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INCOME INEQUALITY, MARKET POTENTIAL, AND DIFFUSION OF MOBILE TELEPHONY

By

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ABSTRACT

INCOME INEQUALITY, MARKET POTENTIAL AND DIFFUSION OF MOBILE TELEPHONY

BY

Sungjoong Kim

The diffusion of many previous innovations eventually slowed down and reached an equilibrium level. Despite continued rapid growth, it is possible that the diffusion of mobile telephony will also begin to decelerate and reach a saturation level. Whether universal service can be achieved with the help of mobile telephony will therefore depend considerably on whether the diffusion of mobile telephony will stagnate before such universality is reached. One key question in developing countries is whether inequality will limit or delay the adoption of mobile telephony.

The goal of this dissertation is to contribute to a better understanding of these issues. It investigates mobile telephony diffusion focusing on the effects of income and other forms of inequality on two core aspects of diffusion: the saturation level (market potential) and the speed of diffusion. The dissertation theorizes that market potential and the rate of acceptance are functions of demand-side factors, supply-side factors, and social conditions and tests corresponding hypotheses empirically.

A two-step approach was used to accomplish these goals. In a first step, three

statistical models of the diffusion of innovations (Bass, Gompertz, and logistic) were employed to estimate market potential and parameters reflecting diffusion speed for 160 countries. The factors determining the variation of these parameter estimates across countries were examined in a second step. For this purpose, regression analysis was used to investigate the effects of supply-side, demand-side, and socio-cultural factors on the diffusion parameters. Thus, diffusion models were used predominantly to obtain estimates for the dependent variables used in the second part of the analysis. This second phase is the main innovation and contribution of the dissertation.

The study revealed that income inequality had a statistically significant negative effect on the speed of diffusion but not on the market potential. The dissertation also found a statistically significant association between price and market potential. The effect of income inequality on the speed of diffusion implies that it will most likely take longer to achieve universal service in a society with highly unequal income distribution. The association between price and market potential suggests that regulators could accelerate the diffusion process by coaxing suppliers to provide inexpensive calling plans. Overall, the dissertation contributes additional theoretical insights and empirical evidence to the mobile telephony and the universal service literature.

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1. Introduction

Mobile telephony has experienced remarkable growth in the past two decades, not only in the wealthiest parts of the globe but also in poorer regions. According to Madden et al. (2004), the number of mobile subscribers doubled annually during the 1990s, from 11 million in 1990 to half a billion in 1999. The International Telecommunication Union (ITU) reported that the total number of mobile phone subscribers surpassed the number of fixed line subscribers in 2003, reaching 3 billion in August 2007.[1] Global mobile penetration surpassed 50 % of the population in early 2008 and was expected to reach 61% by the end of 2008.[2] An industry white paper predicts that the number of mobile subscribers will grow to as many as 5 billion by 2012, driven largely by fast market expansion in developing countries (Ericsson, 2007). In some countries, the number of mobile subscriptions is larger than the total population[3], for example in Lithuania (138.1%) and Luxembourg (151.6%). With the introduction of low cost handsets and inexpensive calling plans, the mobile industry in developing countries is rapidly growing even in countries where fixed voice service had not been very

[1] See http://www.itu.int/ITU-D/ict/statistics/ict/index.html
[2] See http://www.newkerala.com/topstory-fullnews-26209.html
[3] This is possible because a single user can have multiple subscriptions. The ITU reports mobile penetration by the number of subscriptions.

successful.[4]

Such rapid development of mobile markets led to optimistic expectations as to the possibility of achieving universal service or at least universal access[5] in countries with very low fixed line penetration and to hopes of overcoming the Digital Divide with the help of wireless broadband (James, 2003; Ericsson, 2007). At first glance it seems that there is finally a technology that could achieve the dream of universal service at a global level if mobile telephony were to continue to grow at such fast speeds. But will the present trends continue unabated until universal service is reached? Previous diffusion processes of innovations eventually slowed down and reached an equilibrium ("saturation") level. A relevant question for policy-makers and other stakeholder is, therefore, whether the diffusion of mobile telephony might slow down or even stop at some point. If this is the case, corollary questions are at which level such a saturation might occur and what factors might influence the process and outcomes.

The existing literature on mobile diffusion provides only partial answers. Previous studies on mobile diffusion focus on the variables affecting the speed of

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[4] According to Ericsson (2007), the number of mobile subscribers outnumbers the number of the mainline telephone in most countries. Among 160 countries of which mobile diffusion patterns were investigated in this study, there were only ten countries that the number of fixed line telephone exceeded the number of mobile subscriptions in 2005. In 37 countries, mobile subscriptions outnumbered fixed line by more than five times and as many as more than ten times in 13 countries.

[5] Unlike the concept of universal service, which implies having subscription to a type of voice service, the term universal access refers to a state in which every resident in a given area has access to phone service with or without actually subscribing to a voice service. For example, if there is a public telephone in a town that every resident may use, all townspeople have access.

diffusion rather than those influencing the size of potential demand. This tendency is partly due to a widespread methodological practice in diffusion of innovation studies, which is to transform the non-linear statistical models into linear forms.[6] Because of this practice, the question of what affects the ceiling level in mobile telephony diffusion has been left largely unanswered. However, unless one assumes that mobile telephony will reach the same saturation level in all countries, finding the determinants of the market potential must be considered as important as discovering the factors that are influencing the speed of diffusion.

Countries at a similar level of economic development may nonetheless have socio-economic differences that may cause the size of potential demand for a new product to differ considerably. One important candidate for such structural differences are forms of inequality, from economic to other types. Income inequality may influence both aspects of diffusion: market potential and the speed of diffusion. From an economic point of view, different degrees of income inequality may result in a different proportion of people who can afford mobile telephone service. Furthermore, high socio-cultural

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[6] Because of the usual S-shape of diffusion of innovations, the statistical models are in non-linear forms – for example, a logistic equation. To solve the equations, in other words to acquire parameter values, it is necessary to run non-linear regressions. However, currently available techniques for non-linear regression do not allow a very sophisticated analysis compared to available techniques for linear regression. To avoid such a limitation, researchers often transform the formula into a linear form. The transformed linear equation is still not solvable unless the value for one of the parameters is known or fixed. A common solution is to assume the ceiling level as a known value – for instance to apply a common ceiling value of 1 (100% of potential adopters) to all of the countries (Stoneman, 2001).

inequality, which often causes the relationships between different classes or socio-cultural groups to be less harmonious, may slow down the diffusion process by impeding information flows about an innovation between different social groups. Especially in developing countries, where high levels of inequality have persisted and have been identified as obstacles to economic development, mobile diffusion may show quite different patterns depending on the level of inequality.

The goal of this dissertation is to investigate whether socio-economic differences among and within nations, especially inequality, have a discernible effect on the diffusion of mobile telephony. To this end, the dissertation focuses on the relationship between income distribution on the one hand as well as market potential and speed of diffusion on the other.

A complication in investigating the factors influencing the ceiling is that the diffusion of mobile telephony in many countries is still in progress. However, the ceiling can only be observed empirically after the market has reached its saturation point. Thus, we need an alternative means to acquire the eventual ceiling values. One way is to predict it from the available preliminary observations. Statistical models of diffusion of innovation can provide a methodological solution to this problem as they allow an estimation of diffusion parameters from longitudinal adoption data.

Diffusion processes may follow different patterns, and it is a matter of actual observation which specification, if any, produces the best fit. This dissertation will use three widely used statistical diffusion models to acquire estimates of the market potential and the rate of acceptance (or equivalent characteristic parameters) for every country, with longitudinal data of mobile penetration as input. This first step was carried out for 160 countries for which data was available. The market potential determines the level at which the diffusion of a new product will end while the rate of acceptance decides how fast the market will reach this national saturation level. Only countries in which mobile diffusion could be described by one of the three models were included in the next step of analysis. For these 160 countries, the diffusion parameters derived from step one were used as dependent variables in phase two of the study. Regression analysis was used to identify the factors that influence them. Thus, the first part of the investigation can be seen as a preliminary stage to acquire data for the second phase of the analysis. The primary goal of the dissertation is to investigate the factors that influence market potential and the speed of diffusion (rather than a comparison of performance of the three diffusion models).

The dissertation is organized as follows: the next chapter reviews the literature on the diffusion of innovations, mobile diffusion, and on the effects of income inequality on diffusion of innovations. The following chapter presents the theoretical model, research questions, and hypotheses. Chapter four presents empirical methods and the data, including information on data collection and a detailed description of the variables. Chapter five reports findings and the following chapter six is dedicated to a discussion of findings. Concluding remarks offer an outlook on future research questions.

2. Literature Review

This chapter reviews the literature pertinent to the topic. The first section is a brief discussion of the history of mobile telephony. The next section reviews the research on diffusion of innovations focusing on contributions relevant to mobile telephony diffusion. A review of studies on income inequality and the diffusion of innovations is provided in the third section.

2.1. History of mobile telephony

Observing the mobile industry at the turn of the Millennium, Gans et al. (2001) divided the history of the sector into four periods: pre-cellular, first generation (1G), second-generation (2G), and third-generation (3G). In the meantime, the next chapter in mobile communication is being written with the gradual emergence of the next generation of technologies, often summarily referred to as "4G". Mobile technology was invented at the beginning of the twentieth century. Before the introduction of cellular technology, due to technological limitations, scarce spectrum was used inefficiently, limiting its commercial potential (Gruber & Verboven, 2001b). The invention of cellular technology in the 1960s was a major technological breakthrough that opened the possibility of mobile voice service as used today. In most countries, cellular mobile telephone service was not launched until the 1980s often because of regulatory delays. Japan is one of the few exceptions and started mobile cellular service in 1979 (Gans et al., 2001).

First generation mobile telephones used analog technology. Several incompatible technology standards were developed and adopted independently in different countries. The U.S. opted to have a single standard, the Advanced Mobile Phone System (AMPS). In contrast, multiple standards were adopted in European countries, including TACS (Total Access Communications System), NMT (Nordic Mobile Telephone), and C-450. The use of spectrum had become far more efficient with cellular technology and subsequent technological improvements. Mobile telephony, however, was not widely adopted because of its high price. During the early stages of market development carriers mainly served businesses demand (Gans et al., 2001). On average, penetration of analog mobile telephony in developed countries remained at less than five percent by the mid-1990s (Rouvinen, 2006).

It was the introduction of 2G mobile telephones based on digital technology that facilitated wide adoption. The first 2G service was launched in 1992 in Finland (Koski &

Kretschmer, 2006). Digital had several advantages over analog technology: first, compared to analog service, due to a more efficient use of spectrum, the number of users that could be served using a given bandwidth increased by 3-4 times even for the first versions of digital technology. It increased further with technological improvements in subsequent years (Gruber & Verboven, 2001b). Second, digital mobile telephony offered better sound quality, fewer dropped calls, lower prices, and a greater variety of ancillary services. In addition, data transmission was made possible including short message service (SMS) and email (Gruber & Verboven, 2001b; Madden et al., 2004). Contrary to the experience with analog service, the U.S. did not mandate a single national standard for digital mobile. It was left to the industrial consortia and market coordination to develop standards with the only condition that they were backwards compatible. In the end, three (mutually incompatible) 2G standards emerged in the U.S. market (Gruber, 2005). On the other hand, European countries adopted a single 2G standard proposed by the Groupe Spéciale Mobile (GSM) - which was later renamed to Global System for Mobile Communications (Gans et al., 2001). The introduction of digital technology accelerated diffusion considerably (Gruber & Verboven, 2001b).

Transition from 2G to 3G has been gradual. 2.5G and 2.75 G services offer limited versions of the features that full-fledged 3G services provide. 3G services were first introduced in Japan and South Korea in 2001. Even though 2G was also based on digital technology, it was still voice-centric (Tilson, 2006). Data services delivered via 2G networks were mostly limited to simple text message services. 3G mobile telephony was developed to meet anticipated demand for mobile data service. The success of the fixed Internet sparked the interest of the suppliers of mobile data services (Tilson, 2006). In addition, mobile voice services had reached or neared saturation levels in many richer countries by the end of the twentieth century. Wireless companies shifted their focus to the realization of "Wireless World Wide Web" services (Tanguturi, 2006). On top of further improved voice quality, 3G allowed offering multi-media services and broadband Internet access through mobile handsets. Six radio interfaces[7] are approved under the ITU-created global IMT-2000 (the International Mobile Telecommunications-2000) standard. Except in the East Asian markets, 3G so far has achieved slower than anticipated market acceptance.

2.2. Diffusion of innovations

According to Rogers (2003), the history of diffusion studies traces back to "early

[7] Originally, the ITU approved five radio interfaces – IMT DS (Direct Sequence), IMT-MC (Multi-Carrier), IMT-TD (Time-Division), IMT-SC (Single Carrier), and IMT-FT (Frequency Time). On Oct. 18th of 2008, The ITU Radiocommunication Assembly formally recognized technology derived from IEEE 802.16 as the sixth interface of IMT-2000.

sociology" at the beginning of 20th century. Rogers (1976) credited Gabriel Tarde (1903) with proposing the typical S-shaped diffusion curve and saw him as an important opinion leader from the very beginning of the diffusion of innovation research tradition. Diffusion of innovation studies had been conducted in several disciplines largely independent of each other until 1960s, including anthropology, rural and medical sociology, education, communication, marketing, and others.

It was the research of Ryan and Gross (1943) on hybrid corn diffusion in Iowa from which the revolutionary paradigm in diffusion research arose (Rogers, 1976). The authors reported that the rate of adoption followed an S-shaped pattern. Furthermore, innovators were more cosmopolitan and had higher socio-economic status. In addition, even though the main source of product information was the salesperson, it was interpersonal communication with fellow farmers that was most influential in the adoption decision. However, modeling and forecasting diffusion of innovation came much later with several pioneering works in the 1950s and 1960s (Meade & Islam, 2006).

Rogers (2003) defined diffusion as "the process by which an innovation, that is a new idea, is communicated through certain channels over time among the members of a social system." There are four elements that affect the process: characteristics of innovation, social system (individual, group, organization, or country), time, and communication channel. Rogers distinguished five (perceived) characteristics of innovation that may affect the diffusion process: trialability, relative advantage, compatibility, observability – further divided into result demonstrability and visibility (Van Slyke et al., 2007) - , and complexity.

Diffusion of innovation research has been carried out in various disciplines; anthropology, communication, economics, education, geography, marketing, political science, sociology, and others. Everett Rogers (McGrath & Zell, 2001) credited Jack L. Walker (1966) with starting the tradition of diffusion of innovations study in political science and Torsten Hägerstrand (1967) in geography. The types of innovations investigated are also very diverse including technology or products that embody it, ideology, information/knowledge/news, practice, policy, and so on. In a study that set up a model for following news event studies, Deutschmann and Danielson (1957) investigated diffusion of three news events – President Eisenhower's stroke, the Explorer I satellite, and Alaskan statehood, and found S-shaped patterns with flattening of the curves due to "shut down for the night." Rogers (2000) summarized that news event studies had found that the news event diffusion process varies by the perceived salience of the news events and timing of the news. Tremayne (2007) investigated a relative new phenomenon of diffusion of dynamic contents (i.e., video clip) in online newspapers.

Using Roger's theory as well as agenda-setting, general systems, and social change theories, Strodthoff and his colleagues (1985) analyzed the diffusion of environmentalism in the U.S. and the roles of mass media and social movement in the process. There is also substantial literature on information technology (IT) diffusion. Prescott and conger (1995) provided a review of the research tradition on IT diffusion. Rogers and Peterson (2007) investigated factors that influence diffusion process of clean air ordinances in U.S. communities.

Depending on the type of social system a study focuses on, theory and method may differ greatly. Previous studies (Downs & Mohr, 1976; Tornatzky &Klein, 1982) pointed out that it is not reasonable to generalize findings from the research on individual adoption to the organizational innovation process. In a meta-analysis of studies on organizational innovation, Damanpour (1991) listed 13 determinants of the diffusion process (i.e., specialization, functional differentiation, formalization, centralization, administrative intensity, vertical differentiation). Different factors are at work at national level as well. In a cross-national diffusion research, Gatignon et. al. (1989) reported that country-specific factors such as cosmopolitanism, mobility and women in labor force had effects on the adoption process.

It is not possible, nor is it necessary, to provide a comprehensive review of all strands of diffusion research in the context of dissertation. Rather, the discussion will focus on research that is directly relevant to the topic of mobile telephony, most importantly the research on diffusion of product and service innovation.

Even though the idea that the pattern of diffusion of innovations often follows an S-shaped curve had been introduced from the very beginning of the research tradition, it was not until the 1950s that researchers began to propose statistical models that fit the pattern. Griliches (1957) was among the first researchers to do so. In a study on hybrid corn diffusion among US farmers, he reported that the pattern of hybrid corn diffusion followed an S-shaped curve.[8] The observed pattern of diffusion was represented by a logistic curve.[9] However, a statistical model per se does not explain why the pattern is S-shaped. Thus, an open question was why diffusion followed this particular pattern.

Meade and Islam (2006, p.522) pointed out that "the two extreme hypotheses that explain this shape are those based on the dynamics of a (broadly homogeneous) population and those based on the heterogeneity of the population." Bass (1969) proposed that there are two characteristics of individuals that affect the diffusion of innovations: their tendency to innovate; and their tendency to imitate others. The Bass

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[8] Ryan and Gross (1943) did not propose a statistical model.

[9] Later, Dixon (1980) re-examined the same data and argued that the Gompertz curve is a better representation of the diffusion process. The Gompertz curve is asymmetric and has an inflection point at one-third of the number of potential adopters while that of a logistic curve, which is symmetric, is at the half point.

diffusion model assumes that the chance of purchasing a new product is determined (1) by a person's own inherent attitude towards an innovation, and (2) by influences (or pressures) from those who have already adopted the product. In his diffusion model, if the tendency to innovate (represented by the coefficient of innovation p) is smaller than that to imitate (represented by the coefficient of imitation q) the resulting curve is S-shaped.[10] In other words, Bass theorized that the diffusion of innovations follows an S-shaped path because the influence from the adopters has greater impact on the decision to purchase a new product than the desire to innovate of potential adopters.[11] The Bass diffusion model was developed to fit an S-shaped curve. For diffusion patterns that deviate considerably from an S-shaped path, the Bass model may not be the best approach.

In contrast, Rogers (2003) suggested a heterogeneous distribution of the propensity to innovate in the population as the main cause of the particular shape of the diffusion path. Adopters are grouped into five categories depending on the time of the adoption; the first to adopt are "innovators" (approximately 2.5% of the eventual adopters according to his studies), followed by "early adopters" (13.5%), then "early majority"

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[10] Talukdar et al. (2002) used the term "external influence" for innovation and "internal influence" for imitation and this dissertation will use the same terminology.

[11] In BDM, The relationship between two parameters determines the shape of the graph. In the case when $p > 0$, $q = 0$, a pure innovation scenario, the diffusion path will resemble a modified exponential function. When $p = 0$, $q > 0$, a pure imitation case, it becomes identical to the logistic model (Meade & Islam, 2006)

(34%), the "late majority" (34%), and lastly "laggards" (16%). Individuals have different threshold levels for adoption with innovators having the lowest. If thresholds are distributed normally, the diffusion path takes an S-curve form. Of course, this condition may not be met in all societies. The exact form of the diffusion path will depend on the skewness of the threshold distribution. Higher levels of education, literacy, social status and wealth are related to favorable attitudes towards innovation (or a lower adoption threshold).

Heterogeneity of income distribution, the fact that income is not equally distributed among the population, has often been considered as one of the main causes of an S-curved diffusion path (Meade & Islam, 2006). Usually, as diffusion of an innovation proceeds, the price falls with technological improvements reducing production and service costs. Price can decrease further if the market expands to reach a critical size that enables economies of scale. When the price of a new product approaches or falls below the threshold price of a potential customer – which will be determined by his income and preferences – the likelihood of a purchase increases. If income is normally distributed and the price falls monotonically, an S-curve diffusion path will result (Van den Bulte & Stremersch, 2004; Meade & Islam, 2006). Liebermann and Paroush (1982) reported that income inequality, price and advertising are main drivers of diffusion. From a meta-analysis of research that used the Bass Diffusion Model (henceforth: BDM), Van den Bulte and Stremersch (2004) found that income distribution has a significant effect on the shape of the diffusion curve.

The three diffusion processes used in this dissertation are 'epidemic' models that view the process of diffusion as a rather automatic process. It mainly occurs through contacts between adopters and potential adopters similar to the process of an epidemic. A potential adopter's probability of purchase is predicted solely by the proportion of adopters in the total number of potential adopters. In other words, the only independent variable is the number of adopters. Acknowledging the fact that diffusion of innovations does not occur in a static environment, scholars have attempted to make diffusion models 'dynamic' by incorporating variables that influence parameter values. This was carried out by the inclusion of explanatory variables in the estimation of (1) the market potential, (2) the probability of adoption, or (3) both (Meade & Islam, 2006).

Mahajan and Peterson (1978) explained the market potential as a function of explanatory variables, price and advertising expenditure. Proposing a new dynamic model, they used housing starts in the U.S. to predict the saturation level for washing machines. Horsky (1990) argued that the market potential is related to income (more precisely wage) distribution and price. In his model, the saturation level increases with a lower price, income growth, and with more equal distribution of wage. While examining business telephones market in the UK, Islam and Meade (1996) compared the performance of fixed saturation models and those of the models where saturation levels were determined by indices that reflected changes in economic environment. The authors found that the latter did not produce significantly better forecasts.

Robinson and Lakhani (1975) incorporated price in the probability function of the Bass model. Horsky and Simon (1983) included advertising expenditures and found that their model provided plausible estimates for telephone banking service. Thompson and Teng (1984) proposed a synthesis of the above two models. Bass, Krishnan and Jain (1994) developed a generalized Bass model as a response to these attempts. They found the new modified model produced better forecasts than the original model. Talukdar et al. (2002) provided a theoretical synthesis of what had been accomplished in attempts to improve BDM by incorporating explanatory variables in parameter estimations.

Diffusion of innovations research has experienced continuous theoretical and methodological refinement and sophistication. There has been growing acknowledgement of the dynamic nature of diffusion process and subsequent attempts to make models more dynamic by inclusion of explanatory variables in the parameter estimations. For the diffusion of mobile telephony research, applying a common fixed saturation level of

100% does not seem to be appropriate, given various levels of penetration in the countries where mobile market approaches saturation. Previous diffusion of innovation studies provide methodological tools to investigate mobile telephony diffusion while letting the saturation levels vary by countries.

2.3. Research on mobile telephony diffusion

Research on mobile telephony diffusion may focus on its unique characteristics and investigate the influence of those characteristics on the diffusion pattern. On the other hand, a study may analyze the diffusion of mobile telephony focusing on its similarities with other new products and test whether general tendencies that have been found influential in other studies are applicable to mobile telephony diffusion.

The diffusion of mobile telephony possesses several characteristics that make it an interesting topic. One of them is the fact that there have been several coexisting incompatible standards, sometimes in a single domestic market – for instance, 2G in the United States. This variation provided a good opportunity to observe the effects of technology standardization. Gruber and Verboven (2001a, 2001b) found that standardization accelerated diffusion, while Liikanen et al. (2004) did not find any evidence of such an effect. Rouvinen (2006) reported a positive effect of standardization.

Koski and Krestschmer (2005) also found a positive effect although they pointed out that price was higher in a single standard market.

Another interesting aspect of mobile telephony is that its history is marked by several distinctive generations of a technology. Usually an innovation does not remain unaltered; the technology continues to develop. Sometimes, as it is the case with mobile telephony, the changes are sufficiently important to merit the label of a new generation. An interesting question is what the effects are of preceding and following generations of technology on the adoption of each other. Gruber and Verboven (2001a, 2001b) investigated the effects of the introduction of digital technology (by including a dummy variable) and found a significant effect on the rate of diffusion of mobile telephony. The increased capacity of digital technology accentuated the effect of competition, which in turn facilitated demand. Liikanen et al. (2004) found a positive effect of 1G penetration on 2G diffusion and a negative effect of 2G on 1G diffusion.

As mobile telephony has to use scarce spectrum allocated and assigned by government, the effects of regulation are also of interest, especially that of the licensing policy – which determines the number of service providers and therefore has a strong influence on the level of competition. Central issues are the optimum number of licenses as well as the entry timing and entry mode of competitors. Gruber and Verboven (2001b) found that having more than one operator has a significant effect on the speed of diffusion in the European Union (EU) countries. A similarly designed study with an expanded data set examined the differences in the effect of entry mode; simultaneous or sequential entry of the competitor (Gruber and Verboven 2001a). The authors found that entry of a competitor has a positive effect on the diffusion of mobile telephone service. Sequential entry had a stronger effect - possibly as a result from the efforts of incumbents to acquire as many as subscribers through more aggressive pricing before a competitor enters the market. Rouvinen (2006) also found a positive effect of competition. Liikanen et al. (2004), however, did not find any support for the effect of the number of licensees. Koski and Kretschmer (2005) investigated two regulatory issues, licensing policy and the degree of independence of the regulatory body. Their study of 2G diffusion revealed that having competition from the beginning has a positive effect on the diffusion of digital mobile telephony, even though pricing had been less aggressive[12]. The regulatory body's independence did not to have a significant effect.

Another interesting aspect of mobile telephony is that it typically is introduced in markets with already established fixed line telephone service which can either be a complement or a substitute. Understanding the relationship between fixed line and mobile

[12] They argued that less aggressive pricing might be due to increased non-price competition.

telephony as complements, Rogers (2003) suggested that mobile telephony will benefit from an existing fixed telephony customer base that serves as critical mass[13]. On the other hand, Mariscal and Rivera (2006) pointed out that the mobile telephone has been accepted mainly as a substitute in Latin America. Overall, the findings have been inconclusive so far. Some studies found that higher penetration of fixed line facilitated the diffusion of mobile telephones (Ahn & Lee, 1999; Gruber 2001; Gruber & Verboven 2001b). On the other hand, Gruber and Verboven (2001a) found a negative effect of higher fixed line penetration in the EU, while Koski and Kretschmer (2005) found no statistically significant effect. The wait list for fixed lines was found to have a positive effect on mobile diffusion (Gruber 2001, Gruber & Verboven, 2001b). Koski and Kretschmer (2005) found that liberalization of the fixed line market accelerated the diffusion of mobile telephony. It is probable that mobile telephony will function as a complement of fixed in the early stage of mobile diffusion and that it will become more of a substitute in the later stage. Young (1993) provided a theoretical model in which the relationship between old technology and new technology changes according to the

[13] Borrowing the idea from physics, Markus (1987) introduced the term 'critical mass' to the studies of diffusion of interactive media. Critical mass is "the minimal number of adopters of an interactive innovation for the future rate of adoption to be self-sustaining" (p. 721, Mahler & Rogers, 1999). Mobile telephony has an advantage that other new products normally do not have; if it is introduced to a market where fixed telephony has a sufficient number of customers that can serve as an already reached critical mass for mobile telephony. However, while such may be the case of developed countries, it may not be entirely true for certain developing countries where mainline customer base is too small to serve as critical mass for mobile telephony.

development of the market for the new product. During the early stage of diffusion, a new product (or technology) is more of a complement for an old technology and even creates new rents for the old technology. However, as the market matures, the new product's characteristic as a substitute to the old technology becomes more prominent.

Researchers also have paid attention to non-economic variables. Dekimpe et al. (1998) included ethnic homogeneity as an independent variable arguing that a more heterogeneous social system would have a negative influence on the diffusion rate and the maximum penetration. The authors found that the number of ethnic groups had negative effects on the number of adopters in the first year (the intercept), and penetration growth, but did not find any significant relationship with the penetration ceiling.[14] In addition, they found that the crude death rate, which was used as a measure of poverty, has a negative relationship with the dependent variables. Rouvinen (2006) compared the diffusion of digital mobile telephone in developed countries and that in developing countries. Some differences were found between the two: the effect of market size (population) was stronger in developing countries; the size of largest city had a significant effect only in developed countries; and openness of the economy (the ratio of

[14] Even though the authors let market potential vary by countries, their model was not dynamic in that they simply defined that market potential as "the percentage of the population who is literate, lives in urban areas and has a sufficient income to afford basic telephone service" (p.113).

imports and exports to GDP) was only significant in developing countries.

Economic factors were among the first to be considered and tested in studies of mobile diffusion. Economic prosperity or a country's wealth – typically represented by GDP per capita – turned out to be an important factor in the studies by Dekimpe et al. (1998), Ahn and Lee (1999), Gruber (2001), Gruber & Verboven (2001b), Madden et al.(2004), and Koski and Kretschmer (2005). It had no significant effect in Gruber and Verboven's analysis of European countries (2001a) and in that of Rouvinen (2006).[15]

2.4. Income inequality and diffusion

Inequality has not received much attention in diffusion of innovation studies. This may be due to the fact that most types of inequality are not easy to measure, thus making them less readily available variables in quantitative analysis. Income inequality, especially its relationship with economic growth, has interested economists for a long time. However, its economic effect, let alone social, cultural and political influence, is not theoretically or empirically clear.

There have been two streams of research on income inequality; one is to investigate the relationship between economic growth and income inequality; another is

[15] In both articles the authors pointed out that the result might have been caused by the high multi-collinearity between GDP per capita and other independent variables such as main line penetration.

to investigate inequality and growth independently (Lundberg & Squire, 2003; Garcia-Penalosa & Turnovsky, 2006).

In his influential work in 1955, Simon Kuznets hypothesized an inverted U-shaped relationship between economic growth and income inequality income inequality initially increases with economic growth but it decreases again once the economy has reached a high level of development (Kuznets, 1955). Studies in the first group empirically test the Kuznets' hypothesis by running regressions of economic growth on measures of income inequality. Even though there have been numerous empirical studies, the findings so far have been inconclusive. Several studies (Alesina & Rodrik, 1994; Persson & Tabellini, 1994; Alesina & Perotti, 1996) found a negative relationship. On the other hand, other studies reported a positive relationship (Li and Zou, 1998; Forbes, 2000). Some researchers found different directions of the effects depending on the level of development (Barro, 1997; Smith, 2001).

Theoretical explanations that have been suggested in support of a negative relationship between inequality and growth are: (1) endogenous fiscal policy or political economy (Persson and Tabellini, 1994; Alesina and Rodrik 1994); (2) credit market imperfections that prevent the poor from investing in human capital development (Galor & Zeira, 1993); (3) reductions in investment resulting from socio-political instability caused by high inequality (Alesina and Perotti, 1996); and (4) increased fertility of the poor (Kentor, 2001; Odedokun & Round, 2005).

A number of researchers investigated the effects of income distribution on economic development by focusing on its relationship with demand. Murphy et al. (1989) showed that domestic demand can increase with broadly distributed income. Lambert and Pfahler (1997) developed a model that separates changes of income distribution into a size effect (mean income) and a distribution effect. They examined the effects of two types of income distribution change when the shape of the Engel curve[16] is concave or convex to the origin. Mani (2001) investigated the effect of interactions between inequality and demand patterns for goods on economic development. He argued that high (initial) inequality results in shortage of initial demand for medium-skilled goods and can lead to persistent underdevelopment and poverty. Matsuyama (2002) argued that in order to start the process of development towards a mass consumption society, inequality should not be too high or too low. Too much equality would lead to a poverty trap, while too little of it would result in premature end of development. In an attempt to explain the modern history of economic development, Galor and Moav (2004) presented a unified

[16] An Engel curve shows how demand of a good or service changes with the change in consumers' income. For normal goods, the Engel curve has a positive slope, meaning that the size of demand increases with the increase in the income. On the other hand, the Engel curve for inferior goods has a negative slope, which means that an increase in income is accompanied by the reduction in demand.

growth model. In the model, when accumulation of physical capital is the primary engine of growth, inequality facilitates economic development by concentrating resources on the individuals with higher propensities to save. However, when human capital accumulation emerges as the main engine of development, inequality has a negative effect. It is because the poor with credit-constraints cannot invest in activities that are necessary to accumulate human capital (i.e., education).

Zweimuller (2000) investigated a relatively unexplored area in the income inequality and economic growth literature: the effects of income inequality on market demand for a new product. The author developed a theoretical model of economic development in which the main driver of the growth is innovation. Income inequality affects market demand for a new product, hence incentives to innovate, which in turn affects economic development. If the homothetic preference assumption used in many Schumpeterian models is discarded, the distribution of income will have effects on demand because it determines the number of (potential) buyers. While changes in income distribution do not affect the initial size of the market if the rich are sufficiently rich, it affects how fast a market for a new product grows. Zweimuller and Brunner (2005) suggested that in general more equality is favorable for innovation and hence for innovation driven economic growth. Foellmi and Zweimuller (2006) distinguished two effects generated from more equality on demand for a new product: a market-size effect and a price-effect. The market size effect means that if less concentration of wealth is due to an increased number of the rich without increase of gross income of the rich, it will result in relatively lower individual income of the rich. In such a case, the demand for an innovation would increase because of the increased number of customers who can afford. On the other hand, the price effect means that the rich are less willing to buy a new product because of the decreased individual income and the producers are forced to lower prices. The authors argued that the price effect always dominates the market-size effect. Through a simulation of product diffusion, Reinstaller and Sanditov (2005) found that as differences in socio-economic characteristics between two social groups increase, the speed of diffusion accelerates while the saturation level, or potential demand, is lowered.

There also have been studies that investigated differences in the effects of income distribution between developed and developing countries. The empirical findings provided inconclusive answers. Iyigun and Owen (2004) found that greater income inequality led to reduced consumption in poor countries, but had the opposite effect in richer countries. In studies on the relationship between income and food consumption, Senauer (1990) found that lower-income households in developing countries were more responsive to the price in rice consumption, while Park et al. (1996) reported that the price elasticity for food was similar across different income strata in the U.S.

Talukdar et al. (2002) is a rare empirical investigation of the relationship between income inequality and the diffusion of innovations. The authors theorized that unequal income distribution would negatively affect a customer's ability to pay, hence would lower the ceiling. However, the analysis, using BDM, found an insignificant relationship between the Gini index and market potential. However, it was significantly related to the coefficient of internal influence (q) in the analysis with consumer products.[17] The findings provide a limited number of clues to the relationship between income inequality and diffusion of mobile telephony. Because the authors used pooled data of six products, it is not clear whether the insignificance of the relationship between income inequality and market potential applies to all six products.

Considering these findings of previous studies, what conclusions can be drawn about the relationship between income inequality and diffusion of mobile telephony? At a theoretical level, earlier work supported the idea that income inequality has an effect on diffusion. Despite its theoretical usefulness, the assumption of homothetic preference is empirically questionable. The literature on consumer behavior literature provides plenty

[17] The authors used pooled data of six products - VCR players, microwaves, camcorders, CD players, cellular phones, and fax machines. The first four products were considered as consumer products, and the last two were considered to be both consumer and business products.

of contradicting findings (Zweimuller, 2000). If we accept heterogeneous preferences of customers, it seems that the distribution of income will have effects on demand.

This dissertation, however, deals with a specific type of service. Although theory would expect similar effects to be at work, it is largely an empirical question whether this particular service follows the expected pattern or not. In other words, mobile telephony may or may not have characteristics that cause its diffusion path to differ from the typical diffusion pattern of innovations.

However, some preliminary inferences are possible. It is necessary to check first whether the diffusion of mobile telephony has shown unique tendencies that would make its diffusion atypical. What is frequently pointed out as unique about diffusion of mobile telephony is that it is being adopted very fast in developing countries. However, the speed of diffusion does not affect its ceiling. Thus, fast market expansion does not suggest that the relationship between income inequality and market potential for mobile telephony will be different from the relationships in other products.

Secondly, the price of mobile telephony may continue to decrease to a point where the majority of the population can afford the service. In such a case, income inequality may not have any noticeable effect. However, predicting future price trends is not the goal of this dissertation. The dissertation does not attempt to make any prediction on future trend. On the contrary, the current research attempts to find out factors that influence market potential and the rate of acceptance using past pattern of mobile telephony diffusion. Barrantes and Galperin (2008) indicated that, for the time being, the price of mobile is not low enough for the poor in Latin American countries to afford service.

Lastly, nowadays it is not uncommon to witness a person with more than one hand set. It may be possible that multiple subscriptions of the rich may compensate for lower demand by the poor. This would not be a problem if the mobile penetration data is available in a format that can identify the actual number of users, which is currently not the case. However, subscription to a mobile service is subject to the law of diminishing marginal utility. In other words, marginal utility gained from having another hand set will diminish as the number of handsets a customer possesses increases. Hence, there will be a certain limit to the maximum number of subscriptions for a person, however rich he may be. In addition, higher income inequality offsets some of the additional demand created by the rich's tendency to buy multiple subscriptions.

To summarize, there is no conclusive a priori evidence suggesting that mobile telephony is such a unique service that income inequality will not have an influence on its potential demand. This remainder of this dissertation will explore this question in detail.

3. Theoretical Model and Hypotheses

In this section, I present a theoretical model for the diffusion of mobile telephony expanding Talukdar et al.'s approach (2002). First, rationales for each variable will be presented, followed by related hypotheses. Discussion of the hypotheses referring to independent variables already tested in previous mobile diffusion studies will be kept at a minimum.

3.1. Theoretical model

The dissertation investigates diffusion of mobile telephony by focusing on two main aspects of diffusion of innovations– market potential and the speed of diffusion. In the statistical models of diffusion of innovations used in this dissertation, the latter aspect of diffusion of innovations is captured by parameters that represent influences from the factors that affect the chances of adoption of potential adopters. In the BDM, they are coefficients of internal and external influences. In the logistic model, it is often called the rate of acceptance, and the Gompertz model also has a parameter that is equivalent to the rate of acceptance.

In Talukdar et al.'s (2002) synthesis of various modifications of the Bass diffusion model, the factors influencing market potential[18] are (a potential adopter's) ability to pay, the willingness to pay, and ease of access to the product. External influence was explained as a function of consumers' access to product related information and consumers' inclination and ability to process non-word-of-mouth information. Finally, internal influence was explained as dependent on population homophily and persuasiveness of existing adopters. While the theoretical model is in a complete form, it suffers from the difficulty that some of the factors, for example willingness to pay and persuasiveness of existing adopters, are subjective in nature, thus making them hard to quantify. More importantly, as the model is based on an individual consumer's choice and ability, it has a limited capability to adequately reflect supply conditions. Another potential shortcoming of the individual-based model is that there can be structural characteristics of a society that may slow down or even prevent information trickle down between social groups.

Taludar et al.'s work is based on the BDM. In contrast, research in the dissertation will use three models (Bass, logistic, and Gompertz), of which two have different structures. It was decided to use three models because there is no guarantee that

[18] Talukdar et al. (2002) used the term synonymous with the 'ceiling' or 'saturation point.' Here, it refers to the saturation level as estimated by statistical models of diffusion of innovation using annual mobile penetration data as input.

the BDM is the best representation of mobile telephony diffusion, and which model will fit the data best cannot be known in advance. Presentation of the hypotheses will be limited to those that are common to all three models.

In the model used in this dissertation, market potential is a function of demand-related factors (income and income inequality), supply-related factors (competition, investment, price, standardization, and market conditions of substitutes/complements), and social conditions that may have direct or indirect effects (social/cultural/gender inequality, urbanization, and population density). Demand side factors influence potential adopters' ability to pay and their preference for the service. Supply factors such as investment and price influence or reflect service providers' ability to provide the service and to make the service attractive to a larger number of people. The model shifts the focus from an individual customer to macro and socio-economic factors. The modification allows the inclusion of supply factors in the model that may be as influential as demand factors in the determination of market potential. Supply conditions are important because customers have different ability to pay. In other words, the size of market potential will depend on how far the price will decrease and how much utility of a product can be increased – for example, by improving service quality and providing ancillary services. Carriers may be forced to exert such efforts by competition. A carrier in a fiercely competitive market may have to exert a greater effort to squeeze any untapped demand, while a monopolist would be less enthusiastic about serving additional demand.

All three statistical models of diffusion of innovations used in this paper are epidemic models in that they theorize that an innovation spreads throughout the society mainly through a potential adopters' contact with actual adopters through which necessary information is transferred and social pressure or influence is exercised. Parameters that represent such an influence are the rate of acceptance in the logistic model (b), its equivalent in the Gompertz model, and the coefficient of internal influence (q) in the Bass diffusion model.[19] For an innovation to be adopted, customers need to be aware of it first. However, mere possession of the information is often not sufficient to trigger an actual purchase of a new product. It often involves persuasion. Thus, the interaction between adopters and potential adopters with regard to an innovation will be affected by the chance of encounters that will convey product information and the effectiveness of such an interaction. In other words, the magnitude of the parameters is likely to be influenced by how dense and effective interpersonal communication channels

[19] The Bass diffusion model has another parameter that also determines speed of diffusion, the coefficient of external influence (p). However, unlike the rate of acceptance in the logistic model and its equivalent in the Gompertz model, it represents the influences from sources other than existing adopters in the society. Lim et al. (2003) understood the coefficient of internal influence to represent 'word-of-mouth effect,' and the coefficient of external influence to represent 'mass media effect.'

in a society are. Of course, a decision to adopt an innovation can also happen through simple observation. While such an observation could provide information, it would not as effective as influence from persuasion by an adopter. In this dissertation, I theorize that the rate of acceptance will be influenced by the chance and the effectiveness of interpersonal interaction that can convey information related to a new product.

3.2. Hypotheses related to market potential

The first set of hypotheses addresses the demand factors discussed above: income size and income inequality. Higher income is likely to increase the number of potential adopters due to the income effect known from consumer theory.

[Hypothesis 1-1] Market potential will be positively related to income.

Income distribution will be another factor in determining market potential as it affects the ability to pay, especially of the poor. High concentration of income in a small segment of the population will likely decrease market potential as there will be fewer people who can afford mobile telephone service. On the other hand, Barrantes & Galperin (2008) indicated that the poor in developing countries are willing to spend a larger share of their income on mobile service than their counterparts in developed countries. Thus, it is possible that customers have a higher preference for cellular service that will cause the effect of income inequality on potential demand to disappear. This dissertation will empirically explore the relationship between income inequality and market potential of mobile telephony.

[Hypothesis 1-2] Market potential will be negatively related to income inequality.

The next three hypotheses address supply side factors. Price reduction brings the product closer to an individual's threshold price (Meade & Islam, 2006), which results in an increased number of customers who can afford the product. Thus, price decreases affect the market potential because each individual has different ability to pay.

[Hypothesis 1-3] Market potential will be negatively related to price.

Another important factor is investment volume, which is likely to increase market potential. Greater investment will likely, though not necessarily, result in a larger, more advanced, and better maintained network, more stable connections and better sound quality, improved customer service and so on. All of those improvements would make mobile telephone a more attractive service, thus likely to increase market potential.

[Hypothesis 1-4] Market potential will be positively related to investment volume in the mobile industry.

Conditions in the markets for complements and substitutes will also be important in determining market potential.[20] It is fixed line telephony in this paper. The market conditions of fixed telephone service will have an impact on market potential for mobile telephony because there is network effect. Rogers (2003) argued that higher penetration of fixed telephone would accelerate the diffusion of mobile telephony, especially in the earlier stages of mobile diffusion, if critical mass has already reached in fixed telephony market. He essentially understood fixed line service as a complement. Higher penetration of wired telephony also increases the benefits of joining a mobile network because a new mobile subscriber will be connected not only to existing mobile subscribers but also to fixed telephony subscribers as well. On the other hand, customers in developing countries

[20] One aspect of the relationships between mobile and fixed telephone that cannot be explored in this paper is that the direction of the influence can be either positive (complement) or negative (substitute). Though it was found that mobile telephone may become a substitute to the wired line telephone - thus, reduces demand of wired - once its penetration has reached a certain level. An opposite effect – that high wired penetration reduces demand of mobile - has not been found yet.

have adopted mobile telephone service mainly as a substitute to main line telephone service (Mariscal & Rivera, 2006). Thus, it remains as an open question subject to empirical investigation whether the relationship between mobile and main line telephony is substitutive or complementary.

[Hypothesis 1-5] Market potential will be positively related to fixed line penetration.

The remaining hypotheses are related to socio-cultural factors. The level of urbanization and the population density are likely to affect market potential because of economies of density. In addition, there is a possibility that the urban population will find having mobile phone convenient due to their mobile life style than the rural population.

[Hypothesis 1-6] Market potential will be positively related to the level of urbanization.

[Hypothesis 1-7] Market potential will be positively related to population density.

Lastly, social, cultural, and gender inequality may also affect overall demand, albeit indirectly. Previous research on inequality and economic growth indicates that inequality is harmful for economic growth in that it may lead to disruptive social and political conflict (Gottschalk & Justino, 2006).

[Hypothesis 1-8] Market potential will be negatively related to gender inequality.

It is, however, not easy to quantify socio-cultural inequality. Thus, in the paper, a concept and measure of socio-cultural fractionalization[21] developed in a past study (Alesina et al., 2003) will be used instead of a direct measure of socio-cultural inequality. Fractionalization of a society is a closely related concept to inequality. While it does not necessarily result in a less egalitarian society, it is one of the main sources of inequality. Such inequality in turn may negatively affect economic growth through increased social tensions and conflicts.

[Hypothesis 1-9] Market potential will be negatively related to ethnic, linguistic and religious fractionalization.

[21] A detailed description of the measure is provided in the next chapter.

3.3. Hypotheses related to the rate of acceptance[22]

This dissertation theorizes that the rate of acceptance is affected by demand-side factors, supply-side factors, and social conditions. In addition, since potential adopters need to learn about the new product before they make purchase, factors that affect customers' access to product related information will affect the rate of acceptance.

The first set of hypotheses address economic factors. Income size, fixed line penetration, price and competition have been tested in previous studies and found to be significant in many cases. Rogers (2003) argued that a higher fixed line penetration will positively affect speed of mobile telephony adoption. It is because more number of mainline subscribers increases benefit from subscribing to a cellular service. In other words, network effect is created not only by new mobile users but also emanates from main line subscribers. On the other hand, a higher level of competition usually translates into more aggressive business strategies of the carriers, which often involves greater efforts to 'persuade' potential adopters.

[Hypothesis 2-1]. The rate of acceptance will be positively related to the income.

[22] Even though the term "rate of acceptance" applies only to the parameter *b* in the logistic model, here for the sake of brevity the term also refers to its equivalents in other two models, including the coefficient of external influence in BDM.

[Hypothesis 2-2]. The rate of acceptance will be positively related to fixed line penetration.

[Hypothesis 2-3]. The rate of acceptance will be negatively related to price.

[Hypothesis 2-4]. The rate of acceptance will be positively related to the level of competition.

The following set of hypotheses is about the factors that may influence the flow of product information among the members of a society. As argued earlier, adoption of a new product is necessarily accompanied by the diffusion of product related information – in the form of simple knowledge transmission and that of persuasion. Thus, it is likely that the effectiveness and density of the interpersonal communication network of a society will influence the likelihood of a potential adopter's purchase.

The level of inequality is one indicator of social cohesion. High inequality in a society causes polarization, which will make communication between different social groups less effective. Earlier research found a positive relationship between inequality and various forms of socio-political conflict (Lichbach, 1989; Gupta, 1990; cited from Gottschalk & Justino, 2006). Thus, high inequality in a society will have a negative effect on the coefficient by reducing the chances and effectiveness of interpersonal communications that transmit innovation-related information from one group to others.

[Hypothesis 2-5] The rate of acceptance will be negatively related to income inequality.

Heterogeneity of the population can be rooted not only in the socio-economic structure of the population but also in ethnic and cultural diversity. Even though co-existence of diverse ethnic, linguistic, and religious groups in a society does not necessarily mean that communication among different sub-groups is infrequent and ineffective, it is more likely to be so than in a more homogenous population. Thus, one would expect that socio-cultural fractionalization will be negatively related to the coefficient.

[Hypothesis 2-6] The rate of acceptance will be negatively related to ethnic, linguistic, and religious fractionalization.

Gender inequality also will likely affect the rate of acceptance negatively. In a society with high gender inequality, women's need to subscribe to cellular service is likely given lower priority compared to a more egalitarian society. In addition, women in such settings will likely have a smaller influence on the economic decisions in her household.

[Hypothesis 2-7] The rate of acceptance will be negatively related to gender inequality.

Population density and the level of urbanization are factors that were frequently tested and found to be significantly related to the rate of acceptance in mobile diffusion studies.

[Hypothesis 2-8] The rate of acceptance will be positively related to population density.

[Hypothesis 2-9] The rate of acceptance will be positively related to the level of urbanization.

There are influences and information that is acquired through sources other than interpersonal communication. In the logistic and Gompertz model, influences that affect adoption and information about a new product come from a single source – existing adopters. On the other hand, the Bass model has two separate parameters that represent effects from two different sources. The coefficient of internal influence (q) refers to the influence from adopters within a country or a society while another parameter the coefficient of external influence (p) captures effects from the variables that affect potential adopters' decision independent of existing adopters in the country (Talukdar et al., 2002). It refers to influences exercised through non-interpersonal communication channels and those from non-domestic sources[23]. Such influences increase with "consumers' access to product-related information", and "consumers' inclination and ability to process information from" non-interpersonal channels (p. 103, Talukdar et al., 2002). In a modern society, the most likely candidate for the non-interpersonal source of product-related information is advertisement, most of which is delivered though mass media. Since it is difficult to acquire information about expenses on advertisements, the influence of information through mass media, as measured by the ratio of household with TV sets to all households, will be used in this paper to represent non-interpersonal sources of product information.

[Hypothesis 2-10] The rate of acceptance will be positively related to access to related information through mass-media.

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[23] The coefficient of external influence (p) is similar to the parameter a in the logistic model in that it represents the intercept or the number of adopters during the first time interval. However, the two do not represent the same aspect of diffusion as p in the Bass diffusion model affects the shape of the curve while a in logistic model does not.

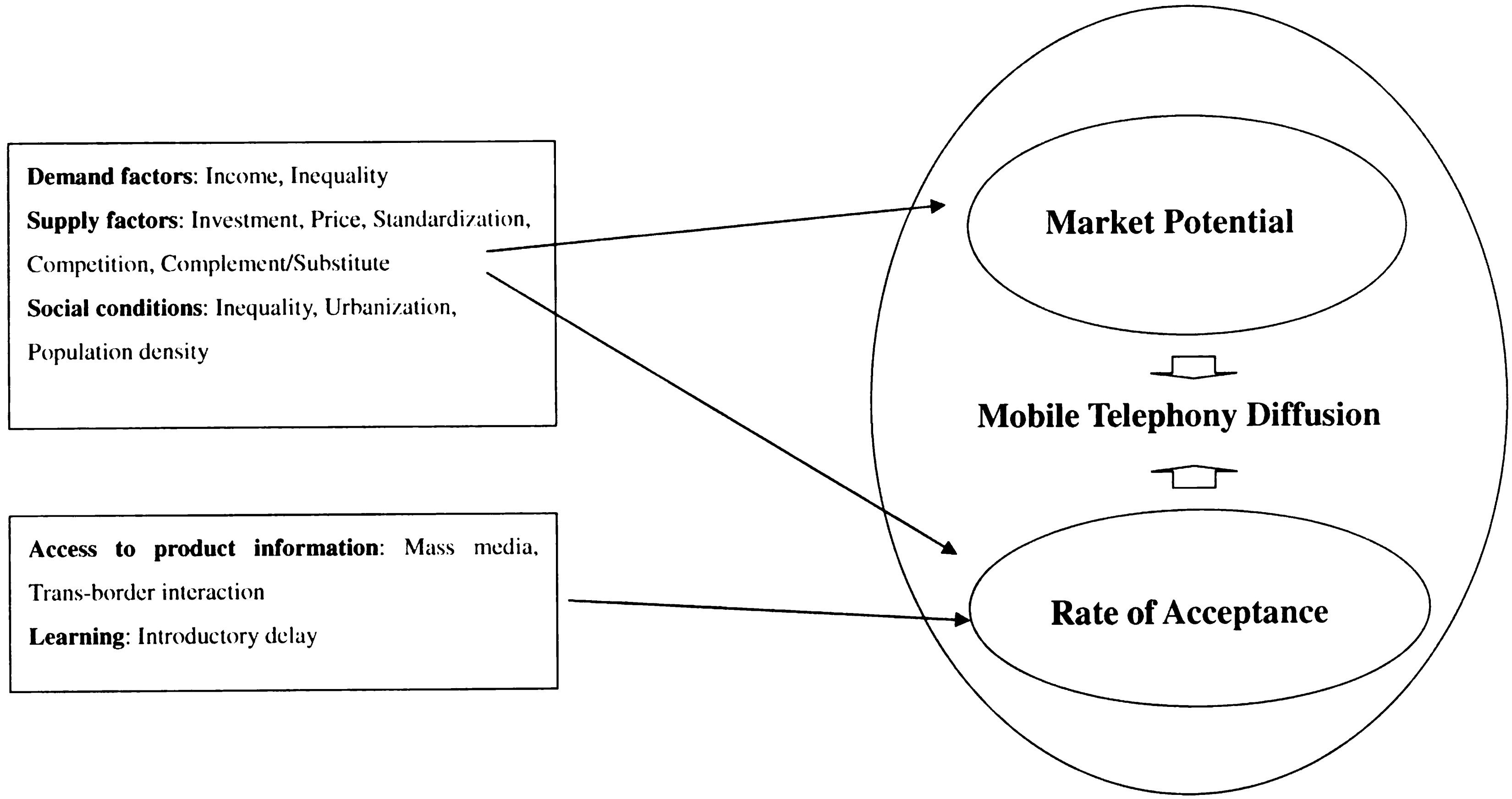
Information can also be acquired from foreign contacts or trans-border media. The chance of acquiring information from foreign sources will depend on how frequent interactions with foreign contacts are. A more open economy, in terms of international trade, will likely increase such chances.

[Hypothesis 2-11] The rate of acceptance will be positively related to the openness of the economy.

Learning from foreign experience is not exclusive to consumers; suppliers can also learn from experiences abroad and better prepare themselves for the eventual launching of domestic service. Thus, as Gruber and Verboven (2001a, 2001b) found in their research, introductory delay will likely have a positive effect because late adopter countries have more time to learn from experience abroad.

[Hypothesis 2-12]. The rate of acceptance will be positively related to introductory delay.

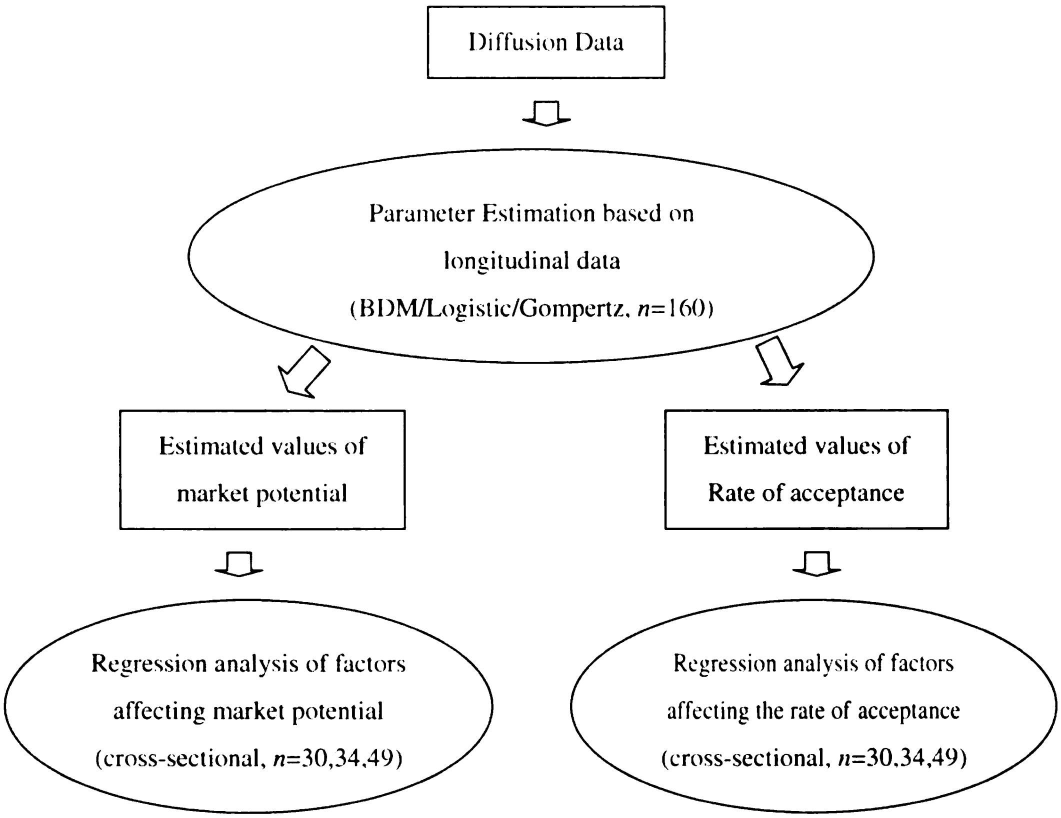
Figure 1. Theoretical model



4. Approaches and Methods

The analysis was carried out in two phases. The first phase was concerned with the estimation of parameters of the diffusion processes. Since it is impossible to empirically observe the market potential until the market has actually reached the saturation point, it was necessary to acquire market potential values through other means. The diffusion of innovation literature provides a plethora of statistical models that allow estimations of ceiling and parameters that characterize the shape of the diffusion curve. The underlying assumption in parameter estimation is that diffusion pattern data closely resembles the pattern portrayed by the statistical model employed. This dissertation used three widely used diffusion models – Bass diffusion model, the Gompertz model, and the logistic model - in estimating parameters of the diffusion processes. Using annual mobile penetration growth data for 27 years since 1980 as the input, the ceiling and the rate of acceptance and its equivalences were estimated for each of n=160 countries. The main goal of the study was to explain the factors influencing the relative magnitude of these parameters. Thus, the statistical models of diffusion of innovations were employed as an intermediate step to acquire estimates for dependent variables that would be inaccessible otherwise.

Figure 2. Analysis process flow chart



In the second phase, using market potential and the rate of acceptance (and its equivalences) estimated in the first phase as dependent variables, a set of regression analysis was carried out to examine the factors influencing the values of the estimated ceiling and the rate of acceptance values. Not all estimations were successful. In some cases, parameters were statistically insignificant at 95% confidence level, or had estimated values that did not seem plausible. In addition, widths of estimated parameter values were very large for some countries. In the estimation using BDM, many countries had coefficients of internal and external influence values that were out of acceptable range ($0 \leq p, q \leq 1$). Consequently, the number of countries included in the second phase of analysis was much smaller than that in the first phase. Each data set had different number of countries. Data set for logistic model had 49 countries, for Gompertz 34, and for BDM 30. Data for this second phase were cross-sectional. In other words, the differences in the diffusion parameters derived from the longitudinal analysis were explained by differences between countries in the data set. The flowchart above describes the analysis process.

Multiple statistical models of diffusion were used because it was impossible to know in advance which model presented a better fit with the data; variations of all three models have been used in previous mobile diffusion studies. The following section introduces the three diffusion models. The regression models for market potential and the rate of acceptance will be introduced in the following sections.

4.1. Statistical models of diffusion

4.1.1. Bass diffusion model

The Bass diffusion model can be categorized as an epidemic model in that it theorizes an individual's inherent desire to imitate others as the main driver of the diffusion of innovations, which is represented by the coefficient of internal influence. An additional coefficient of external influence distinguishes BDM from other epidemic models. The parameters in other epidemic models represent only the influence from adopters, while the coefficient of external influence represents influences from sources other than adopters.

In the Bass diffusion model, the number of adopters between time interval $t\text{-}1$ and t, $X(t)$ is;

$$X(t) = pm + (q-p)N_{(t-1)} - q/mN^2_{(t-1)} \qquad (0 \leq p,\ q \leq 1,\ 0 \leq m,\ t=1,2,3\ldots,\ T) \quad (1)$$

Where $N_{(t-1)}$ is the cumulative number of adopters at time $t\text{-}1$, and m is the eventual number of adopters or market potential, p is the coefficient of innovation, and q is the coefficient of imitation. Since $N_{(0)} = 0$, pm represents the number of adopters that purchased the product during the first time interval of adoption. Originally, Bass used the ordinary least-square estimation (OLS) method to obtain the values of m, p, and q. It has been, however, repeatedly reported that OLS is prone to wrong parameter signs. In addition, it was also found that the BDM does not usually perform well when the number of observations is less than 10 (Meade & Islam, 2006).[24]

Two major approaches were proposed and have been used frequently instead of the original OLS approach. One is maximum likelihood estimation (MLE), introduced by Schmittlein and Mahajan (1982), and the other is nonlinear least squares estimation (NLS), proposed by Srinivasan and Mason (1986). Both alternatives use the probability density function of adoption in BDM – which is not exactly identical to the function for the number of adopters (Schmittlein & Mahajan, 1982) - to derive their statistical models. Schmittlein and Mahajan (1982), Srinivasan and Mason (1986) showed that the performance of the two approaches is equivalent and better than that of OLS. Despite their equivalence, NLS turned out to be the more popular of the two (Meade & Islam, 2006). For the analysis with the Bass model, NLS will be used to determine its parameters in this paper.

The adopters' probability density function *f(t)* for adoption at time *t* is:

$$f(t) = (p + qF(t))(1 - F(t)) \qquad (2)$$

It has the following distribution function:

[24] The latter weakness still applies to alternative methodological approaches.

$F(t) = \{1 - \exp[-(p + q)t\}/\{1+(q/p)\exp[-(p+q)t]\}$ (3)

Sales (the number of adopters) at ith time interval (t_{i-1}, t_i) $X(i)$ is given by:

$X(i) = m[F(t_i) - F(t_{i-1})] + u_i$. (4)

By substituting $F(t)$ in (4) using equation (3), we have;

$X(i) = m(\{1 - \exp[-(p + q)\, t_i\}/\{1+(q/p)\exp[-(p+q)\, t_i]\}$

$- \{1 - \exp[-(p + q)\, t_{i-1}\}/\{1+(q/p)\exp[-(p+q)\, t_{i-1}]\}) + u_i$ (5)

Where u_i is and an additive error term with variance δ^2, and $i = 1, 2, 3, 4, \ldots, T$.

Equation (5) was used in this paper to derive estimates for parameter values.

BDM has restrictions on parameter values. Both coefficient of external influence (p) and coefficient of internal influence (q) should have values between 0 and 1 ($0 \leq p, q < 1$). In addition, in order to be S-shaped, the coefficient of external influence (p) should have a value smaller than that of the coefficient of internal influence (q)

4.1.2. Logistic model

The logistic model was first proposed by Griliches (1957) and has been used in numerous diffusion studies. One of the reasons for the popularity of the logistic model as a representation of growth is because "it may fit empirical data better than other functions with similar shapes" (p. 58, Oliver, 1964). It has a simpler structure from BDM and is free from the problem of unacceptable parameter values. BDM is identical to the logistic model in the pure imitation scenario ($p = 0$, $q > 0$). In some countries, diffusion of mobile telephony exhibits deviations from an ideal S-shaped curve, possibly due to the introduction of a new generation of technology and occasional economic turbulence. For the countries with such mobile diffusion history, the logistic model may fit better than the more complex BDM.

The basic logistic equation is written as:

$$P_{it} = K_i / [1 + e^{-(ai + bit)}] \qquad (6)$$

Where P_{it} represents the proportion of total adopters in country i, at time t, and K is the ceiling value. The parameter b, which is often referred to as the "rate of acceptance", determines the rate of increase in P over time. The rate of acceptance is, even though it does not exactly represent the speed of adoption[25], related to how fast a market will be saturated. The above equation is often transformed into a linear form[26]. The transformed linear equation best describes the role of the rate of acceptance (Dixon, 1980). The equation can be written as:

$$log(Pit/Ki\text{-}Pit) = a_t + b_i t \qquad (7)$$

This dissertation uses the original form – equation (4) - and employs the iterative non-linear square method to estimate parameters, as had been suggested by Oliver (1964).[27]

4.1.3. Gompertz model

In a review of Griliches' work, Dixon (1980) proposed the Gompertz model as a better representation of hybrid corn diffusion. He found that the diffusion pattern of hybrid corn often showed deviations from the logistic curve. Diffusion was skewed with

[25] As it can be seen from the statistical models, the parameter represents the chance of adoption of a potential adopter, while 'speed' means how many years it will take before the market is saturated. In the Bass model, the chance of adoption is represented by two parameters, coefficient of external influence and coefficient of internal influence.

[26] Stoneman (2002) indicates that even though it is a very common practice in diffusion literature, transformation itself does not solve the problem of non-linearity. The left side of equation still contains a parameter of which value is not known. To circumvent this problem, a usual approach is to treat the ceiling as a known value.

[27] He argued that "there is no substitute for full least squares in estimating logistic growth function" (p.65).

long tails and tended to be asymmetric, while a 'true' logistic curve should be symmetric. He found that the Gompertz function provided a better fit with hybrid corn diffusion.

The equation for the Gompertz function may be written as:

$$P_{it} = K_i \alpha_i^{\beta it} \qquad (8)$$

Where P_{it} represents the proportion of total adopters of country *i*, at time *t*, and *K* is the ceiling value, α and β are parameters. The rate of growth equation for Gompertz model can be written as:

$$dP_{it}/dt = ln\ \beta_i * P_{it}(lnP-lnK_i) \qquad (9)$$

Equation (9) was used in the parameter estimation in this paper.[28] $ln\ \beta$ has a similar role to the rate of acceptance in the logistic model (Dixon, 1980).

Estimation was carried out using a statistical software package, NLREG, which allows running a non-linear regression without transforming original equation into a

[28] Dixon (1980) used equation (7) in parameter estimation instead of (8). He, however, fixed the value of ceiling at 1. A trial with mobile diffusion data using equation (7), albeit without fixed ceiling value, was not successful. Thus, I employed equation (8) that has one less parameter to estimate.

linear form. First, mobile penetration data from 1980 to 2005 or 2006 for 160 countries was converted into required formats and fed to the software.[29] Next, one country at a time, the software repeatedly applies different set of values of parameters – each trial is called iteration - until best estimates for parameters were found.

4.2. Regression models for market potential and rate of acceptance

This section introduces the regression models for market potential and that for the rate of acceptance, which are based on the theoretical models discussed in the previous chapter. The sources and definitions of variables are described in the following section.

The model for market potential is specified as:

Market Potential = $a + \beta_1$ [GDP per capita] + β_2 [Income inequality] + β_3[Price] + β_4[Investment] + β_5[Fixed line penetration] + β_6 [Socio-cultural fractionalization] + β_7 [Gender inequality] + β_8 [Urbanization] + β_9 [Population density] + ε_i (10)

[29] As it can be seen from the equations, the Gompertz and Logistic models required cumulative sales as input while BDM required incremental sales. Thus, the number of countries analyzed was slightly smaller for BDM (n=152 compared to 160 for others).

Where ε_i is an error term.

The model for the rate of acceptance is written as below; ε_i is again an error term;

$$\text{Rate of acceptance} = a + \beta_1 [\text{GDP/capita}] + \beta_2[\text{Fixed line penetration}] + \beta_3[\text{Price}] + \beta_4[\text{Competition}] + \beta_5[\text{Income inequality}] + \beta_6 [\text{Socio-cultural fractionalization}] + \beta_7[\text{Gender inequality}] + \beta_8[\text{population density}] + \beta_9[\text{Urbanization}] + \beta_{10}[\text{Mass media}] + \beta_{11}[\text{Openness of economy}] + \beta_{12}[\text{Introductory delay}] + \varepsilon_i \quad (11)$$

Since the coefficient of internal influence in BDM represents only the influence from existing adopters, the regression model is divided into two equations: that for the coefficient of internal influence and that for the coefficient of external influence. The model for the coefficient of internal influence is specified as;

$$\text{Coefficient of internal influence} = a + \beta_1[\text{Income inequality}] + \beta_2[\text{Socio-cultural fractionalization}] + \beta_3[\text{Gender inequality}] + \beta_4[\text{Population density}] + \beta_5[\text{Urbanization}] + \varepsilon_i \quad (12)$$

The coefficient of external influence represents influences from sources other than adopters within the society. The regression model is[30];

$$\text{Coefficient of external influence} = a + \beta_1[\text{Mass media}] + \beta_2[\text{Openness of economy}] + \beta_3[\text{Introductory delay}] + \varepsilon_i \qquad (13)$$

4.3. Data

4.3.1. Data collection and operational definitions

Table 2 on page 69 provides a summary of the variables. Information related to mobile and fixed telephony including penetration, price, and investment was collected from the ITU *World Telecommunication/ICT Indicators* database. Information about income inequality, measured by the Gini coefficient, was collected from the online version of the World Bank *World Development Indicators* database and was partially augmented by information from the *World Factbook*, Central Intelligence Agency (CIA). The rest of the data was collected from the *World Development Indicators* database except the number of carriers per year and the number of standards, for which

[30] The variables such as GDP per capita, fixed line penetration, price, and competition could not be included in the either of regression models for parameters in BDM because theoretically they could not fit into any of them. Talukdar et al. (2002) did not include such variable either.

information was collected from the Telegeography's *GlobalComm* Database.

Mobile penetration was measured by the number of mobile cellular subscribers per 100 inhabitants. The estimated market potential (or ceiling) was also expressed in the number of mobile cellular subscribers per 100 inhabitants. Income was measured by GDP per capita. Fixed line penetration was measured by the number of main lines per 100 habitants as reported by the ITU. The monthly subscription charge (in current US $) was used as a measure for the absolute price, while absolute price divided by GDP/capita was employed to represent the relative price.[31] Due to missing data on investment in mobile industry, investment was approximated by the share of investment in the telecommunication sector in GDP.

The ratio of females in the labor force was used to as an indicator of gender inequality. Fractionalization measures developed and employed by a previous study (Alesina et al., 2003) were used to represent social and cultural heterogeneity. There are ethnic, linguistic, and religious fractionalizations. The authors collected the information about ethnic, linguistic, and religious groups in each country from the *Encyclopedia Britannica*. The *Encyclopedia* "reports the shares of languages spoken as mother tongues,

[31] Though price was measured in two different ways, absolute price was only included in order to gain additional information. Results from the regression analyses with absolute price specification were not considered in the hypothesis tests because it would be price compared to income, not price itself, which may affect market potential.

generally based on census data" (p.159). Though the authors indicated that the information about religion is less controversial and subjective than that of language or ethnicity, it does not distinguish sects within a same religion. The formula for the index is: $FRACT_j = 1 - \sum_{i=1}^{N} s_{ij}^2$, where s_{ij} is the share of group i ($i = 1 \ldots N$) in country j.

Similar to previous research (Rouvinen, 2006), openness of the economy was measured by the ratio of exports and imports to GDP. The average number of major service providers was used to represent the level of competition in mobile markets.[32] The level of urbanization was represented by the percentage of population living in urban areas. Finally, introductory delay was calculated by counting the number of years had passed since 1980 until mobile voice service was introduced in country *i*.[33]

The regressions explaining the factors influencing the estimated market potential and the rate of acceptance are cross-sectional. However, the estimated values for the two parameters are the outcomes of cumulative sales. Thus, it raised a question whether independent variables should be measured as averages or by using the most recent data. Initially, it was planned to use both averages and latest values, for instance the average fixed line penetration from 1980 to 2006 and the main line penetration in 2006. However,

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[32] The information in *GlobalComm* database was extensive but sometimes lacked necessary information in early days of mobile telephony. It has to be augmented by information from various sources such as academic literature, web resources and etc. Thus, there can be some margin of error especially in the number of major carriers in the 1980s.

[33] 1980 was the first year the ITU *World Telecommunication/ICT* database reports a positive number of mobile subscribers in any country - Finland.

the latter approach encountered a difficulty in that for some variables, for instance Gini coefficient, latest data point was as old as 10 years. Though regressions that used latest data were also carried out, they did not produce any significantly different results from those that used average data. Thus, only the results of regression analyses that used average values are presented.

4.3.2. Data sets for regression analysis

Only countries that had at least 10 data entries – in other words those with mobile penetration data for more than 10 consecutive years (ending at either 2005 or 2006) – were included in the parameter estimation. The annual penetration data of mobile telephony in 160 countries from 1980 to 2006 was analyzed with the three diffusion models. Some of the countries were missing mobile penetration information for 2006. Rather than using penetration data only until 2005 for all the countries, all the available information was used. In other words, some countries had penetration data including that of 2006, and the other countries had penetration data only until 2005. It was because an additional observation likely resulted in a more reliable estimate. The parameter values were estimated for each country based on longitudinal data. For the estimation of diffusion related parameters, NLREG, a statistical software package for non-linear regression was used.

The number of countries yielding estimated values of parameters within acceptable range differed greatly by diffusion model. Both the coefficient of external influence (p) and the coefficient of internal influence (q) in BDM should satisfy the condition of $0 \leq p, q < 1$. For the logistic and the Gompertz model, there were cases for which the estimated ceiling values did not appear to be plausible.[34] In addition, such cases were accompanied by very wide confidence interval, which means that the likely range of the market potential is very large. Those cases were not included in the second phase analysis. In addition, p-values of estimated parameter values varied substantially. Countries with parameters that had p-values greater than 0.05 were excluded. Appendix I in page 123 provides detailed information about the estimated parameter values.

Even though the p-values of parameters were usually very small, the widths of confidence intervals (95% level) of the estimated ceiling values were quite large, sometimes greater than 100% of the estimated value. Thus it was deemed appropriate to further limit the number of countries in order to minimize the margin of error. For the Gompertz and logistic models, the threshold was set at 50% of the predicted value. In other words, if the predicted ceiling value was 100, the width of confidence interval

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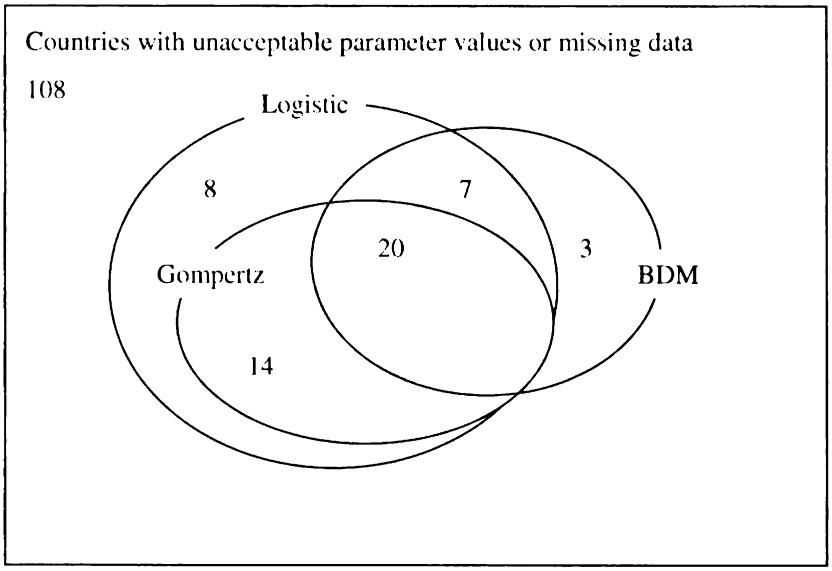
[34] For some countries, the estimated ceiling was a 7 digit number. The cut-off was made at 400 (per 100 inhabitants).

should be less than 50 to be included in the data set. However, due to a lower number of countries with acceptable parameter values, the threshold for BDM was set at 70%. The parameter estimation using the BDM produced insignificant coefficient of external influence at 95% confidence level for the most of countries. The coefficient of external influence was significant in only nine countries. Rather than discarding results from the BDM parameter estimation altogether, it was decided to proceed with the analyses only on market potential and the coefficient of internal influence. Thus countries for regression data set were selected by examining estimated values of market potential and the coefficient of internal influence only. However, the number of countries included in the regression analyses was further reduced due to missing data. In the end, the number of countries included in the data sets was 49 countries for the logistic model, 34 for Gompertz, and 30 for BDM. For the regression analyses of the three parameters, SPSS was used.

Figure 3. Number of countries in data sets (total: 160)



The data sets for the logistic model and the BDM shared 27 countries. This means that almost all the countries in the BDM data set were also included in the logistic model data set. The data set for the Gompertz model and that of BDM shared 20 countries, meaning that one-third of countries in BDM data set were not in the data set of the Gompertz model. On the other hand, all of the countries in the Gompertz model were also included in the data set of the logistic model. However, this does not mean that the two models produced similar estimated values. In terms of the correlation between estimated ceiling values, the logistic model and the Gompertz model showed the greatest difference.

Table 1. Estimated parameter values

	Minimum	Maximum	Mean	Std. Deviation
Bass diffusion model (*n*=30)				
Market potential	3.49	165.52	98.51	31.55
Coefficient of internal Influence	.23	.99	.59	.19
Gompertz model (*n*=34)				
Market potential	6.00	167.13	107.71	28.77
Rate of acceptance	.19	1.03	.42	.28
Logistic model (*n*=49)				
Market potential	5.74	162.39	94.82	28.77
Rate of acceptance	.29	1.56	.68	.28

The 160 countries for which mobile penetration data were analyzed in the diffusion model phase had an average GDP per capita of $ 13,167.4, average fixed line penetration of 21.9 (lines per 100 habitants), and average mobile penetration of 50.7 (subscribers per 100 habitants) in 2005. The data set for the logistic model had an average GDP per capita of $ 18,007.6, Gini coefficient of 34 and fixed line penetration of 32.6.[35] The average price was $ 32.1, and it was 0.44% of the average annual income.[36]

Compared to the average of the full set of 160 countries, the countries included in the phase-two data sets were substantially richer, and had a higher penetration of main

[35] As indicated above, independent variables were measured by the average value of the past 27 years (from 1980 to 2006). The statistics of the countries reported here are averages, not the latest data.
[36] The mean absolute price of the countries in the logistic model data set is higher than those of other two models. It was because of Bosnia and Herzegovina of which absolute price was $ 284.55. Without Bosnia and Herzegovina, the average absolute price is $ 26.3 that accounts for 0.31% of average income.

line telephone. This tendency was also found in the countries in the Gompertz model data set. The data set contained countries that had even greater GDP per capita of $ 20,058.1, and fixed line penetration of 35.9 on average. On the other hand, the average price was $ 28.9 and accounted for 0.26% of the income. The data set for BDM was not an exception. The average income was $ 18,363.5, and the average penetration of main line was 33.2, compared to 21.9 of the entire countries. The average price for the countries in the BDM data set was $ 27.6. Detailed descriptive statistics of the variables in the three data sets are presented in tables 3, 4, and 5 on pages 70-72.

4.3.3. Hypotheses tests

The fact that three models were used in parameter estimation and the fact that regression analyses on estimated parameter values from the three models produced different results poses a question of how hypotheses should be tested. A very strict way of hypothesis testing would accept a hypothesis as supported only when all the regression results produce supporting evidence. Naturally, this approach would lead to more rejections. In addition, there is a problem that the patterns of diffusion of innovations captured by the three models are not identical. It is possible that mobile diffusion data of a country fits very well with one of the models but not with the other two. Even in countries where all three models produced acceptable results, the estimated parameter values from one of the models may be not as good an estimation as those from the other two. In other words, it does not necessarily make the evidence of an independent variable's effect stronger when more number of regressions find significant effects. A more appropriate approach is therefore to carry out hypotheses tests for each diffusion model separately. This is the approach adopted in this dissertation.

Table 2. Operational definitions of variables

Variable	Operational Definition	Source
Independent variable		
Competition	Average number of carriers with more than 5% of market share during 1980 ~ 2006	Telegeography, 2008
Fixed line penetration	The number of main line per 100 inhabitants	ITU, 2007
Income inequality	Gini coefficient	World Bank, 2008; CIA, 2008
Level of economic development	PPP adjusted GDP per capita (in constant international dollars)	World Bank, 2008
Investment	% of investment on telecommunications sector in GDP	ITU, 2007
Population density	Population density transformed by taking logarithm	World Bank, 2008
Relative price	% of monthly subscription cost compared to GDP per capita	ITU, 2007
Absolute price	Monthly subscription cost	ITU, 2007
Gender inequality	% of female in labor force	World Bank, 2008
Urbanization	% of population in urban areas	World Bank, 2008
Introductory delay	The number of years passed since 1980 until a positive number of mobile subscriber is reported	ITU, 2007
Openness of economy	% of import/export in GDP	World Bank, 2008
Info. from mass media	% of households with TV set	ITU, 2007
Ethnic fractionalization	1 – (the sum of squared proportion of each ethnic group)	Alesina et al., 2003
Linguistic fractionalization	1 – (the sum of squared proportion of each linguistic group)	Alesina et al., 2003
Religious fractionalization	1 – (the sum of squared proportion of each religious group)	Alesina et al., 2003
Dependent variable		
Market potential	The number of mobile subscriptions per 100 habitants at saturation point	Estimated
Rate of acceptance		Estimated

Table 3. Descriptive statistics of the independent variables (BDM, *n*=30)

	Minimum	Maximum	Mean	Std. Deviation
Gini coefficient	21.61	55.50	33.75	8.24
Urbanization	15.45	97.65	65.91	20.43
Fixed penetration	.43	64.73	33.18	1.88
GDP per capita	1307.81	48,107.60	18,363.52	11,811.57
Population density	2.30	5790.26	294.03	1044.47
Pop. density (log transformed)	.83	8.66	4.11	1.65
Absolute price	4.03	82.88	27.56	2.12
Relative price	.0168	3.989	.381	.768
Relative price (log transformed)	-3.73	3.32	-1.29	1.64
Investment	.34	1.34	.75	.27
Female labor force	27.89	49.00	41.55	5.41
Ethnic fractionalization	.0119	.8505	.2693	.2238
Linguistic fractionalization	.0178	.8503	.2935	.2210
Religious fractionalization	.0911	.8241	.4480	.2142

Table 4. Descriptive statistics of the independent variables (Gompertz, *n*=34)

	Minimum	Maximum	Mean	Std. Deviation
GDP per capita	1,847.94	48,107.60	20,058.06	10,029.26
Fixed penetration	4.04	64.73	35.91	16.26
Urbanization	29.43	97.65	70.35	16.51
Population density	2.62	5790.26	329.81	988.12
Gini coefficient	21.61	55.50	32.31	7.20
Relative Price	.0042	2.53	.26	.47
Absolute Price	.41	82.88	28.89	1.99
Gender Inequality	24.56	49.00	41.26	5.85
Mass media	56.05	98.33	86.77	8.20
Introductory delay	.00	17.00	7.21	4.07
Openness Economy	21.47	261.05	90.20	51.33
Competition	1.59	5.18	2.66	0.94
Ethnic fractionalization	.0020	.5867	.2130	.1720
Linguistic fractionalization	.0021	.6440	.2425	.2019
Religious fractionalization	.0091	.7222	.3900	.2039

Table 5. Descriptive statistics of the independent variables (Logistic, n=49)

	Minimum	Maximum	Mean	Std. Deviation
GDP per capita	1,307.81	48,107.60	18,007.61	10,753.85
Fixed penetration	.43	64.73	32.59	18.07
Urbanization	29.43	100.00	67.99	17.77
Population density	2.30	5790.26	363.63	1,073.04
Gini coefficient	21.61	55.50	33.95	6.91
Relative Price	.0042	6.47	.44	1.10
Absolute Price	.41	284.55	32.10	4.11
Gender Inequality	22.95	49.33	40.81	5.95
Mass media	26.33	98.68	82.85	15.56
Introductory delay	.00	17.00	7.82	4.07
Openness Economy	21.47	417.45	94.25	66.08
Competition	1.22	5.56	1.74	1.14
Ethnic fractionalization	.0020	.8505	.2815	.2199
Linguistic fractionalization	.0021	.8503	.307271	.2390
Religious fractionalization	.0091	.8241	.4445	.2280

5. Empirical Findings

5.1. Phase I: Estimation of diffusion parameters

Two parameters, market potential and the rate of acceptance, were estimated by three diffusion models.[37] The estimation used annual mobile penetration data from 1980 to 2006 for 160 countries as reported by the ITU. Each model showed a different level of fit to mobile diffusion data.

The logistic model fit reasonably well with the data in terms of parameter values and the significance of parameters. For 113 of the 160 countries, applying a 95% statistical significance level, the analysis produced parameter estimates within permissible value ranges. The average estimated ceiling value was 88.2. Even though *p*-values for the ceiling estimates were very small (0.0001 or less for 90 countries), the widths of the confidence intervals for the parameter estimates were substantial. This width was evaluated by dividing the range of the confidence interval (maximum – minimum) by the estimated ceiling value. It was less than 20% of the predicted ceiling value for 49 countries; for 79 countries the width was 50%; and the average width was 86.6%. Countries for which the width of the confidence interval was below 50% were

[37] For the BDM, three parameters were estimated – market potential, the coefficient of internal influence, and the coefficient of external influence.

selected for the regression analysis whereas the others were excluded. This was a pragmatic choice intended to limit further analysis to case where the endogenous values were established with a level of accuracy deemed acceptable by the analyst.

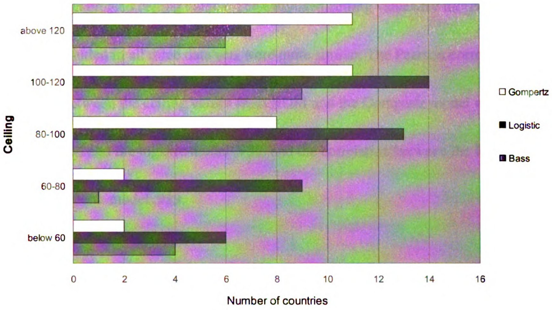
In the estimation using the Gompertz model, 80 of 160 countries yielded parameter estimates with acceptable values at the 95% significance level. Market potential for these countries averaged at 101.8. In general, estimated ceilings were greater than those derived using the logistic model. The widths of confidence intervals for the market potential at 95% levels were even greater than those derived from the logistic model. The widths were less than 50% of the predicted ceiling for 40 countries; 100% for 65 countries; and the average width for all 80 countries was 226.4%. A wider average means that the Gompertz model performs worse than the logistic model in terms of the number of countries of which pattern of mobile diffusion a model fits well with. However, since diffusion patterns are not identical across countries, whether a certain model is a good fit or not should be judged for each country.

The selection of countries for the regression analysis was made with the same criteria to that of logistic model - the width of the confidence should be below 50% of the predicted ceiling value.

Estimation of parameters with the (more complicated) BDM yielded fewer acceptable parameter values. In more than half of the countries the data did not produce parameter values that were within the range that is compatible with the theoretical foundations of the BDM. The widths of the confidence intervals for national ceiling values were even larger than in the other models. Furthermore, the coefficient of external influence was below the 95% significance level for most of the countries. Only for nine countries were the parameter values significant at the .05 level. For another five countries they were significant at the 0.1 level. Parameters were also estimated with the OLS technique but the results were worse than those from the analysis with NLS.

There were some countries of which current mobile penetrations are very close or even above the predicted ceiling values. Still, the number of countries in which the market appears to be saturated varied by the models due to the differences in predicted ceiling values. For instance, Portugal's mobile penetration in 2006 stood at 115.95, while the logistic model predicted Portuguese mobile market will be saturated at 111.54, the Gompertz 117.72, and the BDM 117.49. The logistic model data set had 21 countries of which the estimated ceiling values were lower than the current penetration. The Gompertz model data set had 9 countries, and the BDM data set 6.

Figure 4. Distribution of the estimated ceiling values



Estimates generated by the logistic model predicted that more than half of the countries (28 countries out of 49) in the data set would not reach 100% penetration if past pattern of mobile diffusion continue to hold. The number was 15 (of 30) countries for the BDM, and 12 (of 34) for the Gompertz model. According to the logistic model estimation, saturation levels in 4 countries were predicted to be below 50% of the population.

In the subsets of countries for which acceptable parameter values were derived, strong correlations among estimated ceiling values from the three models existed. This is not unexpected and solidifies the findings somewhat. After all the diffusion patterns depicted by the three models are not radically different from one another and one would expect some level of consistency in the findings. Correlation analyses were carried out to compare the estimated ceiling values. The estimated ceiling values for the 20 countries that were included in all three data sets were quite similar. The Pearson correlation coefficient between the ceiling values from BDM and the Gompertz model was .944, between BDM and the logistic model .955, and the correlation between the logistic model and the Gompertz model .939.

Table 6. Correlation coefficients between estimated ceiling values (*n*=20)

Models	Bass	Gompertz	Logistic
Bass	1		
Gompertz	.944*	1	
Logistic	.955*	.939*	1

* Significant at .01 level.

However, once we expanded the comparison to include all the countries (*n*=46) for which at least one model, but not all models, produced ceiling values within acceptable range, there were considerable differences. In other words, the additional 26 countries are those of which estimated parameters from one or two models were insignificant, or had too wide confidence intervals. The difference was especially large between the ceiling values from the logistic model estimation and those from the Gompertz model (r = .719).

Table 7. Correlation coefficients between estimated ceiling values (n=46)

Models	Bass	Gompertz	Logistic
Bass	1		
Gompertz	.926*	1	
Logistic	.846*	.719*	1

* Significant at .01 level.

5.2. Phase II: Determinants of diffusion parameters

5.2.1. Factors explaining market potential

The factors influencing the estimated market potential (as derived from the diffusion models) were examined using regression analyses. The specification of the empirical model was identical for all three models.

The regression model for market potential (in the chapter 4) has GDP per capita, income inequality, price, investment, fixed line penetration, socio-cultural fractionalization, gender inequality, urbanization, and population density as independent variables. In addition to variables in the empirical model for market potential, independent variable in the model for the rate of acceptance also includes mass media, openness of economy and introductory delay as well.

Not all the factors in the theoretical model were included in the empirical model. The theoretical model of the dissertation includes standardization as one of supply factors that may influence market potential and the rate of acceptance. Various variables intended to capture the degree of standardization were used, including the number of 2G standards, the number of 2G and 3G standards, and a standardization dummy variable, but they turned out not to be significant. Moreover, the inclusion of standardization caused a substantial decrease in the F-value and adjusted R^2. In the final empirical models, the variable of standardization was therefore not included.

There was a noticeable resurgence of penetration growth in some developed countries in recent years, which seemed to be coincided with the introduction of 3G. Even though it was not included in the theoretical model, to check whether it was due to the introduction of 3G service, a dummy variable was created and tested. The test, however, did not provide any supporting evidence and the inclusion of the variable did not improve the explanatory power of the model. One of the likely reasons for this outcome is that the majority of countries in the data set have already started 3G service, making the comparison less meaningful. The variable was therefore dropped from the analysis.

In some cases, different variables could be used to represent a factor. For example, two model specifications were estimated throughout with regard to price – one with the relative price and another with the absolute price. The analysis using the absolute price measure was carried out to acquire additional information rather than as a part of hypothesis test.

Cross-national analyses often suffer from the problem of high correlations among independent variables.[38] Such high correlations were also present in the regression analyses on factors that affect the rate of acceptance. As a consequence, some of the variables had relatively high VIF[39] values. For instance, GDP/capita and fixed line penetration were strongly correlated throughout the data sets, a tendency also found in previous research (Gruber & Verboven 2001a, Rouvinen, 2006). It was especially high in the sets of countries derived from the logistic model (r = .899) and the Gompertz model (r = .852) data sets. GDP per capita and fixed line penetration were also the variables with the highest VIF values. In some cases, fixed line penetration generated a VIF value

[38] See the appendix III on pages 127-131 for detailed information
[39] Variance Inflation Factor (VIF) is an index of multi-collinearity. The index measures the increase of the variance in a coefficient because of the collinearity.

above 10. However, exclusion of one of the two did not improve the β-value of the other substantially and resulted in reduced overall model fit. In addition, though the GDP/capita and fixed line penetration is strongly correlated, we cannot conclude that they are representing a same phenomenon. As it is reported below, both of the variables were found to significantly affect market potential predicted by the logistic model, even with the presence of multi-collinearity. Thus, it was decided to keep both of the variables absent a better alternative specification. Other variables that had relatively high VIF values - though not so high as to raise a serious concern - were mass media (measured by percentage of households with TV set), ethnic and linguistic fractionalization.

Summary results of the regression analyses are presented in table 8 on page 83, table 9, and 10 on pages 85-86. Each regression analysis produced slightly different outcomes. In the analysis using the estimated ceiling from the logistic model, GDP per capita (β = .544, p = .026) as well as fixed line penetration (β = - .518, p = .057) showed significant effects despite the problem of multi-collinearity (VIF = 5.938 for GDP/capita, and 7.559 for fixed line). The effect of the latter variable was negative contrary to the hypothesis. The other two independent variables that were found to have significant effects were urbanization (β = .414, p= .011) and relative price (β = -.430, p= .004), with each variable showing the expected direction of the effect. For purposes of comparison, a model specification using the absolute rather than the relative price was also examined. The outcome was almost identical to that of the relative price specification. An exception was that gender inequality was significant, albeit barely (β = .237, p = .094) in the analysis using the absolute price specification. The other variables, including inequality measures, did not show any significant effect on estimated market potential.

Using the parameter estimates from the Gompertz model as dependent variable revealed a somewhat different pattern. GDP per capita (β = .527, p = .06) and urbanization (β = .402, p = .029) were found to have significant positive effects on the ceiling, while gender inequality (β = .308, p= .1)[40] and price (β = - .48, p= .012) negatively affected market potential. Fixed line penetration was not significant (β = .477, p = .13), possibly due to a high level of multi-collinearity with GDP per capita. On the other hand, in the absolute price specification, GDP per capita (β = .732, p = .021) and urbanization (β = .522, p = .008) were found to have significant positive effects with the ceiling. Gender inequality negatively affected the estimated ceiling value. However, unlike the relative price, the absolute price was not significant.

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[40] Because gender inequality was measured by the ratio of female in labor force, the positive value of the standardized β should be interpreted as a negative effect of gender inequality.

Table 8. Factors influencing estimated ceiling values (BDM) (n=30)

	Relative price specification	**Absolute price specification**
Model (D.V. = market potential)		
F-value	**5.698******	**4.889******
Adj. R^2	.641	.596
Variables	Standardized β	Standardized β
GDP/capita	**.756****	**.725****
Gini coefficient	.155	.150
Fixed Penetration.	- .399	- .120
Population Density	.179	.198
Urbanization	.238	**.349***
Price	-.379	-.070
Investment	**.321***	**.366****
Female labor force	**.291***	.226
Fractionalization		
- Ethnicity	- .329	- .258
- Language	**.464***	.351
- Religion	- .042	- .096

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Results from the analysis using the parameter estimates from the BDM as dependent variable differ from the logistic and Gompertz findings. GDP per capita (β = .756, p= .011), investment (β = .321, p= .056), and linguistic fractionalization (β = .464, p= .099) were found to be positively related to estimated market potential. Gender inequality (p= .099) was found to be negatively related to ceiling values. If the absolute price specification was used, GDP per capita (β = .725, p= .032) and investment (β = .366, p= .044) had significant effects. In addition, urbanization was significant (β = .349, p= .095). However, gender inequality (p= .207) and linguistic fractionalization (p= .213) were no longer significant.

To summarize, GDP per capita had a significant effect on the estimated market potential in all three models. Urbanization and (relative) price had significant effects on estimated ceiling values in the logistic and the Gompertz models. Gender inequality had a negative effect on estimated market potential in the BDM and the Gompertz model. Fixed line penetration was significant only in the diffusion pattern predicted by the logistic model. Investment was significantly associated with market potential predicted by the BDM.

Table 9. Factors influencing estimated ceiling values (Gompertz model)

Number of countries = 34

	Relative price specification	**Absolute price specification**
Model (D.V. = market potential)		
F-value	**3.825*** **	**2.828** **
Adj. R^2	.485	.379
Variables	Standardized β	Standardized β
GDP/capita	**.527***	**.732** **
Gini coefficient	.022	.027
Fixed Penetration.	- .477	- .562
Population Density	.085	.074
Urbanization	**.402** **	**.522** **
Price	**- .480** **	- .271
Investment	.133	.012
Female labor force	**.308***	**.417** **
Fractionalization		
- Ethnicity	-.082	-.038
- Language	.144	.036
- Religion	-.120	-.107

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Table 10. Factors influencing estimated ceiling values (Logistic model)

Number of countries = 49

	Relative price specification	**Absolute price specification**
Model (D.V. = market potential)		
F-value	**6.641*** **	**5.569*** **
Adj. R^2	.569	.517
Variables		
GDP/capita	**.544** **	**.703*** **
Gini coefficient	- .041	- .041
Fixed Penetration.	**- .518***	**- .480***
Population Density	.044	.033
Urbanization	**.414** **	**.501*** **
Price	**- .430*** **	**- .267** **
Investment	.060	.073
Female labor force	.211	**.237***
Fractionalization		
- Ethnicity	- .032	-0.41
- Language	.026	- .027
- Religion	-.099	-.117

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

5.2.2. Test of hypotheses related to market potential

Table 11. Tests of hypotheses relating to market potential

Hypothesis	Variable	BDM	Gompertz	Logistic
H. 1-1	Income	X	X	X
H. 1-2	Income inequality			
H. 1-3	Price		X	X
H. 1-4	Investment	X		
H. 1-5	Fixed penetration			
H. 1-6	Urbanization		X	X
H. 1-7	Population Density			
H. 1-8	Gender Inequality	X	X	
H. 1-9	Fractionalization			

X = supported

Table 11 above summarizes the results of the hypotheses tests. In the regression on the ceiling values estimated by the logistic model, GDP per capita, fixed line penetration, urbanization, and relative price significantly affected market potential. However, contrary to hypothesis 1-5, fixed line penetration had a negative effect. In the regression using the absolute price specification, absolute price turned out to be significant. Thus, hypotheses 1-1 (income), 1-3 (price), and 1-6 (urbanization) were supported in the regression analysis on market potential estimated by the logistic model.

Hypotheses 1-2 (income inequality), 1-4 (investment), 1-5 (fixed line penetration), 1-7 (population density), 1-8 (gender inequality), and 1-9 (fractionalization) were not supported.

The regression on the market potential values estimated by the Gompertz model found that GDP per capita, urbanization, gender inequality, and relative price had significant influences on the saturation level. Thus, hypotheses 1-1 (income), 1-3 (price), and 1-6 (urbanization), 1-8 (gender inequality) were supported in the regression analysis on market potential estimated by the Gompertz model.

The analysis on ceiling values from BDM found that GDP per capita, investment, and gender inequality were significantly associated with the estimated market potential. Thus, hypotheses 1-1 (income), 1-4 (investment), and 1-8 (gender inequality) were supported.

5.2.3. Factors influencing the rate of acceptance

Tables 12 and 13 on pages 90 and 91 summarize the results of the regression analyses using the estimated rates of acceptance as dependent variable. The overall regression analysis using the estimated rates of acceptance by the logistic model, was significant ($F = 4.732$, adj. $R^2 = .521$, $p = 0.001$). Income inequality ($\beta = -.275$, $p = .061$)

and religious fractionalization (β = -.335, p=.021) negatively affected the rate of acceptance. Introductory delay (β = .493, p=.004) had a positive effect. Gender inequality was also found to be significant (β = -.267, p=.08) but had positive effects contrary to expectation. Additional analysis with absolute price specification showed a similar outcome. The model using absolute prices was also significant (F = 4.57, adj. R^2 =.51, p = 0.001). Income inequality was found to slow down the adoption (β = - .281, p=.061). The results seems to indicate that introductory delay sped up adoption (β = .575, p=.003). Gender inequality showed a significant positive effect (β = -.285, p= .65). Lastly, fractionalization measure of religion was found to be negatively associated with the estimated rate of adjustment (β = -.322, p=.021).

Table 12. Factors influencing the estimated rate of acceptance (Gompertz model)

Number of countries = 34

	Relative price specification	**Absolute price specification**
Model (D.V. = rate of acceptance)		
F-value	**3.518*** **	**3.518*** **
Adj. R^2	.517	.517
Variables		
GDP/capita	- .189	- .189
Gini coefficient	**- .410** **	**- .409** **
Fixed Penetration.	- .072	- .059
Population Density	- .004	- .011
-Urbanization	- .209	- .211
Price	.026	.023
Competition	.236	.234
Introductory Delay	**.452*** **	**.452*** **
Openness of Economy	- .072	- .061
Female labor force	**- .517** **	**- .523** **
Mass Media	.041	.028
Fractionalization		
- Ethnicity	- .137	- .132
- Language	.312	.305
- Religion	- .191	- .185

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Table 13. Factors influencing the estimated rate of acceptance (Logistic model)

Number of countries = 49

	Relative price specification	**Absolute price specification**
Model (D.V. = rate of acceptance)		
F-value	**4.732*****	**4.570*****
Adj. R^2	.521	.510
Variables		
GDP/capita	- .031	-.085
Gini coefficient	**- .275***	**- .281***
Fixed Penetration.	- .202	- .217
Population Density	.101	.093
Urbanization	.001	-.020
Price	.187	.112
Competition	.074	.080
Introductory Delay	**.569*****	**.575*****
Openness of Economy	- .118	- .108
Female labor force	**- .267***	**- .285***
Mass Media	.137	.125
Fractionalization		
- Ethnicity	.090	.092
- Language	- .161	- .154
- Religion	**- .335****	**- .322****

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Regression analyses of the factors influencing the rate of acceptance from the Gompertz model showed similar results. The analysis found the model significant (*F*-3.518, adj. R^2 =.517, p = 0.006). Introductory delay (β = .452, p=.049) positively affected rate of acceptance. Gini coefficient (β = - .410, p=.043) and ratio of female in labor force (β = - .517, p=.022) were negatively associated with the estimated parameter value. Additional analysis with absolute price measure also found a very similar result. The model using the absolute price had the same *F*-value and Adjusted R^2 with the model using the relative price. The same variables were found to have significant effects as the previous analysis, though standardized β values and p-values were slightly different.

The Bass diffusion model has two parameters that together determine the rate of acceptance: the coefficient of external influence (q) and the coefficient of internal influence (p). Most of the estimated values for the coefficient of external influence were insignificant at 95% level. The number of countries to which the model fit was too low to ensure sufficient degrees of freedom to run a regression. Therefore, regression analysis was run only on the coefficient of internal influence. The regression model for the coefficient of internal influence was not significant overall. Again, the model proved not to be significant.

5.2.4. Test of hypotheses related to the rate of acceptance

Here, the hypotheses were reviewed in the same way that the hypotheses related to market potential were tested. Table 14 on page 94 provides a summary of the tests.

The regression analysis on the rate of acceptance estimated by the logistic model found that the Gini coefficient, introductory delay, and religious fractionalization had significant effects. Thus, hypothesis 2-5 (income inequality) and hypothesis 2-12 (introductory delay) were supported by the diffusion pattern predicted by the logistic model. Hypotheses 2-1 (income), 2-2 (fixed line penetration), 2-3 (price), 2-4 (competition), 2-6 (fractionalization), 2-7 (gender inequality), 2-8 (population density), 2-9 (urbanization), 2-10 (mass media), and 2-11 (openness of economy) were not supported.

The analysis with the estimated rate of acceptance derived from the Gompertz model found that the Gini coefficient, introductory delay, and gender inequality had significant effects. No other variables were found to be significantly associated with the rate of growth. Thus, hypothesis 2-5 (income inequality) and hypothesis 2-12 (introductory delay) were supported by the diffusion pattern predicted by the Gompertz model.

Table 14. Results of the rate of acceptance related hypothesis testing

Hypothesis	Variable	Gompertz	Logistic
H. 2-1	Income		
H. 2-2	Fixed penetration		
H. 2-3	Price		
H. 2-4	Competition		
H. 2-5	Income inequality	X	X
H. 2-6	Fractionalization		
H. 2-7	Gender Inequality		
H. 2-8	Population density		
H. 2-9	Urbanization		
H. 2-10	Mass media		
H. 2-11	Openness Economy		
H. 2-12	Introductory Delay	X	X

X = supported

6. Discussion

6.1. Discussion of findings

This dissertation started with a question about the effects of inequality on the diffusion of mobile telephony. To study this question, the role of inequality among other factors that influence the shape of diffusion processes had to be examined. The dissertation set out to develop a general model of the factors that shape the diffusion of mobile telephony, exploring the effects of inequality in the context of other variables that can reasonably be expected to influence diffusion. As several of these factors are specific to nations, a cross-national study design seemed appropriate. In a first step, estimates for the market potential and the rate of acceptance were generated using three widely used diffusion models. In a second step, regression analyses were performed to examine the factors that influence the characteristics of the diffusion process.

As ceiling values for mobile service adoption can only be observed in countries that have actually reached saturation, statistical models of the diffusion of innovations were used to generate estimates for all other countries. Whereas a comparative evaluation of the alternative diffusion models was not the primary goal of this paper, the outcomes, nevertheless, deserve a brief discussion. In terms of the number of countries for which the analyses produced acceptable parameter values and acceptable confidence intervals, the logistic model fit the data best. In other words, there are more countries in which mobile diffusion showed patterns that are best approximated by a logistic function rather than one of the others. There are two distinct differences between a logistic function and a Gompertz function: the graph of the latter is more skewed to the right; and its inflection point is at one-third of the ceiling compared to the half point for the logistic function (Dixon, 1980). The data seems to suggest that mobile diffusion has a more symmetric pattern. This is further supported by the fact that the majority of countries that were included in the analysis were developed countries. In these countries, it took many years before the market started to expand more rapidly with the introduction of 2G services. Diffusion curves for these countries indeed have long right tails. However, the lengthy left-tails resulted from the many years of slow growth offset them, resulting in an overall more symmetric diffusion pattern.

Numerous studies employing the Bass diffusion model are testimony to its usefulness. Nonetheless, it has inherent methodological weaknesses. As Meade and Islam (2006) pointed out, the number of data points upon which the estimation is based seems to affect the performance of the model, in particular whether estimated parameter values are within the acceptable range. On average, in the countries for which the Bass model yielded acceptable (but not necessarily statistically significant) parameter values, mobile telephony was introduced 18 years ago. In countries where the Bass model did not yield acceptable parameters, mobile services had been available for only 15 years. In the fourteen countries for which the values for the coefficient of external influence are within the acceptable range ($p \leq .1$), diffusion patterns appear to be smooth without any sudden slow down or take off. In other words, mobile diffusion in those countries resembles an ideal S-shaped path compared to other countries where sudden breaks and accelerations are visible.

All data sets contained more developed countries than developing countries. In fact, the number of low income countries was too small to run an independent regression.[41] There are a couple of possible explanations as to why only a small number of low income countries were included in the data sets. First, it may be simply because the diffusion patterns described by the three models do not fit the diffusion pattern of mobile telephony in the low income countries. A future study with an alternative statistical model of diffusion of innovations would be able to answer whether such is the case. Another possibility is that as low income countries introduced later than developed countries, smaller number of data points may have caused estimated parameter values to have large variance. In addition, in many of

[41] It was true even to the data set for the logistic model that had the largest number of countries. In the logistic model data set, there were 32 high-income countries, 6 upper middle income, 9 lower-middle income, and only 2 low-income countries according to the income classification used by the ITU.

countries with a relatively short history of mobile telephony, diffusion may not have reached the inflection point yet. If this is the case, it could be an additional cause of greater variance in parameter values. Those tendencies may have resulted in the inclusion of fewer low-income countries that met the dual threshold of estimated ceiling values that satisfied the conceptual model requirements and the additional selection criterion of confidence intervals whose width was below 50% of the predicted ceiling value. Subsequent studies which can take advantage of more matured mobile markets may be able to include a higher number of low-income countries.

Even though the ceiling values derived from the three diffusion models were highly correlated, there were still differences. These differences indicate that the patterns of diffusion of innovations represented by the models are different. Testing hypotheses for each model separately was, therefore, a plausible approach.

The estimated ceiling values were below 100 (%) in some countries. The BDM and the logistic model predicted that about half of the countries in the data sets would not be able to achieve universal service[42] if past pattern of mobile telephony diffusion remains unchanged. The Gompertz model also predicted that about one third

[42] How we define universal service for mobile telephony is an open question. For main line telephony, which is designed to be used by family, universal service is reached when every *household* subscribes to the service. On the other hand, mobile telephony is a technology developed to be used by an individual. This dissertation assumes that the universal service for mobile telephony is achieved when every *individual* has a subscription.

of the countries in the data set would not reach a saturation level of 100%[43]. The findings suggest that regulatory efforts will be necessary to make universal service a realistic goal in some countries.

The analyses did not reveal any significant relationship between market potential and income inequality. This is compatible with the findings of a previous study (Talukdar et al., 2002) that, in an empirical study of six products, also failed to find evidence of such a relationship. However, a significant effect of income inequality on the rate of acceptance (and its equivalent parameters) was detected in our study. Several factors may explain that the diffusion ceiling is apparently not influenced by inequality. Barrantes and Galperin (2008) reported that the poor in developing countries are willing to spend considerably more on mobile than their counterparts in developed countries. The higher propensity to spend for mobile service may compensate the (ceteris paribus) reduction of demand caused by lower income. In addition, innovations such as low-cost hand sets and prepaid plans have lowered the cost of mobile service significantly. Prepaid plans are not cheaper than postpaid plans but have lower or no fixed costs and provide users with more control over variable expenses. Therefore, they allow financially constrained customers to purchase mobile service (Samarajiva, 2006; Barrantes & Galperin, 2008). Even

[43] Certain customers may elect not to purchase mobile service even though they can afford to do so simply because they do not want to. Thus, universal service may be achieved at below 100% penetration. On the other hand, since the ITU reports the number of subscribers than users, 100% penetration may not mean every individual subscribes to a mobile service.

though the expense for a mobile service may take a large share of subscribers' income in developing countries, our findings seem to suggest that the cost may have been reduced sufficiently to neutralize any effect of income inequality on expected saturation levels.

Another possibility is that higher consumption by the rich may compensate for lower consumption by poor people. Traditional diffusion models study the initial, first adoption decision in favor of a new product. This is a unavoidable limitation since if repetitive purchase were to be included the model, it would cease to be a model of diffusion of innovations but become a demand model for a product, which could follow any shape. However, it is not uncommon for some users to have more than one subscription, especially in developed countries. It may be possible that in some of the countries rich individual's tendency to own multiple subscriptions makes up for the lower demand due to the inability to pay of the poor segments of the population. There is no available information, however, to verify this hypothesis. Due to the fact that mobile penetration data report the number of subscribers rather than the number of owners, multiple subscriptions of a single person cannot be distinguished from single subscriptions of as many persons.

One could interpret the current data format of mobile penetration to contain two different innovations – mobile telephone service for business and that for private use. In fact, diffusion of innovations research has investigated business fixed telephone service and residential fixed telephone service separately (i.e., Islam & Meade, 1996). Cellular service for business use and that for private use can be regarded as two different innovations in that they are purchased and used for different purposes. In addition, different factors would influence adoption: for business phones, it would depend on the type of business, available budget, company policy towards telecommunications services and so on. Some of factors in this dissertation many not influence the adoption of business mobile telephone service. However, there is no available cross-national data that distinguishes two types of usage.

A third possibility is that the relationship between market potential and income inequality is more complicated than captured in the analysis. First, income inequality may work differently depending on the level of development. Some studies (Senauer, 1990; Park et al., 1996; Iyigun & Owen; 2004) found differences in the relationships between income inequality and consumption in developing and developed countries. If the effect of income inequality is less pronounced in developed countries, the fact that the data set is skewed towards developed countries may have weakened the effect. Unfortunately, the number of low income countries in the data set was too small to run independent regressions on subsets of countries. A future study with a sufficient number of developing countries in the data set may be able to provide an answer.

In addition, there is a possibility that the relationship between the two may not be linear. Wei (2001) reported from surveys on mobile non-adopters conducted two years apart that income had become less influential as the market approached saturation. Thus, it is possible that the relationship may differ depending on the maturity of the mobile market. Secondly, the relationship may be indirect. Income inequality may have an influence on market potential not identified by the one-step regression model in this dissertation. A path model might be an alternative specification to explore such indirect influences. This dissertation did not investigate the question further because it would have required a different theoretical and methodological approach, which would have made another dissertation.

Price for mobile service had a statistically significant influence on the ceiling values. Some customers choose not to subscribe to the service because the price was too high compared to their income and purchasing power. Even though mobile service price is likely to continue to drop, so far it apparently has been too expensive for some potential adopters. The significance of the effects of price as well as that of income reaffirms that the decision to purchase mobile service depends on the income level and the cost of the service compared to income.

Another finding is a negative relationship between mainline penetration and market potential. The outcome suggests that in the set of countries that were included in the analysis mobile telephony is a substitute to fixed line service. A previous study by Mariscal and Rivera (2006) found that in *developing* countries mobile telephony is mainly adopted as a substitute for mainline telephony. The finding in the dissertation is compatible with Young's (1993) econometric model as well as Sawhney's infrastructure development model (2003) in which a new product functions as a complement in the early stage of adoption and gradually becomes a substitute as the market matures.[44] The cellular markets in developing countries may not have matured yet, but the relationship between the mobile and the fixed line telephony was mainly substitutes even at the early stages of diffusion in developing countries. Before the introduction of mobile telephony, many developing countries, especially poorer ones, had a large pool of unmet demand for telephone service that either mobile or fixed voice service could satisfy. In this situation, fixed and mobile telephony compete for a new subscriber from the very introduction of cellular service, making cellular service a substitute to fixed line.

The level of urbanization had a significant positive effect on market potential in both the Gompertz and logistic models, while population density did not. In addition, the analysis with the absolute price using the BDM produced ceiling values

[44] However, Sawhney saw the relationship between mainline and mobile telephony as an exception and predicted that they would coexist in complementary relationship.

also found a significant effect of urbanization on market potential. Economies of density were one of the reasons why the two variables were hypothesized to affect the ceiling values. The insignificant association between population density and the ceiling value may imply that the reason why higher levels of urbanization increase the ceiling values may not be related to cost effectiveness.[45] In addition, neither variable had a statistically significant effect on the rate of acceptance. The rate of acceptance in an epidemic model is related to the chance of social interaction between adopters and potential adopters, through which information is transferred and social pressure is exercised. A higher rate of acceptance can be interpreted as either greater chance of the interaction or greater effectiveness of the interaction, or both. Greater social pressure would positively affect market potential because it would increase the chance of adoption of a potential adopter who is financially capable of the purchase but would chose not to otherwise.

The finding that neither population density nor the level of urbanization is significantly related to the rate of acceptance seems to suggest that the increased market potential is not due to greater social pressure either. A possible answer is that the urban population may have a higher preference for mobile communication due to

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[45] It is still possible that level of urbanization is significantly related to market potential due to economies of density. A country may have a high level of urbanization but relatively low population density. In such a case, mobile service providers can still benefit from economies of density at least in the urban areas where the majority of the population is. The findings only suggest that the significance of level of urbanization is less likely because of economies of density but do not eliminate the possibility.

their mobile life style. Also it may be because there are more people in urban areas who are likely to have favorable attitudes towards an innovation because of higher education, wealth, and social status.

One interesting observation was that estimates for Eastern European countries, including countries that once belonged to the former Soviet Union, revealed relatively high ceiling values compared to the countries with similar levels of economic development in other regions. The average ceiling value estimated from the logistic model for those (seven) countries was 108.8 % (of the population) while the average for the entire data set was only 93.3 %. This observation may be another indication that low availability of fixed line telephone service increases the market potential for cellular service. Gruber (2001) found that long waitlists for mainline telephone service - in other words: the inability of the incumbent telecommunications carrier to meet effective demand - was one of the reasons for the fast growth of mobile subscriptions in Eastern Europe. In addition, competition contributed to faster market expansion.

The negative association between income inequality and the rate of acceptance suggested by theoretical considerations was found in both the logistic and Gompertz models. The effect may be due to economic and socio-cultural reasons. In a society with very unequal income distribution, there will be more people whose threshold prices are relatively low. At any given price level there will be fewer subscribers compared to a more egalitarian society. If the price decreases at similar speeds across countries, it would take more time for a society with high income inequality to reach a certain level of subscribers than for a country with low income inequality. On the other hand, high income inequality, usually coupled with other types of inequality, may be one of the underlying causes of tensions and conflicts between social groups that disrupt economic development and communication among the groups. This in turn negatively affects growth of the mobile market and the flow of information about the new product.

Introductory delay was positively related to the rate of growth. This corroborates findings of previous studies (Gruber & Verboven, 2001a; 2001b) that late-starter countries catch up with early adopters – not in terms of the saturation level but in terms of the time it takes for the market to become saturated. The authors suggested that learning from the experience of other countries reduces uncertainty for both investors and customers and consequently increases the chance of adoption. Another benefit of later introduction of the service is that the risk of technological flaws will likely be reduced. Takada and Jain (1991) reported a similar tendency on a study of diffusion of general consumer durables such as car, TV, and washing machine.

Gender inequality exhibited a significant effect on market potential in the

BDM and Gompertz models. Though it was not statistically significant, gender inequality also had the expected effect in the logistic model. More active participation in economic activity means that more women have independent income sources, hence more freedom to purchase products for their needs. In addition, working women may have a higher demand for cellular service than housewives. However, gender inequality was positively associated with the rate of acceptance in the Gompertz and the logistic models. Thus, the findings suggest that a higher ratio of females in labor force increases the saturation level but slows down the adoption. It may be the case that a higher ratio of female in labor force increases purchasing power of households so that potential demand increases. However, the increased income may not result in faster adoption, which agrees to the insignificance effect of GDP per capita on the rate of acceptance in this dissertation. Access at the workplace to phone service may explain why increased female participation in the labor force does not result in faster adoption of cellular service. On the other hand, it is possible that the findings are simply statistical artifacts or due to an unidentified relationship between the ratio of female in labor force and other measures of independent variable. Subsequent research may be able to shed more light on that issue.

Socio-cultural fractionalization produced few statistically significant results. Exceptions were religious fractionalization in the regression explaining the rate of acceptance derived from the logistic model, and linguistic fractionalization in the regression explaining the ceiling value gained from the BDM model. There are two possible interpretations of the overall insignificance of the fractionalization measure. First, it may simply be because the degree of fractionalization does not have a direct effect on the diffusion of mobile telephony. Second, increased chances of social tension and conflict may not necessarily result in a significant negative effect on the economy. The fractionalization measures are not identical with inequality measures, as was elaborated earlier. Fractionalization only increases the chance of socio-cultural inequality. This dissertation theorized that high inequality may be harmful for the growth of mobile market because (1) it may cause social tension and conflicts; which (2) in turn may be detrimental to the economy; and (3) interrupt the flow of information between social groups. Our observations suggest that even though high inequality in a society may increase social tensions, it may not reach a level that will significantly affect economic processes in mobile markets.

7. Concluding Remarks

7.1. Implications

This dissertation developed a theoretical model building on and expanding an approach used by Talukdar et. al. (2002). A major modification was to shift the focus from an individual's characteristics and capabilities to socio-economic elements. The shift enabled the inclusion of economic factors that influence supply conditions as well as socio-cultural factors, both of which are not easily fit into an individual-based theoretical model. The findings suggest that supply conditions are as important as demand factors in understanding the diffusion of mobile telephony.

With regard to the diffusion literature the findings of this paper suggest that a deeper understanding of the diffusion of innovations in mobile service requires considering both service providers' abilities to create and meet the demand as well as consumers' ability to pay. This dissertation provided some evidence that income inequality affects mobile telephony diffusion. It also provided additional empirical evidence of the effects of variables, such as fixed line penetration, that have been tested in previous studies.

The dependent variables examined in the dissertation reflect two important aspects of universal service. The market potential is directly related to the question of whether universal service is a feasible goal if the market is left to itself. The rate of acceptance is related to how fast universal service will be achieved (if at all). The variables that had a significant influence on the ceiling are income (all three models), price, level of urbanization (logistic model and the Gompertz model), gender inequality (Gompertz and BDM), fixed line penetration (logistic only), and investment (BDM only). It was income inequality, introductory delay (logistic model and the Gompertz model), and gender inequality (Gompertz model only) for the rate of acceptance. For policy makers, the significance of the price variable on market potential suggests that they should target their regulatory efforts towards provision of inexpensive calling plans in order to achieve universal access. For businesses the findings in the dissertation provide insight into additional factors to be considered in a market forecasts, such as how active the female population is in the economy.

7.2. Limitations and Questions for Future Study

One potential limitation of the methodological approach employed in this dissertation is that the values of the dependent variables had to be estimated, which means the reliability of findings in the dissertation depends on the accuracy of estimated parameter values. In addition, the estimated values of the market potential had relatively wide confidence intervals in many cases. An alternative is to assume that a group of countries has identical market potentials, which contradicts the empirical evidence found in this dissertation. Another alternative is to determine the ceiling values outside of the diffusion model although no straightforward methods exist to do so.

It may be interesting to explore the applicability of a 'critical mass' phenomenon in the context of mobile telephony in more detail. Mahler and Rogers (1999) and Rogers (2003) indicated that the diffusion of an interactive medium generally requires more time before reaching critical mass compared to other new products. Once the critical mass is reached, it tends to a show faster rate of diffusion, resulting in a steeper S-shaped pattern. Lim et al. (2003) reported that the late take-off of interactive media diffusion is because potential adopters have a relatively homogenous threshold value. However, whether such a tendency can be applied to mobile telephony is unclear. Mahler and Rogers (1999) and Rogers (2003), for example, argued that mobile telephony has an advantage of already reached critical mass because there is already established fixed line customer base. If their argument were true, mobile telephony should require less time reaching critical mass, showing relatively faster rate of diffusion at early stage of diffusion, compared to other interactive media. A future study that compares diffusion patterns of mobile telephony to those of other interactive media may be able to provide an answer to this open question.

Because countries were included in the data sets only if they showed mobile diffusion patterns that could be explained with one of the three statistical diffusion models, the data sets are not random drawings from the population. The data sets contained more developed countries than developing countries, resulting in higher average GDP per capita, fixed line penetration, and years of adoption. There were not enough developing countries to run independent regressions on a subset representing only low income nations. This prevented testing whether income inequality had different effects dependent on the level of economic development. A future study may be able to work with a broader data set once the diffusion of mobile telephony in developing countries reaches a more mature stage and better data is available.

The dissertation has limitations in allowing the generalization of the findings to all countries. The inclusion of countries in the data sets largely relied on parameter estimation. A country was not included in a data set when estimated parameters had a very wide confidence interval, was insignificant, or was out of acceptable value range. Such results mean that the particular model may not be a good representation of mobile diffusion pattern in that country.[46] It further means that findings from the regression analyses with the data set are not applicable to a country of which data the

[46] A more definite judgment will have to wait until there is sufficient data because model may have not appeared to fit the data well due to small number of data points that may have caused greater variances parameter values.

particular model did not fit. The result from each regression analysis should be considered as applicable only to the countries in corresponding data set and cannot be generalized to the countries that were left out from the data set.

In terms of the relationship between income inequality and demand, this dissertation provides additional insights to the literature. We hypothesized a direct relationship between income inequality and the diffusion of mobile telephony diffusion. At this point in time, there is no theoretical and empirical information available that would suggest a different relation. Thus, the dissertation can be seen as a first step in exploring the phenomenon and future studies could expand the analysis to investigate additional channels of influence.

Income inequality was measured by the Gini coefficient. The Gini coefficient is not the only metric for income inequality nor is it free of limitations. As any constructed measure, it necessarily relies on assumptions and has limitations. This dissertation used the Gini coefficient because it is most widely available. Future studies may try to employ alternative specifications of income inequality,

This study also included socio-cultural inequality under the assumptions that: (1) diffusion of mobile telephony is a social as well as economic phenomenon influenced not only by economic factors but also by socio-cultural factor would have influences; (2) high income inequality usually accompanies other types of inequality, compounding the effect of each other. This paper is one of the few studies that have attempted to include socio-cultural inequality. Future studies of the relationship between socio-cultural inequality and diffusion of mobile telephony could refine the current approach. The related hypotheses were built on assumptions that were not empirically tested. In addition, fractionalization measure may not have been the best measure to represent socio-cultural inequality. A "right" measure for socio-cultural inequality is difficult to find. A previous study (Dekimpe et al., 1998) used the crude death rate as the indicator, which may capture some of the phenomenon but is closer to a national health care measure. As an alternative, this dissertation used a fractionalization measure. Fractionalization is not identical with socio-cultural inequality but is one of the strongest causes of the phenomenon. In addition, it was a measure that led to the largest number of countries in the data set. There are other alternatives such as HDI (Human Development Index), GDI (Gender Development index) that have been reported by the United Nations Development Program (UNDP) in the annual *Human Development Report*. They are also not free from problems in that GDP per capita is one of the components of the indices and data is missing for many countries. Future studies may therefore attempt to use alternative socio-cultural inequality measures.

This dissertation focused on investigation of the effect of socio-economic factors on the diffusion of mobile telephony. Another avenue for future studies may be to include an explicit feedback effect from mobile telephone diffusion to socio-economic factors. Future research on the effect of the mobile telephony industry not only on economic development but also on other socio-cultural factors would also contribute to a better understanding of mobile telephony diffusion. In addition, such research will be able to provide a better understanding of the benefits that mobile telephony can bring to people in need.

The approach this dissertation employed is only one of several possible ways to investigate mobile telephony diffusion. Statistical research necessarily abstracts from the fine-grained historical contexts or unique socio-cultural environments in which an innovation is embedded and the implications of these factors on the diffusion process. It only gives a higher-level understanding of how mobile telephony is actually being adopted and used in poorer countries, though there are scattered evidence that suggest the pattern may be different from that in developed countries. Arnould (1989) suggested that a novel consumer good of Western origin goes through a process of reordering, reconstruction and resignifying in the process of adoption in materially deprived society. Research using different approaches, for example in-depth case studies or ethnographic studies, may be able to provide complementary understanding.

The dissertation investigated diffusion of mobile telephony, which has shown a remarkably fast market expansion, especially in developing countries. Contrary to optimistic expectations, the findings suggest that universal service through mobile telephony may not be a realistic goal in some countries if mobile telephony continues to follow the diffusion patterns exhibited so far. It means that government intervention may be necessary in those countries. The findings also suggest that in order to achieve universal service sooner, regulatory efforts to provide inexpensive calling plans to the poor might be useful.

Appendix I. Estimated ceilings and rates of acceptance

Country	Logistic		BDM		Gompertz	
	Market potential	Rate of acceptance	Market potential	Coef. of internal Inf.	Market potential	Rate of acceptance
Algeria	73.38	1.56			69.46	1.03
Australia	116.51	0.34	121.68	0.31		
Austria	103.68	0.71			109.75	0.42
Belarus	88.03	0.93	88.60	0.93	111.43	0.49
Belgium	89.95	0.90			91.63	0.54
Bosnia	49.46	0.81				
Canada	71.33	0.30	83.02	0.25		
Chile	82.78	0.53	92.22	0.45	94.72	0.29
China	39.65	0.56	46.11	0.46	49.13	0.29
Cyprus	123.86	0.42	115.54	0.47		
Czech Republic	115.91	0.81	114.94	0.83	117.87	0.52
Denmark	112.67	0.41	113.93	0.40	130.54	0.21
Estonia	154.97	0.43				
Finland	107.10	0.41	110.19	0.39	124.07	0.21
France	79.68	0.72	75.63	0.81	83.34	0.44
Germany	98.84	0.63			105.46	0.38
Greece	91.07	0.87			93.76	0.53
Hong Kong	133.72	0.45	144.50	0.39	148.08	0.25
Hungary	99.75	0.71	95.66	0.78	106.82	0.40
Iceland	106.13	0.60	89.58	0.90	115.79	0.30
Indonesia	54.09	0.58				
Ireland	106.83	0.59	105.06	0.63	114.52	0.36
Israel	120.20	0.52	127.83	0.46	132.14	0.30
Italy	129.35	0.53	147.61	0.42	146.74	0.30
Jamaica	93.86	0.71				
Japan	76.89	0.50	83.52	0.42	82.00	0.30
Korea, Rep.	77.58	0.74			79.71	0.48
Latvia	119.85	0.51	134.81	0.44	165.53	0.24
Luxembourg	162.39	0.54	165.52	0.52	167.13	0.34
Macedonia	76.20	0.82				
Maldives			88.42	0.94		
Malta	79.91	1.31			82.45	0.65
Mauritius	74.20	0.48	89.53	0.38		

Country	Logistic		BDM		Gompertz	
	Market potential	Rate of acceptance	Market potential	Coef. of internal Inf.	Market potential	Rate of acceptance
Netherlands	97.35	0.71			102.63	0.44
New Zealand	98.24	0.41				
Nigeria	41.07	0.97	45.49	0.90		
Norway	112.78	0.38	117.12	0.35	132.06	0.19
Philippines	58.63	0.58				
Portugal	111.54	0.70	117.49	0.55	117.72	0.38
Russia	127.18	0.99			138.39	0.56
Singapore	108.85	0.50				
Slovak Republic	92.89	0.71	94.81	0.68	98.32	0.41
Slovenia	90.30	1.21			90.26	0.76
Spain	100.27	0.73	88.64	0.96	105.27	0.44
Sweden	111.34	0.40	107.20	0.43	123.72	0.21
Switzerland	93.29	0.68			100.78	0.37
Tajikistan	5.74	1.41			6.00	0.88
Tunisia	74.78	1.10				
UK	114.21	0.55			125.09	0.31
United States	97.88	0.29	118.96	0.23		
Uzbekistan			3.49	0.87		
Viet Nam			28.20	0.99		

Appendix II. Mobile penetration (subscriptions/100 habitants)

Year	1980	1985	1990	1995	2000	2005
Algeria	0	0	0.0019	0.0167	0.2827	41.5163
Australia	0	0	1.0838	12.4121	44.7022	91.3917
Austria	0	0.1290	0.9599	4.8254	76.3521	105.8143
Belarus	0	0	0	0.0575	0.4921	42.0241
Belgium	0	0	0.4302	2.3246	54.8453	89.9977
Bosnia/Herzegovina	0	0	0	0	2.4699	40.8080
Canada	0	0.0463	2.1561	8.8098	28.3459	52.5098
Chile	0	0	0.1063	1.3822	22.3623	67.7884
China	0	0	0.0016	0.2976	6.6924	29.8976
Cyprus	0	0	0.5376	7.0672	32.1538	93.7129
Czech Republic	0	0	0	0.4731	42.3052	115.2239
Denmark	0	0.9014	2.8862	15.7285	63.1058	100.3428
Estonia	0	0	0	2.0521	38.7021	108.7509
Finland	0.4913	1.3798	5.1595	20.0720	72.0368	100.4001
France	0	0	0.4994	2.2517	49.3308	79.4896
Germany	0	0.0018	0.3769	4.5528	58.5975	95.8664
Greece	0	0	0	2.6124	56.1515	92.2697
Hongkong	0	0.0806	2.4358	12.9688	81.7306	123.4678
Hungary	0	0	0.0255	2.5864	30.1685	92.2955
Iceland	0	0	3.9146	11.5319	76.4754	103.4017
Indonesia	0	0.0012	0.0101	0.1082	1.7789	21.0564
Ireland	0	0.0085	0.7137	4.3819	64.9872	102.9412
Israel	0	0	0.3216	7.9277	70.1799	112.4203
Italy	0	0.0112	0.4613	6.8425	73.7303	123.0785
Jamaica	0	0	0	1.8070	14.1298	74.7440
Japan	0	0.0511	0.7023	9.3272	52.6193	75.3287
Korea (Rep. of)	0	0	0.1844	3.6839	58.3152	79.3933
Latvia	0	0	0	0.5931	16.5541	81.1271
Luxembourg	0	0.0109	0.2158	6.5506	69.1617	154.8280
Maldives	0	0	0	0	2.8278	66.7508
Malta	0	0	0	2.8998	29.3446	80.7930
Mauritius	0	0	0.2078	1.0458	15.0809	52.7573
Netherlands	0	0.0331	0.5284	3.4788	67.2731	97.1471
New Zealand	0	0	1.5969	9.9363	39.9710	87.6148
Nigeria	0	0	0	0.0126	0.0263	14.1315
Norway	0	1.5188	4.6323	22.4555	71.5898	102.9041

Year	1980	1985	1990	1995	2000	2005
Philippines	0	0	0	0.7197	8.4372	41.2980
Portugal	0	0	0.0663	3.4357	66.4952	109.0844
Russia	0	0	0	0.0597	2.2265	83.6237
Singapore	0	0	1.6976	8.6794	68.3824	100.7630
Slovak Republic	0	0	0	0.2295	23.0236	84.0654
Slovenia	0	0	0	1.3736	61.0855	89.4373
Spain	0	0	0.1371	2.4100	59.9140	100.0054
Sweden	0	0.8743	5.3686	22.7214	71.7558	100.6968
Switzerland	0	0	1.8202	6.3541	64.3434	91.6228
T.F.Y.R. Macedonia	0	0	0	0	5.7600	62.0104
Tunisia	0	0	0.0117	0.0356	1.2460	56.3229
United Kingdom	0	0.0883	1.9354	9.7860	72.7035	109.7266
United States	0	0.1427	2.1242	12.6881	38.9019	71.4966
Uzbekistan	0	0	0	0.0164	0.2155	2.7075
Viet Nam	0	0	0	0.0321	1.0023	11.3882

Appendix III. Correlation tables

Table III-1. Correlations coefficients (Logistic model – market potential) *n*=49

	Ceiling	Gini	GDP	Fixed	Urban	Invest	Gender	Pop. Den.	Price	Ethnicity	Language	Religion
Ceiling	1.000											
Gini	-.205*	1.000										
GDP	.595***	-.370***	1.000									
Fixed	.528***	-.446***	.899***	1.000								
Urban	.629***	-.118	.642***	.673***	1.000							
Invest	-.291**	.193*	-.510***	-.493***	-.429***	1.000						
Gender	.234*	-.346***	.144	.258**	.021	.078	1.000					
Pop. Den.	.006	.114	.003	-.043	.079	.214*	-.241**	1.000				
Price	-.700***	.126	-.517***	-.535***	-.531***	.346***	-.211*	.124	1.000			
Ethnicity	-.277**	.221*	-.248**	-.329**	-.278**	.160	.083	-.082	.401***	1.000		
Language	-.240*	.180	-.252**	-.330***	-.232*	.218*	-.008	.010	.389***	.796***	1.000	
Religion	-.103	.032	-.036	.051	-.016	.203*	.425***	.080	.144	.301**	.190*	1.000

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Table III-2. Correlations coefficients (Logistic model – rate of acceptance) *n*=49

	Rate of Accept.	GDP	Fixed	Urban	Gini	Gender	Media	Delay	Competition	Pop. Den.	Open. Econ.	Ethnicity	Language	Religion	Price
Rate of Accept.	1.000														
GDP	-.462***	1.000													
Fixed	-.494***	.899***	1.000												
Urban	-.339***	.642***	.673***	1.000											
Gini	-.006	-.370***	-.446***	-.118	1.000										
Gender	-.389***	.144	.258**	.021	-.346***	1.000									
Media	-.229*	.689***	.716***	.734***	-.379***	.152	1.000								
Delay	.568***	-.662***	-.647***	-.405***	.230*	-.029	-.379***	1.000							
Competition	-.234*	.073	.103	.051	.184	.165	-.020	-.224*	1.000						
Pop. Den.	.071	.003	-.043	.079	.114	-.241	-.117	.017	-.032	1.000					
Open. Econ.	.162	-.011	-.097	.194*	-.065	-.046	.086	.273**	-.318**	.470	1.000				
Ethnicity	.071	-.248**	-.329**	-.278**	.221	.083*	-.456***	.410***	.125	-.082***	.140	1.000			
Language	.075	-.252**	-.330**	-.232*	.180	-.008	-.487***	.387***	.170	.010	.240**	.796***	1.000		
Religion	-.335***	-.063	.020	.010	.120	.393	-.053	.150	.175	.056	-.146	.297**	.180	1.000	
Price	.422***	-.517***	-.535***	-.531***	.126	-.211	-.584***	.475***	-.103	.124	.071	.401***	.389***	.162	1.000

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Table III-3. Correlations coefficients (Bass diffusion model – market potential) *n*=30

	Ceiling	Gini	Urban	Fixed	GDP	Invest	Gender	Ethnicity	Language	Religion	Pop. Den.	Price
Ceiling	1.000											
Gini	-.171	1.000										
Urban	.691***	-.217	1.000									
Fixed	.587***	-.431***	.753***	1.000								
GDP	.659***	-.387**	.695***	.888***	1.000							
Invest	-.081	.220	-.417**	-.607***	-.564***	1.000						
Gender	.337**	-.519***	.357**	.463***	.343**	-.108	1.000					
Ethnicity	-.190	.286*	-.304*	-.344**	-.261*	.264*	-.125***	1.000				
Language	-.063	.244*	-.171	-.285*	-.235	.241	-.171***	.877**	1.000			
Religion	-.226	.245*	-.231	-.321**	-.373**	.387**	.125	.458	.384**	1.000		
Pop. Den.	.164***	.097*	-.052	-.179	-.123	.189	-.186***	-.205**	-.149	-.118	1.000	
Price	-.609	.261	-.709***	-.790***	-.688***	.430***	-.203	.453	.412**	.473***	.015	1.000

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Table III-4. Correlation coefficients (Gompertz model – market potential) *n*=34

	Ceiling	Gini Coef.	GDP	Fixedline	Urbanization	Investment	Gender	Ethnicity	Language	Religion	Pop. Den.	Price
Ceiling	1.000											
Gini Coef.	-.081	1.000										
GDP/capita	.509***	-.330**	1.000									
Fixedline	.436***	-.390**	.852***	1.000								
Urbanization	.549***	-.030	.484***	.559***	1.000							
Investment	-.210	-.036	-.377***	-.354***	-.342**	1.000						
Gender	.236*	-.358**	.002	.126	-.126	.148	1.000					
Ethnicity	.000	.078	-.092	-.283*	-.080	.107	.039	1.000				
Language	.052	.069	-.009	-.167	.046	-.058	.008	.873***	1.000			
Religion	-.087	-.009	-.221	-.117	-.072	.372**	.393**	.022	.069	1.000		
Pop. Den.	.012	.058	.171	.207	.245*	.188	-.243	-.112	.007	.306	1.000	
Price	-.654***	-.007	-.422***	-.469***	-.419***	.363**	-.198	.238*	.213	.170	.181	1.000

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

Table III-5. Correlation coefficients (Gompertz – rate of acceptance) *n*=34

	Rate of Accept.	GDP	Fixed	Urbanization	Gini	Gender	Media	Intro. Delay	Open. Econ.	Competition	Pop. Den.	Ethnicity	Language	Religion	Price
Rate of Accept.	1.000														
GDP	-.451***	1.000													
Fixed	-.526***	.852***	1.000												
Urbanization	-.369**	.484***	.559***	1.000											
Gini	.011	-.330**	-.390***	-.030	1.000										
Gender	-.387**	.002	.126	-.126	-.358**	1.000									
Media	-.292**	.609***	.606***	.699***	-.375**	.100	1.000								
Intro. Delay	.640***	-.668***	-.699***	-.364**	.173	-.051	-.335**	1.000							
Open. Econ.	.073	.196	.052	.312**	-.066	-.118	.364**	.122	1.000						
Competition	-.138	.011	.066	.080	.272*	.251*	.172	-.128	-.086	1.000					
Pop. Den.	-.071	.171	.207	.245*	.058	-.243*	.106	-.089	.467***	.137	1.000				
Ethnicity	.299**	-.092	-.283*	-.080	.078	.039	-.117	.462***	.220	-.121	-.112	1.000			
Language	.269*	-.009	-.167	.046	.069	.008	-.058	.341**	.348**	-.061	.007	.873***	1.000		
Religion	-.199	-.221	-.117	-.072	-.009	.393**	-.055	.063	-.160	.294**	.306**	.022	.069	1.000	
Price	.435***	-.422***	-.469***	-.419***	-.007	-.198	-.412***	.417***	.150	-.228*	.181	.238*	.213	.170	1.000

* significant at 0.1 level, ** significant at 0.05 level, *** significant at 0.01 level

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