Tariff proliferation: Finally, with an increase in competition and increasingly fine market segmentation, the number of tariffs has proliferated enormously. This has two effects: First, it could serve as a collusive device by confusing consumers (Hörnig, 2005), and second, it could enable consumers to make more fine-grained decisions based on their expected calling patterns (Miravete and Röller, 2004, Naranayan et al., 2005). The fact that consumers seem to switch quite readily between contracts to optimize their behavior (Miravete and Röller, 2004) suggests that consumers will have some degree of uncertainty about their future calling patterns, but eventually settle on the contract that suits their consumption behavior best.

III Determinants of cellular usage intensity

In this section, we identify and discuss potential determinants of cellular usage intensity. Specifically, we examine the expected effect of consumer preferences, network effects, and substitute technologies on new technology usage.

Consumer preferences

The distribution of preferences for current users of a technology will affect the usage intensity of a particular technology at any given time. Interestingly, the two most frequently used theories of technology diffusion have different implications for usage intensity over the diffusion path (Cabral, 2006). The epidemic model assumes that all users have identical preferences for a new technology, and the s-shaped path is generated by the different times at which adopters learn about the technology (Geroski, 2000).[8] Conversely, the heterogeneity model postulates that adopters adopt according to their preferences, with the highest-

[7] This process is currently in reverse as operators try to get pay-as-you-go users to switch to monthly fee contracts.
[8] This is the most basic version of the epidemic model, which assumes no external source of information and completely identical adopters. The resulting diffusion curve has its maximum diffusion speed at an adoption rate of 50%, although more sophisticated models can generate asymmetric diffusion patterns as well.

preference adopter moving first, the second-highest moving second and so on. This is called the "rank effect" (Karshenas and Stoneman, 1993). The rank effect implies a decrease in usage intensity over the diffusion curve if, as seems reasonable, the preference to adopt early is correlated to using the technology intensively. We do not have a direct measure of consumer preferences that would let us measure the rank effect directly, but assuming that consumers are heterogeneous, later adopters will have lower preferences than earlier ones, which implies that average usage intensity will decrease as more low-preference adopters join the network. We also control for a share of consumer heterogeneity in the choice of contract (prepaid vs. postpaid), with prepaid consumers typically having lower usage intensity than postpaid ones.

Network and learning effects

Network effects generally make usage of a technology more attractive since there are more potential communication partners (in the case of direct network effects) or a wider variety (or cheaper supply) of complementary products. In the case of cellular telephony, direct network effects may operate across multiple operators and technologies (since users of a particular network can call users from other networks and even fixed line numbers), while indirect network effects may operate predominantly on the operator level (via provision of operator-specific content, ringtones, services etc.). In general, more users of a technology will not only make initial adoption more attractive (which has been widely documented in the literature), but also usage intensity of existing users. The degree of compatibility, or the extent to which users view two competing networks as substitutes, will determine the relative magnitudes of the effect of additional subscribers to one's own network and to a competing network.

Further, users of cellular phones may develop a habit of calling each other while in transit, e.g. on the bus or train. This used to be uncommon in the early stages of diffusion, but has now become quite common as it is often seen as a productive way of spending otherwise idle time.

Substitute technologies

In network industries, substitutes in the product market may have a degree of complementarity via the network effect, especially considering the usage intensity of existing users. To see this, consider a product with network effects whose usefulness increases with the number of potential communication partners. Communication partners can either be users of the same network, of a competing network, or of the previous generation's network. This would imply that the more users overall, the more utility a user will derive from a specific network, which means that existing users of the technology will have a higher incentive to use the technology intensively because there are more potential communication links to be formed. This would not hold, however, if the competing versions were incompatible. In the context of cellular telephony, complete incompatibility is unlikely, although Grajek (2003) finds that compatibility among networks is low, i.e. users do not view competing networks as close substitutes, mostly because there are different on-net and off-net prices.[9] We therefore need to distinguish between substitute technologies within the same generation and previous generations.

Intra-generational effects

The literature studying competition and its effects on product diffusion demonstrates that overall diffusion speed typically increases with competition (Koski and Kretschmer, 2005, Gruber and Verboven, 2001). This is normally attributed to price and non-price competition as well as increased technology-wide network effects. The reason is that in markets with switching costs an early build-up of consumers locks in larger numbers of consumers for the future.

[9] "On-net" prices refer to calls made to members of the same network, "off-net" prices refer to calls to other cellular networks.

The effect of competition on usage intensity is not obvious, however. First, since strategies of winning consumers often take the form of subsidized handsets, the marginal costs of making additional calls may well be the same, suggesting no effect on the usage intensity of individual consumers arising from increased competition. Second, since users will adopt a technology if the overall expected utility exceeds the costs of purchasing, lowering prices will attract adopters with lower preferences and therefore lower expected usage intensity. Intense competition may therefore have the effect of the rapid adoption of a technology (i.e., a steep s-shaped diffusion curve), but decreasing usage intensity because low-preference users end up adopting more quickly than they would otherwise.[10]

Previous generation substitutes

Existing work on the effect of the installed base of an existing technology suggests that a larger installed base typically hinders transition to a new technology. If users of the incumbent generation incur some cost of switching to the new generation, a large installed base may prevent them from switching, and given network effects, the new technology may not be adopted at all unless the degree of technological improvement in large enough (Farrell and Saloner, 1985, Shy, 1996). In markets with backward compatibility, however, this result may be overturned. If early users of the new generation can communicate with "old" users, the start-up problem for the new generation may be alleviated. Koski and Kretschmer (2005) show that in countries with a comparably large number of 1G mobile users, 2G cellular telephony diffused more quickly, which mirrors the results of Liikanen et al. (2004). On the other hand, Barros and Cadima (2002), Sung et al. (2000), and Liikanen et al. (2004) show that mobile and fixed-line telephony appear to be substitutes. Ward and Woroch (2004) find similar results, but look at usage rather than adoption.

[10] This only holds, of course, if later adopters are indeed low-intensity users. Our empirical results show that this is indeed the case, as can be seen in section V.

Overall then, we believe that it is possible that a complementary effect may only be relevant while the start-up problem still exists, i.e. in the early stages of the new generation, whereas in later stages, we may see users replacing their fixed-line connections with mobile connections or new generations of buyers eschewing the old technology completely. Therefore, the effect of fixed-line prices and availability on mobile adoption and usage may vary over the diffusion curve.

IV Data

We draw our data predominantly from two sources: The Informa Telecoms & Media World Cellular GSM Datapack (Informa T&M) and Merrill Lynch's Global Wireless Matrix. The Informa T&M data has been used in previous studies (e.g. Koski and Kretschmer, 2005) and covers the number of subscribers for individual mobile operators, average prices and technological standards in considerable detail. Informa T & M is a provider of market and business intelligence to commercial entities in the mobile and media industries. Buyers of this data base commercial and marketing decisions on the data, thus ensuring a high level of accuracy. Merrill Lynch, a US-based investment bank, publishes a quarterly report on the development of the global cellular telephony market as a service to their clients and industry observers. Merrill Lynch reports, among other data, the total number of called minutes per operator, which can be used to construct the average usage per consumer.

Obtaining data often involves a tradeoff between the level of detail (which is often higher in commercial datasets) and the reliability of the data (which is generally regarded higher for data collected by non-commercial organizations). To minimize these problems, we triangulated the data with available public data sources (OECD's Communications Outlook, ITU's Telecommunications Indicators) and found that the variables common to both private and public data were comparable. We are therefore quite confident that our data is accurate.

To complement our main data sources, we use IMF's International Financial Statistics (for GDP) and World Bank's World Development Indicators (for population, telephone mainlines, and average cost of a local call). The disadvantage of the WDI database is that it only provides yearly time series. To arrive at the quarterly series we therefore linearly interpolated the variables.

Descriptive statistics

Table 1 gives descriptive statistics of our variables. The data coverage depends on a particular variable, but overall our sample covers more than 100 network operators in more than 40 countries. Looking at time trends of our variables of interest in Table 2, we can see that the increased penetration of cellphones in our sample coincides with a significant increase in the share of prepaid consumers. We also find a clear downward trend in cellular service prices in our sample and an upward trend in average usage. Contrary to cellular telephony, subscription of fixed lines decreases slightly over our study period, while fixed-line prices remain constant. Stage is a dummy variable that takes value 1 if cellular diffusion in a country is advanced and zero otherwise.[11] As Table 2 reports, in the beginning year of our sample there were no advanced countries in terms of cellular telephony diffusion, whereas in the last year almost all countries reached an advanced stage.

Our data reflects some of the interesting dynamics in the cellular phone industry in the late 1990 and early 2000s. Diffusion was rapid – penetration rates increased almost four-fold over six years – and prepaid usage went from being an option chosen by one subscriber in four to the option preferred by half of all users. Of course, looking at sample averages is likely to hide a number of idiosyncrasies, in particular some of the effects we are interested in. For illustrative purposes, we therefore consider the diffusion and usage patterns of two individual countries.

[11] The variable Stage will be defined later on, when we describe country-wise cellphone diffusion.

Two examples – Chile and Malaysia

Our goal is to link usage patterns to different stages of the diffusion curve. The following figures plot diffusion and average usage in Chile and Malaysia, respectively.

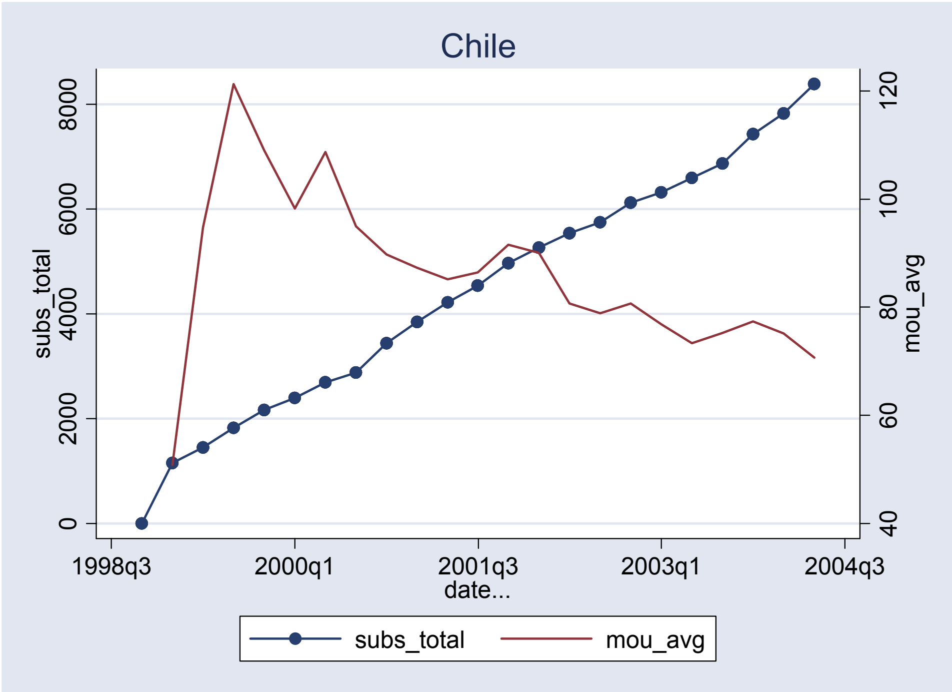

Figure 1: Chile, Diffusion and average usage, 9/98 – 9/04

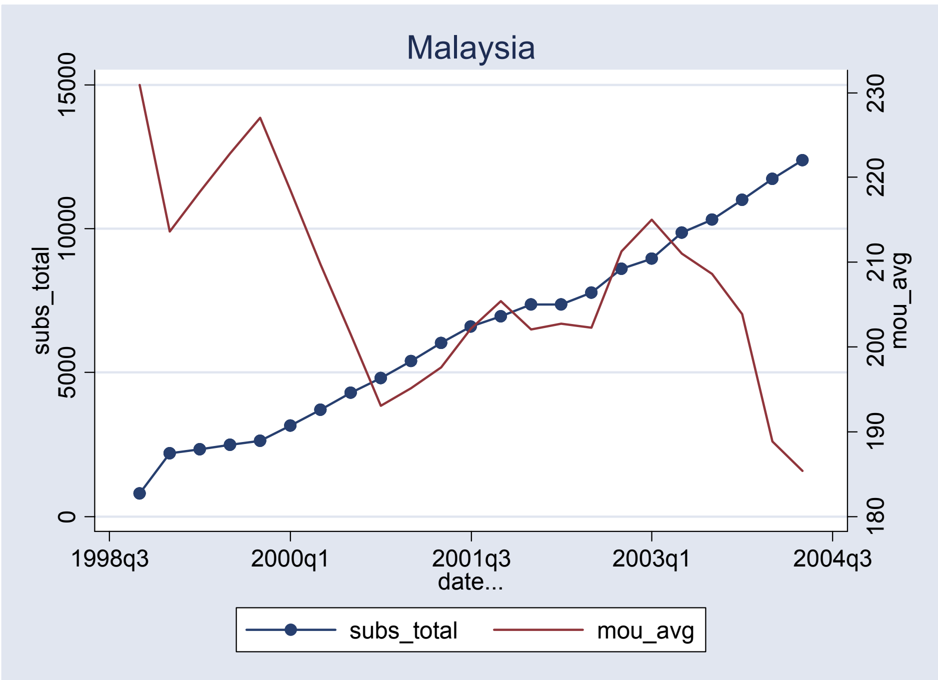

Figure 2: Malaysia, Diffusion and average usage, 9/98 – 9/04

From Figure 1 we can see that Chile displays a pattern of first increasing, then decreasing average usage. Figure 2 shows that average usage in Malaysia is decreasing fairly steadily over time. OLS regressions confirm that a linear time trend yields a poor fit for Chile (Slope: -.201, R^2 = .008), while it generates a better fit for Malaysia (Slope: -1.048, R^2 = .374). Including a nonlinear term improves results for Chile to an R^2 of .253, while results remain similar for Malaysia (R^2 = .423).

The above descriptive statistics suggest that usage patterns can vary significantly across countries, despite the fact that diffusion is s-shaped in both countries. [12] Clearly, these statistics should be interpreted with caution since we do not control for important country- and firm-level variables. For example, Malaysia had an approximately 50% higher penetration rate throughout the sample and the Malay economy grew by about 55% in the sample period compared to 20% growth in Chile. At any rate, the different usage patterns suggest that usage intensity across countries is worth studying in more detail. We will therefore first run a fairly standard diffusion regression for each country before looking at determinants of average usage by cellular operator in the next section.

Global diffusion of cellular telephony

The wide coverage of our sample means that we consider countries that already reached near full penetration alongside countries in which cellular telephony had just taken off in 1998. As mentioned, average usage may differ significantly by the stage of diffusion a country's cellular network is in. To provide a descriptive summary of the diffusion process, we estimate a country-level logistic diffusion equation of the form:[13]

$$SUBS_t = \frac{SUBS^*}{1+\exp(-\beta(t-\tau))}, \tag{1}$$

[12] Note that we are not covering a complete s-shape in our data. The two countries chosen here for illustrative purposes have roughly linear growth during our study period, i.e. we are capturing the linear part in the middle of the diffusion curve for these countries.

[13] Beck et al. (2005) discuss this diffusion equation and contrast it with the others commonly used in the literature.

where $SUBS^* = \gamma POP$.

$SUBS_t$ denotes the number of subscribers at time t, and POP measures the population of a country. The potential number of adopters $SUBS^*$, i.e. the saturation level to which $SUBS_t$ converges, is assumed to be a fraction γ of the total country's population. The other two parameters describing the diffusion process, τ and β, stand for timing and speed of the diffusion respectively. That is, τ indicates the inflection point of the logistic curve, while β gives the growth rate of $SUBS_t$ relative to its distance to the saturation level, i.e. $\frac{dSUBS_t}{dt}\frac{1}{SUBS_t} = \beta\frac{SUBS^* - SUBS_t}{SUBS^*}$. The growth rate reaches its maximum ($\frac{\beta}{2}$) at the inflection point $t = \tau$. Table 3 presents Nonlinear Least Squares (NLS) estimates of the country-specific regressions, where τ is measured in quarters: the average τ is approximately 163, which corresponds to the 4th quarter of 2000 – the average country in our sample reaches its inflection point in late 2000. There are significant differences across countries, however: In Finland, our estimates suggest that diffusion speed reaches its maximum about 18 months earlier (τ = 154.6) than the average, while in Russia, the estimated inflection point was in late 2004 (τ = 178.9). To illustrate the different diffusion stage across countries in our sample, we also pick three country groups – leaders, followers, and laggards, based on our estimates of τ – and plot actual and fitted penetration levels for the three groups in Figures 3 – 5.

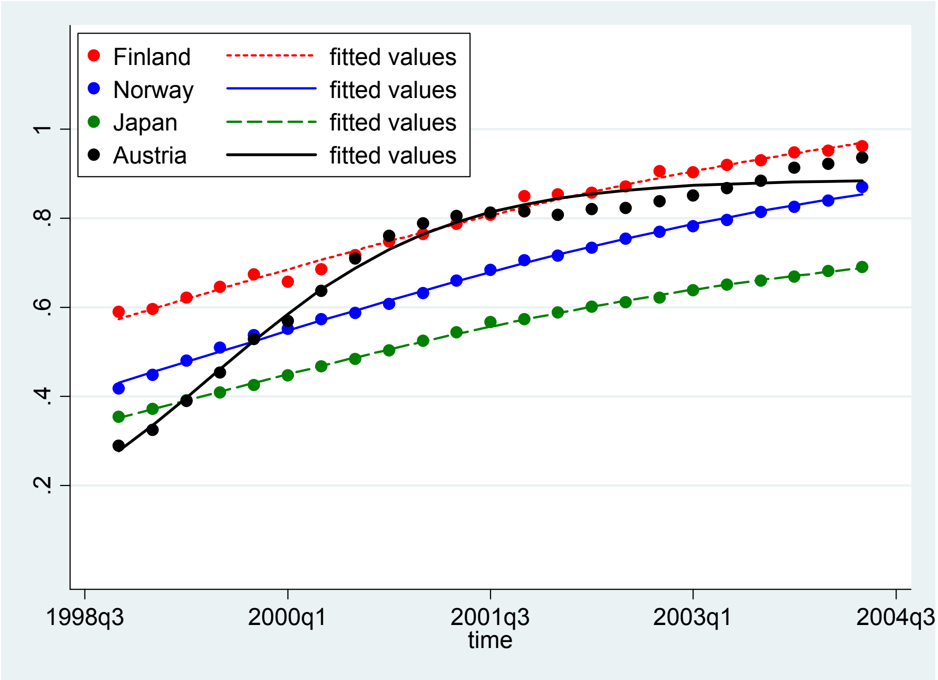

Figure 3. Leaders' mobile penetration diffusion

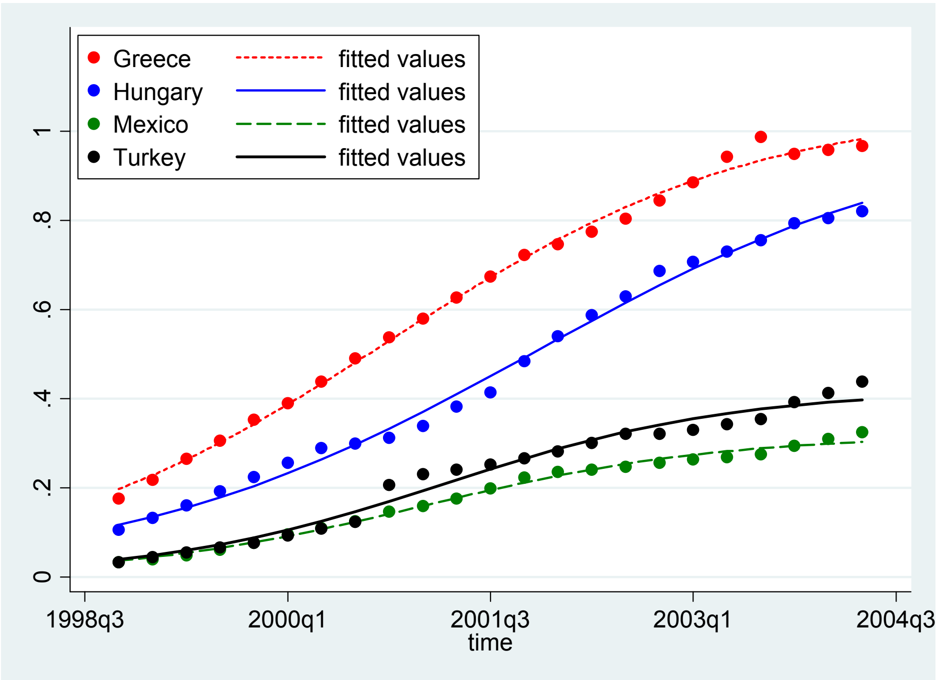

Figure 4. Followers' mobile penetration diffusion

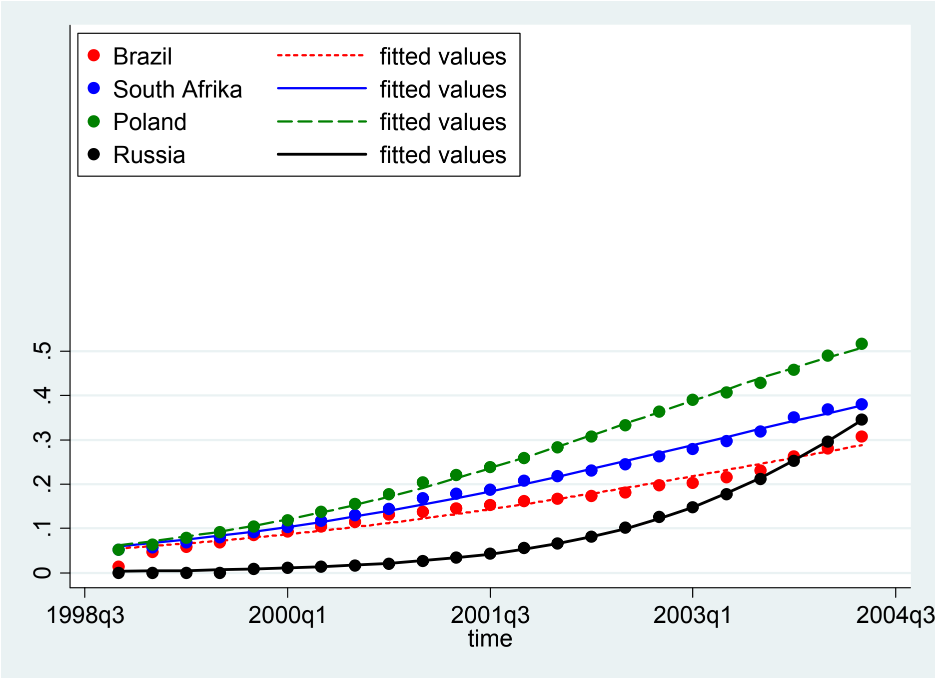

Figure 5. Laggards' mobile penetration diffusion

Our regression estimates fit the actual diffusion curve reasonably well. We do not report the obtained high R^2 in Table 3, as they are common in such non-linear models and do not necessarily indicate a good specification (Trajtenberg and Yitzhaki, 1989). Instead, we report the fixed-line penetration ratios in the last year of our sample. By contrasting it with the estimated cellular penetration thresholds (γ), we see that the fixed-line and the estimated cellular penetration rations correspond to each other quite well. In particular, the countries with very low γ (Argentina, China, and Venezuela) exhibit very low level of fixed-line penetration as well. Finally, the average estimated fixed-to-mobile penetration ratio roughly equals 2, which has some intuitive appeal as there was typically one fixed line per household, whereas with the penetration of cellular telephony two members of a household may own a cellular phone.

Since the logistic diffusion equation is symmetric around the inflection point τ, which cuts the diffusion process into halves, it naturally defines the stage of the diffusion. Further, since the countries in our sample are at very different stages of diffusion and since some of our potential determinants may have different effects across a technology's lifecycle, we want to account for this by allowing for time-varying effects in our regressions. Therefore, we define the variable *Stage*, which takes value 1 if a country's cellular diffusion has reached the estimated inflection point and zero otherwise, and intersect it with our variables of interest.[14] For two countries (Columbia and India) the nonlinear estimation procedure did not converge, as 2G cellphones were just taking off in 2004. We then set the *Stage* to equal zero for them.

V Empirical specification and results

Usage regressions

We use average usage intensity per subscriber as our dependent variable and identify its determinants in our sample. Note that our dataset allows us to run usage regressions on operator level. This is useful since operators in the same country may have different characteristics, for example the proportion of prepaid users or the installed base of subscribers, both of which are expected affect the average usage intensity of this particular operator. Also, including average prices by operator lets us uncover own-price and cross-price effects on communication demands.

Our baseline specification of the cellular phone usage reads as follows:

$$MoU_{ijt} = \alpha_{ij} + \delta_1 * CellP_{ijt} + \delta_2 * CellP_{i(-j)t} + \delta_3 * FixedP_{it} + \delta_4 * CellSubs_{ijt} + \delta_5 * CellSubs_{i(-j)t} +$$
$$+ \delta_6 * FixedSubs_{it} + \boldsymbol{\theta} * \boldsymbol{X}_{ijt} + e_{ijt,} \qquad (2)$$

where subscripts i, j, and t stand for country, cellphone operator, and time, respectively. The dependent variable is the average monthly minutes of use per subscriber. We consider both own and cross price effects on cellphone usage by including the operator's (j) own price, the average price of other cellphone operators in the country ($-j$), as well as the price of local fixed-line connection, in the regressions. Similarly, we distinguish between the operator's

[14] Experiments with defining "advanced diffusion" at a later (or earlier) stage yield effectively the same results.

own network of subscribers, subscribers to other cellphone operators, and fixed-line subscribers. To facilitate comparison across countries, all price variables are in US cents and the subscribers variables are normalized by the total country's population.

The vector $\boldsymbol{X_{ijt}}$ contains a set of control variables: GDP per capita, the share of prepaid-card users in the own subscriber base, and the time on air. Finally, the α's capture the unobserved heterogeneity across countries and operators driven by different pricing regimes (Receiving Party Pays vs. Calling Party Pays), different tastes for communications services (Italians tend to talk more than Swedes), incumbents' first-mover advantages or operators' brand reputation, and other time-invariant country and operator-specific effects.[15]

Expected effects

Based on our discussion in Section III, we now briefly summarize the expected effects on usage intensity of the variables we use in our estimations.

Own subscribers ($CellSubs_{ijt}$). The number of subscribers of one's own and substitute networks are our main variables of interest. With them, we intend to capture the effects of consumer heterogeneity and network effects on usage intensity along the diffusion path. Its sign depends on the presence (or absence) of different factors and the underlying diffusion mechanism. If diffusion is driven by consumer heterogeneity – accompanied by falling price or increasing quality over time – we expect a negative coefficient on the network size variable since subscribers joining the network later on have a lower preference for the product and thus decrease average usage intensity. If, however, strong network effects are present, increasing communications opportunities due to growing network size may offset the rank effect leading to an increasing usage intensity of a network (Cabral, 2006). Depending on

[15] The operator-specific effects would also pick up systematically different consumer groups by operators. If, for example, one operator were especially successful in attracting the high-usage bracket of a particular consumer group, this would manifest itself in a positive fixed effect.

which of the effects dominates – rank/consumer-heterogeneity effect or network effect – the own cellular network variable will carry negative or positive sign, respectively.[16]

Competing network size ($CellSubs_{i(-j)t}$). Unlike the rank effect, the network effect will also be at play for subscribers to the other cellular operators (*-j*) within a country if it originates from cellular users calling each other across different operator networks. This is because additional subscribers to competing cellular networks increase the overall network and thereby communication opportunities while leaving the composition of the own subscriber base unchanged. On the other hand, the competing network size variable also captures the substitution effect between the technologies. Although holding fixed-line and cellular connections at the same time – a prerequisite for usage substitution between platforms – is much more common than holding cellular connections with different operators, the latter is also observed, in particular in mature cellular telecom markets (Wireless Intelligence, 2006, Doganoglu and Wright, 2006). We therefore expect the sign on the competing network size to be determined be the relative importance of the network and the substitution effects.

Fixed-line network size ($FixedSubs_{it}$). To a certain extent, the arguments for competing network size should also apply for fixed-line network size. However, we expect the substitutability to be less pronounced as users are more likely to simultaneously hold a fixed-line and a cellular connection than to hold two cellular connections. However, a negative effect of fixed-line network size on cellular usage would suggest shifting usage between the platforms induced by a subscription decision, i.e. a substitutive relationship.

Share of prepaid users ($Prepay_{ijt}$). Prepaid consumers will typically face higher marginal costs and lower fixed costs, which is consistent with a lower average usage intensity

[16] Word-of-mouth (or epidemic) diffusion models do not deliver any prediction concerning the usage intensity of a diffusing technology.

(Miravete and Röller, 2004). We therefore expect a negative effect of the share of prepaid users on usage intensity as prepaid consumers are likely to be low-intensity callers.

Own prices ($CellP_{ijt}$). Clearly, the price of a product and its substitutes (measured in our study as the average revenue per minute) will have an effect on usage intensity. Controlling for other factors that might shift demand intertemporally (e.g. network or learning effects, quality improvements), we expect own price to have a negative impact on usage intensity.[17]

Competitors' prices ($CellP_{i(-j)t}$). The standard textbook argument suggests positive cross-price elasticity for substitutes. We therefore expect a positive coefficient on the price of competing cellphone operators in our regressions, as the cellular services offered by competing operators are clearly substitutes.

Fixed-Line prices ($FixedP_{it}$). The relationship between fixed-line and cellular phones is less clear-cut. The empirical literature finds evidence of both substitution and complementarity between fixed and cellular telephony by looking at subscription rates (see Ahn and Lee, 1999; Barros and Cadima, 2000; Sung et al., 2000; Rodini et al., 2003). Regarding usage intensity, a higher price of fixed lines may imply users shifting their communication to mobile telephony. However, higher fixed-line prices may also imply lower attractiveness of using communications networks in general as the two act as complements. The balance between these two effects will therefore determine the sign of the coefficient.

Time on air ($Onair_{ijt}$). This variable measures the time passed since the launch of cellular service by an operator, i.e. the "age" of a service. The expected effect of an established network and technology is a gradual increase in the usage intensity since users get in the habit of calling on the move, and the network may develop over time in terms of quality and brand reputation.

[17] Endogeneity and other econometric issues are covered in the next section.

GDP (GDP_{jt}). Finally, we expect cellphone usage to exhibit a positive income effect, captured by a positive coefficient on the level of GDP in a country.

Econometric issues and estimation results

Our estimation strategy is as follows: To strip out operator-specific effects α_{ij}, we apply fixed-effects (FE) as well as first-differenced (FD) estimation. In these regressions we do not correct for the possible endogeneity of our explanatory variables as described above. Comparing the results across these two estimation techniques is, however, a useful exercise, as under endogeneity these two estimators generally have different probability limits, which provides a simple test of endogeneity (Wooldridge, 2002). We also address potential endogeneity by using an instrumental variables (IV) approach accounting for operator fixed effects at the same time.

Further, to test robustness of our results, we consider a log-linear and a log-log specification as alternatives to the linear specification in (2). Besides serving as a robustness check, the log-log specification is useful as its coefficients can be interpreted as elasticities.

Identification

To identify own- and cross-price effects, and thereby the possible complementarity or substitutability between operators, we need to address the likely endogeneity of our price variables, as prices may be set in direct response to a change in usage intensity. Making use of the panel nature of the data, we construct instrumental variables based on the geographical proximity between countries (see Hausman, 1997). To the extent that there are some common cost elements in the cellular service provision across regions (e,g, costs of equipment and materials), we can instrument for prices in a given country by average prices in all other countries of the region. For instance, prices in the UK can be instrumented for with a cellular price index for the rest of Western Europe. To arrive at an operator-specific instrumental variable, we further condition it on the technological standards deployed by each operator.

For instance, we instrument for price of a Chinese operator deploying the GSM standard with prices of GSM operators from other Asian-Pacific countries; the price of a Chinese operator deploying CDMA standard with prices of CDMA operators from other Asian-Pacific countries; and so on.[18]

Among our instruments we additionally include fixed-line employment to proxy for telecom operators' efficiencies, as well as lagged values of all instruments.

As the decision whether to subscribe and how much to call is a joint one, cellular and fixed-line network variables are likely to suffer from endogeneity bias in our usage equation as well – any omitted effects that encourage both more usage intensity and new subscriptions (e.g. promotional campaigns) will lead to correlation between our network variables and the error term. To the extent that the omitted effects are not persistent, lagged values of the network size offer a possible instrument. To avoid equations with lagged dependent variables in the first stage of the IV procedure, we include the lagged values of network size as explanatory variables rather than instruments.

Main results

The first set of results is reported in Table 4. Since preliminary regressions exhibited high autocorrelation in the error term, we used cluster-robust standard errors in our reported results. The results in columns (1) – (3) come from fixed-effects (FE), first-differenced (FD), and instrumental variable (IV FE) estimation respectively.

A useful indicator for the likely importance of endogeneity problems is the extent to which results change across different econometric specifications. Our results are not drastically different between the FE and FD specifications, however, the cluster-robust Hausman test comparing the two rejects the null at the 1% significance. We then ran IV regressions with the

[18] The classification of countries into regions we apply follows the Informa T&M classification and includes: USA/Canada, Western Europe, Eastern Europe, Asia/Pacific, Africa, and Americas.

set of instruments described in the previous section. The instruments performed very well: the partial R^2 of the instruments ranged from 0.08 to 0.27 in the first-stage regressions and the instruments were jointly significant at the 1% level in all of the regressions. Further, Hansen's J statistic, which is a valid overidentification test when observations are correlated within clusters (Hayashi, 2000, Baum et al., 2003), did not reject the null. The instruments performed equally well in other functional form specifications, which we cover in the section on robustness checks. We found that the IV results are close to the OLS results, except that the price effects become larger. The Hausman test, however, —again, we use its cluster-robust version—rejects the null of exogeneity at the 5% level.

Our control variables – the share of prepaid users, time on air, and GDP – have the expected signs (negative, positive, and positive, respectively) and are mostly significant. Reassuringly, we find a significant negative own-price effect on cellphone usage in all three regressions, whereas the cross-price effect is positive but only marginally significant. The magnitudes and significance of these price effects suggests relatively low degree of substitution, consistent with Grajek (2003). From the IV specification we read that a decrease in own price by 1 US cent leads to an increase in the average monthly usage of a customer by 4 minutes. For fixed-line prices, we find some evidence of usage complementarity – the coefficient is negative and significant at the 10% level in the IV regression.

Turning to the subscriber network variables, we find strong evidence of the consumer heterogeneity effect dominating the network effect. The coefficient on own market penetration is significantly negative in all specifications, which implies that additional subscribers to one's own cellular network significantly decreases average cellphone usage. The magnitude of this effect is not marginal: From the IV specification we can see that the average usage intensity decreases by roughly 2 minutes per month with an increase of the penetration by 1 percentage point. In other words, to offset the effect of an additional percentage point of low-intensity users to an existing network, an operator needs to drop the prices per minute by .5 US cent (the average price per minute drops from over 35 cent to below 20 cent in our sample period).

The results in Table 4 also suggest that network effects do not operate across operator networks. The coefficient on market penetration of cellular competitors is insignificant in all three specifications. The apparent absence of network effects in cellphone usage is somewhat surprising given previous results that find network effects to significantly contribute to the speed of cellular diffusion process (Grajek, 2003; Koski and Kretschmer, 2005; Liikanen et al., 2004). However, a number of remarks are in order here: First, our results do not imply that there are no network effects; they merely suggest that they do not outweigh the consumer heterogeneity effect, and that no significant network effects seem to operate across different cellular networks. Further, we consider a different dependent variable – usage intensity – than existing studies. Thus, while network effects may be weak regarding usage intensity, they may be strong for first subscriptions. Finally, network effects may be limited to a very small network of "relevant" users (Birke and Swann, 2006), which would lead to an apparently small network effect if network size were measured at the level of the economy.

Finally, the coefficient on fixed-line market penetration is negative and highly significant. It is also larger in magnitude than the coefficient on cellular penetration. This indicates a degree of fixed-mobile platform substitution. It is interesting to contrast this finding with our previous result on fixed-mobile usage complementarity as evidenced by the negative impact of fixed-line prices on cellphone usage. It appears that the two communication platforms are complements to the extent that keeping both fixed-line and cellular connection at the same time is viable from a household perspective. Once households decide to cut the fixed-line, however, they move the entire telephone usage to cellular. This coexistence of the complementary and the substitution elements is in line with the results in Sung et al. (2000).

They report that the number of Korean mobile subscribers is positively (negatively) correlated with the number of fixed-line disconnects (new connections), which suggests substitution. At the same time, they find the stock of fixed lines being positively correlated with the number of mobile subscribers, providing evidence of complementarity.

Time-varying effects

To further investigate the relationship between old and new telecommunications technologies we also allow for the effects of prices and installed bases to vary over time. The motivation behind time-varying coefficients is that the relationship between the old and the new telecommunications technologies or between competitors might change depending on the diffusion stage of the new technology. For example, when the market penetration of cellphones is low, most cellular communication may go to (and from) fixed lines as there are limited opportunities for cellular-cellular interaction. On the other hand, when cellular penetration reaches full market size, all communications needs can in principle be satisfied on the cellular network alone and fixed lines become obsolete. Therefore, the relationship between the two technologies may change from complements initially (as fixed lines help cellular overcome the installed base problem) to substitutes (as cellular phones replace fixed lines) in later stages of the diffusion process.

To capture this, we interact fixed-line prices and our other variables of interest with a diffusion stage indicator. The indicator is constructed from the estimates of the country-wise diffusion regressions (Table 3) and equals 1 in periods after a country reaches the inflection point of cellular diffusion (τ) and zero otherwise. We report our results in Table 5.

The results are consistent with our earlier results, which gives us additional confidence in the quality of our instruments. We can interpret the sum of the early-stage (with *Stage* = 0) and the late-stage (with *Stage* = 1) coefficients as the net effect in the later stages of diffusion, while for the early diffusion stage only the first coefficient matters.

We find that own-price sensitivity increases in later stages of diffusion, which is consistent with the addition of more low-intensity, high-elasticity users (over and above prepaid consumers, which we control for). This result is not very strong, however, as the change in own-price effect is significant only in the FE specification. We also find some evidence of multihoming becoming significant in the later stages of diffusion, as can be seen from the negative coefficient on $CellSubs_{i(-j)t}$, although it is only significant in our IV specification. The coefficient indicates that the higher the penetration of competing networks, the lower the usage intensity of one's own network – users use their other cellphone to make calls, or divide calls between them (Doganoglu and Wright, 2006).

Finally, we find that the penetration of fixed lines is negative in the early stages of diffusion, but this effect wears off as diffusion progresses (since the interacted variable is positive and significant). Possibly this is because households cutting their fixed line relatively late are the ones with low overall usage as well. Similarly, we find evidence of a "tapering off" of the (negative) own installed base effect, albeit only weakly. We did not find, however, any significant change in the cross-price effects in the late diffusion stage. That is, our hypothesis that fixed-mobile complementarity might be challenged in the later diffusion stage found no support.

Further robustness checks

To further test the robustness of our findings we reestimate the model imposing two alternative functional forms: log-linear and log-log. The results, which are reported in Tables A1 and A2, are consistent with the previous ones. The only change is that the effect of competing network size sometimes becomes significantly negative also in the early diffusion stage. This effect only magnifies in the later stage, which is still consistent with the multihoming story. The interpretation of our main results stays unchanged.

VI Discussion of the results

The relationship between mobile usage and the network size is determined by two countervailing forces: Network effects and consumer heterogeneity effects. Network effects arise as the growing installed base of subscribers allows them to satisfy more communications needs; hence the average number of calls increases with network size. Consumer heterogeneity effects imply that usage of telecommunications services decreases with the installed base of subscribers, as less eager (or poorer) users subscribe to the service over time and "dilute" usage intensity as the installed base grows.

One of the problems in estimating the relative strength of these effects is that adding subscribers has the dual effect of enlarging an operator's network and adding lower-preference users to the network. Our regressions suggest that in all specifications the heterogeneity effect strongly dominates the network effect since the coefficient on own network penetration is consistently negative and significant. A potential strategy to isolate the network from the composition effect was to consider the subscribers of competing networks since the composition of an operator's own network does not change while overall network size grows. In our regressions, however, we find that competing network size does not have a significant positive effect on own usage intensity. While this does not imply that there are no network effects, we can at least conclude that they do not outweigh the heterogeneity effect, and that no significant network effects seem to operate across different cellular networks. That is, if network effects exist, they do not appear to originate from opportunities to call cellular users from other networks. One possible interpretation could be that there are significant network effects from sending and receiving text messages to other cellular users, but not from calling them. This would allow us to reconcile the fact that network effects are regularly found in adoption studies (e.g. Koski and Kretschmer, 2005, Gruber and Verboven, 2001) with the apparent absence of network effects in our usage intensity regressions. That is, adopting a cellphone becomes more attractive if there are many others to exchange text messages with, but this does not imply that users will call each other more.

As already mentioned, there is small but growing literature on substitutability of fixed-line and cellular telephony. Our regression results suggest that one important point is whether we consider telephone usage alone (given subscription decision) or usage and subscription as a joint decision. Given the subscription decision (that is, controlling for the installed base of subscribers) we find some evidence of fixed-mobile complementarity. On the other hand, the two telecommunications platforms seem to be substitutes in terms of subscriptions, as the size of fixed-line network is negatively correlated with cellphone usage. This suggests that an incumbent technology like fixed-line telephony may foster diffusion at the start of cellular diffusion, but is likely to be replaced eventually as the new technology matures.

Finally, we also find no support for increasing usage intensity over time after other determinants are controlled for, as can be seen from the coefficient on *time on air*. Thus, we do not find evidence of learning effects and habit formation, which we do not pick up in our network size variables.

VII Conclusions and further research

We study the usage patterns of 2G cellular telephony over time using data from 41 countries over the 1998-2004 time period. Our reduced-form regressions have uncovered a number of interesting findings. First, it seems that consumer heterogeneity is considerable and network effects are moderate in comparison. Second, we find some evidence of fixed-mobile usage complementarity in the early stages of diffusion. At the same time we observe substitution of fixed-line with cellular minutes driven by the changes in fixed-line subscriber base. This effect seems to wear off later as cellular telephony becomes more established.

These results are consistent across most specifications and benefit from the use of instruments, suggesting that endogeneity needs to be accounted for.

In what follows, we outline a number of potential avenues for future research:

Functional form of network effects and heterogeneity: Our current reduced-form approach does not permit a separate and precise interpretation of the shape of the preference distribution or the functional form of network effects individually, but rather the net effect of both. One way to further separate out composition and network effects would be to assume a sufficiently general distribution of preferences (taken, e.g., from Rogers, 2003), a functional form for network effects (e.g., Swann, 2002), and a degree of compatibility between the networks of different operators (e.g. Grajek, 2003). This would facilitate a quantitative interpretation of the coefficients we obtain, although obviously at the cost of having to make some, possibly quite restrictive assumptions about the functional form of consumer utility and the resulting usage behavior as well as their degree of foresight. However, such an approach may be complementary to ours, as the previously assumed strength of network effects is called somewhat in question by the results reported in this paper.

Role of prepaid consumers: We find unequivocally that the proportion of prepaid consumers has a negative effect on average usage intensity, as expected. We do not, however, study in detail the origins and effects of the number of prepaid consumers in competition between operators. For example, persistent first-mover advantages may imply that later operators can only catch up by offering prepaid services, which may in turn affect the first mover's existing users' incentives to call. In other words, the use of prepaid users as a competitive tool and their contribution to network effects seems an interesting line of research to follow up.

Gaining insight on the shape of consumer preferences has significant implications for firm and policymaker behavior. Strong consumer heterogeneity suggests that early adopters are more profitable than later ones – assuming that their decision to adopt earlier also represents a higher willingness to make calls.[19] This would then make introductory pricing a double-edged sword: On the one hand, securing these early customers is likely to have long-term benefits, while on the other hand these early consumers are likely to represent a large proportion of a firm's profits.[20] Similarly, diffusion policies will be assessed on their expected impact on consumer surplus and firm profits, which depends on the distribution of consumer preferences and the intensity of network effects. Our results indicate that network effects are not overwhelming in determining usage, in which case penetration pricing by operators significantly benefits early consumers (who get lower prices) rather than later ones (who do not benefit much from a larger network).

This study is the first to our knowledge that empirically tries to disentangle the consumer-heterogeneity and the network effect on technological diffusion. Our study is also the first to allow for time-varying effects of an incumbent technology, which has important implications for policymaker and firms in their incentives to phase out existing technologies. We believe that while there have been a number of recent studies on the diffusion of mobile telephony (including our own), recovering some information on the underlying parameters and the subsequent causes of diffusion is a crucial next step in the study of new technologies and their success and impact on society.

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[19] This would not be the case if early adopters had a high preference for *incoming* calls (e.g. for emergency purposes), but not *outgoing* ones. However, we believe such a pattern to be the exception rather than the rule.
[20] There is an extensive literature in marketing science that concerns itself with the optimal pricing path of new products based on assumptions about the s-shaped diffusion curve, but not on the origins of the s-curve (see, e.g., Krishnan et al., 1999).

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Table 1. Variable definitions and descriptive statistics

Variable	Definition	Obs.	Operators	Mean	Std. Dev.	Min	Max
MoU	Average monthly minutes of use	2146	114	174.52	115.54	51	960
CellP	Average revenue per minute (US cents)	2052	109	22.03	10.69	3.26	114.00
FixedP	Price of a local fixed-line connection (US cents)	2839	157	8.33	5.21	0	19
CellSubs(j)	Own subscribers as population's share (%)	3110	150	12.70	12.11	0.002	54.58
CellSubs(-j)	Subscribers to competing operators as population's share (%)	3110	150	31.50	22.47	0.04	99.49
FixedSubs	Fixed-line subscribers as population's share (%)	3199	157	40.96	20.91	2.20	75.76
Prepay	Share of prepay users among own subscribers (%)	3110	150	43.54	29.95	0	100
OnAir	Time since the launch of service (quarters)	3444	150	15.94	13.34	0	50
GDP	GDP per capita (000's US dollars)	3561	157	17.79	13.01	0.36	51.98
Stage	Diffusion stage indicator (1 after a country reached the inflection point of the cellular telephony diffusion; 0 otherwise)	3605	157	0.66	0.47	0	1

Table 2. Descriptive statistics by year (variable definitions as in Table 1)

	1998	1999	2000	2001	2002	2003	2004
MoU	162.42	157.67	170.82	176.68	177.15	185.26	198.44
CellP	35.70	31.88	23.60	19.36	18.30	19.64	19.31
FixedP	8.79	9.63	8.27	7.86	7.75	8.56	9.61
CellSubs(j)	6.64	9.62	12.57	15.02	17.06	18.99	20.38
CellSubs(-j)	12.55	17.00	24.40	32.55	37.55	42.89	45.94
FixedSubs	49.28	48.39	47.37	47.39	46.99	45.22	45.68
Prepay	24.16	30.11	37.76	43.81	47.65	50.71	49.63
OnAir	14.32	15.67	16.80	19.14	22.93	26.43	29.43
GDP	20.45	21.31	20.09	18.84	19.76	22.02	25.39
Stage	0.00	0.17	0.63	0.82	0.88	0.96	0.99

Table 3. Country-wise logistic diffusion coefficients

country	γ	β	τ	fixed lines per capita	mobile-to-fixed ratio
Argentina	0.19	0.28	157.1	0.22	0.84
Australia	0.93	0.12	162.3	0.54	1.72
Austria	0.89	0.29	157.7	0.49	1.80
Belgium	0.82	0.29	160.4	0.52	1.59
Brazil	0.53	0.11	175.5	0.22	2.39
Canada	0.50	0.11	162.1	0.68	0.73
Chile	0.56	0.18	166.2	0.23	2.43
China	0.29	0.18	169.7	0.21	1.39
Colombia*				0.18	
Czech Republic	1.03	0.25	164.5	0.38	2.72
Denmark	1.11	0.14	161.2	0.72	1.53
Egypt	0.10	0.20	168.1	0.13	0.82
Finland	1.13	0.08	154.6	0.56	2.03
France	0.70	0.24	159.5	0.58	1.20
Germany	0.77	0.31	160.2	0.66	1.16
Greece	1.06	0.18	163.0	0.54	1.97
Hungary	1.01	0.17	167.3	0.38	2.66
India*				0.05	
Ireland	0.83	0.29	160.2	0.50	1.65
Israel	1.00	0.18	160.4	0.47	2.12
Italy	1.03	0.18	158.8	0.48	2.13
Japan	0.78	0.10	156.9	0.59	1.33
Korea	0.83	0.12	160.0	0.54	1.54
Malaysia	0.64	0.14	169.4	0.20	3.15
Mexico	0.32	0.23	164.0	0.16	2.02
Netherlands	0.82	0.30	158.7	0.62	1.32
New Zealand	0.71	0.23	160.0	0.49	1.45
Norway	1.00	0.09	157.9	0.73	1.36
Poland	0.70	0.15	170.5	0.32	2.19
Portugal	1.09	0.19	160.6	0.43	2.52
Russia	0.87	0.23	178.9	0.24	3.60
Singapore	0.89	0.23	160.0	0.48	1.83
South Africa	0.58	0.13	172.1	0.13	4.54
Spain	0.93	0.22	161.0	0.51	1.83
Sweden	1.25	0.09	160.7	0.76	1.65
Switzerland	0.88	0.24	159.2	0.74	1.18
Thailand	0.46	0.26	169.9	0.11	4.39
Turkey	0.42	0.23	164.7	0.29	1.47
United Kingdom	0.92	0.26	159.9	0.59	1.56
United States	0.67	0.10	161.3	0.67	1.00
Venezuela	0.27	0.22	159.7	0.12	2.20
average	0.76	0.19	162.9	0.43	1.92

* Missing coefficient indicate that the NLS estimation procedure did not converge.

Table 4. Cellphone usage estimation results

Dependent variable: Avg. Minutes of Use	*MoU*	(1)	(2)	(3)
Price Effects:				
Own Price	*CellP(j)*	-2.714***	-1.729***	-3.988***
		(0.549)	(0.380)	(1.285)
Avg. Price of Mobile Competitors	*CellP(-j)*	0.510	0.120	0.852
		(0.350)	(0.142)	(1.042)
Price of Local Fixed-Line Connection	*FixedP*	-2.575	0.679	-13.388*
		(1.735)	(0.618)	(8.127)
Installed Base Effects:				
Own Penetration	*CellSubs(j)*	-1.251*	-1.534**	-1.886*
		(0.741)	(0.621)	(1.076)
Penetration of Mobile Competitors	*CellSubs(-j)*	0.455	-0.207	-0.449
		(0.565)	(0.273)	(0.543)
Penetration of Fixed Line	*FixedSubs*	-2.667**	-1.385	-4.219***
		(1.198)	(0.951)	(1.531)
Controls:				
Share of Own Prepay Users	*Prepay*	-1.092***	-0.149	-1.103***
		(0.223)	(0.111)	(0.357)
GDP	*GDP*	3.743***	1.552***	6.263
		(1.028)	(0.301)	(3.833)
Time Since the Launch of Service	*OnAir*	-0.179	1.134	1.830
		(1.189)	(0.886)	(1.512)
R^2		0.202	0.099	0.101
Observations		1314	1220	1029
Clusters		91	91	82
Functional Form		linear	linear	linear
Estimation Method		FE	FD	FE IV

* p<0.1, ** p<0.05, *** p<0.01; cluster-robust standard errors in parentheses
operator-specific effects suppressed

Table 5. Cellphone usage estimation results with diffusion stage interaction terms

Dependent variable: Avg. Minutes of Use	*MoU*	(1)	(2)	(3)
Price Effects:				
Own Price	*CellP(j)*	-2.338***	-1.658***	-3.537***
		(0.445)	(0.345)	(0.940)
Avg. Price of Mobile Competitors	*CellP(-j)*	0.681**	0.073	1.053
		(0.283)	(0.153)	(0.961)
Price of Local Fixed-Line Connection	*FixedP*	0.300	0.875	-12.075
		(1.492)	(0.664)	(7.465)
Installed Base Effects:				
Own Penetration	*CellSubs(j)*	-2.354**	-2.399***	-3.125**
		(1.145)	(0.659)	(1.551)
Penetration of Mobile Competitors	*CellSubs(-j)*	0.571	-0.036	0.385
		(0.627)	(0.297)	(0.634)
Penetration of Fixed Line	*FixedSubs*	-2.259***	-1.396	-4.104***
		(0.874)	(0.951)	(1.348)
Controls:				
Share of Own Prepay Users	*Prepay*	-0.943***	-0.125	-1.028***
		(0.209)	(0.114)	(0.346)
GDP	*GDP*	4.056***	1.526***	6.458*
		(0.902)	(0.301)	(3.912)
Time Since the Launch of Service	*OnAir*	-0.623	1.159	1.481
		(0.938)	(0.880)	(1.101)
Interactions with *Stage*:				
Own Price * Stage	*CellP(j) * Stage*	-1.964**	-0.178	-0.200
		(0.859)	(0.370)	(0.774)
Avg. Price of Mobile Competitors * Stage	*CellP(-j) * Stage*	0.091	-0.074	-0.363
		(0.777)	(0.295)	(0.688)
Price of Local Fixed-Line Connection * Stage	*FixedP * Stage*	-1.059	-0.135	-1.750*
		(0.808)	(0.369)	(1.006)
Penetration of Mobile Competitors * Stage	*CellSubs(j) * Stage*	0.840	0.783**	0.950
		(0.692)	(0.348)	(0.853)
Penetration of Fixed Line * Stage	*CellSubs(-j) * Stage*	-0.256	-0.107	-0.592*
		(0.378)	(0.118)	(0.335)
Share of Own Prepay Users * Stage	*FixedSubs * Stage*	1.186***	0.007	0.719***
		(0.262)	(0.093)	(0.255)
R^2		0.322	0.109	0.179
Observations		1314	1220	1029
Clusters		91	91	82
Functional Form		linear	linear	linear
Estimation Method		FE	FD	FE IV

* p<0.1, ** p<0.05, *** p<0.01; cluster-robust standard errors in parentheses
operator-specific effects suppressed

Table A1. Cellphone usage estimation results (alternative functional forms)

Dep. Variable: MoU	(1)	(2)	(3)	(4)	(5)	(6)
Price Effects:						
CellP(j)	-0.015***	-0.578***	-0.012***	-0.410***	-0.029***	-0.243
	(0.002)	(0.096)	(0.002)	(0.060)	(0.007)	(0.482)
CellP(-j)	0.005**	0.021	0.002	0.062	0.004	-0.081
	(0.002)	(0.087)	(0.001)	(0.038)	(0.006)	(0.460)
FixedP	-0.005	-0.045	0.005	-0.045	-0.046	0.374
	(0.009)	(0.064)	(0.004)	(0.040)	(0.032)	(0.376)
Installed Base Effects:						
CellSubs(j)	-0.004	-0.094	-0.007**	-0.019	-0.010*	-0.038
	(0.004)	(0.066)	(0.003)	(0.020)	(0.005)	(0.041)
CellSubs(-j)	-0.000	-0.230***	-0.003**	-0.141***	-0.006**	-0.162
	(0.003)	(0.059)	(0.001)	(0.024)	(0.003)	(0.123)
FixedSubs	-0.019***	-0.032	-0.010**	0.015	-0.025***	-0.443
	(0.007)	(0.308)	(0.005)	(0.216)	(0.008)	(0.462)
Controls:						
Prepay	-0.005***	-0.049*	-0.001**	-0.034**	-0.006***	0.034
	(0.001)	(0.029)	(0.001)	(0.017)	(0.002)	(0.079)
GDP	0.019***	0.590***	0.010***	0.235***	0.040***	0.207
	(0.005)	(0.093)	(0.002)	(0.050)	(0.015)	(0.276)
OnAir	-0.001	-0.003	0.005	0.016	0.005	-0.053
	(0.005)	(0.041)	(0.004)	(0.029)	(0.006)	(0.077)
R^2	0.321	0.417	0.184	0.243	0.211	0.307
Observations	1314	965	1220	888	1029	730
Clusters	91	74	91	74	82	61
Functional Form	log-lin	log-log	log-lin	log-log	log-lin	log-log
Estimation Method	FE	FE	FD	FD	FE IV	FE IV

* p<0.1, ** p<0.05, *** p<0.01; cluster-robust standard errors in parentheses
operator-specific effects suppressed

Table A2. Cellphone usage estimation results with diffusion stage interaction terms (alternative functional forms)

Dep. Variable: *MoU*	(1)	(2)	(3)	(4)	(5)	(6)
Price Effects:						
CellP(j)	-0.014***	-0.444***	-0.012***	-0.391***	-0.027***	0.034
	(0.003)	(0.154)	(0.003)	(0.064)	(0.006)	(0.552)
CellP(-j)	0.006***	0.054	0.003	0.092*	0.006	-0.285
	(0.002)	(0.103)	(0.002)	(0.054)	(0.005)	(0.487)
FixedP	0.008	0.006	0.004	-0.035	-0.042	0.305
	(0.008)	(0.079)	(0.004)	(0.049)	(0.037)	(0.411)
Installed Base Effects:						
CellSubs(j)	-0.011**	-0.085	-0.008***	-0.009	-0.018**	-0.045
	(0.006)	(0.072)	(0.003)	(0.024)	(0.007)	(0.051)
CellSubs(-j)	0.000	-0.146	-0.003**	-0.138***	-0.003	-0.071
	(0.003)	(0.092)	(0.001)	(0.031)	(0.003)	(0.103)
FixedSubs	-0.018***	-0.158	-0.010*	-0.088	-0.025***	-0.677
	(0.006)	(0.345)	(0.005)	(0.232)	(0.009)	(0.563)
Controls:						
Prepay	-0.004***	-0.068**	-0.001**	-0.028*	-0.006***	0.018
	(0.001)	(0.027)	(0.001)	(0.017)	(0.002)	(0.073)
GDP	0.021***	0.599***	0.010***	0.257***	0.041**	0.316
	(0.004)	(0.095)	(0.002)	(0.055)	(0.017)	(0.266)
OnAir	-0.003	0.015	0.006*	0.036	0.004	-0.016
	(0.005)	(0.050)	(0.004)	(0.028)	(0.005)	(0.093)
Interaction terms:						
*CellP(j) * Stage*	-0.010**	-0.170	-0.000	-0.015	-0.000	-0.297
	(0.004)	(0.116)	(0.002)	(0.058)	(0.004)	(0.236)
*CellP(-j) * Stage*	-0.001	-0.039	-0.001	-0.051	-0.004	0.128
	(0.003)	(0.095)	(0.002)	(0.038)	(0.004)	(0.187)
*FixedP * Stage*	-0.000	-0.010	0.002	-0.007	-0.005	-0.023
	(0.005)	(0.061)	(0.002)	(0.030)	(0.005)	(0.081)
*CellSubs(j) * Stage*	0.005	-0.040	0.001	-0.023*	0.006	-0.029
	(0.004)	(0.036)	(0.001)	(0.012)	(0.004)	(0.035)
*CellSubs(-j) * Stage*	-0.001	-0.058	-0.002***	-0.082***	-0.002	-0.118**
	(0.002)	(0.053)	(0.001)	(0.023)	(0.002)	(0.054)
*FixedSubs * Stage*	0.005***	0.243**	0.001**	0.140***	0.003***	0.258**
	(0.001)	(0.114)	(0.000)	(0.040)	(0.001)	(0.104)
R^2	0.415	0.443	0.175	0.273	0.304	0.260
Observations	1272	938	1179	862	1029	730
Clusters	91	74	91	74	82	61
Functional Form	log-lin	log-log	log-lin	log-log	log-lin	log-log
Estimation Method	FE	FE	FD	FD	FE IV	FE IV

* p<0.1, ** p<0.05, *** p<0.01; cluster-robust standard errors in parentheses
operator-specific effects suppressed