The effect of inequality on technology diffusion

Non-homothetic preferences and the demand for consumer goods

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Abstract

This thesis investigates how income inequality as a determinant of consumer demand influences the diffusion of technology. In this analysis technology is related to special consumer goods that either contain a certain technology or are an output measure of technology. Based on a model of non-homothetic preferences income inequality is expected to increase technology diffusion at low levels of average income and slow it down at higher levels of income. An empirical analysis on a panel of 18 consumer goods, using the Gini index as measure of income inequality brings forth preliminary results that support the model implications. Analyses of single technologies suggest that diffusion dynamics are different for more modern technologies. An additional attempt made to analyze the effect of income inequality on national technology adoption fails to return meaningful results.

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1 Introduction

Technological development has been emphasized in economic theory as one of the main drivers to long-run economic growth. Classic models such as the Solow model feature technological improvements as a main driver of growth and a determinant of differences in income per capita across countries. Empirical evidence support the theoretical assumption that there is a strong relation between economic development and technology. Klenow and Rodriguez-Clare (1997) as an example provide a review of neoclassical growth theory in which they show that there is a high correlation between total factor productivity (TFP) and GDP per worker. The national differences in TFP come from different levels of technology usage. There are two measures of technology usage in which countries differ: First there are differences in the actual adoption, meaning whether a country uses a certain technology or not; and second, once adoption has taken place there are differences in the intensity with which the respective technology is used.

If a new technology is associated with an increase in productivity and economic growth, to not make full use of this technology will cause for countries to suffer a slow-down in development relative to other countries that fully adopt. As the usage of this technology would lead to higher output production and improvement in welfare the fact that some countries do not adopt it must be related to obstacles hindering them. This question why countries adopt technologies at different points in time and use them with different intensity has been studied with increasing interest by scholars. Economic studies usually relate these differences in technology adoption to characteristics of the production side of an economy. Only little research so far has considered consumer demand as a determinant of national technology usage. This analysis intends to further explore the role of consumer demand on diffusion of technologies. The specific focus lies on the influence of unequal distribution of income on national consumption of technology that relates to consumer goods. To approach the topic of technology diffusion through consumer demand is not common in economic research. Income and consumption demand is typically analyzed as a result of rather than a cause to technological development. Especially in the 1980s and 1990s when a number of industrialized countries saw hikes in income inequality many scholars related this to changes in factor prices that result from technology advances. Skill-biased technologies reduced labor intensity of production and relayed more on physical capital or high-skilled human capital[1]. This shift that enhanced returns on physical capital and highly educated individuals was

[1] For more detail on skill-biased technical change see e.g. Acemoglu (2002).

further augmented by the outsourcing of labor intensive productions to low income countries. In this context technological change is considered a cause to changes in income and income distribution. But there is increasing evidence that consumer income and demand should also be studied as a determinant of technology diffusion.

At the latest the rise of modern information and communication technologies (ICTs) such as computers, mobile phones and the internet made it obvious though that technology usage is a topic not limited to the corporate sector of the economy. The contribution of consumer demand to technology diffusion has so far been largely neglected in economic research. It is the aim of this paper to provide empirical evidence of the importance of the topic. How consumer demand drives the diffusion of consumer technologies is examined with a specific focus on the effect of income structures and inequality. This influence of income inequality on consumer demand for technology goods is assumed to be non-linear in this study, based on the theory of non-homothetic preferences. To better understand the effect of unequal distribution of income is of special interest for the case of developing countries which lag behind in technology use. Whether and to what extent national income structures may have part in this technological drawback could matter for better orientation of development initiatives.

The paper is build up as follows: in the next section a short overview over literature on technology diffusion is given. The theoretical assumptions to technology diffusion are discussed in section three, including the development of a simple model that introduces income distribution as a determining factor to the diffusion process. Section four provides a detailed statistical overview over the data used. In section five the empirical approach and regression results are discussed and the final section concludes the paper.

2 Literature overview

As the use of technologies is fundamental to a countries production process the diffusion of technologies across and within countries is typically related to the production side of the economy. Accordingly it is mainly industrial demand but also industrial capacity that are studied as drivers of technology diffusion. A range of studies have been carried out on economies lagging behind in use of available technologies, and what are the reasons to this. Most studies thereby focus on geographic data, openness to trade, endowment of human and physical capital, and political institutions in a country as determining factors. These characteristics have been identified to be the most important determinants to the adoption of technologies in countries (Comin and Hobijn, 2003). The effect of these determinants is outlined in a short review of research on each of the factors.

The literature of technology diffusion across countries or regions builds on an early study of technology diffusion that was published by Griliches in 1957. In his study Griliches related the use of advanced hybrid seeds in different states of the United States to the respective local conditions and geography. Also Comin, Dimitriev and Rossi-Hansberg (2012) look at the effect of geographical distance between countries on the diffusion of technology among them. They find that increasing distance between nations and the technology leading countries slows down the speed of diffusion and thereby delays adoption. In their research on adoption timing, Dekimpe et al. (2000) include geographical measures. They provide evidence for a demonstration effect, according to which a country adopts a new technology the sooner the more other economies have already done so. Geographical measures have also been shown to play a role for trade between countries[2]. This closely relates these studies that examine the effect of distance on technology diffusion to the strand of research that focuses on the influence of trade. Many studies include openness to trade as a control variable to technology diffusion. Studies from Grossman and Helpman (1991) provide more detail on the actual effect of trade on technology diffusion. The focus of their research is on R&D spillovers induced through trade. Although R&D spillovers are related to innovation which is a distinctly different process from technology adoption such spillovers are also considered to be a driver of the latter.

Another approach in technology diffusion research focuses on the appropriateness of new technologies for adopting countries. These studies pursue the idea, that technology, which is typically developed in more advanced nations is not applied in less developed economies because it is inappropriate to the state of development or factor endowments of these economies. Basu and Weil (1998) introduce a model of appropriate technology. In their model, new technologies can only be implemented successfully in countries with the appropriate portfolio of endowments. The empirical evidence supports the inclusion of factor endowments as determinants of technology diffusion. Jovanovic (1998) and Hobijn (2001) also use theoretical models in which factor endowments, specifically human capital is crucial to technology diffusion. In these models factor endowment in terms of human and physical capital complements technology and thereby influences the technologies marginal value by increasing or decreasing it. In that model, a country with relatively higher factor endowments

[2] See Feenstra, R. C. (2002). Border effects and the gravity equation: consistent methods for estimation. *Scottish Journal of Political Economy*, 49(5), 491-506.

than others adopts new technologies first. Specifically for more recent technological innovation human capital and skills have become a major focus of research. The idea that missing human capital works as a barrier to skill-biased technology adoption in developing nations has been analyzed by Caselli and Coleman (2001) for computers and by Lee (2001) for ICTs, cable TVs and telephone lines. Human capital, measured as higher levels of education is found to have a significant impact on the diffusion of computer technologies that is robust to control for a number of other economic characteristics.

Another factor that is often considered a barrier to the diffusion of new technologies are political or institutional structures. While appropriate institutional settings may even work as a pull-force to technology diffusion, inappropriate or corrupted institutions may act as a barrier. Parente and Prescott (1994, 2000) focus their research on the technology adoption decision taken by firms and the barriers to such adoption that are often placed in the path of entrepreneurs. These barriers take different forms such as regulatory and legal constraints. Whatever their form, each has the effect of increasing the cost of technology adoption. The analysis shows how differences in policies across countries that constrain the individual production units map into differences in relative TFP. They also find that barrier differences need not to be large to account for the observed differences in international incomes. A study by the World Bank further combines the question of institutional structures with factor endowment, arguing that developing countries face regulatory impediments in resource allocation to complement new technologies. This inability to deploy resources to their effective use slows down technology adoption and economic growth (Bergoeing, Loayza and Piguillem, 2010).

While these papers that base on macroeconomic theory focus on technology adoption by countries, research in microeconomics has studied diffusion of technology among firms within an industry. In the firm specific context the decision to adopt a new production technology or not is found to depend on technology-specific investments. Firms face sunk costs from investments made for older vintages and the need for new investments necessary to implement a new technologies. Technology specific investment often comes in form of specialization in human capital. Specific skills or knowledge that is direct towards the use of a certain technology or technology vintage is referred to as vintage human capital. The cost of new investments and the loss in utility of specialized personnel both influence the firm decision on whether to adopt a new technology and when. Chari and Hopman (1991) show that especially vintage human capital slows down diffusion of new technologies. The theory of vintage human capital can also be applied in a broader scope to national adoption of technologies. Also nations specialize on specific production and related technologies. Generally, nations which use a certain technology the most intensive and accordingly have invested the most, suffer from the biggest loss when switching to newer technologies. Beyond technology specific investments further factors that influence the firm decision to adopt relate to market structure among competing producers and network externalities (Hoppe, 2002).

Both, research focusing on macroeconomic and microeconomic factors analyze technology adoption through the production side of the economy. Consumer and their preferences do not directly enter into these models. Factors that are important to consumer demand are typically studied in literature on technology diffusion that comes from marketing research. The object of these studies is the diffusion of a specific product in a market. The basic model of technology diffusion in this literature is the epidemic model. It describes the process of diffusion driven by the flow of information about the technology and how to use it. According to this model the diffusion process follows the interaction of individuals and is thereby self-perpetuating. Empirical studies meanwhile do not only consider forces of interaction and flow of information as determinants. Also the role of change agents[3] and individuals' socioeconomic characteristics play a major role in the consumer's propensity or willingness to try out new products. Wealth thereby is one among many other characteristics that determine socioeconomic status (Rogers, 2003). The classical model of technology diffusion in a market comes from Bass (1980). It separates consumers into five different categories of adoption timing based on their socioeconomic status. The distribution of consumers over these categories and how they interact defines the diffusion process within the market. With the rise of modern ICTs the importance of consumer demand has more recently also been introduced into some macroeconomic studies of technology diffusion. Typically macroeconomics considers consumers to have homogenous and homothetic preferences. That technologies are not simultaneously adopted by all individuals however demonstrates that there is heterogeneity in individuals' consumption. Determinants of consumer demand used in these studies are typically income, education and national demographics. Typical technologies considered are internet usage and personal computers. Beilock and Dimitrova (2003) as well as Kiiski and Pohjola (2002) study the diffusion of internet usage in a cross-country sample. Both find that income per capita is the most important factor to explain national differences in internet usage. In their research infrastructure and cost of access have also been identified as significant factors. Although looking at a limited country sample of OECD countries Beilock and Dimitrova (2003) find that average income plays a bigger role at lower levels of income.

[3] For more information on change agents see Rogers (2003).

Chinn and Fairlie (2010) find similar evidence in their study on cross-country differences in usage of internet and personal computers. Besides factors of human capital, demographics and institutional characteristic they also identify income per capita the main explanatory variable, especially when comparing the subsets of developed and developing countries.

These results indicate that the effect of average income on technology diffusion is not linear and that further research on the topic is necessary. Few studies take a step in this direction by including measures of income distribution in their analysis of technology diffusion. Assuming for income distribution to play a role for aggregate demand of certain products implies to assume that consumers have non-homothetic preferences. Fuchs (2009) includes the Gini index as a measure of income distribution in his cross section analysis of internet access. Among the eleven explanatory variables included income inequality is identified as one of the most important determinants of differences in national use of the internet pointing to the need of integrating measures of user inequality into these models. His research identifies the effect of inequality to be negative. Other results are found by Conceição et al. (2003). They build their research on the results from Beilock and Dimitrova, extending the set of countries that are analyzed beyond OECD countries and the dependent variables to include all three ICTs. A crucial difference to the work from Beilock and Dimitrova is the inclusion of the Theil index as a measure of income distribution. However, while agreeing with Fuchs in their hypothetical expectation of a negative influence of income inequality their empirical research suggest for this effect to be positive. Acknowledging that also the effect of income inequality might not be linear at all levels of diffusion or development Hyytinen and Toivanen (2011) take a more differentiated approach. While using overall measures of distribution such as the Gini index they also use the income share of population with the highest dezile of income as a measure of inequality. They specify their analysis on the early diffusion of mobile phones arguing that greater mass in the upper tail of the income distribution, meaning more individuals with high income has a positive effect on early take up of mobile phone usage. This hypothesis is confirmed by empirical evidence of the diffusion of mobile phone in a sample of developing countries.

The analysis in this thesis intends to further explore the role of consumer demand on diffusion of technologies. The influence of unequal distribution of income on a nation's consumption of technology that relates to consumer goods is studies in an empirical approach. The studies that discussed this topic so far typically analyze single or a limited sample of ICTs and a subsample of developed or developing countries over a limited time period. The presented empirical analysis uses panel data of 18 technological consumer goods in a vast number of countries, both developed and developing. In its theoretical orientation the analysis is related to the work of Hyytinen and Tovianen (2011). The effect of income inequality is also assumed to be non-linear. Dynamics on technology diffusion are studied however beyond its early stage. The empirical approach follows previous work from Comin and Hobijn (2003, 2010) as the dataset used was compiled for their studies. In the aim to account for the difference in of cross-country diffusion and within-country technology diffusion the effect of income inequality is analyzed in separate steps. The main part the thesis concerns national diffusion of consumer technologies while the national adoption of technologies is analyzed in a shorter attempt. In the following section a simple model of consumer induced technology diffusion that features a non-linear effect of income inequality is introduced as a theoretical foundation to the analysis.

3 Theory

As stated in the introduction, the relation between technology diffusion and income inequality has usually been discussed concerning the effect of the first on the latter rather than the other way around. Thereby technological change is considered as a cause to increasing income inequality based on the hypothesis, that this process is skill biased and leads to rising white collar wages and a drop in blue collar wages (Acemoglu, 2001; Ganica, 2012). The influence that consumers have on technology diffusion through consumer demand has meanwhile been largely neglected. Research on diffusion today does not consider that technologies which are primarily used by consumers may also add to national total factor productivity. The rise of ICTs stresses this role. Private use increase human capital that is also necessary to use these technologies on a wide basis in the corporate sector. For each generation everyday life is becoming more technology intensive through modern multimedia goods and it therefore is important to study the influence of consumer demand on technology diffusion.

Classical economic theory assumes preferences to be homothetic such that all consumers spend their income in the same proportions on the same basket of goods. In that case aggregate demand can be determined from aggregate income and income distribution is negligible. In this paper individual income is considered as the determining factor for consumer demand. Under the assumption of non-homothetic preferences the composition of the goods basket consumed differs with individual income. Consumers will change their allocation of income to different goods dependent on their individual income. This implies that at higher levels of income consumers will not only consume proportionally more than poorer individuals, but they will also spend a higher share of their income on certain type of goods or even consume goods that poorer individuals do not buy at all. For example, the share of income spend on staple food like rice or potatoes may be very high for poor individuals. As individuals grow richer they will not keep this share constant, but reduce it. Rich individuals are more likely to spend a higher share of their income on products which do not serve to cover basic needs and they may also consume goods which are beyond poor individuals' means (e.g. vacation or cars). Such goods are often labeled luxury goods. Under such preference structures not only aggregate income but also income distribution has an effect on the aggregate demand for consumer goods and their diffusion. The first research to consider non-homothetic preferences that returned great echo was Linder's essay on "Trade and Transformation" (Linder, 1961). In this study Linder applied the theory that variation in aggregate demand comes from variation in individual income to trade. His study was followed up by a number of papers from other scholars that discuss non-homothetic preferences predominantly in the context of trade. A number of these studies also provide empirical evidence of the implications of such preference structures for aggregate consumer demand[4]. If variation in expenditure shares between individuals with different income levels has an effect on aggregate demand, they also influence consumer demand for technology goods and technology diffusion. Especially in the early stage of diffusion consumer goods that entail a new technology may be considered luxury goods. They do not serve a basic need and consumers will only buy them after having met basic needs. Income distribution thereby is a direct determinant to the diffusion of consumer technologies within a country. Although Hyytinen and Toivanen do not explicitly relate their hypothesis to non-homothetic preferences they also take the view that "the early phases of diffusion reflect consumption demand by the rich" (Hyytinen and Toivanen, 2011, p.385)[5].

3.1 Diffusion theory

Classic diffusion theory typically assumes S-shaped diffusion curves for within-country or within-market diffusion. This type of cumulative distribution function of use or consumption are often modeled as a logistic function and have been supported empirically as a good approximation to the diffusion process. The most popular model to explain such curves is the

[4] E.g. empirical research by Hunter and Markusen (1988), or Hunter (1991) provides evidence for expenditure functions that support non-homothetic preferences. Markusen (2010) further empirically analyses the effect of such preferences on consumption and trade in the context of classical trade models.

[5] Of course demand is not the sole factor driving technology diffusion. An overview over studies that discuss technology diffusion related to other factors is provided in the introductory section of this paper. Besides the pull-forces to diffusion like industrial demand and political interests there are also push forces like trade enabled spill-overs.

epidemic model. It relates the diffusion of technology to the diffusion of information enabled by the interaction of users. Information and use diffuse like an epidemic in this model. It is predominantly used in marketing literature or sociological studies of diffusion. The foremost used alternative is a probit model in which different time of adoption follows from differences in socioeconomic characteristics among adopters. These usually reflect differences in factor endowment and abilities of firms, consumer risk aversion, heterogeneous reservation-prices, different needs or income. While in epidemic models the diffusion process is driven by adopter learning the driving factor in probit models is adopter heterogeneity. To combine the two theoretical models reinforces the logistic shape of the diffusion curve (Hall and Kahn, 2003).

Based on the assumption of non-homothetic preferences income and its distribution are considered as the determining factors of technology diffusion in this study. In this study a probit model of technology diffusion is assumed where individuals buy a product following a simple decision rule. Technology goods are considered luxury goods rather than necessity goods and individuals will only consume these goods once their income surpasses a certain threshold. The diffusion of this technology over time is described by the cumulative consumption of all individuals at each point in time. Diffusion of the product meaning an increase in cumulative consumption follows either from an increase in income, a decrease in price, or both. To derive how income distribution influences the shape of this diffusion curve I introduce a simple model of consumer demand featuring threshold income.

The diffusion process of technologies is analyzed in two separate approaches that distinctly differentiate between the adoption of a new technology and the technology diffusion process. There are a number of scholars which have pointed out the importance to consider these two steps of a countries technological development in separate approaches. Dekipme et al. (2000) and Kauffmann and Techatassanasoontorn (2005) assume in their studies that initial technology adoption by a country and consecutive technology diffusion among consumers in the national market involve different decision making units. Therefore they analyze the two stages, technology adoption and technology diffusion, in separate empirical approaches. Wu and Chu (2010) meanwhile test the appropriateness of different empirical models to explain diffusion of mobile telephony in Taiwan. From their cross-sectional study they conclude that at different stages of diffusion different models are appropriate and thereby these stages should be analyzed in separate approaches. Also Comin and Hobijn (2010) and Comin and Mestieri (2010) differentiate between technology adoption and technology diffusion, calling them the “extensive" and “intensive" margins. They relate the adoption of new technologies to investment costs however do not consider consumer behavior as an influence[6]. Acknowledging that there is a distinct difference between the process leading to technology adoption and the process of technology diffusion they are considered separately in the presented analysis. The main part of the empirical work is focused on the analysis of technology diffusion while adoption lags are only analyzed in a short attempt due to data limitations. This will be discussed in more detail in section four.

3.2 The model

The proposed model describes the adoption and diffusion of a good in a consumer market depending on income and its distribution. It is not a product cycle model and therefore does not concern consumer decisions taken once a consumer technology is replaced by a better one and sees a decline in usage. The model also abstracts from the opportunity that different generations of the same consumer technology may change the consumption decision. The technology good that is subject of the analysis is assumed to be the same during the whole distribution process. The proposed model which is explained below includes consumption as a conditional variable, dependent on a threshold income and income distribution. This is based on the theory of non-homothetic preferences. Following assumptions are fundamental to the model: 1) Potential adopters have the same valuation for the new product; 2) while the price of the product is constant consumer income is increasing over time, following $Y_i(t) = Y_i(0)e^{gt}$[7]; 3) individuals will only adopt the new consumer technology once income has passed a certain threshold level $Y'(t)$ (see Figure A.1 in appendix).

Individuals consume a selection of different consumer goods, indexed j, that are distributed across an interval $[0, \infty)$. On this interval goods have the same price $p_j = p$ and are equally valued by all potential consumers[8]. An individual i's utility is given by his total consumption of goods $U_i(t) = C_i(t) = \int_{j=0}^{\infty} c_{ij}(t)\, dj$, where $c_{ij} \in \{0,1\}$. Accordingly goods are consumed in discrete amounts and individual demand is saturated after consumption of one unit. Lower j goods constitute basic need goods and are given higher consumers preference. At all levels of income individuals will first consume lower j goods and use remaining income for higher j

[6] In their analysis of the "intensive" margin Comin and Mestieri (2010) also do not relate differences between countries to their economic characteristics like income distribution. They rather focus their analysis on the importance of difference in this intensive margin for cross-country differences in total factor productivity.

[7] Diffusion theory often assumes decreasing prices of goods due to economies of scale and scope. The presented model implications under constant prices and increasing total income are equivalent to the case of decreasing prices and constant income.

[8] The assumption that all goods have the same price $p_j = p$ is made to simplify the definition of the threshold income. Given that an individual only gains utility from consumption of good $j = x$ if he also consumes good $j = x - 1$ the hierarchy of goods consumed is determined by preferences and prices only matter for the time of consumption. Therefore the assumption simplifies the model but does not change its implications.

goods. Goods with higher j are only consumed by individuals with higher income and may therefore be considered luxury goods. An individual only gains utility from consumption of good $j = x$ if he also consumes good $j = x - 1 > 0$. The variety in of goods in the consumption basket of an individual is then limited by his income. The model abstracts from intertemporal dynamics and assumes that each period all individuals spend their full income on consumption. Combining this the budget constraint reads

$$\text{BC: } Y_i(t) = \int_{\mathrm{j}=0}^{\infty} c_j p \, dj$$

Income $Y_i(t)$ is distributed uniform among individuals on the interval $Y(t) \sim U(Y_P(t), Y_R(t))$. The limits of the interval are defined by the lowest individual income Y_P (poor) and the highest individual income Y_R (rich). Given that the distribution of income is uniform total and average income are determined as

$$\text{Total income: } Y(t) = L \int_{Y_P(t)}^{Y_R(t)} x f(x) dx \; = \; \frac{L\big(Y_R(t) + Y_P(t)\big)}{2}$$

$$\text{Average income: } Y_\mu(t) = \int_{Y_P(t)}^{Y_R(t)} x f(x) \, dx = \frac{Y_R(t) + Y_P(t)}{2}.$$

The new technology good indexedj' is only consumed by individuals with income $Y_i(t) \geq Y'$ where $Y' = \int_{j=0}^{j'} c_j p \, dj$. Since goods are consumed in single units this can be simplified to $Y' = j'p$. The individual consumption decision of good j' is determined as follows:

$$c_{ij'} = \begin{cases} 0 \text{ if } Y_i(t) < j'p \\ 1 \text{ if } Y_i(t) \geq j'p \end{cases}$$

Initial technology adoption in the described model takes place when the first unit of j' is consumed. This happens when the richest individual first reaches sufficient income $Y_R(t) = Y_R(0)e^{gt} = j'p$. The time that passes from period zero until then is defined as the adoption lag t':

$$t' \equiv \frac{\ln(j'p)}{\ln(Y_R(0))g}. \tag{1}$$

Diffusion thereafter is measured as relative market penetration or consumption per capita. Total consumption of good j' is determined by the mass of the income distribution above $Y_i(t) = j'p$. This is given by $C_{j'}(t) = 1 - F_t(j'p) = \frac{L\big(Y_R(t) - j'p\big)}{Y_R(t) - Y_P(t)}$, for $j'p \in [Y_R(t), Y_P(t)]$. The diffusion of good j' is defined as $D_{j'}(t)$:

$$D_{j'}(t) \equiv \frac{C_{j'}(t)}{L} = \begin{cases} 0 & \text{if } Y_R(t) < j'p \\ \frac{Y_R(0)e^{gt} - j'p}{Y_R(0)e^{gt} - Y_P(0)e^{gt}} & \text{if} Y_P(t) < j'p \leq Y_R(t) \\ 1 & \text{if } Y_P(t) \geq j'p \end{cases}. \tag{2}$$

As individual incomes are continuously increasing while all other variables remain unchanged, the share of individuals that consume j' is rising over time.

A special case of the uniform income distribution is a collapsed distribution where all individuals earn the average income. Income is equally distributed such that $Y_P(t) = Y_R(t) = Y_\mu(0)e^{gt}$. Then either none or all individuals consume j' and the diffusion is discontinuous, jumping at time t' from zero to one. For this special income distribution the two measures of interest are determined as

$$t' = \frac{\ln(j'p)}{\ln(Y_\mu(0))g}$$

$$D_{j'}(t) = \begin{cases} 0 & \text{if } Y_\mu(0)e^{gt} < j'p \\ 1 & \text{if } Y_\mu(0)e^{gt} \geq j'p \end{cases}.$$

This shows that under the collapsed distribution function average income as a measure of income distribution is sufficient to model the diffusion process. Under unequal distribution of income more moments of the distribution have to be considered to determine the diffusion path. In the following the effect of different measures of income distribution in the proposed model are examined to derive the influence of income on technology adoption and diffusion.

3.2.1 The effect of higher inequality in income

First the effect of an increase in income inequality is examined[9]. While leaving total income and population unchanged an increase in income inequality is equivalent to a mean preserving transfer of income from below to above average individuals. The transfer is proportional to the income levels to not change the distributional form. The largest transfer takes place between the richest and the poorest individual. Individual income $Y_i(t)$ is still uniformly distributed on an interval which is now limited by $\widetilde{Y_R}(t) = (Y_R(0) + k)e^{gt}$ and $\widetilde{Y_P}(t) = (Y_P(0) - k)e^{gt} > 0$.

Proposition 1 a. An increase in income inequality through a regressive redistribution of income implied by transfer $k > 0$, that leaves the distributional form unchanged, reduces the time until first adoption. **b.** The increase in income inequality increases technology diffusion among above average income individuals that receive a positive transfer, but reduces it for lower incomes which suffer from a negative transfer.

Proof. The mean preserving proportional transfer of income from below to above average individual's changes equation (1) and (2) to

[9] Note that the proposed proportional growth path of individual income does not change income distribution.

$$t' = \frac{\ln(j'p)}{\ln(Y_R(0)+k)g}$$

$$D_{j'}(t) = \begin{cases} 0 & \text{if } Y_R(t) + ke^{gt} < j'p \\ \frac{(Y_R(0)+k)e^{gt} - j'p}{(Y_R(0)-Y_P(0)+2k)e^{gt}} & \text{if } Y_P(t) - ke^{gt} < j'p \leq Y_R(t) + ke^{gt}. \\ 1 & \text{if } Y_P(t) - ke^{gt} \geq j'p \end{cases}$$

The effect of a change in income distribution on the adoption lag and technology diffusion is then determined by:

$$\text{a. } \frac{dt'}{dk} = \frac{-\ln(j'p)}{\ln(Y_R(0)+k)^2(Y_R(0)+k)g} < 0 \tag{3}$$

$$\text{b. } \frac{dD_{j\prime}}{dk} = \frac{2j'p - (Y_R(0)+Y_P(0))e^{gt}}{e^{gt}(Y_R(0)-Y_P(0)+2k)^2} = \frac{2(j'p - Y_\mu(0)e^{gt})}{e^{gt}(Y_R(0)-Y_P(0)+2k)^2} \begin{cases} > 0 \text{ if} Y_\mu(t) < j'p \\ = 0 \text{ if } Y_\mu(t) = j'p \\ < 0 \text{ if} Y_\mu(t) > j'p \end{cases} \tag{4}$$

These results are intuitive as the regressive redistribution of income entails individuals with income above the mean to have higher income than before the redistribution. They therefore will sooner have sufficient income to consume j' what reduces the time until first consumption and increases diffusion at each point in time. This is the case for the time until income grew sufficient for the individual with average income to consume j'. As the mean is not affected by the redistribution time until $Y_\mu(t) = j'p$ is unchanged under the increase in inequality. Beyond this period diffusion will run slower compared to the case without regressive transfer. As the individuals with below average income were put at disadvantage by the redistribution they will now consume j' later. ■

Therefore higher income inequality changes the slope of the diffusion curve. The diffusion curve rotates at the mean income making the curve flatter overall.

3.2.2 The effect of an increase in population

We look at a change in population L, while total income and income inequality remain unchanged. For the distribution of income to remain uniform there has to be a change in all incomes proportional to the increase in population. In the presented model this imposes a proportionate change to the limits of the income interval and implies a uniform distribution over the new interval. The new limits are defined as $\widetilde{Y_P}(t) = \theta_P e^{gt}/L$ and $\widetilde{Y_R}(t) = \theta_R e^{gt}/L$ while total income $\bar{Y}(t) = \frac{L(\widetilde{Y_R}(t)+\widetilde{Y_P}(t))}{2} = \frac{(\theta_R+\theta_P)e^{gt}}{2}$ is unaffected by changes in population.

Proposition 2 a. An increase in population without a change in total income to be distributed among individuals will reduce individual incomes and increase the adoption lag. **b.** The increase in population and respective decrease in individual income also reduces technology diffusion at each point in time.

Proof. When including the size of population as a determinant of individuals' income, while leaving total income unchanged and the distributional form of income remains uniform, equation (1) and (2) change to

$$t' = \frac{\ln(j'p)}{\ln(\theta_R/L)g}$$

$$D_{j'}(\mathrm{t}) = \begin{cases} 0 & \text{if } \frac{\theta_R e^{gt}}{L} < j'p \\ \frac{\theta_R e^{gt} - L \cdot j'p}{(\theta_R - \theta_P)e^{gt}} & \text{if } \frac{\theta_P e^{gt}}{L} < j'p \leq \frac{\theta_R e^{gt}}{L} \\ 1 & \text{if } \frac{\theta_P e^{gt}}{L} \geq j'p \end{cases}.$$

The effect of a change in population on the adoption lag and technology diffusion is determined by:

$$\text{a. } \frac{dt'}{dL} = \frac{\ln(j'p)}{\ln(\theta_R/L)^2 g \cdot L} > 0 \qquad (5)$$

$$\text{b. } \frac{dD_{j'}}{dL} = \frac{-j'p}{(\theta_R - \theta_P)e^{gt}} < 0 \qquad (6)$$

As the increase in population is not met by a proportional increase in total income to be distributed, income at all individual levels have to decrease. Then individuals are poorer compared to the case with lower population at all individual levels and all income will need more time to grow until they reach Y'. Therefore initial adoption takes place later and the diffusion is lower compared to the case without population growth. ■

3.2.3 The effect of an increase in total income

As a final case we look at a change in total income while population and distribution remain unchanged. The one-off increase again has to be proportional across individuals for the distribution to be preserved uniform. This is equivalent to a multiplication of all income levels by factor $\alpha > 1$ such that $\tilde{Y}(t) = \alpha Y(t) = \frac{\bar{L}(\alpha Y_R(t) + \alpha Y_P(t))}{2}$.

Proposition 3 a. A higher total income through a multiplicative increase at individual levels that leaves population and distribution unchanged, will decrease the adoption lag. **b.** The higher total and individual income also increase technology diffusion at each point in time.

Proof. The proportional increase of all income levels by factor α change equation (1) and (2) to

$$t' = \frac{\ln(j'p)}{\ln(\alpha Y_R(0))g}$$

$$D_{j'}(t) = \begin{cases} 0 & \text{if } \alpha Y_R(0)e^{gt} < j'p \\ \frac{\alpha Y_R(0)e^{gt} - j'p}{(\alpha Y_R(0) - \alpha Y_P(0))e^{gt}} & \text{if } \alpha Y_P(0)e^{gt} < j'p \leq \alpha Y_R(0)e^{gt}. \\ 1 & \text{if } \alpha Y_P(0)e^{gt} \geq j'p \end{cases}$$

The effect of a change in total income on the adoption lag and technology diffusion is determined by:

$$\text{a. } \frac{dt'}{d\alpha} = \frac{-\ln(j'p)}{\ln(\alpha Y_R(0))^2 g \cdot \alpha} < 0 \quad (7)$$

$$\text{b. } \frac{dD_{j'}}{d\alpha} = \frac{j'p}{(Y_R(0) - Y_P(0))e^{gt}\alpha^2} > 0 \quad (8)$$

The scenario describes the opposite case of an increase in population under constant total income. As now all individuals are now subject to a proportional increase in income they will sooner be able to consume j'. Therefore time to technology adoption will be shorter and diffusion will be higher at each point in time compared to the case of no increase in total income. The derived influence of a change in total income also holds for average income since population is kept constant.■

The three discussed cases are chosen such that each captures the effect of a different moment of the income distribution. An increase or decrease in one of these factors leaves the others unchanged. The primary measure of income inequality used in the empirical analysis is the Gini index. The coefficient increases in case of a regressive redistribution but is orthogonal to multiplicative changes through population or total income. A mathematical derivation of this is provided in Proof.A1 in appendix.

Based on this model two working hypotheses are defined.

Hypothesis 1 Time until first adoption of a technology is reduced by an increase in total income and income per capita, holding other variables constant. Also a rise in income inequality reduces the time until first adoption. Meanwhile a rise in population without a consecutive rise in income has negative implications on technology adoption, prolonging time until adoption.

Hypothesis 2 Once a consumer technology is adopted, an increase in total income and income per capita will increase technology diffusion. An increase in population will reduce technology diffusion. Income inequality meanwhile has a discontinuous effect. At lower per capita incomes higher income inequality increases technology diffusion but it reduces diffusion at higher levels of income per capita.

3.3 Considerations for application

When relating this theory to the dataset at hand there are certain deviations from the model assumptions that need to be considered. The most obvious difference is that income distribution typically follows a log-normal rather than a uniform distribution which has direct implication for the shape of the diffusion curve. Under log-normal income distribution the diffusion curve will take its typical S-form rather than the exponential process described in the model above. However, whether income is log-normal or uniform distributed and the following shape of the diffusion curve as sole difference does not change the model implications.

A further deviation from the model assumptions that should be discussed are the special characteristics of certain consumer technologies. Generally, for some goods more income is necessary than for others. E.g. to buy a car takes more income than to buy a telephone. Additionally some goods require infrastructure, which imply fixed cost that need to be covered before usage in a country is possible. For these consumer technologies to be adopted in a country a certain market size is necessary to make the investment in infrastructure profitable. The set of technology consumer goods analyzed in the empirical part of this study are all characterized by the need of infrastructure. The magnitude of these infrastructure costs and the price that may be charged for a good determine a minimum consumer market that is necessary to cover the infrastructure investment make introduction profitable for a provider. At what point demand and willingness to pay is sufficient to enable technology adoption depends on national income and income distribution. In the outlined model the derived propositions hold as long as the necessary minimum customer base is less than half of the total population. This is due to the fact that the dynamics that determine the adoption time of the richest individual are the same for all other individuals with above mean income. However, once the assumption of a uniform income distribution is relaxed these dynamics may develop differently. Especially when considering a log-normal distribution of income the effect of an increase in income inequality is ambiguous. Depending on the distributional form but also on the type of transfer which leads to the increase in inequality the number of individuals that qualify as initial customer base might be increased or decreased. Thereby the influence of income inequality is unclear and maybe adverse for the adoption of technologies that imply fixed cost of infrastructure. The empirical analysis supports these concerns on ambiguity. It however is not clear whether the results relate to misspecification of the model or maybe to a lack of quality in the data.

The goods in the data sample differ in further concerns. An important difference when analyzing diffusion driven by consumer demand is the differentiation between durable and non-durable consumption goods. In the sample some technologies relate to durable goods, like cars. For those goods the consumer decision describes an investment decision over ownership or non-ownership rather than consumption (Beerli, 2010). Nevertheless, the decision to buy follows a benefit-cost-analysis and depends on the available income, no matter whether usage wears out the good in the short or only in the long term. While for non-durable goods diffusion over time implies repeated consumption in every period, durable goods last beyond the period or moment of purchase. To align the two type of goods in the model the following assumptions are made: 1) given that a non-durable good is consumed in a certain quantity in one year, the same quantity will be consumed in the next year if income (aggregate and its distribution) and price does not change; 2) given that under the current income structure a certain number of consumers have made the decision to consume a durable good, if preferences, income and prices do not changed they will decide anew to buy the good once it runs out. Then for durable goods the market penetration will also be the same in the following year if income does not change, independent of whether the good needs to be replace in that exact period or not. Accordingly, for both type of consumer goods the current penetration level is determined by current income.

The following section of this paper provides detailed descriptive statistics of the used data. Information and illustration over measures of technology diffusion as well as explanation of applied data transformation are an important step to the later empirical analysis. They are fundamental to assessment of quality and interpretation of results.

4 Data

This section gives an overview of the dataset for the empirical analysis. The description focuses on technology diffusion and not much on the independent variables of the analysis. Understanding the used measures of technology adoption and technology diffusion is essential to the following section.

4.1 The CHAT dataset

The data on consumer goods that is used in the empirical analysis comes from the Cross-country Historical Adoption of Technology dataset (CHAT)[10]. This panel has been gathered and made available by Diego Comin and Bart Hobijn in 2009. The two scholars have already conducted extensive research on the topic of technology diffusion also using this data panel. The CHAT dataset contains information on the diffusion of 104 technologies in over 150 countries. For some technologies the time series starts as early as 1800, while the latest technology data included is from 2003 (Comin and Hobijn, 2009).

Compared to measures of TFP such reports of single technologies have a specific advantages for the current analysis. Firstly, disaggregated measures of technology are less prone to heterogeneity in measurement practices across countries and over time compared to measures of TFP. Secondly, the focus on demand side dynamics in this thesis puts up the need for measures of technologies that can be associated to consumer goods. A measure of technology in single goods better serves this purpose than TFP which is more related to the production side of the economy. Data on individual technologies enables to explore the adoption and diffusion in an economy based on demand side dynamics. The relevant factors that determine these dynamics might be different, depending on the specific technology or country. The use of railway for example highly depends on the topography and size of a country, whereas this is not the case for financial technologies. These differences could not be considered in an aggregate technology measure. The use of disaggregate measures of technological development also reduces the problem of endogeneity in econometric analyses.

In the CHAT dataset technologies are reported in two types of intensive measures. For some technologies the usage is measured as the number of capital goods in a country that embody a certain technology. Examples are the number of mobile phones, the number of passenger vehicles or the number of credit cards. The other technologies are measured as output that was produced using a certain technology or as input that was used for production. Examples of this are the production of electricity and steel or the amount of synthetic fiber used in a certain year for textile production.

For the analysis a panel of 18 technologies from the CHAT dataset is selected which relate to consumption goods. The diffusion of these technologies are considered to be driven by consumer demand. The technologies and their measures are listed in Table A.1. Five of them relate to the finance sector, seven to telecommunications, four relate to the field of

[10] The dataset is available for download at: http://www.nber.org/data/chat.

transportation and three are modern ICTs. All of the chosen technologies need some type of local infrastructure before they can be used. Therefore a minimum number of local consumers are needed to cover the fixed cost from installation of infrastructure to make introduction into a new market profitable. For such goods, other than for goods that do not require any infrastructure the global market cannot substitute a local client base.

The reported numbers in the dataset do not give indication whether technologies were applied in household consumption or in corporate use. For some technologies, like credit card transactions, this might be less of an issue. For mobile phones, computers and internet access on the other hand the use stemming from corporate rather than private demand could be substantial. This has to be considered when evaluating the empirical results. For the empirical analysis the data has to be converted to measures of technology diffusion and technology adoption.

4.2 Penetration rates

The usage data of technologies are difficult to interpret in absolute terms. For example in Switzerland the absolute number of mobile phones multiplied more than 10-fold between 1995 and 2000, increasing by 4.2 million. In Norway mobile phones increased 3.5-fold in the same period, equaling a total increase of 2.4 million. Also in the United States the usage of mobile phones more than tripled increasing in number by 76.2 million. To make these numbers better comparable and to determine technology diffusion the reported absolute measures are scaled by population. This simplifies comparison of the levels of technology diffusion across countries and over time. Looking at scaled rates Norway can be identified as the technology leading country, with an increase in market penetration of mobile phones from 22% to 75%. Switzerland which is the laggard among the three nations in 1995 with a penetration rate of only 6% increases this to 63% until 2000 while the United States only increases the rate of mobile phones per capita from 12% to 39%.

Scaling absolute measures of usage by the number of potential adopters to determines how intensively a technology is used in a certain country. Then diffusion determines what share of potential adopters consumes or uses a certain technology. This intensity margin is how diffusion of technology has traditionally been measured in the related literature and is equivalent to the diffusion rate defined in the proposed model. For an empirical analysis of the diffusion rate micro data on the number of actual and potential adopters is needed which is not available in the CHAT dataset. As mentioned before, measures in the CHAT dataset do not determine the units allocated to private consumption from units allocated to corporate or institutional use. Also not for each technology the whole population is the potential market but maybe rather households, neighborhoods or else. Therefore the applied transformation by scaling absolute numbers over population only leads to an approximation of technology diffusion. The calculated rates are thus labeled “penetration rates” rather than diffusion. When assessing and interpreting empirical results one needs to be kept in mind that these penetration rates are an approximate measure and may be biased.

The data panel contains 19’592 observation of penetration rates and is very unbalanced. While for some technologies there are as many as 2’419 observations (TV sets) for others there are only 102 (telegrams). Table A.2 provides summary statistics of the calculated penetration rates for all technologies. That some categories show substantially less observations than others is due to shorter time series for newer technologies but also due differences in the country sample per technology. For financial technologies developed countries and specifically European countries are dominating the sample. The country sample is much more balanced for the other sectors. Overall there are more observations from developed nations than from developing ones. This does not necessarily indicate a selection bias in the sample. Since more developed economies typically adopt technologies earlier they report numbers of usage for more years. Hence their time series per technology are usually longer than those of developing countries.

Table A.2 also demonstrates that the calculated rates do not measure the level of diffusion in a market. Despite making the usage of technologies more comparable across countries and time the penetration rates still take very different values between different types of technologies. For those technologies that are measured as capital goods people normally consume a maximum of one good. These are typically durable goods and the penetration rates for these technologies can be interpreted as percentages of population. For some of the durable goods however, it is not feasible or efficient to provide one good per consumer because there is little rivalry in consumption. This applies to the financial technologies like ATMs. Also the penetration rates of those technologies that are reported in a measure of output produced may take values larger than one as consumers can consume multiple units of output in the course of a year. Penetration rates for these technologies vary from an average of 17 transactions per person using payment cards at points of service, to an average of 446 km of journey by rail per person.

When plotting the calculated penetration rates, depending on stage of technology and country, the time series do not always take the expected S-shaped curve. For some mature technologies the observed shape does resemble a logit function while for other technologies the process does not take this shape. This is not necessarily a contradiction to theory but might indicate that the observations in the panel describe only a part of the diffusion curve within countries. The steepness and shape of diffusion curves vary across technologies and are staggered over time. As in this study technology adoption is assumed to be demand side determined it is interesting to relate penetration rates to GDP per capita, as a measure of average income in the respective countries. As Figure 1a and 1b show that the development of penetration rates of mainline phones over different levels of GDP per capita takes a more homogeneous form across countries than the development of technology penetration rates over time.

The correlation between penetration rates and GDP per capita is significant and positive for all technologies. Especially for older technologies the correlation is stronger. For example for mail, TV sets, mainline phones and cars the correlation is above 0.85. The lowest correlations we find for telegrams and the financial technologies POS and EFT (see Table A.3).

Figure 1a: Penetration rates of mainland phone lines over time

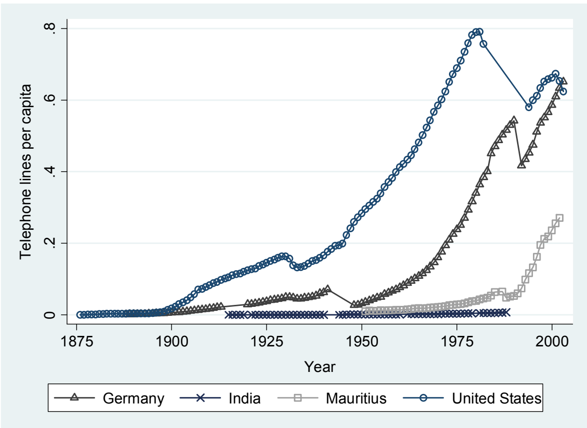
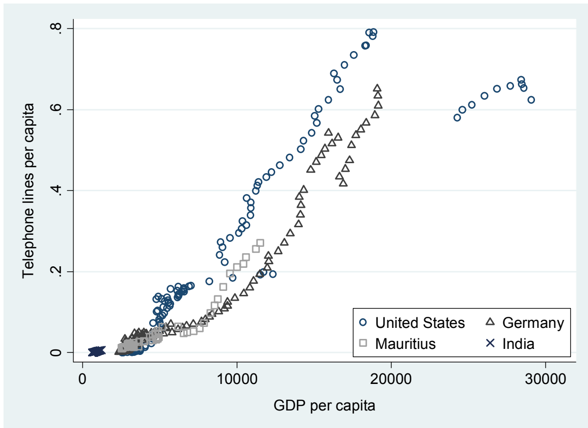


Figure 1b: Penetration rates of mainland phone lines over average income



For some goods time series are shorter because the respective technology became outdated by the introduction of a new, dominating technology. This especially concerns telegrams, but in the future may also be an issue for mainland phone lines, mail and newspapers which are replaced by newer information and communication services. As the current analysis focuses on technology adoption and diffusion observations of technology usage that describe the phasing-out process of a technology are not considered in the analysis[11].

[11]The technologies which are identified to be in a phasing-out process are: cheques, newspapers, passenger rail journeys and telegrams. While these technologies are replaced in some countries by more advanced technological options in other more backward countries their use still increases. For each country the maximum penetration rate for these technologies is identified. For the analysis only data describing the diffusion process until that maximum is reached is considered. The observations for later years are excluded. This process is only applied to the technologies which are identified to be in the phasing-out stage, and not to all technologies. Volatility and peaks in diffusion time series of other technologies therefore are not eliminated.

4.3 Diffusion lags

As stated before, the initial adoption of a technology and the consecutive diffusion are two different processes to be analyzed separately. They relate to different consumer groups changes in income may have diverse effects on them. The penetration rates described above are used to study the within country diffusion process. Measures of initial adoption and specifically time until adoption are not as straight forward. Data for the initial adoption of technologies is typically not available. National statistics on technologies and related consumer goods are usually only taken up after these have established and proven to be of a certain importance. Therefore we often do not have data on the early introduction period of technologies for all countries and hence do not know when technologies were used for the first time. Lacking this information global technology adoption cannot be determined directly from the dataset. Some scholars overcome this lack in available data by estimating the diffusion curves of technologies. From this estimation they extrapolate the curve to define the zero-intersection and initial adoption[12]. In the presented study a different approach is pursued to determine a measure of time until adoption. Technology adoption is approximated based on the time when countries reach a certain minimum penetration rate that is available in the data. The time to adoption is then measured following the concept of adoption lags proposed in Comin, Hobijn and Rovito (2008): Their lags capture the years of delay with which countries reach a certain penetration rate compared to the United States. The lag in the current analysis measures the delay in years with which a country reaches the defined minimum penetration rate, compared to the technology leading country. Since they measure a delay in reaching a certain level of diffusion rather than a delay in adoption they will be labeled diffusion lags.

The minimum penetration rates, which serve as a threshold take different values depending on the technology. They represent penetration rates that one can think of as a minimum market (e.g. 10%) but are also chosen such that diffusion lags can be calculated for many countries. Only when a country's time series of penetration rates actually covers values around the threshold level a diffusion lag can be calculated. Countries which do not reach this threshold rate within the reporting period, or countries which start reporting at levels far beyond the threshold rate have to be excluded from the analysis. The threshold rates for each technology are chosen following these two criteria. From the defined threshold penetration a reference year follows for each technology. This year is equivalent to the time $t = 0$ in the model. It is determined as the year when the technology leading country (or countries) first passes the

[12] See e.g. Comin, Hobijn and Rovito (2008), Comin and Hobijn (2010), Comin and Mestieri (2010) or Comin and Mestieri (2013).

threshold penetration rate. The number of years which other countries take to reach the threshold rate after the technology leader equals their diffusion lag. Table A.4 lists the threshold values defined for each technology, the respective technology leading country and the reference year. For TV sets e.g. the threshold penetration rate is set at 15%. While the United States reaches this market penetration in 1954 other developed countries like Japan or Germany show the same penetration only in the following decade when in the United States market penetration reaches 40%. For some developing countries like Namibia it takes more than 40 years longer to reach the threshold level than the United States. Figure A.2 illustrates this example.

Picking low threshold values means that the developed economies reach the threshold early in the time series. Following the theory, the level of development and demand side characteristics of nations in the benchmark year of technology diffusion determines how many years it will take them until adoption takes place (recall equation (2) defining t' as a function of $Y_R(0)$). The further back in time this initial adoption of technology takes place, the less national statistics on economic characteristics are available. Especially for older technologies the leading countries reach the defined thresholds in years for which average income data may still be available but no measure of income inequality. This considerably limits the estimation sample.

The approximation of time to adoption via the calculated diffusion lags is disputable. As there is additional arbitrariness in the definition of the minimum penetration rates the analysis of the diffusion lags has to be considered as a preliminary attempt to the topic of technology adoption. While the results have to be valued with caution they might still give directions for future research.

The derived diffusion lags vary widely across technologies and countries. While for some countries diffusion lags are available for all technologies for others only some lags could be calculated. Figure A.3 depicts the range of diffusion lags per country, ordered by their GDP per capita in 2003. The graph shows that the range of diffusion lags is not significantly smaller for developed countries compared to developing countries. This is counter intuitive as we expect more developed countries with higher income to adopt technologies relatively faster than developing countries. That we do not see this pattern in the data at first sight relates to the fact that developed countries have longer time series of technology diffusion and national statistics which allow to construct diffusion lags for older technologies. Figure A.4 plots diffusion lags and their reference years which shows that for older technologies lags are larger than for technologies with more recent reference years. The tendency for newer technologies to be adopted faster than older ones has also been observed by Comin and Hobijn (2008) and Comin, Hobijn and Rovito (2008). When considering that adopting a new technology with a delay in years entails countries to a relative disadvantage in productivity some adoption lags are rather large. The longest diffusion lag in the constructed sample is 123 years, more than a century (see Table A.5). This lag relates to passenger-kilometers by rail for private journeys and is observed for Argentina and Burma.

Figure A.5a and b illustrate the general relation of calculated diffusion lags to income measures in the respective reference year. While there is a negative correlation between average income and the diffusion lag the relation between income inequality, measured by the Gini index and time lag is slightly positive. This is not directly in line with the implications from the model based on which average income as well as income inequality is expected to have a negative influence on the diffusion lag reducing. In theory both are derived to reduce time to adoption. Whether the relation between income inequality and the diffusion lag is still positive when controlling for other variables will be analyzed in section 5.4.

5 Empirical estimation

The analysis of income inequality on technology diffusion is pursued in two approaches. As laid out in theory diffusion can be analyzed as cross-country diffusion and within country diffusion. The first concerns technology adoption while the second is a matter of market diffusion. Both together determine how intensive certain technologies are used by countries at a specific point in time and thereby their level of development. The derived hypotheses are tested in two approaches. The main part of the empirical analysis focuses on within country technology diffusion. Although the data panel is reasonably acceptable the results shall still be considered preliminary until confirmed in other studies. The attempt on analysis of technology adoption lags serves as indicator for future research

5.1 Analysis of penetration rates

5.1.1 Baseline specification

In the existing literature there are two approaches to empirical analysis of technology diffusion within a country. One is to estimate the speed of technology diffusion, the other approach is to model penetration rates of technologies. This thesis focuses on levels of penetration rather than speed of diffusion. The analysis of penetration rates follows a linear model which is a usual approach in recent studies of ICTs[13].

The effect of income inequality on diffusion is estimated following a reduced form approach.

$$penetration_{c\tau t} = \alpha + \beta X_{ct} + dummy_{\tau t} + \delta Z_{ct} + \varepsilon_{c\tau t} \tag{9}$$

$penetration_{c\tau t}$ refers to the penetration rate of a certain technology τ in country c in year t and X_{ct} denotes the vector of explanatory demand variables (income, population and inequality). Z_{ct} is a vector of country specific control variables and ε_{ict} is the error term. For each technology a technology-year dummy is included to capture the global trend in diffusion and to demean the sample (Comin and Hobijn, 2003). The relation is estimated in an OLS approach. Penetration rates take very different values depending on technology. For the analysis over the full sample of goods the penetration rates that cannot be interpreted as percentage of population are logarithmized. Because diffusion is a measure that converges towards a technology and country specific level of saturation the relation between diffusion and the explanatory variables is non-linear. Taking logs of explanatory variables is a further measure to better approximate this relation[14]. Based on Hypothesis 2 the influence of income inequality is expected not to be constant but to change from positive to negative over the course of economic development. This will be introduced into the analysis by an interaction term between the Gini index as the inequality measure and average income, measured by GDP per capita.

5.1.2 Explanatory and control variables

The data for the explanatory variables population and GDP, are from the Maddison historical dataset (Bolt and van Zanden, 2013). GDP serves as a variable capturing the overall market size, while GDP per capita is a measure for average income. Both variables describe demand and the market potential for a consumer good. In a model with non-homothetic preferences further moments of income are needed to determine consumer demand. The primary measure used in the empirical analysis is the Gini index. The Gini measures used are from the Standardizing the World Income Inequality Database (SWIID; Solt, 2009). The SWIID data combines and standardizes income distribution data from different sources such as the United

[13]See Rouvinen (2006) or Kiiski and Pohjola (2002) for the application of a Gompertz model to estimate the rate of change in diffusion. Comin and Hobijn (2004) estimate the speed of convergence. Bergoeing et al. (2010) or Hyytinen and Tovianen (2011) both apply a linear model to estimate penetration rates.

[14]The best estimation approach to S-shaped diffusion curves is a logit regression. However, the available penetration rates are not exact diffusion measures. As we do not know the technology and country specific saturation levels we cannot determine actual levels of diffusion and a logit transformation or regression is not feasible.

Nations University's World Income Inequality Database, the OECD Income Distribution Database and the Luxemburg Income Study. The variance in income distribution shall capture the importance of heterogeneity in individual income and therefore the influence of consumer demand. Further instrumental variables for income inequality are used as an addition to the analysis and robustness. The respective measures and results are explained in section 5.2.5. A usual challenge to the inclusion of income inequality measures in empirical analysis is the limited variance in the data. Concerning this, the available panel data has a significant advantage over the cross-sectional analysis from other authors introduced in section 2. By running a regression over panel data the analysis can exploit cross-sectional variation and time variation in income inequality.

The set of control variables used have been identifies in the literature on diffusion as relevant influences on technology diffusion. These typically include measures of factor endowments, openness and trade, some indicator for political system and a measure of relative economic development. As a measure of human capital stock variables of education levels provided by Barro and Lee (2013) are used. The dataset provides shares of population which have completed primary, secondary or tertiary education. As the data is provided at five year intervals linear interpolation between intervals was applied to enlarge the data series. National endowment of human capital and skills is considered to be determining to the ability of adopting new technologies as well as to its benefit. The level of schooling and education within a country specifically may be important to the usability and benefit that a consumer gains when buying a consumer good that entails new technology. Besides income the expected benefit also has a strong influence on the individual adoption decision. Beyond the theoretical argument there is vast empirical evidence supporting the role of human capital as a determinant of technology adoption and diffusion (Keller, 2001; Foster and Rosenzweig, 2010). Further electricity production per capita is included as a measure for physical factor endowments and approximation of TFP. Utility of technology and consumer goods not only dependent on individual skills to fully use it but its marginal value may also increases with complementary infrastructure. The included measure of electricity production comes from the CHAT dataset and sometimes is also interpreted as a proxy for general level of development (Comin and Hobijn, 2006).

Further control variables included are land area and urbanization. For some technologies, like transportation or communication technologies the size of a country, for a given population might have a positive or a negative influence on the usage and diffusion of the technology. Urbanization, measuring the share of population that lives in urban areas is another measure of concentration of population. For many consumer goods it is assumed, that provision and distribution of goods can be accomplished at lower prices in areas where consumers are more concentrated. This would have a positive influence on diffusion. Both measures used are from the World Bank database (World Bank, 2014b).

Total trade as a share of GDP is included to control for an economies interaction with the global market. Trade is assumed to influence technology adoption especially for production technologies. Foreign competition increases local producers' incentives to apply the newest technology while access to such technologies is simplified through imports and knowledge spillovers. Information about new technologies and how to use them is preferential to their adoption. This may also hold for the diffusion of technologies incorporated in consumer goods.

The influence of political institutions meanwhile can be either positive or negative. Measures of political freedom are included to control for potential barriers to technology diffusion put up by policies and regulations. Since the diffusion of new technology is part of the process of creative destruction it can create winners and losers. Depending on the influence of certain interest groups on policy makers they may hinder the introduction of new technologies to protect their own interests. Parente and Prescott (1994, 2000) study this in detail and provide ample empirical evidence. Market protection and regulations through policies can also hinder the introduction and diffusion of consumer goods. In the empirical analysis the influence of political institutions is controlled for by including the Freedom House measure of political rights and civil liberties retrieved from the QOG dataset (Teorell et al., 2013).

Despite different control variables there remains considerable unobserved heterogeneity among countries that may influence consumer behavior and technology diffusion. These include among others the relative distance to technology leading countries or cultural aspects that are not captured by the other control variables[15]. While some scholars include country fixed effects to account for this heterogeneity this approach is not feasible when intending to use the Gini index as explanatory variable. Typically the national Gini index show relatively little variation over time, compared to other measures such as GDP per capita or stocks of human capital. Therefore the effect of income distribution measured by the Gini index is absorbed together with other time invariant national characteristics when including a country

[15] See Keller (2001) and Comin, Dimitriev and Rossi-Hansberg (2012) for more information on the influence of geographical distance. See Sundqvist, Frank, and Puumalainen (2005) for the effect of cultural characteristics and traits.

fixed effects. Only when the run regressions do not include country fixed effects the Gini index enters the analysis as a variable with significant explanatory power.

5.1.3 Empirical results

The reduced regression equation (9) states the basic approach to the analysis of technology diffusion measured in penetration rates. For the full sample analysis across all technologies I logarithmize penetration rates of certain variables and include technology-year dummies as done in Comin and Hobijn (2003). In a first regression the effects of total income and population is estimated. Income inequality is added as explanatory variable in a second step. Based on Hypothesis 2 the influence of total and average income is expected to be positive for technology diffusion and the effect of population to be negative. Following from theory the influence of inequality on technology diffusion is non-constant, changing from positive to negative. In the second step of the analysis this tested by adding the Gini index to the regression both as a single variable and in an interaction term with GDP per capita. The estimation model then reads

$$Penetration_{\mathrm{c\tau t}} = \beta_1 GDPpc_{ct} + \beta_2 Population_{ct} + \beta_3 Gini_{ct} + \beta_4 GDPpc_{ct} \cdot Gini_{ct} + dummy_{\mathrm{\tau t}} + \delta Z_{ct} + \varepsilon_{\mathrm{c\tau t}}$$

The relation is estimated in an OLS approach allowing for clustered error terms given the serial correlation in the data. Table 1 and 2 below list the results from this primary analysis. From Column (1) in Table 1one can see that the predicted effect of total income and population is supported by the empirical analysis.

As predicted in Hypothesis 2, an increase in total income, keeping other variables constant, increases the rate of technology diffusion. The opposite holds true for an increase in population. When GDP per capita is included as a measure of average income, in place of population, this variable dominates total income. This provides empirical support to the assumption of non-homothetic preferences under which individual incomes are more important to aggregate consumer demand than aggregate income. Columns (3) to (6) confirm that the results remain significant and in line with the model predictions in a reduced sample and under inclusion of control variables. In the consecutive step of the analysis the dominance of GDP per capita over total income is not tested anew. The different specifications including total income and population or average income and population hold the same explanatory power.

Table1: OLS regression of Penetration rates

Dependent Variable: Penetration rates

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP	0.691***	0.00910	0.576***	0.00180	0.392***	0.0351
	(0.0317)	(0.0241)	(0.0294)	(0.0198)	(0.0529)	(0.0241)
Log Population	-0.682***		-0.574***		-0.357***	
	(0.0418)		(0.0339)		(0.0603)	
Log GDPpc		0.682***		0.574***		0.357***
		(0.0418)		(0.0339)		(0.0603)
Tertiary education stock					0.00282	0.00282
					(0.00775)	(0.00775)
Elecprodpc					0.00285**	0.00285**
					(0.000918)	(0.000918)
Trade share					0.000554	0.000554
					(0.000787)	(0.000787)
Land area					-2.76e-08	-2.76e-08
					(1.52e-08)	(1.52e-08)
Urbanization					0.00431*	0.00431*
					(0.00199)	(0.00199)
Freedom Index	No	No	No	No	Yes	Yes
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	51992	51992	19235	19235	19235	19235
adj. R^2	0.933	0.933	0.951	0.951	0.952	0.952

Notes: Clustered standard errors in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include technology-year fixed effects. Penetration rates that do not describe shares are logarithmized. Column (5) and (6) include additional control variables for human capital, infrastructure and TFP, land area and urbanization as well as a 3-level index rating civil and political freedom.

Table 2 adds the inequality measure to the regression. The first two columns list the primary result of the regression. Including the Gini index limits the data sample to only include observations after 1960. Besides the time range the country sample is reduced since not for all nations inequality measures are available. This limitation specifically reduces time series of older technologies. As we see in Table A.2 these older technologies such as radios, telephones and cars overweigh in the sample analysis in Table 1, Column (1) and (2). The reduction implied by the smaller availability of reported Gini index leaves the cross-technology sample more balanced. Including control variables to the regression in Table 1 has the same effect on the respective sample.

The results in Column (1) and (2) of Table 2 show that the effect of total income and population are still highly significant and show the expected sign when including income inequality and the interaction term with average income as explanatory variables. In this second analysis is the estimated coefficient for the inequality measure itself and the coefficient of the interaction term are the results of greatest interest. While the estimated coefficient for the Gini itself is positive, the estimator for the interaction term comes out negative. Thereby at low levels of income the Gini as unpaired explanatory factor dominates and exerts a positive effect on diffusion. However as income rises the negative interaction term increases and reduces the positive influence. After a critical income level is passed an increase in the Gini index will have a negative effect on technology diffusion. Also this result for the Gini is robust in a limited sample and under the inclusion of control variable, reported in Column (3) to (6).

Table 2: OLS regression of Penetration rates including the Gini index

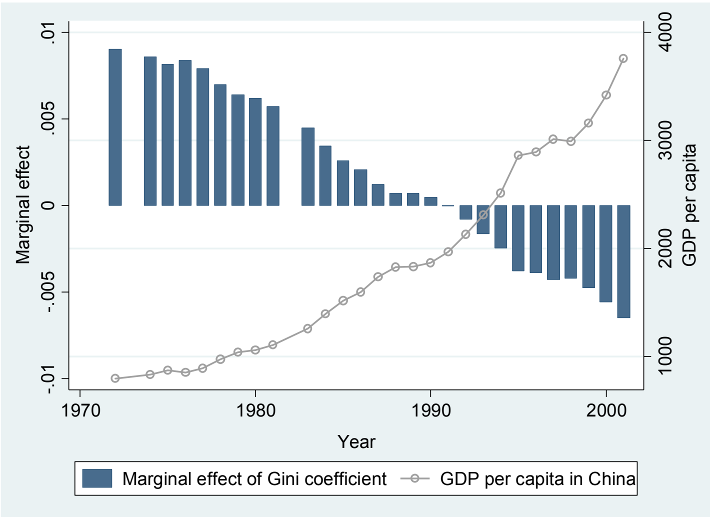
Dependent Variable: Penetration rates

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP	0.809***		0.879***		0.852***	
	(0.104)		(0.122)		(0.156)	
Log Population	-0.828***	-0.0191	-0.890***	-0.0113	-0.856***	-0.00470
	(0.105)	(0.0187)	(0.122)	(0.0209)	(0.159)	(0.0251)
Log GDPpc		0.809***		0.879***		0.852***
		(0.104)		(0.122)		(0.156)
Gini	0.0639**	0.0639**	0.0741**	0.0741**	0.0762*	0.0762*
	(0.0216)	(0.0216)	(0.0261)	(0.0261)	(0.0297)	(0.0297)
Log GDPpc*Gini	-0.00884***	-0.00884***	-0.00981**	-0.00981**	-0.0101**	-0.0101**
	(0.00254)	(0.00254)	(0.00304)	(0.00304)	(0.00352)	(0.00352)
Tertiary education stock					0.00176	0.00176
					(0.00730)	(0.00730)
Elecprodpc					0.000588	0.000588
					(0.000921)	(0.000921)
Trade share					0.000295	0.000295
					(0.000777)	(0.000777)
Urbanization					0.00231	0.00231
					(0.00193)	(0.00193)
Land area					-3.79e-09	-3.79e-09
					(1.47e-08)	(1.47e-08)
Freedom Index	No	No	No	No	Yes	Yes
Technology-year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	20780	20780	13676	13676	13676	13676
adj. R^2	0.953	0.953	0.953	0.953	0.954	0.954

Notes: Clustered standard errors in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include technology-year fixed effects. Penetration rates that do not describe shares are logarithmized. Column (5) and (6) include additional control variables for human capital, infrastructure and TFP, land area and urbanization as well as a 3-level index rating civil and political freedom.

These empirical results are in line with the expected influence derived in the theoretic model. Changes in income or population exert a level effect on technology diffusion, increasing or decreasing the penetration rate across the whole diffusion curve. The Gini index in comparison changes the slope of the diffusion curve. As it lifts the early phase of the curve and decreases penetration levels in the long run it rotates the diffusion curve at the critical income value, making the curve flatter overall. Figure 2 illustrates this change in marginal influence of Gini based on the estimated coefficients in Column (6). It plots the marginal effect of a change in the Gini index for China against its development of average income. Only with the rise in GDP per capita the marginal effect of income inequality turns to be negative and thereby will slow down diffusion.

Figure 2: The marginal effect of income inequality on penetration rates in China



Given the results reported in Table 1 and 2 the empirical analysis supports Hypothesis 2. The assumption of non-homothetic preferences shaping consumer demand for technology goods is legitimate and therefore measures of income distribution have a significant influence on technology diffusion. To determine if this influence is not only empirically but also economically significant the magnitude of the coefficients have to be assessed. Their value gives an impression of the absolute impact of inequality on technology diffusion. As the dependent variable in Table 1 and 2 is a diffusion measure that is heterogeneous in units the listed coefficients are difficult to interpret. The absolute effect of income inequality on technology diffusion is analyzed in more detail in technology-wise analyses which are discussed in the following section 5.1.4.

5.1.4 Technology specific analysis

Given the panel data structure technology diffusion can be analyzed at more disaggregate levels. The results from the full sample analysis are tested in regressions on subsample groups of technologies as well as on every single good. The three groups where defined as suitable for a subsample analysis based on combining goods from the same technology sectors or goods with similar unit measure. The first group contains the ICTs, the second combines a sample of older technologies with comparable units (cable TV, newspapers, telephones, TV sets and cars) while the third entails the transport technologies.

Comparing between modern ICTs and older technologies the regression results for total income, population and inequality in both samples are in line with Hypothesis 2, turning out slightly larger for the older sample. The results for the two groups are robust when controlling for other influential factors. Concerning control variables it is interesting to notice that while for older technologies human capital is the most important control variable and TFP is just slightly significant for ICTs education does not seem to play a determining role. TFP and the trade share meanwhile are highly significant. This can be interpreted as that the increase in global trade has led to knowledge spill-overs and flow of information that diminish the role human capital for the diffusion of consumer technologies. For penetration rates of cell phones land area that determines population density additionally is a significant factor. Another interesting comparison between groups concerns the level of critical GDP per capita at which the marginal effect of a change in income inequality switches from positive to negative. The higher this level, the longer consumption of the technology good is arguably reserved to more wealthy individuals as technology diffusion increases following an income redistribution in favor of the wealthy. Only after this average income level consumption of a good is eligible for all individuals and diffusion is adversely affected by higher income inequality. This critical level of average income indicates how exclusive a good actually is during the phase of introduction. While the critical GDP per capita for ICTs is 3’136 GK$ for the group of older technologies it is 2’030 GK$, a third less. This result has to be interpreted with caution though as there is significant variation in the countries as well as the length of time series covered in the two subsamples. Since ICTs have not been available for many years indicates that during their diffusion GDP per capita was generally higher compared to the early diffusion of older technologies. The difference in critical average income yet could still be an indicator that access to consumer technologies has gotten more difficult for the poor population in developing countries. A conclusion on this topic will only be possible following more detailed analysis.

Results from the analysis of the third technology group also confirm Hypothesis 2. Other than ICTs and old technologies the coefficient of the Gini and the interaction term is not significant when including a set of control variables. That the proposed theory does not explain the diffusion of transport technologies as well as that of other technologies is confirmed in the technology-wise analysis. Demand for transport technologies such as rail and aviation is special as it highly depends on topography and other geographical factors beyond land area and urbanization. Based on comparison of regression results of penetration rates cars better fit into the group of telecommunication technologies. The estimated coefficients in the car penetration analysis are in line with model predictions and very close in value to the telecommunication goods. That the diffusion of cars is better comparable to the diffusion of TV sets is also reasonable since the penetration rate refers to a stock of goods in an economy and not to output measures as it is the case for the other transport technologies.

For all telecommunication technologies, with the exception of telegrams, the estimated effect of the Gini index and its interaction term with GDP per capita is in line with expectations. The results are significant and robust to the inclusion of control variables. Also human capital measured by the share of population that attained tertiary education has a significant positive effect on the diffusion of these technologies. Exceptions are newspapers and mail for which the stock of secondary education plays a more important role. Based on these technology specific analyses an evaluation of the absolute effect of income inequality is made. Table A.6 and Table A.7 show the results of the respective regressions for the diffusion of cars and mainline telephones. The results from Colum (5) in Table A.6 suggests that a one percent increase in GDP, conditional on other variables entails countries to a 0.2%-points higher penetration rate of cars. The effect of an increase in the Gini index by 5 units at the sample mean GDP per capita of 8.52 implies a decrease in the diffusion of cars by 1.5%-points. The immediate absolute effect is not large; however a change in income inequality in the model does not shift the diffusion curve but changes its slope. Thereby it is not the immediate difference in diffusion rate that matters most, but the long-term effect that accumulates with the growth in average income. This long-term effect is illustrated in Figures A.6a-d giving examples for developed and developing countries. Figures A.6a and b show the predicted diffusion curves of cars for the United States and Norway based on their actual development. A second line traces a fictive penetration rates that would result if the Gini was held constant after 1967 with 90% confidence intervals. While the Gini in Norway was already as low as 26 in 1967 it has even decreased since to 24 in 2002. In the United States meanwhile the Gini has increased from a level of 28 in 1967 to 36 in 2002. Given that all other characteristics besides the Gini follow their actual development path, the regression results suggest that if inequality did not increase since 1976 the United States would have seen a penetration rate of cars about 10%-points higher in 2000. For Norway the difference is diminishing, suggesting a slightly positive effect from the reduction in Gini which however is not significant. Figure A.6c and d depict the development of penetration rates for Mauritius and India. Mauritius is of special interest to economists for being a developing country that saw a significant reduction in income inequality. At the start of the reporting period in 1960 the Gini is as high as 46, decreasing in the following years to a very low 15 in 2002. The Figure A.6c shows the predicted penetration rates for the actual decrease and the fictive case keeping the Gini at the average level of 30 over the whole period. The actual decrease in inequality results in a 10%-points higher market penetration of cars in 2000 compared to a case of stable average inequality. India on the other hand has seen an increase in income inequality since the 1960s from a Gini of 46 to a peak of 53 in 1997. The fictive scenario for India applies the Gini index of 1997 for all years. Other than for Mauritius, the fictive case of a higher Gini would have resulted in higher penetration rates, especially in the early years. This case illustrates the positive effect of income inequality on technology diffusion in the early stages of diffusion at low levels of average income. Given that the absolute effect is rather small it is however not significant at the 90% confidence level.

For the last sector of financial technologies the influence of income inequality is only significant and robust for EFTs and POS. The tertiary education stock meanwhile is only a significant influence to the penetration rates of credit and debit card usage. One reason why results for income inequality are weak in this sector can be found in the country sample. Data on the diffusion of financial technologies are primarily available for developed countries and the sample is clearly dominated by western European economies. Thereby the variation in Gini within these samples is much smaller, nearly half compared to regressions for the other technologies. Thus the Gini index can explain less of the variation in diffusion rates.

5.1.5 Other measures of income inequality

In the model presented in section 3.2 the increase in inequality comes through a regressive redistribution of income across all levels of income. This kind of transfer increases the mass in the upper tail of the income distribution and reduces mass in the lower tail. An increase in the Gini index meanwhile does not necessarily imply this kind of redistribution. An increase in the Gini may also follow from redistributions limited to the upper, middle or lower section of the income distribution. As the Gini index is a rather general measure of inequality it does not perfectly capture the dynamics that were implied in the outlined theory. The Gini index is still used for the main analyses as it is the best measure of inequality available to apply in a panel analysis over many countries and years. While the empirical results from the regressions that use the Gini are significant and reasonable the underlying dynamics of demand can be examined in more detail by applying different measures of inequality to the analysis. Alternative measures that were used are the income share of the top 1% and of the top 10% of tax fillers, as well as mortality rates of children under five and male adults[16].

In the cross-technology analysis neither of the two measures of top income shares return significant coefficients. Also in technology wise analysis the only significant and robust effect examined is for some telecommunications technologies using the top 1% measure. The empirical results using these measures of the upper tail of the income distribution are very weak and do not support the prior findings. For the top 1% measure this may relate to the fact that this measure does not capture inequality well but refers to the absolute richest individuals in a population. It is reasonable to assume that their consumption of goods is not limited to local availabilities as they are typically more mobile and have access to different markets. For the top 10% the same argument might still hold true. Data on the income share of top 10% earners also covers a smaller sample of countries, mainly comprised of developed nations. While the income share of the top 1% is available for the same broad panel as the Gini index, measures of the income share of the top 10% is only available for about a quarter of this panel. The results nevertheless question the validity of the presented theory. Further research using measures of income share of the top 20% of wage earners would be necessary to shed more light on this issue.

Other than the top income share mortality rates of male adults or children under five rather represent the lower tail of the income distribution. Higher mortality, given a certain total or average income, indicates that some people have reduced access to basic medical services. This rate of people at disadvantage can be applied as a proxy for poverty or income inequality. While the relation between income inequality and mortality rates of male adults is under debate empirical research widely supports the relation between inequality and child mortality[17].

[16] Data in the income share of the top 1% tax fillers comes from the SWIID (Solt, 2009), for the income share of the top 10% wage earners data from the World Top Incomes Database is used (Facundo, Atkinson, Picketty and Saez, 2014) while the measures of mortality are both retrieved from the World Bank Database (World Bank, 2014a).

[17] For a review of this debate see Lynch et al. (2000) and Torre and Myrskylä (2014)

Using these mortality rates as measures of inequality in a sample analysis including all technologies also returns weaker results than the Gini index. For child mortality the estimated coefficients show the expected signs, yet they are only significant at the 10% confidence level. For adult mortality only the coefficient for interaction term with GDP per capita is significant. The estimated coefficient is negative and also for child mortality this coefficient of the interaction term is negative and larger in magnitude than the positive coefficient of the single variable. In analyses including the Gini index the opposite is observed in terms of magnitude of coefficients. Only when the coefficient for the inequality measure itself is larger than the interaction term with GDP per capita it can dominate the marginal effect for some low levels of GDP per capita. That for both measures of mortality the negative interaction term dominates as explanatory effect implies that at practically every level of average income mortality has a negative influence on the penetration rate. Because mortality is rather a measure of poverty than overall inequality this is in line with the lined out theory. As described in section 3.2.1, while more high income individuals support technology diffusion an increase in poor individuals slows it down in the long run. The analysis using mortality rates instead of the Gini index empirically supports this theory.

The two mortality measures are also significant explanatory variables in the single technology analyses as the Gini. The exception to this are transportation technologies. For the single technology analyses not only the interaction term is significant but also the influence of the variable by itself, showing the expected signs for both coefficients.

5.1.6 Robustness

The panel structure of the data sample allows to test for robustness of results across technologies, time and countries. As described above, the results for the Gini index are robust when analyzing subsamples that group certain technologies. They are also persistent in most single technology regressions, provided that the sample includes sufficient data and variation in the explanatory variables. Two further options of robustness test have not been discussed so far: regional variation and testing the influence of the explanatory variables on production technologies.

The derived influence of inequality on technology diffusion for the full sample analysis, technology groups as well as for most single technology regressions are robust to inclusion of regional and continental dummies. The only exceptions are cell phones, mail, and the financial technologies. The last group does not cover sufficient countries to make regional controls a sensible instrument. Of special interest are the results for transport technologies under regional control. These technologies are highly sensitive to geographic factors. For personage-kilometers by plane results do not change much under inclusion of regional dummies. In the analysis of personage-kilometers and passenger journeys by rail meanwhile the Gini enters as significant explanatory variable once regional dummies are introduced.

Results from analyses of split samples between developed and developing countries are much weaker. For all technologies the estimated model fits better for developed countries than for developing ones. This could relate to the fact that in many developing countries technologies are still in the early diffusion stage. In these lower levels of penetration rates, the curve is rather flat and the applied fixed effect regression is better suited to give an estimation of the middle, increasing part of the diffusion curve. As the chosen estimation approach does not well model the initial and final asymptotic sections of the curve, the model performs worse on developing countries. This argument has to be considered with caution though as the model fit is difficult to compare for the two data samples that differ in many factors. Beyond this, one may also argue that in developing countries certain omitted factors, which are not of the same importance in developed countries, play a bigger role on technology diffusion.

An important issue to be considered in robustness tests is the potential simultaneity between technology diffusion and measures of income inequality. Under simultaneity or endogeneity the identifying assumption of uncorrelated error terms for OLS regression is violated. As mentioned in the introduction there is reason to assume causality running not only from inequality to technology diffusion but also in the opposite direction. For the presented analyses independence of the explanatory variables from technology diffusion is still reasonable as very disaggregate measures of technology are used. It is not necessarily reasonable to assume that the diffusion of a single good such newspapers have an impact on the same period income distribution. Therefore income inequality is assumed to be exogenous and simultaneity as potential bias to the estimation results is ruled out by assumption. To test whether the shown effects can truly be interpreted as demand side dynamics the same regression model is applied on the diffusion of production technologies. The sample of production technologies used ranges from the number of motor ships, over tonnage-kilometers by rail and a variation of steel production to the amount material used for textile production. The data is taken from the CHAT dataset. For some of the production technologies the Gini is estimated to have a negative effect. However, for all production technologies the estimated coefficients for explanatory variables fail to describe the demand side dynamics that were derived in the model. This indicates that the shown effect of income distribution on diffusion of consumer goods may be accounted to represent consumer demand and not general dynamics of economic development.

5.2 Attempt on diffusion lags

While technology diffusion has already been studied in different approaches only few authors have analyzed the time to adoption. Comin, Hobijn and Rovito (2008) as well as Comin and Hobijn (2010) focus their analysis on the estimation of diffusion lags and on their effect on countries TFP and income per capita. They do not concern the question what determines the length of adoption lags. In their analysis they find that usage lags are highly stable over time and conclude that the past is more important in the determination of usage lags than the current state of development. As the analysis in this paper bases on the same dataset it faces the same problem of lacking observations for actual technology adoption. To overcome this approximate measures are used which however are arbitrarily defined. Therefore the approach and results on technology adoption presented in this paper have to be considered an attempt.

5.2.1 Baseline specification

Based on Hypothesis 1 the following reduced form of equation (1) is applied as regression model to diffusion lags:

$$diffusionlag_{c\tau t} = exp(\alpha + \beta X_{ct} + dummy_{technology} + \delta Z_{ct} + \varepsilon_{c\tau t}) \qquad (10)$$

The dependent variable $diffusionlag_{c\tau t}$ refers to the constructed diffusion lags of a certain country c in technology τ with reference year t. In the model presented in section 3 of this paper income and its distribution at time $t(0)$ determine how long it will take for income in a country to be sufficient for technology adoption. Following this the calculated diffusion lags are related to the explanatory variables as they are reported in the relevant benchmark year. X_{ct} denotes the vector of explanatory demand variables (total income, population and inequality) in reference year t. Z_{ct} is a vector of control variables and $\varepsilon_{c\tau t}$ is the error term. Additional to the control variables included in the analysis of penetration rate the 5-year compound annual growth rate of average income is included. This follows from equation (1) in which time to adoption is not only a function of current income but also its growth path. Further for each technology a technology dummy is included to capture the trend that for older technologies lags are larger on average.

The calculated diffusion lags are bound below by zero and represent the occurrence of an event. The effect of demand factors on diffusion lags are therefore estimated in a Poisson regression. The estimation sample of diffusion lags is significantly limited by the availability of data on income distribution for years prior to 1960 and a general decrease in national statistics on technology usage back to the 19^{th} century.

5.2.2 Empirical results

The empirical analysis follows the same approach as the analysis of penetration rates. In a first step the effect of total income and population is estimated running the reduced regression equation (10) on the panel of constructed adoption lags. The respective results are reported in Table 3. Column (1) shows that the estimated effect of GDP and population are both highly significant. The listed coefficients are exponentiated and have to be interpreted in a multiplicative manner. Coefficients smaller than one imply that a factor has a negative effect on the diffusion lag while variables with an estimated coefficient larger than one prolong the time lag. Thus an increase in GDP will reduce the diffusion lag whereas higher population, without a consecutive increase in income will prolong the time to adoption. These findings support the formulated Hypothesis 1. Column (2) adds average income instead of population. Corresponding to the analysis of penetration rates average income dominates the total income in terms of explanatory power. That the effect of average income is a more important predictor for aggregate demand than aggregate income in both analyses strongly supports the assumption of non-homothetic preferences. Columns (3)-(6) report results of the same regression for a reduced sample and under inclusion of control variables for human capital, TFP, openness to trade and growth expectations. While the data sample is substantially reduced in these regressions all explanatory variables remains to have a significant effect. Explicitly, higher total income remains supportive of earlier technology adoption and an increase in population would still prolong the time to adoption. Estimation results from Column (6) suggest that an increase in total income by one percent, keeping average income constant, will reduce the adoption lag to 95% of its prior length. A respective change in average income by one percent, keeping all other variables constant, will reduce the adoption by 21%. The estimated effects of income and population are in line with the model predictions and the derived Hypothesis 1. While the results are robust in regressions with control variables and of considerable magnitude they have to be evaluated rather conservatively due to concerns with the used data.

Table 3: Poisson regression of Diffusion Lags on income and population

Dependent Variable: Adoption Lags

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP	0.635***	0.944***	0.638***	0.949***	0.752***	0.949***
	(0.0243)	(0.0159)	(0.0225)	(0.0146)	(0.0306)	(0.0152)
Log Population	1.488***		1.487***		1.262***	
	(0.0648)		(0.0530)		(0.0544)	
Log GDPpc		0.672***		0.672***		0.792***
		(0.0293)		(0.0239)		(0.0341)
Tertiary education stock					0.973**	0.973**
					(0.00822)	(0.00822)
Elecprodpc					0.995***	0.995***
					(0.00108)	(0.00108)
Trade share					0.999	0.999
					(0.000827)	(0.000827)
CAGR5yr					0.345	0.345
					(0.305)	(0.305)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
N	616	616	366	366	366	366
Pseudo R2	0.650	0.650	0.440	0.440	0.468	0.468
Prob>chi2	0	0	3.45e-227	3.45e-227	1.74e-304	1.74e-304

Notes: Exponentiated coefficients. Robust standard errors in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include technology fixed effects. Column (3) and (4) additionally control for human capital, TFP, openness to trade and growth expectations.

To include the Gini index as an explanatory variable in the second step of the analysis significantly reduces the estimation sample. The results from regressions that include the Gini as a measure of income inequality are reported in Table 4. Column (1) and (2) display estimated coefficients for total income and population in the reduced sample. They are of similar magnitude as the coefficients in Table 1 and do not change much following the inclusion of the Gini and control variables. Including the Gini index as explanatory variable into the regression in Column (3) and (4) returns significant coefficients. The estimated coefficient remains significant at the 10% confidence level under inclusion of control variables. In all Columns (3) to (6) the estimated coefficients for the Gini are larger than one meaning that more income inequality prolongs the adoption lag. Thereby a country with a Gini index equal to the sample mean of 34 compared to an economy with a Gini that is five units lower, ceteris paribus, would have an adoption lag that is 2.5% larger[18]. This is contradictory to Hypothesis 1 based on which more income inequality is expected to reduce

[18] 1.005^5=1.025

time to adoption. The positive influence and significance of the estimated effect of the Gini index is robust in regressions including different control variables such as civil freedom, urbanization or growth expectations over longer horizons. In regressions with other measures of income inequality such as the income share earned by the top 1% of wage earners, rates of child mortality or adult mortality the estimated coefficients are significant and positive as well[19]. Also the magnitude of the estimated absolute effect of changes in income inequality on time to technology adoption is equivalent for different measures of inequality.

Generally there is a strong tendency for underdeveloped countries to report high Gini index. As discussed in section 4.3 and illustrated in Figure A.3 developing countries do not report larger lags than developed economies in the constructed data sample. This would be the case though, when grouping the lags technology wise. The empirical analysis of diffusion lags does not break down the sample to technology subsets but it includes technology fixed effects. Thereby the sample is demeaned by technology and the explanatory variables actually capture a deviation from the technology specific mean lag. These deviations, displayed in Figure A.7 are positive for nations with low levels of average income today and mostly negative in more developed countries. This coincides with higher Gini index for countries with lower levels of income. Given this, in this limited data sample the Gini enters as an indicator for level of development rather than income distribution. Its estimated coefficient then captures the influence of other omitted variables which are not controlled for, that distinct developing countries from developed ones. A subsample analysis is not feasible given the already limited dataset and number of regressors. However, in regressions that include dummies for developed countries or Sub-Saharan countries the estimated effect of the Gini index is persistently positive when significant. Also control variables such as education, electricity production and trade share which are also indicators to relative level of development do not alter the result.

[19] Especially for developing countries the share of top earners might be more important to technology adaption than the distribution at the lower levels of income.

Table 4: Poisson regression of Diffusion Lags including the Gini index

Dependent Variable: Adoption Lags

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP	0.621***	0.970	0.650***	0.971	0.790***	0.957*
	(0.0289)	(0.0191)	(0.0336)	(0.0186)	(0.0404)	(0.0168)
Log Population	1.562***		1.495***		1.212***	
	(0.0801)		(0.0816)		(0.0661)	
Log GDPpc		0.640***		0.669***		0.825***
		(0.0328)		(0.0365)		(0.0450)
Gini			1.007**	1.007**	1.005*	1.005*
			(0.00274)	(0.00274)	(0.00223)	(0.00223)
Tertiary education stock					0.989	0.989
					(0.00762)	(0.00762)
Elecprodpc					0.995***	0.995***
					(0.00123)	(0.00123)
Trade share					0.998**	0.998**
					(0.000722)	(0.000722)
CAGR5yr					0.192	0.192
					(0.177)	(0.177)
Technology FE	Yes	Yes	Yes	Yes	Yes	Yes
N	237	237	237	237	237	237
Pseudo R2	0.245	0.245	0.249	0.249	0.286	0.286
Prob>chi2	1.21e-45	1.21e-45	2.32e-55	2.32e-55	2.57e-113	2.57e-113

Notes: Exponentiated coefficients. Robust standard errors in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include technology fixed effects. Column (5) and (6) additionally control for human capital, TFP, openness to trade and growth expectations.

There are different explanations to this contradiction with theory. The factor that limits the quality of empirical results is the used data sample. First, the dataset of calculated diffusion lags that could be exploited in empirical analysis is significantly limited by the lack of income data for many countries in years prior to the second half of the 20th century. Especially data on income distribution is only available for less than half of the sample used in Table 3. Second, and more important to consider is the arbitrary definition and calculation of diffusion lags. As discussed in more detail in section 4.3 they are only approximate measures of time to adoption. Another reason why the estimation results are not in line with expectations from theory relates to misspecification of the model. As briefly discussed in section 3.3, model implications may be different in a more sophisticated model including fixed cost of technology adoption and log-normal income distribution.

Summarizing the results on diffusion lags there is a constant pattern that GDP, ceteris paribus, decreases the diffusion lags, while population size has a prolonging effect. GDP per capita as a measure of average income dominates total income in explanatory power and also exerts a negative influence on diffusion lags. These results support Hypothesis 1 and the assumed role of non-homothetic preferences for technology adoption. The results of the second part of the analysis suggest that the effect of income inequality on the diffusion lag of consumer technologies is negative. Following this Hypothesis 1 is to be rejected.

Given the limited data sample and arbitrary definition of diffusion lags these result have to be considered a preliminary attempt on the analysis of what factors drive technology adoption. The findings indicate that there is need to further develop models of technology adoption through consumer demand. This would improve understanding of the influence of different economic factors and lead to better empirical models. Future research on the topic should also needs to find better approaches to overcome the lack of data on initial adoption. Collection of national data as done by Dekimpe et al. (2000) for mobile telecommunication should be expanded to further technologies for panel analysis.

6 Conclusion

The focus of this thesis lies on the effect of income inequality on technology diffusion. For this purpose the diffusion of technology is measured through consumption of consumer goods that either contain a technology or are produced under the use of a certain technology. Under the assumption of non-homothetic preferences a model of consumer demand is described in which income inequality has a non-constant effect on the diffusion of these consumer goods. Following from this model, in the early stages of economic development, when average income is low, unequal distribution of income has a positive effect on total national consumption of the technology related goods. In the long term however more income inequality is slowing down the process of diffusion. The empirical results from a panel analysis in large support the effect of income inequality on diffusion that was derived from theory. These results are in line with findings from Hyytinen and Tovianen (2011) that estimate a positive effect of income inequality on the early stage of technology diffusion. As the presented analysis goes beyond the early stage of diffusion it aligns the research from Hyytinen and Tovianen with work from other scholars such as Fuchs (2009). He finds for income inequality to have an overall negative effect on technology diffusion. Also this is confirmed in the presented analysis where income inequality exerts a negative influence in the long term of diffusion. Since this is the first analysis that tests for both effects at the same time via an interaction term between the Gini index and GDP per capita the results will have to be validated and studied in more detail in future research. Especially studies that use more specific measures of income distribution such as the income share of the top 20% wage receivers could help to confirm presented findings. Attempts in this paper that use the income share of the top 1% and the top 10% failed to return meaningful results.

The thesis features a second approach on the influence of income inequality on the timing of national technology adoption relative to other economies. The empirical results on did not confirm a negative effect of income inequality on time to adoption as it is expected from theory. This failure to confirm the model predictions can be related to the limited data sample and arbitrary definition measures used for adoption lags. The failure however also raises concerns that the described model is miss-specified as it lacks fixed cost of infrastructure. It is up to future research to improve theoretical modeling of the effect of consumer demand and income inequality on technology adoption and test them empirically. A potentially more suitable empirical approach to studying the determinants of technology adoption is taken by Dekimpe, Parker and Sarvary (2000) which study adoption lags as a hazard rate. Including measures of inequality in this approach may yield better results than the presented analysis that relates adoption lag to economic characteristics of past periods.

Among the technology specific analyses the ICTs are of special interest as they have been studied in similar approaches in prior research. For these technologies the estimated coefficients imply a smaller influence of income inequality on diffusion than for telecommunication technologies and results are weaker. The influence of inequality also is not robust to controlling for regional heterogeneity through dummies. Combined with the fact that diffusion lags are shorter for more recent technologies than for older technologies this is an indicator that diffusion of modern ICTs follows somewhat different patterns than diffusion of older technologies. Rouvinen which has analyzed the effect of income inequality on the diffusion of mobile telephony comes to a similar result, stressing that "Late entrants experience faster diffusion promoting cross-country convergence” (2006, p.46). Future research thereby should go one step further, not only analyzing the determinants of adoption lags and technology diffusion, but whether the time to adoption holds some implications for the diffusion process thereafter.

The presented results show up the need to further develop theory and empirical research on the effect of consumer demand on technology diffusion. They provide support to the assumption that demand dynamics do play a determining role on the process of technology diffusion and that this demand is characterized by non-homothetic preferences.

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Appendix

Proof

Proof A.1. The effect of changes in moments of income on the Gini index

The Gini index is defined as $G = 1 - 2\int_0^1 L(p)dp$ where $L(p)$ is the Lorenz Curve. See Gastwirth (1971) for the derivation of $L(p) = \mu^{-1}\int_0^p F^{-1}(t)dt\ , 0 \leq p \leq 1$. For the chosen model of uniform income distribution we can derive $F^{-1}(t) = t(Y_R - Y_P) + Y_P$.

$$L(p) = \mu^{-1}\int_0^p t(Y_R - Y_P) + Y_P\, dt = \mu^{-1}\left(pY_P + \frac{1}{2}p^2(Y_R - Y_P)\right)$$

$$G = 1 - 2\int_0^1 \mu^{-1}\left(pY_P + \frac{1}{2}p^2(Y_R - Y_P)\right) = 1 - \frac{1}{2}\mu^{-1}\left[\frac{1}{2}Y_P p^2 + \frac{1}{6}p^3(Y_R - Y_P)\right]_0^1$$

$$G = 1 - \frac{2Y_P + Y_R}{3\mu} = 1 - \frac{2(2Y_P + Y_R)}{3(Y_R + Y_P)} = \frac{Y_R - Y_P}{3(Y_R + Y_P)}$$

Reintroducing the income growth path proposed in the model demonstrates that income distribution and the Gini are unaltered by proportional growth in individual incomes.

$$G(t) = \frac{Y_R(0)e^{gt} - Y_P(0)e^{gt}}{3(Y_R(0)e^{gt} + Y_P(0)e^{gt})} = \frac{Y_R(0) - Y_P(0)}{3(Y_R(0) + Y_P(0))} = \bar{G}$$

Effect of increase in income inequality:

$$G = \frac{Y_R - Y_P + 2k}{3(Y_R + Y_P)} \;\rightarrow\; \frac{dG}{dk} = \frac{2}{3(Y_R + Y_P)} > 0$$

Effect of increase in population:

$$G = \frac{\theta_R/L - \theta_P/L}{3(\theta_R/L + \theta_P/L)} = \frac{\theta_R - \theta_P}{3(\theta_R + \theta_P)} \;\rightarrow\; \frac{dG}{dL} = 0$$

Effect of increase in total income:

$$G = \frac{\alpha Y_R - \alpha Y_P}{3(\alpha Y_R + \alpha Y_P)} = \frac{Y_R - Y_P}{3(Y_R + Y_P)} \;\rightarrow\; \frac{dG}{d\alpha} = 0$$

■

Tables

Table A.1: Technologies with demand side effects

Finance	
ATM	Number of electromechanical devices that permit authorized users, typically using machine-readable plastic cards, to withdraw cash from their accounts and/or access other services. Requires infrastructure and minimum market.
Cheque	Number of payments by cheque (in millions). Needs minimum market to be introduced, however is not common in all countries.
CreditDebit	Payments by credit and debit cards (in millions). Requires infrastructure and minimum market.
EFT	Number of electronic financial transactions using payment cards at points of service (retail locations). Requires infrastructure and minimum market.
POS	Number of retail locations at which payment cards can be used. Requires infrastructure and minimum market.
Telecommunications	
Cable TV	Number of households that subscribe to a multi-channel television service delivered by a fixed line connection. Requires infrastructure and minimum market.
Mail	Number of items mailed/received, with internal items counted once and cross-border items counted once for each country. Mail service is provided by public institutions in many countries.
Newspaper	Number of newspaper copies circulated daily. Needs minimum market; in some countries may depend on government involvement in and control of media.
Radio	Number of radios. Requires infrastructure and minimum market.
Telegram	Number of telegrams sent, in thousands. Requires infrastructure and minimum market.

	Out dated technology also reporting declining rates. Initial installation of infrastructure may have served war-interests rather than consumer market demand.
Telephone	Number of mainline telephone lines connecting a customer's equipment to the public switched telephone network as of yearend.
	Requires infrastructure and therefore minimum market size
	Good is characterized by primary and secondary network effects; phone services have been public service in many countries!
TV	Number of television sets in use.
	Requires infrastructure and therefore minimum market size; in some countries may depend on government involvement in and control of media.
Transportation	
AviationPKM	Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned.
	Need to control population density (may additionally depend on topography).
RailP	Thousands of passenger journeys by railway.
	Need to control for population density (optionally for rail line lengths).
RailPKM	Passenger journeys by railway in passenger-KM, in millions.
	Need to control for population density (optionally for rail line lengths).
Car	Number of passenger cars (excluding tractors and similar vehicles) in use.
	Need gas station infrastructure (might suffer from negative network effects).
Information and Communication Technologies	
Computer	Number of self-contained computers designed for use by one person.
Mobile phone	Number of users of portable cell phones.
	Needs network provider and minimum market.
Internet user	Number of people with access to the worldwide network.
	Depends on infrastructure and availability of computer.

For more detail on definitions and measures see Comin and Hobijn (2009).

Table A.2: Penetration rates summary statistic

	count	mean	sd	min	max
atmpen	351	0.0004	0.0003	0.0000	0.0014
avpkmpen	4160	209.2924	430.6263	0.0002	4004.2410
cablepen	820	0.0856	0.0980	0.0000	0.4019
cellpen	1581	0.0842	0.1768	0.0000	0.9840
chequepen	119	17.2472	27.0796	0.0055	170.6390
computerpen	1354	0.0738	0.1175	0.0000	0.7018
creddebpen	366	24.1867	29.6032	0.0044	178.3272
eftpen	332	16.9283	20.0904	0.0010	91.5401
iuserpen	1309	0.0535	0.1095	0.0000	0.6127
mailpen	4893	67.3058	86.7312	0.0553	664.8532
newspen	3414	0.0879	0.1230	0.0001	0.7016
pospen	335	0.0054	0.0050	0.0000	0.0224
radiopen	5953	0.0002	0.0003	0.0000	0.0021
railppen	2897	9.5216	21.0588	0.0001	186.1784
railpkmpen	4691	309.9506	415.0778	0.1042	3243.3408
telegpen	2242	0.0006	0.0008	0.0000	0.0050
phonepen	6440	0.0796	0.1458	0.0000	1.0135
tvpen	4629	0.1369	0.1687	0.0000	0.9371
carpen	6106	0.0611	0.1116	0.0000	0.7792
N	51992				

Table A.3: Correlation between penetration rates and GDP per capita

GDPpc	rho	p	count
atmpen	0.60	0.000	351
avpkmpen	0.69	0.000	4160
cablepen	0.65	0.000	820
cellpen	0.52	0.000	1581
chequepen	0.62	0.000	119
computerpen	0.80	0.000	1354
creddebpen	0.60	0.000	366
eftpen	0.43	0.000	332
iuserpen	0.63	0.000	1309
mailpen	0.85	0.000	4893
newspen	0.70	0.000	3414
pospen	0.46	0.000	335
radiopen	0.82	0.000	5953
railppen	0.53	0.000	2897
railpkmpen	0.52	0.000	4691
telegpen	0.72	0.000	2242
phonepen	0.84	0.000	6440
tvpen	0.80	0.000	4629
carpen	0.87	0.000	6106

Table A.4: Adoption lags

Technology	Penetration threshold	Benchmark country and reference year
ATMs	18ATMs/100'000 People	United Kingdom, 1988
Aviation PKM	180Km/Person	United States, 1954
Cable TV	3.5% of Population	United States, 1975
Cell phones	5% of Population	Finland, Norway, Sweden, 1989
Cheques	Time series of diffusion are short and do not cover common value ranges across countries. They don't serve to construct meaningful diffusion lags.	
Computer	7% of Population	United States, 1984
Credit-/Debit card payments	22 Payments/Person	Canada, 1987
EFTs	10 EFTs/Person	Finland, France, 1989
Internet user	2% of Population	Norway, 1992
Mail	180 Items/Person	United States, 1908
Newspaper circulation	0.5 Newspaper/Person	United Kingdom, 1946
POS	0.005/Person	Finland, 1990
Radios	0.6/1'000 People	United States, 1951
Rail Passengers	12.5 Rail journeys/Year and Person	Australia, 1881
Rail Passenger-KM	110 Passenger-KM/Year and Person	Germany, 1870
Telegrams	0.7/1'000 People	Austria, 1870
Mainline Telephones	10% of Population	United States, 1913
TV sets in use	15% of Population	United States, 1954
Passenger cars	15% of Population	United States, 1925

Table A.5: Adoption lags summary statistic

	count	mean	sd	min	max
lag	616	23.57	25.05	0	123

Table A.6: Diffusion of Cars

Dependent Variable: Penetration rates of Cars

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP	0.125***		0.294***		0.220***	
	(0.0110)		(0.0250)		(0.0350)	
Log Population	-0.119***	0.00590	-0.283***	0.0111	-0.215***	0.00541
	(0.0111)	(0.00720)	(0.0224)	(0.00661)	(0.0344)	(0.00680)
Log GDPpc		0.125***		0.294***		0.220***
		(0.0110)		(0.0250)		(0.0350)
Gini			0.0391***	0.0391***	0.0274***	0.0274***
			(0.00430)	(0.00430)	(0.00489)	(0.00489)
Log GDPpc*Gini			-0.00505***	-0.00505***	-0.00356***	-0.00356***
			(0.000512)	(0.000512)	(0.000613)	(0.000613)
Tertiary education stock					0.00313	0.00313
					(0.00259)	(0.00259)
Elecprodpc					0.000500	0.000500
					(0.000372)	(0.000372)
Trade share					0.0000666	0.0000666
					(0.000187)	(0.000187)
Urbanization					-0.000805	-0.000805
					(0.000444)	(0.000444)
Land area					5.22e-09	5.22e-09
					(4.07e-09)	(4.07e-09)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1441	1441	1441	1441	1441	1441
adj. R^2	0.823	0.823	0.893	0.893	0.913	0.913
F-Test	16.98	16.98	24.49	24.49	30.61	30.61

Notes: Clustered standard errors in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects. Column (5) and (6) include additional control variables for human capital, infrastructure, openness to trade, land area, urbanization and civil freedom.

Table A.7: Diffusion of Phones

Dependent Variable: Penetration rates of Phones

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP	0.183^{***}		0.438^{***}		0.239^{***}	
	(0.0180)		(0.0529)		(0.0535)	
Log Population	-0.183^{***}	0.000672	-0.431^{***}	0.00704	-0.227^{***}	0.0115
	(0.0204)	(0.00804)	(0.0514)	(0.00749)	(0.0533)	(0.00726)
Log GDPpc		0.183^{***}		0.438^{***}		0.239^{***}
		(0.0180)		(0.0529)		(0.0535)
Gini			0.0584^{***}	0.0584^{***}	0.0323^{***}	0.0323^{***}
			(0.00935)	(0.00935)	(0.00839)	(0.00839)
Log GDPpc*Gini			-0.00756^{***}	-0.00756^{***}	-0.00411^{***}	-0.00411^{***}
			(0.00115)	(0.00115)	(0.00108)	(0.00108)
Tertiary education stock					0.00812^{*}	0.00812^{*}
					(0.00343)	(0.00343)
Elecprodpc					0.00204	0.00204
					(0.00104)	(0.00104)
Trade share					0.00123^{***}	0.00123^{***}
					(0.000344)	(0.000344)
Urbanization					-0.000693	-0.000693
					(0.000749)	(0.000749)
Land area					-1.55e-09	-1.55e-09
					(4.55e-09)	(4.55e-09)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	1215	1215	1215	1215	1215	1215
adj. R^2	0.787	0.787	0.861	0.861	0.907	0.907
F-Test	18.20	18.20	28.00	28.00	42.19	42.19

Notes: Clustered standard errors in parentheses. *** significant at 1 percent, ** significant at 5 percent, * significant at 10 percent. All regressions include year fixed effects. Column (5) and (6) include additional control variables for human capital, infrastructure, openness to trade, land area, urbanization and civil freedom.

Figures

Figure A.1: Decision Rule of consumption

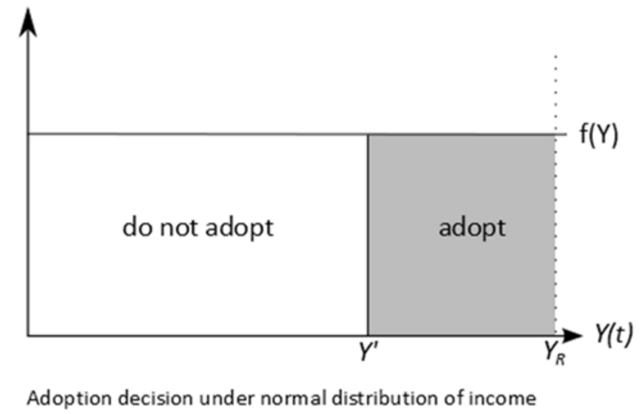


Figure A.2: Illustration of television diffusion lags

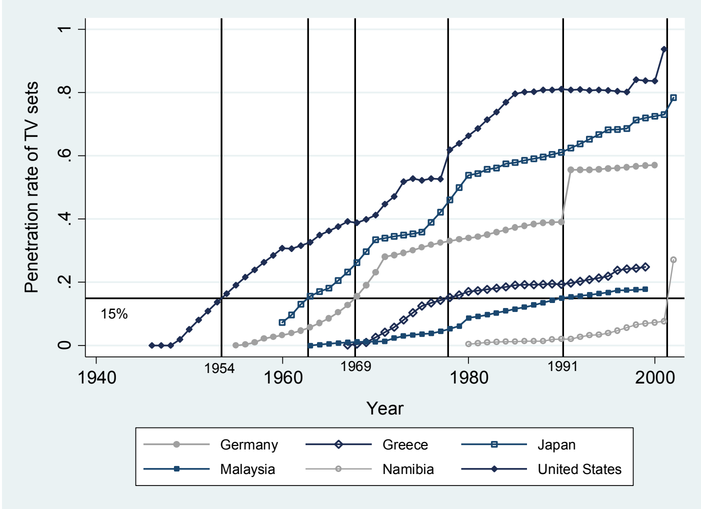


Figure A.3: Diffusion lags across countries

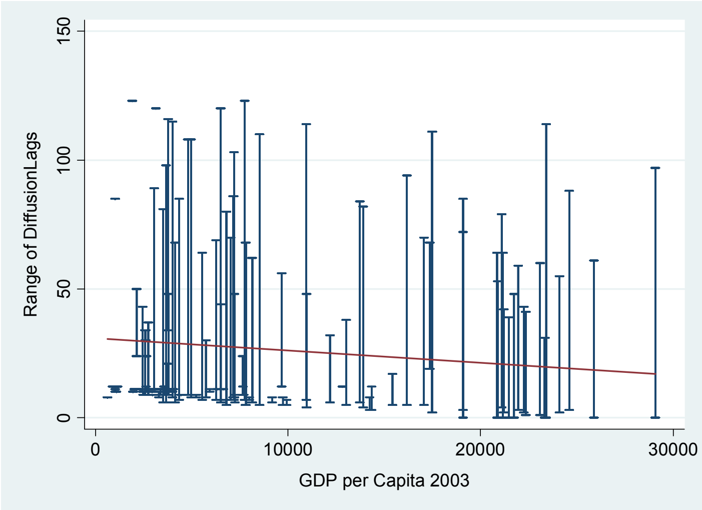


Figure A.4: Diffusion lags of different technologies

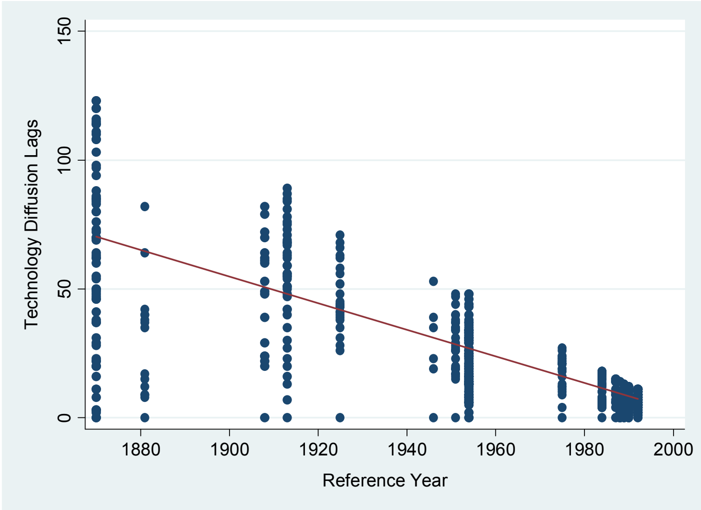


Figure A.5a: Diffusion lags and average income

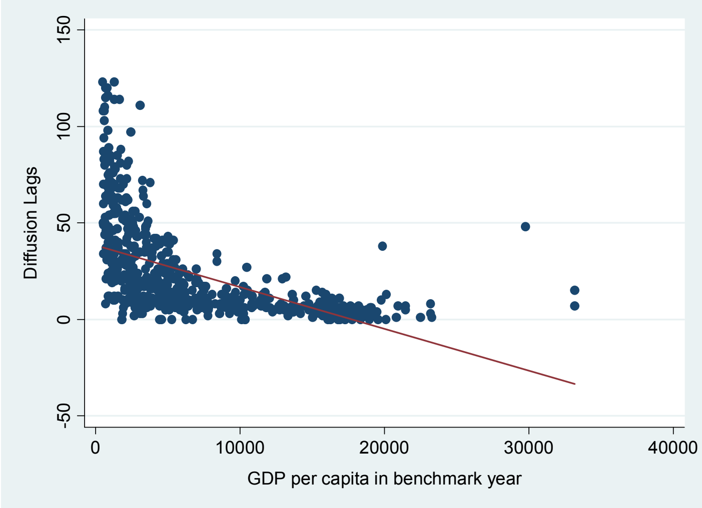


Figure A.5b: Diffusion lags and income inequality

Figure A.6a: Diffusion of cars in the United States

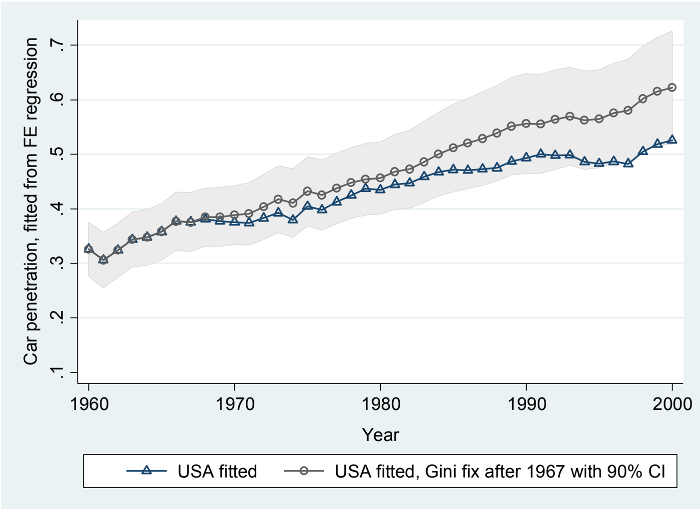
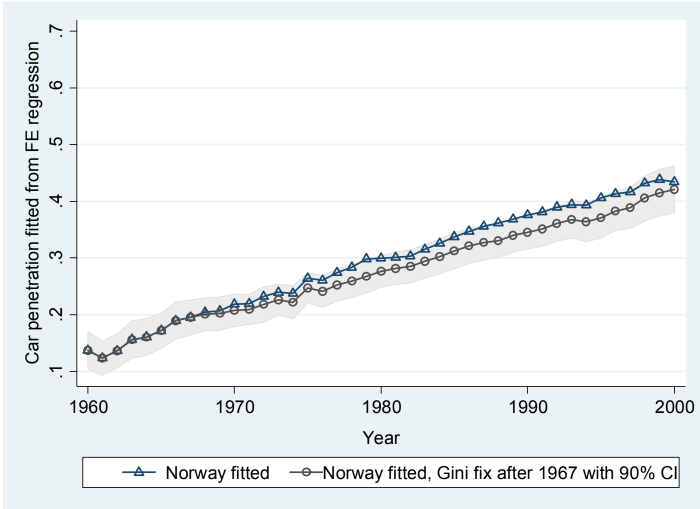


Figure A.6b: Diffusion of cars in Norway



The regression model includes control variables for human capital, openness to trade, land area and urbanization. Control for infrastructure was neglected to not limit the time span covered in the model.

Figure A.6c: Diffusion of cars in Mauritius

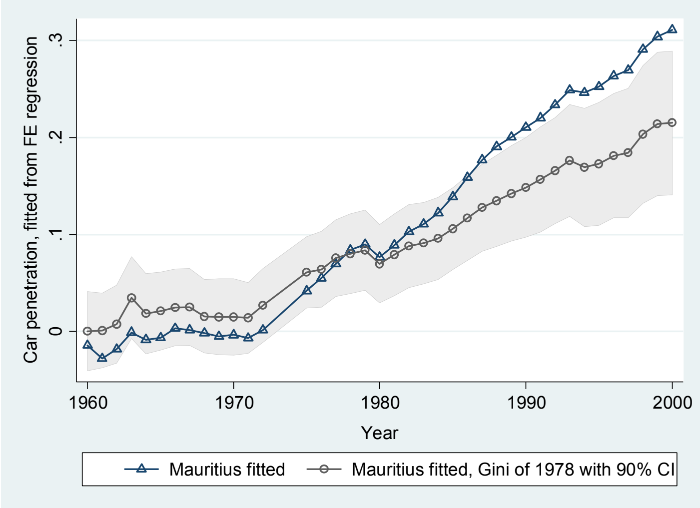
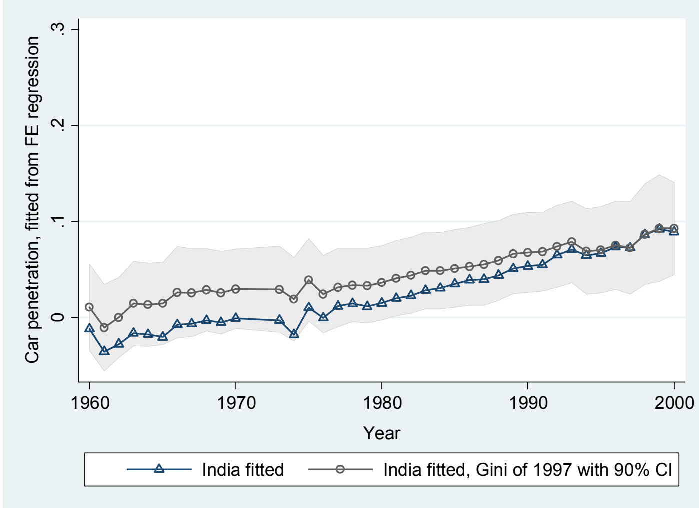


Figure A.6d: Diffusion of cars in India



The regression model includes control variables for human capital, openness to trade, land area and urbanization. Control for infrastructure was neglected to not limit the time span covered in the model.

Figure A.7: Deviation in diffusion lags from mean