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# The Role of Inequality in Technology Diffusion

**Author:** Dimitri Lenzin \*

**Supervisor:** Paul S. Segerstrom

**Examiner:** Yoichi Sugita

**Discussant:** Markus Eyring

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## Abstract

We study the effects of income inequality on technology adoption lags and on long-run technology penetration rates. Building on the model and findings of Comin and Mestieri (2013a), we analyze a sample of 72 countries between 1960 and 1995. They find converging adoption lags and diverging penetration rates between Western and non-Western countries. This evolution explains 80% of the Great Income Divergence between those country groups. Applying pooled OLS, we find that it matters where in the income distribution the inequality appears, which confirms our theoretical predictions. Hence, quantile income shares are crucial. Distortion-free redistribution from the rich to the poor decreases the adoption lag. Moreover, a higher income share of the middle class at the expense of the rich increases the adoption lag and the penetration rate. Whereas higher overall inequality, measured by the Gini coefficient, is not significant for the adoption lag, it has a significant negative effect on the penetration rate. Our results suggest that inequality between the rich and the middle class may have increased the adoption lags in Western countries and decreased the penetration rates in non-Western countries.

**Keywords:** Inequality, Technology Diffusion, Great Divergence, Mass Production, Process Innovation, Product Innovation, Growth.

**JEL Classification:** E13, O11, O14, O15, O33, O41, O57

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\*40602@student.hhs.se

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# 1 Introduction

In the past 200 years large cross-country differences in per capita incomes could be observed. Maddison (2004) finds an 18.5 fold increase in per capita income in Western countries compared to an increase of factor 5 for non-Western countries between the years of 1820 and 2000. This phenomenon is known as the Great Divergence. Our knowledge about drivers of long-term growth is limited. Klenow and Rodriguez-Clare (1997) show that only 10% of cross-country differences in productivity growth between 1960 and 1985 are due to physical and human capital accumulation. This leaves 90% of the variation of income growth to the total factor productivity (TFP). Comin and Mestieri (2013a) therefore explore whether the technology channel can account for some of these cross-country income differences. They identify two margins of technology adoption. First, the adoption lag (extensive margin), which measures how many years after their invention new technologies have been adopted in a country. Second, the penetration rate (intensive margin), which is a measure of the long-run intensity at which a technology is used in a country. We argue that it makes a difference for the productivity level in a country, whether for example only one computer is available in China or whether every worker has access to the use of a computer. Clark (1987) provides evidence that around 1910 the intensity of using spindles and looms can account for much of the cross-country variation in the productivity of cotton mills.

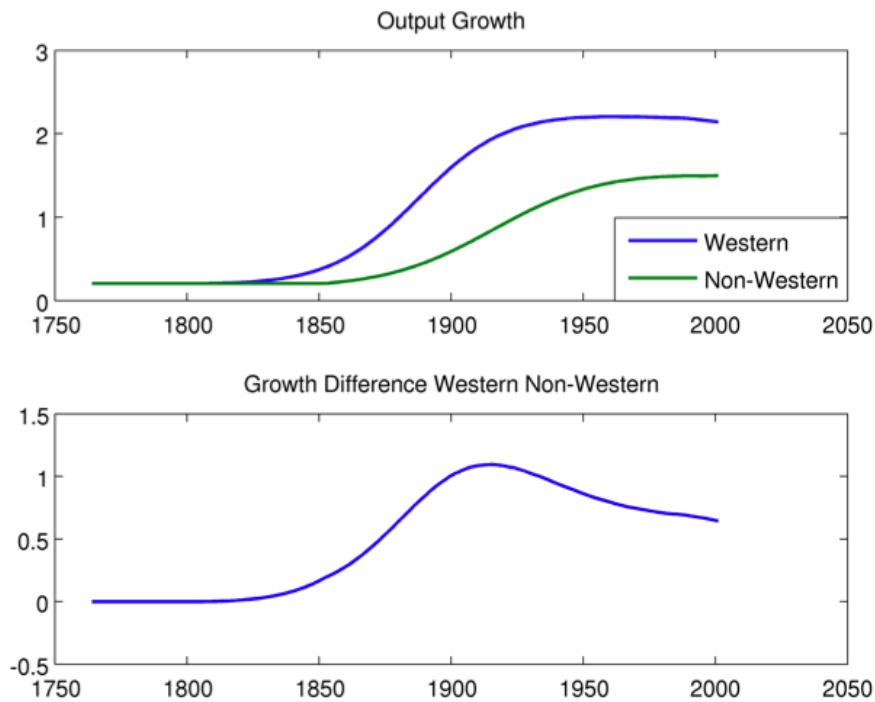
To demonstrate the importance of investigating in detail the characteristics of the diffusion of technologies consider the case of general purpose technologies (GPT), such as electricity and IT. Jovanovic and Rousseau (2005, p. 1185) define three characteristics of GPTs: pervasiveness, improvement and innovation spawning. Pervasiveness represents the fact that the technologies spread to most sectors. Improvement stands for the idea that the GPTs get better over time and lower the cost of the users. Third, innovation spawning means that GPTs make it easier to invent and produce new products and processes. It is noteworthy that it took several decades until electricity produced 60% of the total horsepower. Jovanovic and Rousseau (2005, p. 1186) state that most technologies do have to some degree the same characteristics as the GPTs <sup>1</sup>.

Comin and Mestieri (2013a) divide the countries in Western and "Rest of the World" or non-Western countries. Then, they simulate the evolution of the GDP of Western countries and the Rest of the World by including the adoption lags and penetration rates calculated for the respective countries. They make three important findings. First, they find an income widening between these groups of factor 3.2, compared to Maddison (2004) who finds a 3.9 fold widening. This leads Comin and Mestieri (2013a) to the conclusion that these two margins of adoption can account for 82% of the cross-country differences. The remaining 18% are due to factor accumulation. Second, they conclude that adoption lags are the key driver of differences in the nineteenth century. GDP growth differences were largest in the beginning of the twentieth century. Over time the adoption

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<sup>1</sup>In this thesis we do not focus exclusively on GPTs but our model, described in the subsection 'Model', does feature similar characteristics.

lag decreased in all countries, however, much faster in non-Western countries. As one can see in figure 1, the growth difference of non-Western countries compared to Western countries decreased since the beginning of the twentieth century. Finally, the income gap due to the adoption lag reached pre-industrial levels in the year 2000. Nevertheless, the Great Divergence persisted in the twentieth century, even though at a lower level as at the end of the nineteenth century. Comin and Mestieri (2013a) conclude that the diverging penetration rate is the driver of the persistence of the Great Divergence in the twentieth century.



**Figure 1:** Growth of Western and non-Western countries inputting the estimated evolution of the intensive and extensive margins (Comin and Mestieri, 2013a, p. 42)

Adoption lags converged and penetration rates diverged between Western and non-Western countries. However, the drivers behind this evolution remain unclear. Our particular interest is to identify whether within-country income inequality can account for some of these differences.

Vernon (1966) developed three stages of a product cycle. Krugman (1979) and later Grossman and Helpman (1991) introduced frameworks, which included the product cycle theory into their theoretical models. However, both models only focus on the supply-side of the product cycle theory. We use here the terms North-South as synonyms to the terms Western, non-Western countries. In both models the demand patterns are identical in the North and the South due to homothetic constant-elasticity-of substitution (CES) preferences. However, Vernon (1966) clearly stresses that goods are not consumed in the South until later in the product cycle. The product cycle theory

contains three stages. First, new products are introduced in the North due to innovation. Second, with a time lag, the North exports these products to the South. The time lag of introduction decreases with a rising GDP per capita. Third, the production migrates from the North to the South due to lower production costs. The North starts as a net exporter and later on will become a net importer of a specific good. (Foellmi, Hanslin and Kohler, 2012)

We suggest that additionally to different demand patterns between countries, within-country inequality matters for technology diffusion as well. Therefore, we put forward the hypothesis that within-country inequality can explain part of the technology adoption patterns across countries. In order to explain how within-country income inequality affects the two margins of technology adoption we build our idea on the model developed by Foellmi, Würigler and Zweimüller (2009) who include non-homothetic preferences. They introduce the idea of product innovation and process innovation. Product innovation is the invention of new products for the luxury wants of the rich. Process innovation on the other hand, is understood as the decrease of cost per unit of quality, to transform the luxury goods into mass products. In the product cycle first only the rich are served with luxury goods. Later on, mass products are sold to the poor, due to process innovation. A historic example is the Model T from Ford that made cars available to the middle class. Hence, in an unequal society only the rich can afford the luxuries and the new technologies reach only this circle. Higher inequality decreases the adoption lag as they can afford the luxury goods earlier, compared to a more equal society with the same average income. On the other hand, consider a more equal society where the middle class has a higher income share compared to the rich. Then more mass products are sold and the penetration rate is higher in the long-run.

Our analysis extends the existing literature in at least three dimensions. First, we combine the literature of within-country income distribution and technology diffusion in order to improve the understanding of the Great Divergence of Income between Western and non-Western countries. We do this in order to formulate the relevant channels on how the income distribution affects the adoption lag and the penetration rate. Second, we are the first who estimate how inequality affects the two margins of technology adoption. Furthermore, we introduce quantile income shares into technology diffusion estimations. Third, we evaluate whether within-country inequality is able to explain part of the convergence and divergence of the two margins between Western and non-Western countries.

We apply a pooled OLS estimation with a sample of 72 countries and 186 observations. We include eight technologies, which are ships, cars, aviation - freight, blast oxygen steel, cellphones, pc, MRI and internet. In our core specifications we include either the Gini coefficient or quantile income share dummies to control for inequality. Moreover, we include GDP, education, trade openness and institutions as covariates. We find that redistribution from the rich to the poor decreases the adoption lag and redistribution to the middle class increases adoption lag and the penetration rate. Due to opposing effects of inequality on the adoption lags, it is crucial to use

quantile income shares.

The remainder of this thesis is organized as follows. The subsequent section reviews the economic literature on income distribution effects on technology diffusion in more detail. The subsection 'Model' elaborates a micro foundation. This allows us to identify in the data the two margins of technology adoption. In section 'Identification Strategy' we describe the identification of these margins. In section 'Data', we provide an overview over the data sources and definitions. Section 'Estimation Method' presents the empirical framework of our analysis. Our results are presented in section 'Results', and section 'Discussion' summarizes and discusses the implications of our work.

## 2 Literature Review

In the literature review we first elaborate the determinants of technology diffusion. In the second part we discuss channels of income inequality on economic growth. We argue that these channels are relevant for technology diffusion as well. Finally, we focus on the channels of inequality on the two margins of technology adoption.

### 2.1 Determinants of Technology Diffusion

In this section we point out factors that influence technology diffusion. We assume that the channels described here affect negatively the adoption lag and positively the penetration rate. First, we describe how trade openness and institutions affect adoption barriers. Second, we introduce channels of education on technology diffusion such as skill-biased technical change and the appropriate technology hypothesis. Finally, we consider the effect of the level of economic development on technology diffusion.

Parente and Prescott (1994) develop a model to describe how barriers of technology adoption matter for the adoption lag of a particular technology. In their view the big income disparity between countries is due to the adoption barriers in the West. The lower adoption barriers in the Western countries allowed them to grow richer. They assume that a firm must make an investment in order to upgrade to a higher technology level. This depends on two factors. First, the level of general scientific knowledge in the world. Second, the size of barriers in the firm's country. The general scientific knowledge is assumed to be available to every firm and grows exogenously. Due to the growth of this world knowledge the amount of necessary investment to go to a higher technology level decreases over time. This implies that the level of development in a country will even increase with unchanged adoption barriers. Furthermore, they assume that all firms have the same initial technology level. Parente and Prescott (1994, p. 305) argue that this is a plausible assumption. Decreasing marginal returns on investment leads to an optimal allocation with higher investments into firms that have a low technology level. After an finite number of time periods, all firms will have the same capital stock. Parente and Prescott (1994) point out that greater trade openness can weaken the forces of resistance to technology adoption.

Comin and Hobijn (2006, p. 17) mention two possible channels for how trade openness could affect the technology adoption lag. First, as proposed by Holmes and Schmitz (2001), increased foreign competition increases the pressure on domestic firms to adopt faster. Second, trade causes knowledge spillovers. Evidence from Coe and Helpman (1995) suggests that foreign R&D is beneficial for domestic productivity. Knowledge spillovers reduce adoption costs and therefore the adoption lag. Holmes and Schmitz (2001) main result is that lower tariffs and lower transportation costs shift the relative returns away from unproductive entrepreneurship to productive entrepreneurship. They define unproductive entrepreneurship as activities that limit competition through the regulatory process. Blocking is not rewarding anymore with low tariffs. So, in order

to invent or adopt new technologies, firms do shift activities into research. The federal system of the United States is one example where low tariffs encourage productive entrepreneurship. Special interest groups are not rewarded if they block the use of new technologies in State A. Due to the absence of tariffs between different states, firms in the other states can simply use the more productive technologies, produce more efficiently and export the goods to A. Low transportation costs cause the same effect.

Similar to the findings of Holmes and Schmitz (2001) are those of Comin and Hobijn (2009b). They find that lobbies and institutions matter for technology diffusion. Comin and Hobijn (2009b) include an interaction term of different characteristics of institutions with a binary dummy variable, whether a technology has a competing predecessor technology. They find a significant negative effect of a military regime and legislative flexibility on the speed of technology diffusion. On the other hand, do democracy and judicial effectiveness increase the pace of technology diffusion. Lower lobbying costs lead to higher institutional barriers towards the adoption of new technologies. Accordingly, different types of institutions can affect the costs of erecting barriers and influence technology diffusion.

A model developed by Kiley (1997) suggests that in the long-run, an increase in skilled labor accelerates the skill-biased technical change. This implies faster upgrading to new technologies and therefore shorter adoption lags. However, in the short run an increase of supply in skilled labor may lower the relative wage of skilled workers. Acemoglu (1998) applies this framework to US data. He argues that the increase in the relative amount of college graduates in the 1970's caused a decline in the college premium in the 1970's and then increased inequality in the 1980's. This may suggest that a higher share of educated people attracts complementary technology. Then, the skill-biased technical change increases the skill premium which leads to higher inequality. We propose the hypothesis that higher inequality within a country, due to education, leads to a decrease in the technology adoption lag and an increase of the penetration rate. However, this is not our main hypothesis. We control for this effect by including the education variables. Caselli (1999) describes how skill-biased and de-skilling technologies influence the wage of slow and fast learning workers. Skill-biased technologies shift capital from slow learning workers to fast learners and therefore raise their absolute and relative wage. On the other hand, de-skilling technologies do exactly the opposite. Shifting capital from fast to slow learning workers and increasing absolute and relative wages of slow learners. Consequently, depending on the technology adverse effects on wage inequality can be expected. Therefore, we will do an instrumental variable regression as a robustness check in order to control for the potential endogeneity.

Do countries use the same technology if it is available in both countries? Basu and Weil (1998) suggest that this is not the case. In India a lot of manual work is used for harvesting, while in the United States farmers ride a combine. Hence, India and the United States use different combinations of inputs due to differences in factor prices. Do India and the US equally benefit

if the productivity of combines increases? Obviously not. Basu and Weil (1998) developed a model based on their so called appropriate technology hypothesis where technological advances only improve certain types of technologies and not others. They define that each technology is appropriate for a specific capital-labor ratio only. Any adoption barriers are neglected in this model, technical improvements made in one country are immediately available around the world. As a result, technology leaders benefit less from other countries than do followers. However, a follower country can only adopt a new technology after achieving a sufficiently high level of development. The richer and thus closer a country is to the technology frontier, the lower is the cost of adoption. Hence, this model predicts that the higher relative development is, the faster new technologies are adopted.

There is little empirical work on technology diffusion. One is from Kiiski and Pohjola (2002) who explore the factors that determine the diffusion of internet across countries. They find that GDP per capita (positive effect) and internet access costs (negative effect) explain most of the growth in computer hosts per capita. Surprisingly, they find no significant effect of education on the diffusion in OECD countries. For an extended sample that also includes development countries, education has a positive and significant impact. As data of internet access costs are not available for non-OECD countries, they use the GINI coefficient as an instrumental variable to determine access costs. Income inequality has a strong positive impact on the access costs and therefore increases the adverse effects of high prices on technology diffusion. (Kiiski and Pohjola, 2002, p. 308)

## 2.2 Income Inequality

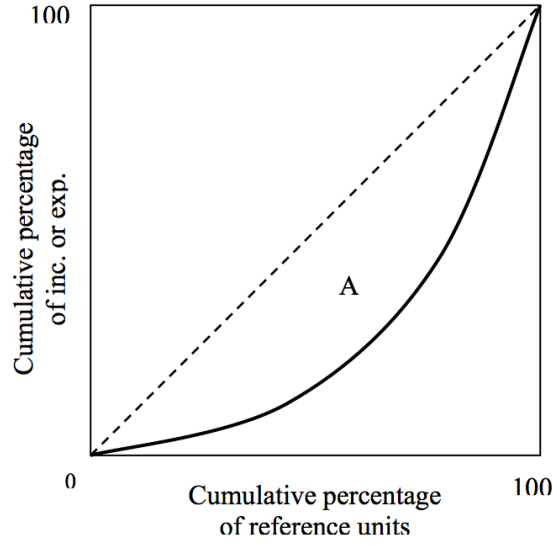
In this section we introduce the channels of Easterly (2007) and Foellmi, Oechslin and Zahner (2011). They describe channels that account for the effects of inequality on economic growth. We build on the ideas of these channels by applying them to technology diffusion. Finally, we discuss the Gini coefficient.

First, Easterly (2007) makes the distinction between structural and market inequality. Easterly (2007, p. 756) writes: "Structural inequality reflects such historical events as conquest, colonization, slavery, and land distribution by the state or colonial power; it creates an elite by means of these non-market mechanisms. Market forces also lead to inequality, but just because success in free markets is always very uneven across different individuals, cities, regions, firms, and industries. So the recent rise in inequality in China is clearly market-based, while high inequality in Brazil or South Africa is just as clearly structural." Based on this distinction Easterly (2007) introduces an instrumental variable that represents measures of factor endowments. The empirical strategy is based on the idea introduced by Engerman and Sokoloff (1994) and Sokoloff and Engerman (2000). In these papers Engerman and Sokoloff suggest that factor endowments are the main determinant of what Easterly calls structural inequality. They elaborate a theory, where

high inequality, determined by factor endowments, is the main cause of bad institutions, low human capital investment and underdevelopment. They argue that a higher share of arable land suitable for products and commodities that feature economies of scale increased the probability that a small elite captured the political power. The elite then created institutions that helped preserve the unevenly distributed power. Consequently, the higher for example the suitable arable land for sugar cane production is, which is scalable, the higher the scope for structural inequality. (Easterly, 2007, p. 756)

Second, in the literature on income inequality effects on economic growth, an important view is that high inequality is bad for subsequent growth, due to an imperfect credit market. Galor and Zeira (1993) argue that access to the credit market depends on individual wealth. Therefore, marginal returns are not equalized across investment opportunities. A distortion-free reduction of inequality increases economic growth because marginal returns are more equal. On the other hand, Foellmi and Oechslin (2008) point out that even with credit market imperfections higher inequality can be beneficial for the economic performance. This holds only under the assumption of investment functions that are concave in wealth and considering a distortion-free redistribution from the richest to the middle class. Equalizing marginal returns has a positive effect on growth. However, it also increases the demand for capital in the economy and therefore an increase in the borrowing rate. With a higher borrowing rate the poorest can borrow less and remain with high marginal returns. This is bad for the economic performance. Following these described channels, Foellmi, Oechslin and Zahner (2011) do disentangle these effects by analyzing quantile share inequality data. Given these effects, the Gini coefficient may be too imprecise to discover the interesting effects.

To see why the Gini coefficient may be too imprecise consider first how the coefficient is calculated. The User Guide and Data Sources of the WIID (UNU-WIDER, 2009) states that the calculation is based on the Lorenz curve. In figure 2 on the x-axis shows the cumulative percentage of the population, starting on the left with the poorest. On the y-axis the cumulative percentage of income or expenditure that are related to the units on the x-axis. In case of a equal income distribution, we would get the dashed 45-degree line. The more unequal the more shifts the thick line toward the corner in the bottom-right and area A gets bigger. The Gini coefficient is the proportion of the area A divided by  $1/2$ , which is the area below the Lorenz curve. The coefficient is given either in proportion with a maximum of 1 or in percentages. We use percentages. The more unequal an economy is the closer to 100% approaches the Gini coefficient. An advantage is that neither population size nor the GDP matters. A disadvantage is that different Lorenz curves can intersect and hence different distributions yield the same coefficient. (Deaton, 1997)



**Figure 2:** The Lorenz Curve and the Gini coefficient (UNU-WIDER, 2009)

## 2.3 How does Inequality affect Technology Diffusion?

In the two subsequent subsections we give an overview over the relevant channels of inequality on the two margins of technology adoption described in the literature. We start with the channels for the adoption lag and then proceed with penetration rate.

### 2.3.1 Channels of Inequality on the Adoption Lag of a Technology

What is the effect of inequality on the adoption lag? Consider a society where one individual owns all the resources and buys a new technology at a given price. On the other hand, let us consider a society with an even income distribution and the same mean income. This decreases the income of the richest individual and hence below a certain threshold of the given price, nobody can afford the new technology. We focus here on channels that affect the adoption of a new technology, in the long-run these channels may be less relevant.

Hyytinen and Toivanen (2011, p. 365-366) describe two main channels how high within-country income inequality can positively affect the early diffusion of mobile phones. We interpret that our measure of the technology adoption lag is similar to their measure of the early stage diffusion. The first channel they describe is that mobile phones can only be afforded and therefore adopted by the rich, high-earning elite. Hence, increasing the mass of people in the upper end of the income distribution leads to a higher short-run penetration, while keeping the mean income constant. They assume taste homogeneity and initially a price at which nobody adopts. A higher share of people in the high income segment, increases the short-run penetration after a price reduction. In the second channel, they argue that if mobile phones are an especially useful production technology for the poor, a higher mass of people in the bottom of the income distribution increases the penetration rate. Consequently, higher inequality may increase the penetration rate, either by many poor

or many rich adopting the technology. Therefore, we apply quantile shares measures for income inequality, as it allows us to disentangle in which part of the distribution inequality does matter.

Hyytinen and Toivanen (2011) study the effect of income inequality on technology diffusion in developing countries. This is the only paper we are aware of which studies these effects in developing countries. They investigate the diffusion of mobile phones and use data of market penetration in a sample of developing countries in the period 1985 and 1998. The focus lays on the early stages of the diffusion process. They find a positive impact of inequality, measured as the income share of the highest earning decile, on mobile phone diffusion. Due to a potential endogeneity problem, they use an instrumental variable for inequality and find an even stronger effect. The instrument they use is the above mentioned instrument of suitability of arable land applied by Easterly (2007).

The crucial difference between Hyytinen and Toivanen (2011) and our estimation in this thesis is that we calculate the adoption lag differently to their early stage diffusion measure and we furthermore consider the long-run penetration rate.

Hypothesis 1: The adoption lag decreases under the following two conditions. First, if the rich increase their income share the adoption lag decreases, because they can afford the new technologies earlier. Second, it may be the case that a technology is particularly useful to the poor or the middle class, then a higher income share of those would decrease the adoption lag.

### **2.3.2 Channels of Inequality on the Penetration Rate of a Technology**

How does inequality affect the long-run penetration rate? Consider again a society where one individual holds all the resources. This leads as explained above to a fast adoption. On the other hand, compared to a society where income is evenly distributed and the same mean income, the long-run penetration is lower, as except for the one rich guy, nobody can afford the technologies. Even when lowering the price of the technology due to mass production, first only the middle class is able to afford it. As a consequence, we emphasize the importance of a strong middle class. In the following section we describe first positive effects described in the literature that a strong middle class has on a society and characteristics of such a middle class. Subsequently, we describe how income inequality and a high income share of the middle class affect the long-run penetration rate of technologies. Hereby, we especially consider the model of Foellmi, Würgler and Zweimüller (2009) as important. Finally, we state some differences between the model of Foellmi, Würgler and Zweimüller (2009) which describes the relevant channel and Comin and Mestieri (2013a) which is our main model that we describe in the subsection 'Model' and explains the mechanisms of the adoption of the two margins.

Easterly (2001) puts forward many positive effects that appear in countries with a strong middle class. He finds that increasing the income share of the middle class and lowering ethnic divisions is associated with higher education, higher income, higher economic growth, better health, better

infrastructure, better economic policies, less political instability, less civil war, less minorities at risk, more democratization and more democracy. Easterly (2001) suggests similar to the argument described above by Easterly (2007) that factor endowment and the subsequent inequality due to a small elite capturing the political power are the main causes for these differences.

In an empirical analysis Banerjee and Duflo (2007) identify characteristics of the middle class. The most important characteristic is the likelihood to hold a steady job. Further characteristics are that members of the middle class have fewer, healthier and better educated children compared to the poor. Even when they can distinguish clear differences between the poor and the middle class, there are many characteristics that are country specific. These particular characteristics may be either due to relative prices, which affect consumption decisions, or norms that determine consumption patterns.

Matsuyama (2002) develops a model to understand the mechanisms that allowed mass consumption societies to emerge. He describes that due to an increase in productivity, products can be sold cheaper and are affordable for a larger share of households. Therefore, these products are not only available for high-income but also for low-income households. This larger market of high- and low-income households increases the productivity. According to the model, inequality should neither be too high nor too low. If a society is too unequal, diffusion stops quickly as the poor cannot afford it. If the society is too equal the diffusion does not even start. Whether redistribution from the upper middle class to the lower middle class is positive for the diffusion is ambiguous. Redistribution may make the products affordable to the lower middle class or may even prevent the upper middle class from buying the good due to the now too low level of income. Katona (1964) was the first to notice that mass consumption societies are the last stage of a process. First, only few rich consume luxury goods. Then these goods get transformed into mass consumption goods. Many products have made this transformation, such as cars, radios, television sets, washing machines, refrigerators and recently computers.

Foellmi, Würzler and Zweimüller (2009) point out that two effects are important in the product cycle. First, a higher income makes the product affordable to more consumers. Second, process innovations that reduce the cost of producing the product extend the group of buyers to lower income classes. A famous historical example is the Ford Model T, the first automobile affordable for a large population. Crucial for the success of Model T was the process innovation of Ford in the assembly line production instead of individual hand crafting. Another important reason was the payment of workers by output. Their wage was proportional to the cost of the car. Therefore, they were able to afford the car themselves. Ford produced over 15 million Model T's between 1908 and 1927. The penetration of car ownership rose impressively in the United States. In 1908 1% of the households owned a car. In the year 1924 already 50% of the households owned a car (Bowden and Offer, 1994). The mechanism of mass-production, described for Fords Model T, was an important step in the history of manufacturing. Since then, the mass-production can be observed in developed

countries for many products and is getting more important in developing countries in recent years. The example illustrates that process innovation and mass production go together. Process innovations reduce the production costs which is crucial in order to make products affordable to the mass consumption market. The model of Foellmi, Würgler and Zweimüller (2009) includes only rich and poor consumers and takes into account non-homothetic preferences. The rich consume more and better goods than the poor. With homothetic preferences and the same prices they would demand the same goods and the same quantity. In our empirical analysis we do include quantile shares and can distinguish the rich, the middle class and the poor and therefore can account for the different demand patterns. The model of Foellmi, Würgler and Zweimüller (2009) is in line with empirical evidence and allows to discover the effects of how inequality affects the incentive to invent new products and process innovation. They find that higher income inequality increases the purchasing power of the rich, the demand for variety and the number of product innovations (new luxuries). On the other hand, a more equal society increases the number of mass consumption markets and incentives for process innovation (low-cost versions of existing luxuries such as Model T). (Foellmi, Würgler and Zweimüller, 2009, p. 6-9) We consider the channels described by Foellmi, Würgler and Zweimüller (2009) as the most relevant for the mechanisms of income inequality on technology adoption we are estimating.

Finally we discuss some differences between the two main models we consider in answering our research question. One important difference in the understanding of productivity gains due to new vintages between the models of Foellmi, Würgler and Zweimüller (2009) and Comin and Mestieri (2013a) is that the former implies higher productivity due to process innovation. Comin and Mestieri (2013a) do not explicitly mention process innovation, but assume continuous reduction in the production costs over time. As a consequence, they may imply process innovation, which makes vintages affordable to more people. In their model productivity gains stem from the use of more productive vintages and not necessarily due to improvement of the production process of a vintage. Another difference is that Comin and Mestieri (2013a) do assume homothetic preferences. On the other hand, Foellmi, Würgler and Zweimüller (2009) do assume non-homothetic preferences in their model. So, not individuals in a country has the same preferences. Finally, the model of Foellmi, Würgler and Zweimüller (2009) does not embody quality upgrading of existing products. We build our estimation on the model of Comin and Mestieri (2013a). They include in their model an effect which is that new vintages of a technology appearing each instant exogenously. The increase of vintages increases the productivity in a country, this effect is called the embodiment effect. We explain this in detail below.

Hypothesis 2: The interpretation that the intensive margin is the long-run penetration rate of an economy. We formulate the hypothesis that higher inequality decreases the penetration rate. Especially a large middle class compared to the rich may be relevant in order to achieve a higher penetration in the long-run.

## 2.4 Model

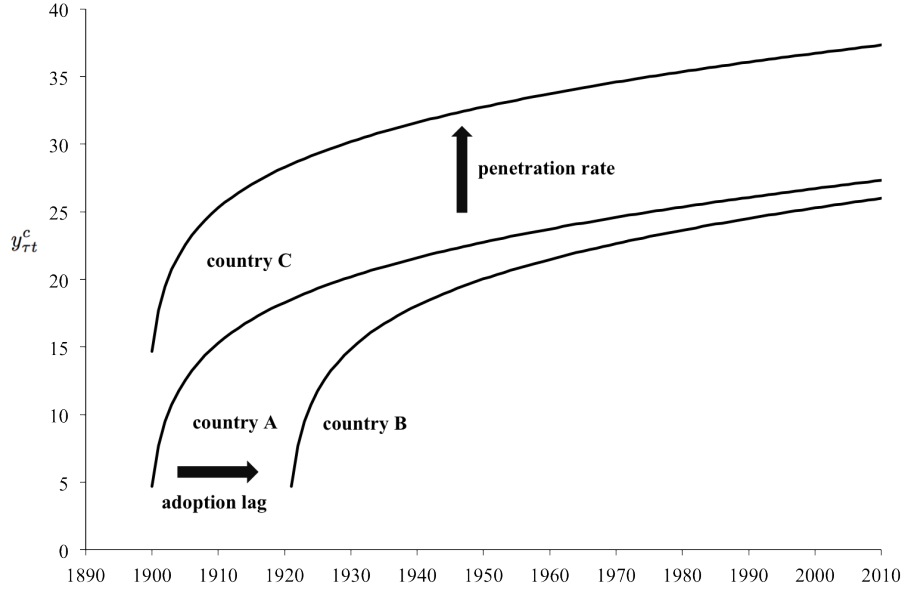
### 2.4.1 The Shape of Diffusion Curves

Now we introduce the model that was developed by Comin and Hobijn (2010), Comin and Mestieri (2010) and studied in detail by Comin and Mestieri (2013a+b). They identify two margins of technology adoption. The first margin is the adoption lag (extensive margin) and the second margin is the penetration rate (intensive margin). The adoption lag is the time that has elapsed between the invention of a particular technology until the technology arrives in a country. The penetration rate is measured as the logarithm of the units used of a technology in a country. In figure 3 we show an illustrative example of the shape and the two possible shifts of the diffusion curve of a technology.

We measure the diffusion of cars with the log of the number of passenger cars available. We use technology measures from the Cross-country Historical Adoption of Technology (CHAT) dataset provided by Comin and Hobijn (2009a). This dataset is particularly useful, as the observed diffusion curves are embedded in an aggregate model. In contrast to the macroeconomic models of technology adoption by Parente and Prescott (1994) and Basu and Weil (1998) which are difficult to match with data. Basu and Weil (1998, p. 1029-1030) for example build on the idea that technologies are related to a specific capital-labor ratio. For this specific capital-labor ratio new technologies are developed up to a certain point. Once, this point is reached, no new technologies are developed. According to Comin and Hobijn (2009a, p. 3) define a technology as mentioned in the Merriam-Webster's Collegiate Dictionary: "a manner of accomplishing a task especially using technical processes, methods, or knowledge." Following this idea the CHAT dataset contains data measuring either "(i) the number of capital goods specifically related to accomplishing particular tasks, (ii) the amounts of particular tasks that have been accomplished, (iii) the number of users of a particular manner to accomplish a task." (Comin and Hobijn, 2009a, p. 3). Examples for these three measures that we use in our dataset are (i) the number of magnetic resonance imaging (MRI) units in place. An example for (ii) is metric tons of steel produced using blast-oxygen steel furnaces. And for (iii) the number of people with access to the internet. Then the log of these measures is scaled either by population or GDP, in order to account for the size of the economy (Comin and Mestieri, 2013b, p. 8).

In the following section we describe an illustrative example of a diffusion curve of the technology cars. We measure cars as the number of available cars in a country, which fit in the second definition described above. In figure 3 the x-axis denotes the time. On the y-axis the log of the technology  $\tau$  at time  $t$  in country  $c$  is denoted by  $y_{\tau t}^c$ . Cars were invented in 1885. Country A and C adopted cars first in 1900, country B adopted them 20 years later. We see that all three countries have the same concave shape of the diffusion curve. This is a crucial assumption we make. Comin and Mestieri (2013a) conjecture that the shape of the curve is affected by technology-specific characteristics which are identical across countries. For each technology the curves look the same

across countries and the country-specific differences are reflected in the two margins of technology diffusion. Therefore, this thesis aims at identifying the country-specific characteristics that drive these two margins. In particular income inequality may play a crucial role in explaining the technology diffusion patterns among countries. Another feature of the curve is that it is initially steep and then gets flatter. Country A adopted the technology in the year 1900 and country B in the year 1920. The only difference between them is the adoption lag of twenty years and hence the horizontal shift of the curve. The only difference between the countries A and C is the penetration rate and therefore a vertical shift of the curve. Both, country A and country C, adopted the cars in the year 1900. Country C has a higher penetration and thus the number of passenger cars is higher in country C compared to country A. The curves of country B and C are shifted horizontally and vertically compared to each other.



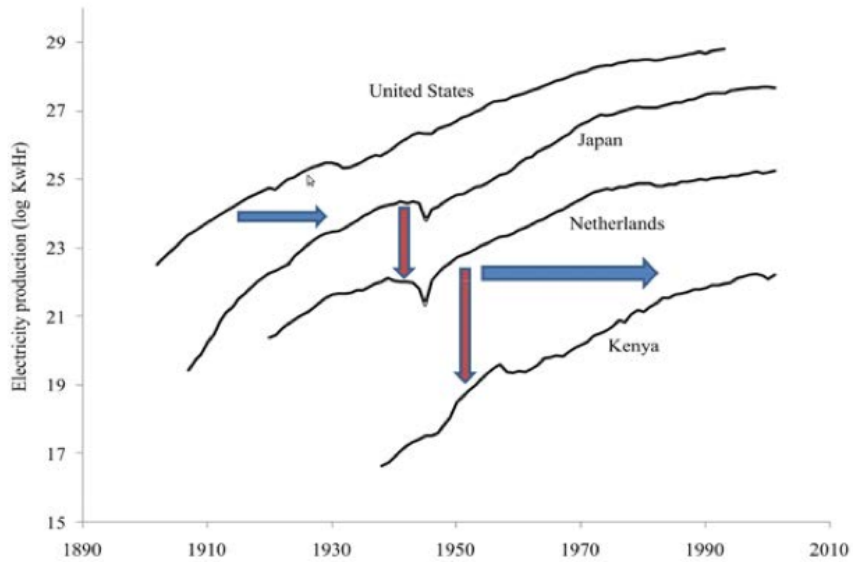
**Figure 3:** Illustrative Example of the Diffusion Curve

At this point it is only clear what the difference of the shifts between the diffusion curves is but not how to interpret the horizontal and vertical shift and how they can be identified in the data. Comin and Hobijn (2010) and Comin and Mestieri (2010), do answer these questions. Comin and Hobijn (2010) explores the extensive margin and Comin and Mestieri (2010) the intensive margin. In order to better understand the diffusion curves consider the following simple equation (1) that describes the shape of the diffusion curve

$$y_{\tau,t}^c = \underbrace{\beta_{\tau 1}^c}_{\text{Vtcal Shift}} + \beta_{\tau 2} t + \beta_{\tau 3} \overbrace{\ln(t - \tau - \underbrace{D_{\tau}^c}_{\text{Hztal Shift}})}^{\text{Concave Shape}}. \quad (1)$$

The left hand side is the log-output produced,  $y_{\tau,t}^c$ , with a technology  $\tau$  at time  $t$  in country  $c$ . The variable  $\beta_{\tau 1}^c$  captures the vertical shift and hence the penetration rate in each technology-country pair. The  $\beta_{\tau 2}$  measures the time trend so that the technology measure behaves asymptotically log-

normal. The term  $\beta_{\tau 3}$  captures the concave shape of the diffusion curve with the log function. The estimated terms  $\beta_{\tau 2}$  and  $\beta_{\tau 3}$  are assumed to be constant across countries and are only estimated for the U.S., where the data is most accurate. The estimation process is explained in detail in the section 'Identification Strategy'. The expression  $t - \tau$  represents the time elapsed from the invention date  $\tau$  to the moment  $t$  the technology output is measured. The variable  $D_{\tau}^c$  shifts the curve horizontally and therefore captures the adoption lag. The larger  $D_{\tau}^c$ , the more is the curve shifted to the right. The term  $\ln(t - \tau - D_{\tau}^c)$  is only well defined if  $t - \tau - D_{\tau}^c > 0$ . Note that  $\beta_{\tau 1}^c$  and  $D_{\tau}^c$  are the intensive and extensive margin, which are at the center of our interest. Hence, they are estimated by this approximation of the diffusion curves. In figure 4 we show an empirical example of the diffusion curve. The technology electricity is measured as the electricity production in log KWhr for the four countries USA, Japan, Netherlands and Kenya. This measure fits in the definition (i) described above.



**Figure 4:** Example of Diffusion Curve (Comin and Mestieri, 2013b, p. 11)

The crucial point for the estimation of the diffusion curves is the following. As the measure of varieties adopted depends on the adoption lag, Comin and Hobijn (2010) identify the adoption lag due to the curvature of the diffusion curve. Hence, longer adoption lags imply fewer vintages and the steepness of the diffusion curve decreases faster. (Comin and Hobijn, 2010, p. 2037-2040) To make their estimation feasible, Comin and Hobijn (2010) assume that the adoption lags for each country and technology are constant over time. However, the adoption lags can differ across countries and technologies. The main prediction of the model is that only the variety effect is affected by a change of the adoption lag. An increasing variety effect makes the slope of the

diffusion curve diminish. Accordingly, one can conclude that if at a certain point in time the diffusion curve is decreasing faster in country A than in country B, this must be due to the fact that country A adopted the technology earlier than country B. This, in case everything else is equal. (Comin and Hobijn, 2010, p. 2041-2042)

This approximation of the diffusion curves and interpretation of their shifts is intuitive. Nevertheless, to understand the role of income we require a micro founded model of demand and production. Therefore, Comin and Mestieri (2013a) developed a model that provides the relevant mechanisms. Income has two opposite effects on the diffusion measures. First, with a higher GDP, there is a larger demand for products and services that embody or use technologies. The Engel curve effect implies a positive effect of income on technology. The Engel curve is a microeconomic concept, which says that the demand for normal goods increases with income whereas the demand for inferior goods decreases with income. Here, we assume products produced by technologies we measure in this thesis to be normal goods. On the other hand, in richer countries wages are higher and therefore the cost of producing products and services that embody technology increase. The model described below explains the horizontal and vertical shifts. The extensive margin measures the average adoption lag at which new vintages of a technology arrive in a country. The intensive margin measures the intensity with which a technology is used, when the technology is fully diffused in a country. (Comin and Mestieri, 2013b, p. 12)

#### 2.4.2 A Microfoundation for the Diffusion Curve

The model presented in the following is taken from Comin and Mestieri (2013a).

*Preferences and Endowments.* First, we describe the preferences and endowment in the model. The economic environment is the following. There is a unit measure of identical households in the economy. Each household supplies inelastically one unit of labor and earns a wage  $w$ . Households can save in domestic bonds which are in zero net supply. The utility of the representative household is given by the following equation:

$$U = \int_{t_0}^{\infty} e^{-\rho t} \ln(C_t) dt \quad (2)$$

$C$  is the abbreviation for consumption and  $\rho$  for the discount rate. The representative household maximizes its utility subject to the budget constraint (3) and a no-Ponzi scheme condition (4) (Comin and Mestieri, 2013b, p. 13-15):

$$\dot{B}_t + C_t = w_t + r_t B_t \quad (3)$$

$$\lim_{t \rightarrow \infty} B_t e^{\int_{t_0}^t -r_s ds} \geq 0. \quad (4)$$

$B_t$  denotes the bond holdings of the representative consumer,  $\dot{B}$  is the increase in bond holdings over an instant of time and  $r_t$  is the return on bonds.

*World technology frontier.* Now consider the world technology frontier. At a given instant

in time,  $t$ , it consists of a set of technologies and a set of vintages specific to each technology. Each instant, a new technology,  $\tau$ , appears exogenously. Technology is denoted by the time it was invented. Consequently,  $\tau$  represents the invention date and the technology. The range of invented technologies is  $(-\infty, t]$ . Every instant a new and more productive vintage appears in the world frontier for each existing technology. Vintages of technology- $\tau$  are denoted by  $v_\tau$ . Vintages are indexed by the time in which they appear. Therefore, at time  $t > \tau$  the set of existing vintages of technology- $\tau$  available is  $[\tau, t]$ . The productivity of a technology-vintage pair consists of two constituents. First,  $Z(\tau, v_\tau)$  which is a general measure that is equal across countries. It is determined only by technological attributes

$$\begin{aligned} Z(\tau, v_\tau) &= e^{(\chi+\gamma)\tau+\gamma(v_\tau-\tau)} \\ &= e^{\chi\tau+\gamma v_\tau} \end{aligned} \tag{5}$$

where  $(\chi + \gamma)\tau$  represents the productivity level related to the first vintage of technology  $\tau$ . Productivity gains related to the introduction of new vintages,  $v_\tau \geq \tau$ , are captured by  $\gamma(v_\tau - \tau)$ . The second constituent is the technology-country specific productivity term,  $a_\tau$ . This term is discussed below separately. To make the notation easier in the following, time subscripts,  $t$ , and  $\tau$  from the vintage notation are omitted, when possible. Hence, we write  $v$  instead of  $v_\tau$ .

*Adoption lags.* Economies are usually below the world technology frontier.  $D_\tau^c$  denotes the age of the best vintage available for production in a country for technology  $\tau$ . Therefore,  $D_\tau^c$  represents the time that elapsed between the invention and the adoption of the best vintage in the country. Hence, it is the adoption lag. The set of technology- $\tau$  vintages available in this economy is  $V_\tau = [\tau, t - D_\tau^c]$ . Both, the time it takes for an economy to start using technology  $\tau$  and the distance of the country to the technology frontier in technology  $\tau$  is represented by  $D_\tau^c$ . This is the mathematical representation for the assumption that adoption lags are constant over time.

*Intensive margin.* New intermediate goods embody the new vintages  $(\tau, v)$ . The intermediate goods are produced competitively using one unit of final output to produce one unit of intermediate good. Combining intermediate goods with labor leads to the output related with a given vintage,  $Y_{\tau,v}$ .  $X_{\tau,v}$  denotes the number of units of intermediate good  $(\tau, v)$  used in production.  $L_{\tau,v}$  is the number of workers that use the intermediate goods. Hence,  $Y_{\tau,v}$  is given by the Cobb-Douglas production function in equation (6):

$$Y_{\tau,v} = a_\tau Z(\tau, v) X_{\tau,v}^\alpha L_{\tau,v}^{1-\alpha} \tag{6}$$

The important value in equation (6) is  $a_\tau$ , which represents factors that reduces the effectiveness of a technology in a country. The long-run penetration rate of a technology in a country is determined by  $a_\tau$ . So, it is the measure for the intensive margin of adoption of a technology in the model. In the estimation strategy the term  $a_\tau$  is denoted as  $\beta_{\tau 1}^c$ . Factors that determine the intensive margin may be "differences in the costs of producing the intermediate goods associated with a technology, taxes, relative abundance of complementary inputs or technologies, frictions in capital,

labor and goods markets, barriers to entry for producers that want to develop new uses for the technology, etc.” (Comin and Mestieri, 2013a, p. 7). Comin and Mestieri (2013a) take the intensive and extensive margin as exogenous variables, as their goal is to study how they affect productivity growth. In contrast, the goal of this thesis is to examine the determinants of the two margins. In particular, the effect of within-country inequality on these margins.

*Production.* We combine the output related to different vintages of the same technology to produce competitively the sectoral output,  $Y_\tau$ . We use a CES production function of the following form:

$$Y_\tau = \left( \int_\tau^{t-D_\tau} Y_{\tau,v}^{\frac{1}{\mu}} dv \right)^\mu, \text{ with } \mu > 1. \quad (7)$$

Likewise, final output,  $Y$ , is the aggregate of the sectoral outputs,  $Y_\tau$

$$Y = \left( \int_{-\infty}^{\bar{\tau}} Y_\tau^{\frac{1}{\theta}} d\tau \right)^\theta, \text{ with } \theta > 1 \quad (8)$$

$\bar{\tau}$  denotes the most advanced technology adopted in the economy. This is the technology  $\tau$  for which  $\tau = t - D_\tau^c$ . Furthermore, we define the aggregated productivity of a technology as

$$Z_\tau = \left( \int_\tau^{\max\{t-D_\tau, \tau\}} a_\tau Z(\tau, v)^{\frac{1}{\mu-1}} dv \right)^{\mu-1}, \quad (9)$$

aggregated labor input  $L_\tau$  in sector  $\tau$  as

$$L_\tau = \int_\tau^{t-D_\tau} L_{\tau,v} dv, \quad (10)$$

and aggregated intermediate goods  $X_\tau$  in sector  $\tau$  as

$$X_\tau = \int_\tau^{t-D_\tau} X_{\tau,v} dv. \quad (11)$$

*Factor Demands and Final Output.* Now consider the demand factors and final output. The price of the final output is the numéraire. For the produced output with a particular technology the demand is

$$Y_\tau = Y p_\tau^{-\frac{\theta}{\theta-1}} \quad (12)$$

where  $p_\tau$  is the price of the output in sector  $\tau$ . The output produced with a given technology is affected by the income level of a country and the price of a technology. Due to the homotheticity of the production function, the income elasticity of technology  $\tau$  output is one. Likewise, the demand for output produced with a given technology vintage is

$$Y_{\tau,v} = Y_\tau \left( \frac{p_{\tau,v}}{p_\tau} \right)^{-\frac{\mu}{\mu-1}} \quad (13)$$

where  $p_{\tau,v}$  represents the price of the  $(\tau, v)$  intermediate good. At the vintage level the demands for labor and intermediate goods are

$$(1 - \alpha) \frac{p_{\tau,v} Y_{\tau,v}}{L_{\tau,v}} = w \quad (14)$$

$$\alpha \frac{p_{\tau,v} Y_{\tau,v}}{X_{\tau,v}} = 1. \quad (15)$$

The price of intermediate goods equals their marginal cost due to perfect competition in the production of intermediate goods. We solve the demand for labor and the intermediate goods for  $X_{\tau,v}$  and  $L_{\tau,v}$ . Then we substitute them into equation (6), solve for  $p_{\tau,v}$  and we get the following:

$$p_{\tau,v} = \frac{w^{1-\alpha}}{Z(\tau,v)a_\tau} (1-\alpha)^{-(1-\alpha)} \alpha^{-\alpha}. \quad (16)$$

We assume that  $Z_\tau = \left( \int_\tau^{\max\{t-D_\tau, \tau\}} a_\tau Z(\tau,v)^{\frac{1}{\mu-1}} dv \right)^{\mu-1}$  and  $p_\tau = \left( \int_\tau^{t-D_\tau} p_{\tau,v}^{\frac{1}{\mu-1}} dv \right)^{-(\mu-1)}$ . Therefore, the price index of technology- $\tau$  output is

$$\begin{aligned} p_\tau &= \left( \int_\tau^{t-D_\tau} p_{\tau,v}^{\frac{1}{\mu-1}} dv \right)^{-(\mu-1)} \\ &= \frac{w^{1-\alpha}}{Z_\tau} (1-\alpha)^{-(1-\alpha)} \alpha^{-\alpha}. \end{aligned} \quad (17)$$

By combining (13), (14), (15), we get the following expression for the total output produced with technology  $\tau$ :

$$Y_\tau = Z_\tau L_\tau^{1-\alpha} X_\tau^\alpha. \quad (18)$$

The model of Comin and Hobijn (2010) includes two mechanisms how adoption lags determine the level of TFP in the production of the capital good. First, the embodiment effect and second the variety effect. New adopted production methods, new vintages, allow to produce more efficiently. So, the new vintages embody higher productivity and the level of embodied productivity increases in the economy. This effect is called embodiment effect. The variety effect represents the productivity gain due to additional vintages available in the economy. Hence, the range of available vintages increases the level of embodied productivity of the new technology. An important feature of the variety effect is that, when the number of available varieties is small, an increase in the number of available vintages has a relatively large effect on the level of embodied productivity. However, as the number of adopted vintages increases, the productivity gains from an additional vintage decline. Therefore, the variety effect leads to a nonlinear evolution of the level of embodied productivity and hence drives the curvature of the diffusion curve. (Comin and Hobijn, 2010, p. 2039) The productivity of a technology,  $Z_\tau$  related to a technology, is determined by the intensive and extensive margin. We get the following:

$$\begin{aligned} Z_\tau &= \left( \int_\tau^{\max\{t-D_\tau, \tau\}} a_\tau Z(\tau,v)^{\frac{1}{\mu-1}} dv \right)^{\mu-1} \\ &= \left( \frac{\mu-1}{\gamma} \right)^{\mu-1} \underbrace{a_\tau}_{\text{intensive mg.}} \underbrace{e^{(\chi\tau + \gamma \max\{t-D_\tau, \tau\})}}_{\text{embodiment effect}} \underbrace{\left( 1 - e^{\frac{-\gamma}{\mu-1}(\max\{t-D_\tau, \tau\} - \tau)} \right)^{\mu-1}}_{\text{variety effect}}. \end{aligned} \quad (19)$$

*extensive margin*

In this model the productivity of a technology,  $Z_\tau$  consists of three main determinants shown in equation (19). First, the intensive margin. Second, the productivity level of the best vintage used (embodiment effect). Finally, the productivity gains from using more different vintages (variety effect). The embodiment and variety effect together are the extensive margin of adoption.

Therefore, the shorter the adoption lag is, the higher is the productivity level of the used vintages (embodiment effect) and the higher is the variety of the used vintages (variety effect). (Comin and Mestieri, 2013a, p. 7-9)

The microfoundation allows us to better understand the mechanisms how the extensive and intensive margin work. In section 'Identification Strategy' this model is used to measure the adoption lag and the penetration rate in the data.

### 3 Identification Strategy

In the following section, the identification strategy to determine the extensive and intensive margin in the data is explained. The strategy builds directly on the microfoundation described in subsection 'A Microfoundation for the Diffusion Curve'.

*Diffusion equation.* In order to obtain the diffusion equation, first we combine the demand for sector  $\tau$  output (12), the sectoral price deflator (17), the equilibrium wage rate (14) and the expression for  $Z_\tau$  (19). Logs are denoted as lower-case letters. One obtains the following expression:

$$y_\tau = y + \frac{\theta}{\theta - 1} [z_\tau - (1 - \alpha)(y - l) + \alpha \ln \alpha] \quad (20)$$

In equation (19) we can see that, to a first order approximation,  $\gamma$  only affects  $y_\tau$  through the linear trend. Accordingly, a second-order approximation of  $\log Z_\tau$  around the starting adoption date  $(\tau + D_\tau^c)$  can be made:

$$z_\tau \approx \ln a_\tau + (\chi + \gamma)\tau + (\mu - 1) \ln(t - D_\tau - \tau) + \frac{\gamma}{2}(t - D_\tau - \tau) \quad (21)$$

Now, by substituting (21) into (20) derives the estimating equation:

$$y_{\tau t}^c = \underbrace{\beta_{\tau 1}^c}_{\text{vertical shift}} + y_t^c + \beta_{\tau 2} t + \beta_{\tau 3} \underbrace{((\mu - 1) \ln(t - \overbrace{D_\tau^c}^{\text{horizontal shift}}) - \tau)}_{\text{Concave Shape}} - (1 - \alpha)(y_t^c - l_t^c) + \epsilon_{\tau t}^c \quad (22)$$

where  $y_{\tau t}^c$  denotes the log of the output produced with technology  $\tau$ ,  $y_t^c$  is the log of output,  $y_t^c - l_t^c$  is the log of output per capita and  $\epsilon_{\tau t}^c$  is an error term. Equation (22) is the equation used to approximate the diffusion equation and to estimate the variables of interest. As described above, there are three different technology measures in the CHAT dataset. In contrast to Comin and Mestieri (2010) in the estimation of equation (22) we do not distinguish between the different measures.

*Calibration.* In the following paragraphs, the estimation procedure is explained. The estimation of equation (22) gives us the two important measures  $\beta_{\tau 1}^c$  and  $D_\tau^c$ . Where  $\beta_{\tau 1}^c$  is essential to calculate the intensive margin and  $D_\tau^c$  is the extensive margin. For the estimation of equation (22) we follow exactly Comin and Hobijn (2010). Therefore, we first have to define certain parameters. The trend-parameter,  $\beta_{\tau 2}$  and parameter  $\beta_{\tau 3}$  are assumed to be constant across countries. As they only depend on variables  $\theta$  and  $\gamma$ . Accordingly, we calibrate our model as in Comin and Hobijn (2010) with labor income share set at  $\alpha = 0.3$ . This is consistent with the postwar US labor share. After 1765 the technology frontier growth rate equals  $\chi + \gamma = (1 - \alpha) * 2\%$ , which matches a balanced growth path of 2%. The literature does not mention how to split up the contribution of increased productivity between new technologies ( $\chi$ ) and new vintages ( $\gamma$ ). Hence, Comin and Hobijn (2010) divide the contribution evenly and define the productivity due to new vintages as  $\gamma = (1 - \alpha) * 1\%$ . To calculate the intensive margin we need to define the elasticities of substitution between technologies. As in Comin and Mestieri (2010) we define  $\theta = 1.31$ , which is calculated as

the average across technologies, implied by the values of  $\beta_{\tau 3}$ . We need  $\theta$  for the calculation of the intensive margin. The value of  $\theta$  is similar to values implied by the estimates of the price markups from Basu and Fernald (1997) and Norbin (1993). Based on Basu and Fernald's (1997) estimates of the markup in manufacturing, we define  $\mu = 1.3$ .

Having defined the parameters we now execute a two-step approach following Comin and Hobijn (2010). In the first step we estimate equation (22) and use only data for the United States. From this estimation we get values for  $\beta_{\tau 1}$  and  $D_{\tau}^c$  for the United States. Moreover, we get estimates for  $\beta_{\tau 2}$  and  $\beta_{\tau 3}$ , which are assumed to be constant across countries. In a second step  $\beta_{\tau 1}$  and  $D_{\tau}^c$  are estimated separately for each country. The estimated values of the United States for  $\beta_{\tau 2}$  and  $\beta_{\tau 3}$  are plugged into equation (22). We apply a two-step procedure because the adoption lag enters nonlinearly in the estimation equation for each country. This makes a system of equations for all countries together not feasible. Furthermore, this approach has two advantages over the system estimation method. First, we consider the data for the United States to be the most reliable. Hence, we get the most precise estimates for parameters that are constant across countries. Second, the model is based on a set of neoclassical assumptions. These assumptions hold most probably in the United States, where relatively low frictions on capital and product markets exist. (Comin and Hobijn, 2010, p. 2042-2043).

*Estimation with the adoption lag.* Equation (22) is estimated by nonlinear least squares. We estimate  $\beta_{\tau 3}$  only for the United States. Therefore, the identifying assumption is that in the United States, the logarithm of per capita GDP is not correlated with the technology-specific error,  $\epsilon_{\tau, t}^c$ . This assumption is only necessary for the United States, but not for all the other countries, as we take the value of  $\beta_{\tau 3}$  from the United States for all the other countries. Comin and Hobijn (2010) show that for a large majority of technology-country pairs they cannot reject the null hypothesis that  $\beta_{\tau 3}$  is common across the countries, when estimating  $\beta_{\tau 3}$  country by country.

The described estimation yields values for the adoption lag for all technology-country pairs in the sample. As we approximate the diffusion curves, some values are implausible or imprecise. We define implausible estimates as if they imply that the adoption date is more than ten years before the invention date. The ten years are considered in order to allow for inference error. Comin and Hobijn (2010, p. 2043-2044) identified three main reasons why implausible estimates may occur. First, for some countries the data is too noisy to capture the curvature. Second, for some countries the curvature of technology diffusion is convex and not concave as implied by the model. Examples are African countries that have experienced events such as decolonization or civil wars. Third, for some countries data is only available a long time after a technology was adopted. We consider estimates with high standard errors as imprecise. The cutoff values is chosen at  $\sqrt{2003 - v_{\tau}}$ . Comin and Hobijn conclude that 65% of the technology-country pair estimates are plausible and precise.

*Estimation with the penetration rate.* The country-technology specific intercept  $\beta_{\tau 1}^c$  is calculated for technologies measured by output produced as we show in the following equation:

$$\beta_{\tau 1}^c = \beta_{\tau 3}(\ln a_{\tau}^c + (\chi + \frac{\gamma}{2})\tau - \frac{\gamma}{2}D_{\tau}^c + \alpha \ln \alpha) \quad (23)$$

where  $(\chi + \gamma)\tau$  is the productivity level of the first vintage of technology  $\tau$ . Equation (23) shows that the intensive margin,  $a_{\tau}^c$ , is the only driver of cross-country differences in the intercept  $\beta_{\tau 1}^c$ . The intensive margin is identified in the data relative to a benchmark. The benchmark is the value for the United States, as in Comin and Hobijn (2010). As a consequence, the intensive margin is calculated as we show in equation (24):

$$\ln a_{\tau}^c = \frac{\beta_{1,\tau}^c - \beta_{1,\tau}^{US}}{\beta_{3,\tau}} + \frac{\gamma}{2}(D_{\tau}^c - D_{\tau}^{US}) \quad (24)$$

*Evolution of adoption lags and penetration rates.* Comin and Mestieri (2013a, p. 17-18) regress the intensive and extensive margin on a constant and an independent variable, which represents the difference between the invention year and the year 1820.

The adoption lag regression is shown in figure 5. The extensive margin decreased in Western and as well in non-Western countries. Interestingly, the adoption lag decreased faster in non-Western countries than in Western countries. In figure 6 we have bars showing the median for each of the 25 technologies at their invention date. The more recent the adoption date, the smaller is the adoption lag. The fitted lines show the convergence of the adoption lags over time, even though for both groups the lags are declining.

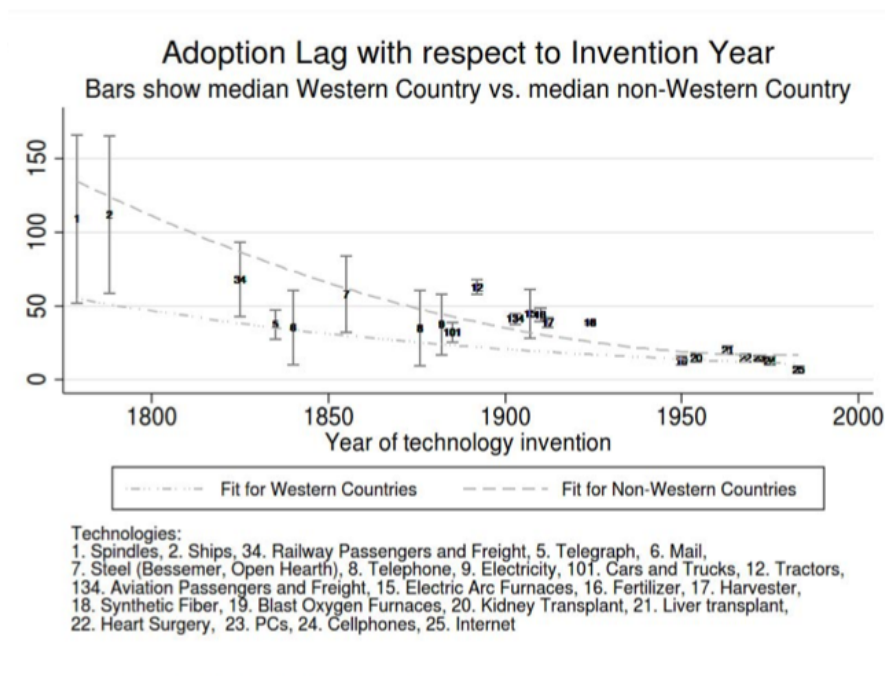
For the intensive margin, one can see that in the year 1820 the average penetration rate was negative. The more recent the invention date, the lower is the penetration rate compared to the benchmark, the United States. By definition the intensive margin of Western countries has not changed over the years. It is remarkable that the intensive margin of countries of the Rest of the World decreased relatively to the Western countries. We observe a divergence of the intensive margin between Western countries and the Rest of the World. This means that on average a non-Western country compared to a Western country did have a higher penetration rate in 1850 than in 1950. Nonetheless, the absolute level of penetration may be higher. This fact is also shown in figure 8 graphically. The bars show the median for 25 technologies at the invention date for Western and non-Western countries. The more recent the date, the longer are the bars. The fitted lines show clearly a divergence of the median penetration rates between the two country groups.

In order to identify the drivers of the respective divergence and convergence we include covariates into these two regressions. The estimation method is described in the subsequent section.

| Dependent Variable is: | (1)<br>Log(Lag)<br>World | (2)<br>Log(Lag)<br>Western Countries | (3)<br>Log(Lag)<br>Rest of the World |
|------------------------|--------------------------|--------------------------------------|--------------------------------------|
| Year-1820              | -0.0106<br>(0.0004)      | -0.0081<br>(0.0006)                  | -0.0112<br>(0.0004)                  |
| Constant               | 4.27<br>(0.06)           | 3.67<br>(0.07)                       | 4.48<br>(0.05)                       |
| Observations           | 1274                     | 336                                  | 938                                  |
| R-squared              | 0.45                     | 0.34                                 | 0.53                                 |

Note: robust standard errors in parentheses. Each observation is re-weighted so that each technology carries equal weight.

**Figure 5:** Evolution of the Adoption Lag (Comin and Mestieri, 2013a, p. 17)

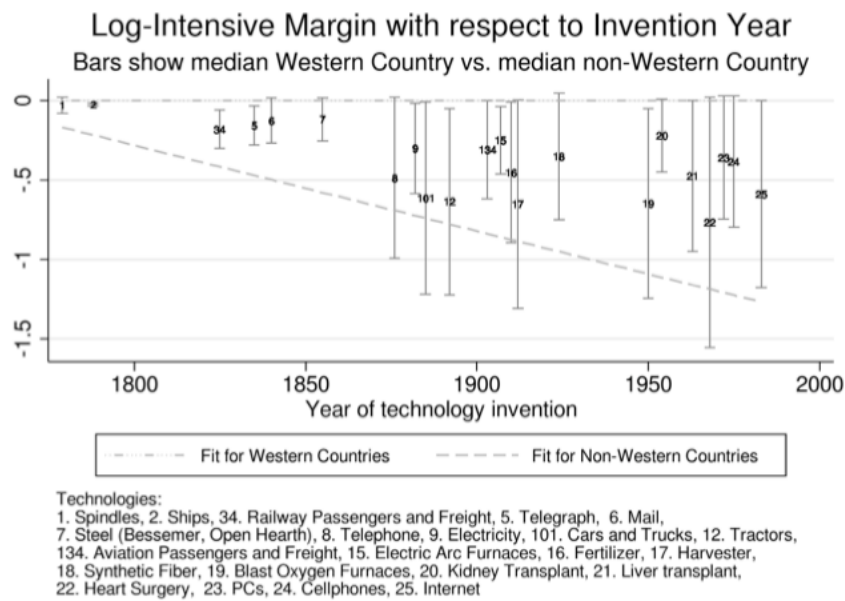


**Figure 6:** Adoption Lag with respect to Invention Year (Comin and Mestieri, 2013a, p. 17)

| Dependent Variable is: | (1)<br>Intensive<br>World | (2)<br>Intensive<br>Western Countries | (3)<br>Intensive<br>Rest of the World |
|------------------------|---------------------------|---------------------------------------|---------------------------------------|
| Year-1820              | -0.0029<br>(0.0005)       | 0.0000<br>(0.0002)                    | -0.0054<br>(0.0005)                   |
| Constant               | -0.32<br>(0.05)           | -0.00<br>(0.06)                       | -0.39<br>(0.07)                       |
| Observations           | 1306                      | 350                                   | 956                                   |
| R-squared              | 0.042                     | 0                                     | 0.13                                  |

Note: robust standard errors in parentheses,\*\*\* p<0.01. Each observation is re-weighted so that each technology carries equal weight.

**Figure 7:** Evolution of the Intensive Margin (Comin and Mestieri, 2013a, p. 18)



**Figure 8:** Log-Intensive Margin with respect to Invention Year (Comin and Mestieri, 2013a, p. 18)

## 4 Data

To measure technology adoption lag and the penetration rate for each technology-country pair we build on the model and estimation of Comin and Mestieri (2010). They use the CHAT dataset compiled by Comin and Hobijn (2009a). This dataset contains information on technology diffusion. It contains 104 technologies in 161 countries during the last 200 years (Comin and Hobijn, 2009a). Technology diffusion is measured in three possible ways, as already described above in subsection 'The Shape of Diffusion Curves'.

*Technology Diffusion data.* We follow Comin and Hobijn (2010) in the selection of a sub-set of technologies. The selection is based on the coverage over rich and poor countries and technologies which are available at initial phases of the diffusion. This is in order to maximize the quality of the included covariates. We are aware that these restrictions may cause a selection bias. Especially for older technologies only countries with long adoption lags are included. We use the publicly available data of Comin and Hobijn (2010) of adoption lags, which contain 830 observations. They could identify 830 plausible and precise observations of adoption dates for 15 technologies. The 15 technologies are described in Appendix 'A Data Description'. We show their summary statistics in table 5. This table 5 is identical to table 2 in Comin and Hobijn (2010, p. 2048). The earliest adoption date is in the year 1817 (ships in the USA), the latest in the year 1993 (internet in Belgium). After matching additional covariates, we obtain a sample of 186 observations. We show the summary statistics for the adoption lags of this sample in table 6. In the last column we see that for three technologies with the oldest invention year, ships, cars and aviation - freight, that the mean of the adoption lag of these three technologies is big compared to the mean of the same technologies in the initial sample of 830 observations. This is a sample selection bias, which is intuitive, as only the observations with a recent adoption date are included. Additionally, they must have a long adoption lag if the invention year is early. We test below in sub section 'Robustness Checks' whether excluding these observations does affect our results.

In general, the more recent the invention date, the more observations we were able to match. In total we obtain a dataset of 186 observations, which is 22.41% of the initial 830 observations. This is mostly due to missing control variables for observations prior to 1960. The matching of our explanatory variables restricts our sample further.

We start with the dataset of Comin and Hobijn (2010) which includes adoption lags and is publicly available. We replicate the penetration rate as described in Comin and Mestieri (2010). Because only the data of the adoption lags but not the penetration rates are publicly available. The only difference we are aware of is that in the estimation of equation (22) we do not distinguish between the different measures of technology diffusion as Comin and Mestieri (2010) do. This distinction caused even larger deviations for our estimates. We show in table 7 our estimates for the penetration rates for the sample of the 830 observations. In table 8 we show the summary statistics of our estimation sample of 186 observations. We identify small deviations of the estimates

in our sample compared to the summary statistics of Comin and Mestieri (2010) and show them in the last column in table 8. We calculate the deviations by taking the exponential function of the means of the penetration rates in our sample and do the same with the means of table 13 in Comin and Mestieri (2010, p. 39). This gives us the penetration rate in percentages compared to the United States. Then we take the difference of the percentage values of our sample and the sample of Comin and Mestieri (2010). We note that for the technologies ships, cars and aviation-freight we get big differences between 13 and up to 50 percentage points. These three technologies sum up to only six observations in our sample. In section 'Robustness Checks' we exclude the technologies ships, cars and aviation - freight and test whether this affects our results. We think the deviations of up to 8.1 percentage points for the technologies invented in 1950 or more recently are acceptable. Furthermore, in the second last column in table 8 we see that the difference of the means of the 186 matched observations from the 830 initial observations does not exceed 6.1 percentage points for these technologies.

Our sample starts with the first observation in the year 1960 and continues in five year steps up to the year 1995. Consequently, we end up with a sample of 186 observations. The highest number of observations is six for South Korea. Hence, we have little within-country variation. In table 9 we show the 17 Western countries, which sum up to 59 observations in total. The 17 Western countries are defined by Maddison (2004)<sup>2</sup>. We choose this definition in order to be in line with Comin and Mestieri (2013a) and therefore be able to build on their result of convergence and divergence of the two margins between the two country groups. The 55 non-Western countries are listed in table 10 and sum up to 127 observations. Given the fact that the education control variable provided by Barro and Lee (2010) is only available every five years and the quantile shares of income inequality provided by UNU-WIDER (2009) are not available before the year 1960 in adequate quality, our sample is restricted. Therefore, we have rounded the technology adoption dates to these five year steps. As one can see in table 1, the observations are unevenly distributed over the investigated time. Therefore, we will include in our core specification time dummies. This allows us to control for time-specific differences.

In tables 2 and 3 we show the 8 technologies and the corresponding summary statistics of the adoption lags and the penetration rates for the in total 186 observations. We sorted the technologies corresponding to their invention date. In general, the later the invention date, the more observations are available. In absolute as well as in relative terms. The mean of the adoption lag decreases over time. For the penetration rate we do not find a decrease over time. This is in line with the finding of Comin and Mestieri (2013a). They show that the average adoption lags decreases for all countries over time. Furthermore, no convergence of the penetration rate is expected. We do not see a decrease in the mean of the penetration rates. On the other hand, by adoption year we do not observe a decrease of the adoption lag, as shown in table 1. It may be

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<sup>2</sup>The 17 Western countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, United Kingdom and United States.

**Table 1:** Distribution of Observations over Time

| Year         | Frequency  | Percent    | Cumulation in % | mean LAG | mean PEN |
|--------------|------------|------------|-----------------|----------|----------|
| 1960         | 2          | 1          | 1.08            | 2.44     | -1.04    |
| 1965         | 7          | 4          | 4.84            | 3.46     | -0.75    |
| 1970         | 6          | 3          | 8.06            | 3.56     | -1.34    |
| 1975         | 7          | 4          | 11.83           | 2.05     | -0.70    |
| 1980         | 15         | 8          | 19.89           | 1.91     | -0.34    |
| 1985         | 60         | 32         | 52.15           | 2.40     | -0.65    |
| 1990         | 77         | 41         | 93.55           | 2.44     | -1.16    |
| 1995         | 12         | 6          | 100.00          | 2.49     | -1.72    |
| <b>Total</b> | <b>186</b> | <b>100</b> |                 |          |          |

that the big variation of the convergence and divergence of the two margins has been finished by 1960, when we start our analysis.

To sum up, we base our dataset initially on the 830 precise and plausible estimates of Comin and Hobijn (2010). By matching them to covariates we generate a balanced dataset of 186 observations.

**Table 2:** Summary Statistics of ln Adoption Lags by Technologies

|                    | Obs        | mean | sd   | Min   | Max  | Invention Year | % of C&H (2010) estimates |
|--------------------|------------|------|------|-------|------|----------------|---------------------------|
| Ships              | 3          | 5.18 | 0.01 | 5.17  | 5.19 | 1788           | 5.88%                     |
| Cars               | 1          | 4.51 | .    | 4.51  | 4.51 | 1885           | 1.37%                     |
| Aviation - Freight | 2          | 4.24 | 0.09 | 4.17  | 4.30 | 1903           | 6.67%                     |
| Blast Oxygen Steel | 17         | 2.97 | 0.31 | 2.37  | 3.43 | 1950           | 43.59%                    |
| PCs                | 46         | 2.60 | 0.19 | 1.90  | 2.94 | 1973           | 65.71%                    |
| Cellphones         | 59         | 2.50 | 1.09 | -5.35 | 2.98 | 1973           | 71.08%                    |
| MRI                | 10         | 1.47 | 0.37 | 0.96  | 1.97 | 1977           | 83.33%                    |
| Internet           | 48         | 1.97 | 0.39 | 0.00  | 2.39 | 1983           | 80.00%                    |
| <b>Total</b>       | <b>186</b> |      |      |       |      |                | <b>22.41%</b>             |

*Income Inequality data.* The variable of interest is a within-country inequality measure. In order to increase the precision we choose, additionally to the Gini coefficient, quantile income share data. As described above, the Gini coefficient is a single inequality statistic with the drawback, that different distributions yield the same coefficient. As described in the Literature Review we expect different parts of the distribution to be important for technology diffusion.

Deininger and Squire (1996) describe that income inequality data often suffers quality problems.

**Table 3:** Summary Statistics of Penetration Rates by Technologies

|                    | Obs        | mean  | sd   | Min   | Max   | Invention Year | % of C&H (2010) estimates |
|--------------------|------------|-------|------|-------|-------|----------------|---------------------------|
| Ships              | 3          | 0.07  | 0.39 | -0.17 | 0.52  | 1788           | 5.88%                     |
| Cars               | 1          | -2.38 | .    | -2.38 | -2.38 | 1885           | 1.37%                     |
| Aviation - Freight | 2          | -0.36 | 0.07 | -0.41 | -0.31 | 1903           | 6.67%                     |
| Blast Oxygen Steel | 17         | -0.99 | 0.94 | -2.79 | 0.55  | 1950           | 43.59%                    |
| PCs                | 46         | -0.68 | 0.55 | -1.86 | 0.06  | 1973           | 65.71%                    |
| Cellphones         | 59         | -1.20 | 1.02 | -3.84 | 0.06  | 1973           | 71.08%                    |
| MRI                | 10         | -0.52 | 0.49 | -1.81 | 0.00  | 1977           | 83.33%                    |
| Internet           | 48         | -0.99 | 0.88 | -4.33 | 0.00  | 1983           | 80.00%                    |
| <b>Total</b>       | <b>186</b> |       |      |       |       |                | <b>22.41%</b>             |

Furthermore, different definitions cause problems to compare the estimates between countries. In order to reach the best possible comparability between countries and to the literature, we follow Foellmi, Oechslin and Zahner (2011) in the construction of the dataset.

Foellmi, Oechslin and Zahner (2011) merge the World Income Inequality Database (WIID release 2c, UNU-WIDER (2009)) and the database constructed by Deininger and Squire (1996). The WIID dataset already contains an update from Deininger and Squire in 2004. Observations which are not from surveys that cover the whole country and the whole population are excluded. In case that observations of several datasets are available, observations from the three favored sources are preferred in the following order. Observations from the Luxembourg Income Study (LIS) are preferred over observations from Deininger and Squire in 2004 over observations from the original Deininger and Squire database from 1996. All other sources are ranked lowest and are only considered if the WIID quality rating is either 1 or 2. Observations with quality ratings 3 and 4 are neglected. From Deininger and Squire (1996) only observations of the quality "accept" are included. The three favored sources are preferred even when measured in the previous period over observations from other sources. The advantage of the Luxembourg Income Study is that it is comparable across countries and years as it always measures income inequality with the income-based measure. Furthermore, based on the WIID rating, good quality is preferred over bad quality, income-based over expenditure-based measures, and net income values over gross income values. Deininger and Squire (1996) propose to add the value of 6.6 to expenditure-based measures of the Gini coefficient to decrease the difference between the income-based measure and the expenditure-based measure. Foellmi, Oechslin and Zahner (2011) apply this idea on the quantile shares. Each expenditure-based quantile is multiplied by the ratio between the sample mean of quantile share for the income-based measures and the sample mean of quantile shares for the expenditure-based

measures. They sum over all available countries (i) and time periods (t):

$$\bar{Q}_{inc}^s = \sum_{i=1}^N \sum_{t=1}^T Q_{inc,i,t}^s \quad (25)$$

$$\bar{Q}_{exp}^s = \sum_{i=1}^N \sum_{t=1}^T Q_{exp,i,t}^s \quad (26)$$

$$\bar{Q}_{corr}^s = Q_{exp,i,t}^s * \frac{\bar{Q}_{inc}^s}{\bar{Q}_{exp}^s} = Q_{exp,i,t}^s * x \quad (27)$$

where  $s=1, \dots, 5$  represents the 5 quantiles. The corrected quantile shares do not sum up to 100 anymore and rescaling is necessary. The sum of all quantile shares is divided by 100, which gives us  $z_i$ . With  $z_i$  we can then correct the quantile shares:

$$z_i = \frac{Q_{corr,i,t}^1 + Q_{corr,i,t}^2 + Q_{corr,i,t}^3 + Q_{corr,i,t}^4 + Q_{corr,i,t}^5}{100} \quad (28)$$

$$Q_{inc,i,t}^s = \frac{Q_{corr,i,t}^s}{z_i}. \quad (29)$$

This correction allows us to correct for some differences between the expenditure-based and income-based quantile shares. The Gini coefficient is corrected by 6.6 as done by Deininger and Squire (1996) in order to make the measure comparable to the literature. (Foellmi, Oechslin, Zahner, 2011, p. 8-10) Nevertheless, we try to only use data of high quality and make them comparable as possible among countries, we are aware that income inequality measures still may suffer from measurement errors. Atkinson and Brandolini (2001) show that only relying on 'high quality' observations from the WIID dataset and accounting for the difference between expenditure- and income-inequality still causes substantial comparability problems between different datasets. Therefore, Atkinson and Brandolini (2001) state to only use data of the LIS dataset. However, this has the big drawback to keep only one of ten observations, which reduces the sample even further. Here, we try to get as many possible observations of good quality as possible. This may cause measurement error. Measurement errors in an explanatory variable can cause inconsistent estimates. For example attenuation bias shrinks the estimate toward zero. A positive estimate will be underestimated and a negative estimate overestimated. To test this issue we run an IV regression as a robustness check for our core specifications. (Wooldridge, 2002, p. 73-75)

In table 11 we give an overview over the variables included in the regressions. In tables 12, 13 and 14 we show the summary statistics of all the variables. Table 12 shows the summary statistics for the full sample, table 13 for the sample of the Western countries and table 14 for the sample of the non-Western countries. We see clearly that as expected the mean of the penetration rate is higher and of the adoption lag is lower in the Western countries compared to the non-Western countries. Furthermore, we see that the Q5, the richest 20%, have a much higher share in non-Western countries with 48.59% compared to 38.43% in the West. The middle class, which consists

of quantiles Q2, Q3 and Q4, receives 53.82% of income in the West compared to 45.62% in non-Western countries. The poorest, Q1, are relatively better off in the West with an income share of 7.75% compared to 5.79%. We conclude that in our sample, the richest 20% in a country are relatively better off in non-Western countries, but the middle class and the poorest are relatively better off in the West. The lower mean of the Gini coefficient in the West supports this finding. Furthermore, we note that the standard deviation is for all measures much higher in the non-Western countries. As a consequence, this sample is much more heterogeneous.

*Control Variables data.* In terms of control variables we follow the estimation of Comin and Hobijn (2006). Hence, we include the percentage of primary, secondary and tertiary schooling attained of the population over 25 years old by Barro and Lee (2010) as explanatory variables for human capital. To account for restrictions on the flow of ideas and capital we measure the sum of imports and exports as a fraction of GDP as trade openness. For the level of economic development we include the log of real GDP per capita provided by Maddison (2007). As control variable for institutions we take the polity IV dataset, which combines the score of autocracy and democracy into one measure. The construction of the polity IV dataset is described in Marshall, Jaggers and Gurr (2011) and is provided by Marshall and Jaggers (2013). An overview over the variable definitions and sources is given in table 11.

We compare the summary statistics in tables 13 and 14. As expected, the mean of GDP is higher in Western countries. We see that the share of primary educated people in the population of over 25 years is slightly higher in non-Western countries. In line with our expectation, the shares of secondary and tertiary educated people much higher in the West. On average, are non-Western countries more open for trade compared to the West. Finally, as expected, institutions are better in the West.

*Instrumental Variable data.* As in the literature described, we face a potential endogeneity problem. Adopted technologies can influence the wages and therefore inequality through various channels. A potential instrument is the variable of agricultural endowment, introduced by Easterly (2007). It is constructed by data offered by the Food and Agriculture Organization (FAO). The IV measures the relative proportion of arable land of wheat compared to sugar cane (Easterly, 2007, p. 762):

$$Lwheatsugar_c = \log \left[ \frac{(1 + \text{arable land suitable for wheat})}{(1 + \text{arable land suitable for sugar cane})} \right] \quad (30)$$

We use the ratios of  $Lwheatsugar_c$  published by Easterly (2007, p. 773) and match them to our data. Note that we require only one observation per country, as we assume that the structural inequality is constant over time. Easterly (2007, p. 758) finds that a higher proportion of arable land suitable for wheat compared to sugar cane is negatively correlated to the Gini coefficient. The two requirements for an instrumental variable seem to be plausible. First, resource endowment affects structural inequality, due to the channels described by Sokoloff and Engerman (2000). Second, the

exogeneity restriction seems reasonable. Hence, we can assume that resource endowment is not correlated to the error term may hold. Exogeneity is assumed because the suitability of land does not influence directly the adoption lag or penetration rate of a technology. We are aware that for agricultural technologies the exogeneity restriction could be violated. In our final sample of 186 observations we do not have any technology, such as tractors, that are intensively used in agriculture industries. Hence, we assume resource endowment cannot affect the adoption of technologies other than through inequality.

We are able to match 175 of our 186 observations. The countries for which we do not have an observation of the suitability of arable land are Mauritius, Morocco, Singapore, Slovak Republic and Taiwan.

## 5 Estimation Method

In this section we first describe the estimation method for our core specifications. In the second subsection we describe the estimation method for the instrumental variable estimation we run as a robustness check of our core specifications.

### 5.1 Core Specifications

Following the research question and the respective channels in the literature, there are two approaches to estimate the respective effects.

Our core specifications for the adoption lag are based on the estimation of Comin and Mestieri (2013a) shown in figure 5. The aim is to estimate the effect of within-country inequality on the technology adoption lag. As explanatory variables we use as Comin and Hobijn (2006, p. 10) determinants of the size of adoption barriers. In the second approach we examine how within-country inequality affects the penetration rate of technology. Accordingly, the dependent variable is the intensive measure, as used in figure 7 and as calculated in Comin and Mestieri (2010). In conclusion, both estimations (i.e. adoption lag and penetration rate) are relevant and explore interesting effects. In the following section we first describe our core specifications for the two adoption margins.

We use in our core specifications a pooled ordinary least square (POLS) method. As dependent variables we include adoption lags and the penetration rates. We have 186 observations for 72 countries and 8 technologies. We choose a pooled OLS with the following specification for adoption lag estimation:

$$\ln D_{t,c,\tau} = \beta_0 + \beta_1 INEQUALITY_{t,c} + \beta_2 INSTITUTIONS_{t,c} + \beta_3 GDP_{t,c} + \beta_4 EDUC_{t,c} + \beta_5 OPENNESS_{t,c} + \beta_6 TD_{t,c} + u_{t,c,\tau} \quad (31)$$

for  $t=1,...,T$ ,  $c=1,...,N$  and  $\tau=1,...,M$ .  $D_{t,c,\tau}$  represents the technology adoption lag at the time of adoption  $t$ , in a particular country  $c$  for a particular technology  $\tau$ .  $TD$  stands for the included time dummy.

As explanatory variables we include the following variables. All these independent variables help to explain barriers to technology adoption.  $\beta_0$  is the intercept and starting from  $\beta_1$  we have the coefficients of the covariates which show us the marginal effects of the covariates on technology diffusion. We expect the following signs of the included covariates. Higher inequality decreases the technology adoption lag. Accordingly, measuring income inequality with income shares, implies that a higher share of the middle class compared to the rich, should increase the technology adoption lag. Better quality of institutions (Marshall and Jaggers, 2011) are expected to decrease the adoption lag, as they represent lower expropriation risk. The higher the relative overall advancement of a country (log of real GDP per capita of country (Maddison, 2007)) the more likely is a country to have the appropriate resources and endowments to adopt a new technology.

Basu and Weil (1998) propose this in their appropriate technology hypothesis. Human capital is measured as the fraction of eligible aged children enrolled in primary, secondary or tertiary school (Barro and Lee (2010)). Nelson and Phelps (1966) introduce the idea that better educated people introduce earlier new technologies, and therefore speed up the technology diffusion. Hence, higher education decreases the technology adoption lag. Higher trade openness, measured as the sum of imports and exports as a fraction of GDP (Heston, Summers and Aten, 2011), may cause faster technology adoption through two channels. First, as proposed by Holmes and Schmitz (2001), increased foreign competition increases the pressure on domestic firms to adopt faster. Second, trade causes knowledge spillovers. Evidence from Coe and Helpman (1995) suggests that foreign R&D is beneficial for domestic productivity. Knowledge spillovers reduce adoption costs and therefore the adoption lag. Additionally, dummies for time are included. These are important in order to isolate the effect of inequality on technology diffusion, for example to take care of time-specific effects of time-specific measurement error due different income definitions over time. (Hyytinen and Toivanen, 2011, p. 372)

To measure inequality we include the Gini coefficient and a dummy of income shares. Q1 is the income share of the poor. The middle class consists of the three quantiles in between the rich and the poor. The rich are denoted with Q5. To capture all effects, we run three regressions. In the first regression we include the Gini coefficient, as a general measure of inequality. In the second and third specifications we include quantile income shares. In the second specification we exclude the richest quantile (Q5). In the third specification we exclude the poorest quantile (Q1). Accordingly, the interpretation of the core specifications is that increasing the income share of the middle class compared to Q5 by 1%, does increase or decrease the adoption lag respectively the penetration rate by  $x$  %. Where  $x$  is the value of the coefficient  $\beta$ . As described in the literature review, redistribution from the rich to the middle class, may give more people the means to adopt the new technologies, and hence increases the intensive margin.

To estimate the effect of inequality on the intensive margin we consider the following pooled OLS estimation with the same properties as described above:

$$\begin{aligned} \ln a_{t,c,\tau} = & \beta_0 + \beta_1 INEQ_{t,c} + \beta_2 INST_{t,c} + \beta_3 GDP_{t,c} + \beta_4 EDUC_{t,c} \\ & + \beta_5 OPENNESS_{t,c} + \beta_6 TD_{t,c} + u_{t,c,\tau} \end{aligned} \quad (32)$$

The determinants of the intensive margin are factors that may be "differences in the costs of producing the intermediate goods associated with a technology, taxes, relative abundance of complementary inputs or technologies, frictions in capital, labor and goods markets, barriers to entry for producers that want to develop new uses for the technology, etc." (Comin and Mestieri, 2013a, p. 7) We include the same covariates for the penetration rate estimation as for the adoption lag estimation.

To consistently estimate  $\beta$  we require two assumptions. Assumption POLS.1 is that we impose exogeneity in the same time period, consequently the error term is not correlated with any

regressor  $x$  in the same time period:  $E(x'_{t,c}u_{t,c,\tau}) = 0$ . However, we do not impose strict exogeneity. So,  $x$  and  $u$  can be correlated over time, hence if  $s \neq t$ . Assumption POLS.2 is the full rank condition:  $\text{rank}[\sum_{t=1}^T E(x'_{t,c}x_{t,c})] = K$ . The rank condition rules out perfect linear dependency among the covariates. If POLS.1 and POLS.2 hold, our estimates are consistent and asymptotically normal. In addition, we add homoskedasticity and no serial correlation assumption in order to get additionally to consistent, moreover efficient results. POLS.3 is the following: (a)  $E(u^2_{t,c,\tau}x'_{t,c}x_{t,c}) = \sigma^2 E(x'_{t,c}x_{t,c})$ ,  $t=1,...,T$ ,  $c=1,...,N$  and  $\tau=1,...,M$ , where  $\sigma^2 = E(u^2_{t,c,\tau})$  for all  $t$ ,  $c$  and  $\tau$ ; (b)  $E(u_{t,c,\tau}u_{s,c,\tau}x'_{t,c}x_{s,c}) = 0$  where  $s \neq t$  and  $t, s=1,...,T$ . POLS.3a assumption is a strong homoskedasticity assumption. For this to be fulfilled we require that  $E(u^2_{t,c,\tau}|x_{t,c}) = \sigma^2$  for all  $t$ . This implies that not only the conditional variance is not dependent on  $x_{t,c}$  but as well that the unconditional variance is the same in every time period. Finally, the assumption POLS.3b restricts the conditional covariance of the error terms across time periods to be zero. As a consequence, we assume no serial correlation. That POLS.3b is fulfilled we require:  $E(u_{t,c,\tau}u_{s,c,\tau}|x_{t,c}x_{s,c}) = 0$ , where where  $s \neq t$  and  $t, s=1,...,T$ . (Wooldridge, 2002, p. 170-171)

Heteroskedasticity is present if the variance of the error varies with different values of a control variable. In figure 9 and then 10 we show in the graphs below from left to the right residual plots of our three sub specifications for each estimation on the two margins. The corresponding estimations are shown in table 4. The first graph on the left shows the sub specification for the Gini coefficient, the second and third for the dummy variables of the quantile income shares. For the adoption lag we see big deviations for some observations of the fitted values from the actually observed ones and thus high residual values. For the regression with dependent variable adoption lags, we find China and Mauritius above a deviation of two and the countries Finland and Switzerland below. Finland is a huge outlier with a deviation of -7.64. For the penetration rate the boundary in which the residuals are distributed around the zero residual line is more narrow. This is intuitive because the dispersion of the adoption lags is as well higher compared to the penetration rate. We find in figure 10 thirteen countries that are below or above one deviation point for the penetration rate estimation. Above are Denmark, Morocco, Peru, South Korea and Tunisia. Below these are Bangladesh, China, Colombia, Hungary, India, Panama, Poland and Vietnam. Nevertheless, we find that the outliers for the adoption lag are further away. This may explain why we only find significant results for the inequality measures in the adoption lag regression after applying heteroskedasticity-robust standard errors. Consequently, we conclude that we find signs for heteroskedasticity by interpreting the residual plots of our core specifications in figures 9 and 10. If we did not correct the standard errors for heteroskedasticity we would still have consistent estimates and therefore we can interpret the coefficients. But the estimates are no longer BLUE. Hence, POLS is not the estimation method with the smallest variance and hence the most efficient one among the unbiased methods. With heteroskedasticity we get biased standard errors and therefore biased test statistics and significance levels. We know that POLS minimizes

the squared residuals, and hence gives the highest weight to the observations with the largest error terms. With the heteroskedasticity-robust error terms, we weight the observations less, which are far away from the regression line. Because we consider these observations as less relevant to give us information about the true regression line. Hence, instead of giving equal weight to all observations we give more weight to the observations that are close to our regression line.

## 5.2 Instrumental Variable Estimation

Subsequently, we describe the two-stage least instrumental variable estimation that we run. Our core specifications may suffer an endogeneity problem. As a consequence, our assumption POLS.2  $E(x'_{t,c} u_{t,c,\tau}) = 0$  may not be valid anymore. If this is the case, our estimates are inconsistent and hence, we cannot interpret them anymore. In our case we have three different sources that may cause endogeneity. First, measurements errors in income inequality data. Second, we could have an omitted variable bias, due to for example different preferences of individuals at different parts of the income distribution. For example, we suggest in our hypothesis 2 that for the poor or the middle class new technologies are particularly useful. But as we cannot control for different preferences, we may get biased estimators. Third, we could have the issue of a simultaneity bias. We suggest that inequality affects technology diffusion. But at the same time there are studies that suggest that technology diffusion influences the distribution of income. One example is the paper of Acemoglu (1998). Acemoglu (1998) says that higher educated people attract new technologies which contribute to increasing the wage premium for their education. To see why the simultaneity bias causes biased estimates, consider the following two equations, where in our case  $y_1$  is technology diffusion and  $y_2$  inequality:  $y_1 = \alpha_1 y_2 + \beta_1 x_1 + u_1$  and  $y_2 = \alpha_2 y_1 + \beta_2 x_2 + u_2$ . Replacing  $y_1$  in the second equation with the  $y_1$  from the first one gives us:  $y_2 = \alpha_2(\alpha_1 y_2 + \beta_1 x_1 + u_1) + \beta_2 x_2 + u_2$ . Now we see that  $y_2$  depends on  $u_1$ , which violates our assumption POLS.2. Hence, we get inconsistent estimates due to endogeneity.

In order to get consistent estimates and eliminate the potential endogeneity that causes POLS.2 to not hold anymore, we apply a Two-Stage Least Squares (2SLS) approach. To be able to use the 2SLS we need a valid instrument. This instrument has to fulfill the following two requirements: First,  $cov(z_c, u_{t,c,\tau}) = 0$ , which means that the instrument is exogenous. Second,  $\theta_1 \neq 0$  in the first stage, so that the instrument has a significant effect on the endogenous variable. Due to the channels described above by Easterly (2007), the suitability of land does affect the income distribution. Furthermore, we assume that instrumental variable has only a causal effect on the endogenous variable, but not on the dependent variable. In our case we assume that this is given, as the suitability of land should not affect the adoption lag or the penetration rate, except by influencing the income inequality.

In the first stage we run a pooled OLS regression of all covariates and the instrument  $z$  on the endogenous variable:

$$\begin{aligned} INEQUALITY_{t,c} = & \delta_0 + \delta_1 INSTITUTIONS_{t,c} + \delta_2 \ln GDP_{t,c} + \delta_3 EDUC_{t,c} \\ & + \delta_4 OPENNESS_{t,c} + \theta_1 z_c + \delta_6 TD_{t,c} + r_{t,c,\tau} \end{aligned} \quad (33)$$

As the first stage is a pooled OLS regression we assume  $E(r_{t,c,\tau}) = 0$  and  $r_{t,c,\tau}$  to be uncorrelated to any covariate. The first stage gives us the fitted value of the endogenous variable which is:  $\widehat{INEQUALITY}_{t,c}$ . In the second stage we regress a pooled OLS as in equations (31) and (32). Instead of INEQUALITY we include the fitted value obtained from the first stage regression:

$$\begin{aligned} \ln D_{t,c,\tau} = & \beta_0 + \beta_1 \widehat{INEQUALITY}_{t,c} + \beta_2 INSTITUTIONS_{t,c} + \beta_3 \ln GDP_{t,c} + \beta_4 EDUC_{t,c} \\ & + \beta_5 OPENNESS_{t,c} + \beta_6 TD_{t,c} + u_{t,c,\tau} \end{aligned} \quad (34)$$

$$\begin{aligned} \ln a_{t,c,\tau} = & \beta_0 + \beta_1 \widehat{INEQUALITY}_{t,c} + \beta_2 INSTITUTIONS_{t,c} + \beta_3 \ln GDP_{t,c} + \beta_4 EDUC_{t,c} \\ & + \beta_5 OPENNESS_{t,c} + \beta_6 TD_{t,c} + u_{t,c,\tau} \end{aligned} \quad (35)$$

We describe in the following the required assumptions. Assumption 2SLS.1 says that for some  $1 \times L$  vector  $z$ ,  $E(z'_c u_{t,c,\tau}) = 0$ . 2SLS.2 is the rank condition which says that (a)  $\text{rank } E(z'_c z_c) = L$ ; (b)  $\text{rank}(z'_c x_{t,c}) = K$ . Part (a) is only needed when more than one instrument is used. The rank condition rules out perfect collinearity. In addition, we require the order condition  $L \geq K$ , which says that at least as many instruments as endogenous variables are required. Under 2SLS.1 and 2SLS.2 the estimates are consistent. Moreover, we have assumption 2SLS.3 which assumes that  $E(u_{t,c,\tau}^2 z'_c z_c) = \sigma^2 E(z'_c z_c)$ , where  $\sigma^2 = E(u_{t,c,\tau}^2)$ . For 2SLS.3 to hold we need  $\text{Var}(u_{t,c,\tau} | z_c) = \sigma^2$  if  $E(u_{t,c,\tau} | z_c) = 0$  to hold. If furthermore 2SLS.3 holds, we get the most efficient 2SLS estimator in the class of all instrument variable estimators using instruments linear in  $z_c$ . (Wooldridge, 2002, p. 83-95)

## 6 Results

In the following we first describe our results of the core specifications. Second, we describe some robustness checks we run in order to check how strong our core results are.

### 6.1 Core Specifications

In table 4 we present our core specifications with pooled OLS, time dummy and heteroskedasticity-robust standard errors. For each of the two adoption margins, the adoption lag and the penetration rate, we have three sub specifications. In columns (1) and (4) we include the Gini coefficient as inequality measure. In columns (2), (3), (5) and (6) we include quantile income shares of Q1, middle class and Q5 as dummy variables.

Our main findings are that higher inequality, measured by the Gini coefficient, does not have a significant effect on the adoption lag. The coefficient of the Gini is positive which is the opposite of the expected sign. Distortion-free redistribution from the rich to the poor decreases the adoption lag, significantly on the 5% level. This emphasizes either the channel that the poor have different preferences than the rich and therefore new technologies are particularly useful to them. Or, credit constraints prevent them from affording the new technologies and therefore increasing their income share decreases the adoption lag. Moreover, redistribution from Q5 to the middle class increases the adoption lag and is significant on the 5% level. This further supports our first hypothesis that the rich can afford new luxuries earlier. Hence, we find two opposing effects in the income distribution on the adoption lag. Higher top-end inequality decreases the adoption lag, but higher inequality due to a higher income share of the rich at the expense of the poor, increases the adoption lag. These opposing effects may be the reason why we do not get a significant effect of the Gini coefficient on the adoption lag, which only measures overall inequality. Furthermore, higher inequality, measured by the Gini coefficient, decreases the penetration rate. This result is significant on the 10% significance level. Distortion-free redistribution from Q5 to the middle class increases the penetration rate, but is only significant on the 10.3% significance level. This result is as expected, it indicates that overall inequality is an obstacle for the diffusion of technologies in a country and emphasizes the importance of the middle class.

As long as we assume that there is no omitted variable bias, we can interpret all regressors. To answer our research question we require only the estimates of inequality to be consistent. We may keep in mind that there is a potential endogeneity problem of inequality and technology adoption. For the covariates there may be other omitted variables, which we do not discuss as it beyond the scope of this thesis. Therefore, all interpretations should be taken cautiously.

We furthermore find, in accordance with what the literature suggested, negative effects of GDP and institutions on the adoption lag. These effects are significant at the 1% and 5% level. Primary, secondary and tertiary education and openness do have the expected negative sign, but are not statistically significant. In magnitudes, GDP has the highest impact on the technology adoption

lag, followed by the effect of a higher income share of Q1. This emphasizes the importance of including the high marginal returns of the poorest. The  $R^2$  little over 23%, which is not very high. This means the included control variables are able to explain 23% of the variation of the adoption lag. We conclude that we cannot support our hypothesis 1 unconditionally, as we expected higher inequality to decrease the adoption lag. Nevertheless, we find that new technologies could be particularly important to the poor and therefore increasing their income share decreases the adoption lag.

As expected, we find positive and significant effects for GDP, primary, secondary and tertiary education and for openness on the penetration rate. All these effects are significant at least at the 1% significance level. Institutions do not seem to be relevant for the penetration rate. The three education measures supports the theory of skill-biased technological change proposed by Acemoglu (1998). A higher share of high educated people does increase the speed of adoption of new technologies because they have skills to productively use these technologies. Moreover, openness does decrease the cost of the diffusion in a country, due to increasing international competition. Hence, the higher education the higher is the penetration rate. The  $R^2$  is above 60% in all three core specification for the penetration rate. This is much higher as for the adoption lag, where it is only above 23%.

By including time dummies we account for time-specific effects that otherwise may drive our results. Additionally to time-specific effects, these dummies can account for measurement errors in income inequality measures that result due to worldwide changes in the calculation of the income share. Interestingly, time dummies for the adoption lag are only significant for the year 1965 and 1970. This is the time period, which we expect to suffer from selection bias. In the estimates for the penetration rate the time dummies are significant from 1980 until 1995. The time dummies may even control to some extent for the selection bias in of the observations in the early period, where the selection bias is most severe.

**Table 4:** Core Specifications. Including Time Dummies and Heteroscedasticity-Robust Standard Errors.

| VARIABLES      | (1)                     | (2)                    | (3)                    | (4)                     | (5)                               | (6)                     |
|----------------|-------------------------|------------------------|------------------------|-------------------------|-----------------------------------|-------------------------|
|                | LAG                     | LAG                    | LAG                    | PEN                     | PEN                               | PEN                     |
| GINI           | 0.00481<br>(0.00536)    |                        |                        | -0.00885*<br>(0.00527)  |                                   |                         |
| Q1             |                         | -0.108**<br>(0.0466)   |                        |                         | -0.0228<br>(0.0417)               |                         |
| MiddleClass    |                         | 0.0342**<br>(0.0167)   | 0.142**<br>(0.0618)    |                         | 0.0256 <sup>(*)</sup><br>(0.0156) | 0.0484<br>(0.0555)      |
| Q5             |                         |                        | 0.108**<br>(0.0466)    |                         |                                   | 0.0228<br>(0.0417)      |
| lnGDP          | -0.102***<br>(0.0390)   | -0.117***<br>(0.0387)  | -0.117***<br>(0.0387)  | 0.102***<br>(0.0302)    | 0.0906***<br>(0.0304)             | 0.0906***<br>(0.0304)   |
| primary_educ   | -0.00185<br>(0.00440)   | -0.000317<br>(0.00414) | -0.000317<br>(0.00414) | 0.0195***<br>(0.00421)  | 0.0195***<br>(0.00422)            | 0.0195***<br>(0.00422)  |
| secondary_educ | 0.000778<br>(0.00394)   | 0.00199<br>(0.00415)   | 0.00199<br>(0.00415)   | 0.0210***<br>(0.00476)  | 0.0207***<br>(0.00484)            | 0.0207***<br>(0.00484)  |
| tertiary_educ  | -0.00654<br>(0.00629)   | -0.0110<br>(0.00680)   | -0.0110<br>(0.00680)   | 0.0411***<br>(0.00692)  | 0.0389***<br>(0.00742)            | 0.0389***<br>(0.00742)  |
| OPENNESS       | -0.000953<br>(0.000721) | -0.00103<br>(0.000731) | -0.00103<br>(0.000731) | 0.00381***<br>(0.00111) | 0.00363***<br>(0.00114)           | 0.00363***<br>(0.00114) |
| INSTITUTIONS   | -0.0295**<br>(0.0132)   | -0.0337**<br>(0.0137)  | -0.0337**<br>(0.0137)  | 0.00971<br>(0.00956)    | 0.00748<br>(0.00971)              | 0.00748<br>(0.00971)    |
| Constant       | 3.444***<br>(0.633)     | 2.724***<br>(0.741)    | -8.105<br>(5.099)      | -3.138***<br>(0.470)    | -4.412***<br>(0.655)              | -6.690<br>(4.566)       |
| Time Dummy     | Yes                     | Yes                    | Yes                    | Yes                     | Yes                               | Yes                     |
| Observations   | 186                     | 186                    | 186                    | 186                     | 186                               | 186                     |
| $R^2$          | 0.232                   | 0.248                  | 0.248                  | 0.606                   | 0.613                             | 0.613                   |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1, (\*) p&lt;0.11

Note: We apply pooled OLS to a sample of 186 observations, including 72 countries and eight technologies. The dependent variables are ln adoption lag denoted as LAG and ln penetration rate denoted as PEN. The regressors are the Gini coefficient and quantile income shares. The MiddleClass consists of the quantiles Q2, Q3 and Q4. Q1 are the poorest and Q5 are the richest 20% of a country. GDP is measured in logarithms. Education is measured as the percentage of schooling attained in population of people above 25 years. Openness is the sum of imports and exports as a fraction of GDP. Institutions are measured on a scale of -10 up to +10. Where -10 is full autocracy and +10 is full democracy.

## 6.2 Robustness Checks

In the following section we perform six different robustness checks in order to address the potential problems of endogeneity, selection bias and to check the validity of our core specifications results. First, we start by discussing the IV regression to check potential endogeneity. Second, we exclude specific observations which may cause a selection bias. Third, we include technology dummies. Fourth, we include country-group dummies and moreover do separate estimates for Western and non-Western countries. Fifth, we include the dummy (Invention Year-1820) which is included in the figures 5 and 7 in order to see whether we get the same results as Comin and Mestieri (2013a) and to evaluate whether this effect is still significant after including the covariates of our core specifications. Sixth, we discuss the residual plots for our core specifications and the issue of heteroscedasticity.

First, we show the results for the IV estimation in table 15. The instrument for the Gini coefficient is the suitability of arable land provided by Easterly (2007). In column (1) we show the first stage regression. Our instrument variable is highly significant on the 1% level with an effect of a huge magnitude on the Gini coefficient. In column (2) we see that, like the Gini coefficient in the core specification in table 4, the IV estimate has no significant effect on the adoption lag. We conclude again that the Gini may have no significant effect, due to opposing effects in the income distribution on the adoption lag. Nevertheless, the IV estimate on the adoption lag is negative as we expected. Accordingly, it may be that endogeneity leads for the adoption lag in the core specification to an upward bias. On the other hand, our IV estimate in column (3) is significant on the 10.8% significance level and the magnitude of the effect is more negative than our estimate in the core specification in column (4) in table 4. Consequently, if our core estimates are biased due to measurement error, simultaneity bias, or omitted variable bias due to hidden preferences, this does rather causes an upward bias in our coefficients. In case that we suffer from an attenuation bias due to measurement error, the estimate is biased towards zero. This may be the case here for the penetration rate. This may be explained through the IV estimate being more negative than the Gini coefficient in our core specification. We conclude that structural inequality, accounted for by the IV, is relevant for the penetration rate. Furthermore, for both, the adoption lag and the penetration rate the potential biases cause an upward bias. This supports the validity of our core specifications, as the effect may be even stronger than what we observe.

Second, we check whether our sample suffers from selection bias. Due to the fact that we restrict our sample to observations made as of onwards 1960, we include of technologies with an early invention year only observations of countries with a long adoption lag. As discussed in section 'Data' the technologies, for which this selection bias is most severe, are cars, ships and aviation - freight. Therefore, we exclude these observations, which sum up to only six. The countries are China, Mauritius, South Korea, Sri Lanka and Thailand. Interestingly, we already identified China, South Korea and Mauritius as outliers the analysis of the residual plots in section 'Estimatin

Method'. In table 16 we show the estimation output of the smaller sample. We find no significant results of the inequality measures on the adoption lag anymore. The standard errors are similar, but the magnitudes drop. GDP and institutions remain significant. We conclude that the adoption lag estimation suffers from a selection bias. Hence, either there is no significant effect of inequality on the dependent variable or our sample may be too small to measure the effect significantly. For the penetration rate we find for the Gini coefficient the same effect as in the core specifications. The magnitude for the middle class estimates drops. Accordingly, we interpret that for the penetration rate there may also be a selection bias, which triggers an upward bias for the middle class effect. Another possible explanation is that the effects are driven by technology-specific effects. Therefore, we do check this next, by including technology dummies.

Third, we check and technology-specific effects. Including technology dummies or technology and time dummies together, gives us no significant results for income inequality anymore. We do not show these results. Except for a negative effect of the Gini coefficient on the penetration rate with a lower magnitude and significance on the 10% level. We conclude that especially technology-specific factors are important and neglected in our specifications. We have relatively few observations for each technology. With a bigger sample it would be interesting to disentangle the different effects. This is a drawback of our analysis.

Fourth, we investigate whether the results are driven by specific country groups and whether the marginal effects are different for the Western and non-Western samples. We start by including country group dummies into the core specifications. We follow the classification of Comin and Hobijn (2010) and create five groups: OECD, Latin, Sub Saharan, Tigers and Other Countries. In table 17 we observe significant and positive effects of the dummies for Latin, Tigers and Other Countries for the adoption lag. Consequently, these regions have on average higher adoption lags compared to the OECD countries. For the penetration rates we find that the Tiger countries have on average higher and Other Countries have on average lower penetration rates. Consequently, these regions seem to have different patterns compared to the OECD countries. For the adoption lag we can again support the fact that redistribution from the rich to the poor decreases the adoption lag and that redistribution from the rich or the poor to the middle class increases the adoption lag. For the penetration rate we do not find any significant effects anymore. Hence, for the penetration rate the effects may be driven in particular by the Tigers and Other Countries groups. Interestingly, does the Tigers country group have longer adoption lags and higher penetration rates. This is counterintuitive. Analyzing the summary statistics of the inequality measures for the Tigers, which we do not show, we find a smaller income share of Q5 and higher income shares for Q1 and the middle class compared to non-Western countries. This supports the hypothesis that low income share for the rich decreases the adoption lag and high income shares for the middle class increase the penetration rate. Now we investigate for the samples of the Western and non-Western countries separately. In the tables 18 and 19 we show the estimations. We find that redistribution

from the poor to the rich or to the middle class increases the adoption lag in Western countries. Moreover, increasing the share of the rich compared to the middle class decreases the adoption lag in Western countries. The magnitudes are much higher than in the core specification for these results. Finally, increasing the income share of the middle class compared to the rich increases the penetration rate in non-Western countries. As shown in tables 13 and 14 is the income share of the rich higher in non-Western countries and the income shares of the poor and the middle class higher in Western countries. This suggest that the strong middle class hampers the initial adoption and therefore increases the adoption lag in the West. Therefore non-Western countries could catch up in the adoption lags to the Western countries. Nevertheless, the income share of the poor is high in Western countries too, and this decreases the adoption lag. Furthermore, does the high income share of the rich in non-Western countries decrease the penetration rate and cause the divergence of the penetration rates between the two groups. We conclude that we find some support for the convergence and divergence between Western and non-Western countries. Nevertheless, the hypothesis hold only to a certain extent. It may be that we look at the wrong time period or not at the relevant drivers. Interestingly, do education and openness significantly influence the penetration rates in non-Western countries, but not in the West. A further interesting robustness test would be to include an interaction term of Western countries, to check whether the returns of inequality differ between the two country groups.

Fifth, we include in table 20 a 'difference of years to invention' dummy to check how adoption lags and penetration rates developed over the years. We see that the more recent the invention year, the lower are the adoption lag and the penetration rate. In contrast to Comin and Mestieri (2013a) we do not find convergence in the adoption lag and divergence in the penetration rate in our sample. The adoption lag decreases faster in the Western countries and the penetration rate decreases compared to the US faster in the West than in non-Western countries. Even, when excluding the possible sample selection bias, we do not get different results. This suggests that convergence and divergence may not be driven by the technologies we include in our sample. Or we may have too many observations of technologies with a similar and recent invention date. This may suggest that we look at the wrong point in time to explain convergence and divergence of the two margins. The dummy coefficients are still highly significant. We therefore include this dummy into the core specifications, shown in table 21, in order to determine whether we account for the relevant variables that drive the margins over time. We find highly significant estimates for the 'difference of years to invention year'. However, no more inequality measures are significant. There may be hidden effects, we do not control for, that drive the evolution of the two adoption margins.

Finally, in the figures 9 to 14 we show the residual plots for our core specification estimations. In the figures 9 and 10 we show above the plots of the fitted values of the adoption lag respectively the penetration rate, versus selected inequality measures. The graphs are ordered from left to right the same way as the core specifications in table 4. For the adoption lag we conclude that

there are many outliers, which cause high standard errors. Consequently, our core specification may suffer from heteroskedasticity. Nevertheless, this does not bias our estimator, but makes them inefficient. Due to high standard errors we do not get significant results in our estimations without our heteroskedasticity-robust standard errors. Therefore, we correct this. Furthermore, in figure 10 we see that the higher the fitted values for the adoption lag are the error terms to be lower. Hence, there may be a slight downward trend, which could be a sign of autocorrelation. For the penetration rates there is a cluster of countries in the top right of the middle class graphs. In the bottom left there are no observations. In the figures 13 and 14 we see similar patterns as described above. We conclude that we may suffer from heteroskedasticity, but do not identify any other severe issues.

## 7 Discussion

In this section we present a short overview of our core findings and their robustness. Then we discuss the strengths and weaknesses of our findings and what further research opportunities we identify.

We find support for our hypotheses to some extent. Our core specifications provide evidence that increasing the income share of the rich at the expense of the poor increases the adoption lag. In contrast increasing the income share of the rich at the expense of the middle class decreases the adoption lag. However, we cannot conclude that a higher Gini coefficient does decrease the adoption lag. Due to the opposite effects in the quantile income shares, this overall inequality measure may be too broad. On the other hand, for the penetration rate higher overall inequality is bad for the penetration rate. Moreover, we find strong support for the fact that a strong middle class over the rich increases the penetration rate.

We perform six different robustness checks to examine whether our core specifications suffer from any bias. First, we do an IV estimation and find support that overall inequality does affect the penetration negatively. Possible measurement error, omitted variable bias or simultaneity bias might cause a downward bias of our inequality measure. We may suffer from a selection bias which causes biased estimates, especially for the adoption lag estimation. For the penetration rate the selection bias is rather small. On the other hand, including technology-dummies results in non-significant estimates. Therefore, we should be cautious about our findings. There may be some underlying factors, we do not observe. Omitted variable may cause our estimates to be biased or the marginal effects for the technologies may be different. Moreover, we control for country groups and find that the regions Latin, Tigers and Other Countries drive our results, in particular for the penetration rate where we do not find any significant inequality results anymore. For the adoption lag this specification further supports our hypothesis 1. Furthermore, we find different marginal effects in Western and non-Western countries. We find to some extent support for the convergence and divergence of the two margins. The high income share of the rich reduces the adoption lag in non-Western countries and the high income share of the middle class in Western countries increases the penetration rate there. Nevertheless, it may be that it is more relevant to investigate an earlier time period for this pattern. As in our sample we do not find convergence and divergence of the two margins between Western and non-Western countries, as Comin and Mestieri (2013a) do. Furthermore, the 'difference off years to invention year' dummy is highly significant and turns the quantile income share dummies insignificant. This suggests that we have not controlled for some relevant hidden factors and hence suffer from omitted variable bias. Yet, the Gini coefficient remains significant and negative on the penetration rate, as we expected and also in line with previous estimations. Finally, we observe in the residual plots some outliers. By applying heteroskedasticity-robust standard errors we get correct standard errors and consequently, more efficient results. In conclusion, we find support for our two hypotheses. Nevertheless, some

results of our robustness checks require us to interpret our results cautiously. More precisely, we rule out simultaneity bias, but we can not rule out all doubts about measurement error or omitted variable bias. Measurement error may be due to bad quality of inequality data while omitted variable bias may be caused by a selection bias or technology-specific factors.

In conclusion, our estimations are robust to some extent. We highlight the importance of applying quantile income shares. Without such a inequality measure we would not be able to detect any significant results on the adoption lag. Furthermore, our results may only be relevant for the eight technologies, we were able to match to our covariates. These are ships, cars, aviation - freight, blast oxygen steel, cellphone, pc, MRI and internet. Further research may be able to investigate whether the effects are equal for the diffusion of other technologies. This conclusion is further emphasized by the robustness check including technology-specific factors. This may suggests that we may have not controlled for some hidden characteristic.

Further research could be done by in various aspects. Either by improving the dataset or controlling for further channels that compete with our hypotheses or by including a variable we have not controlled for. The dataset may be improved with regard to technology data. By including more technologies, it may be feasible to control better for technology-specific effects or to discover different marginal returns of the covariates on the technology diffusion of different technologies. As proposed by Caselli (1999), different kind of technologies may have different effects on the wage. Accordingly, the simultaneity bias may be hidden due to these possibly opposing effects. Furthermore, is the possibility to investigate a longer time period promising, rather than use only a short period from 1960 to 1995. It may be that this period is too short or not the relevant one to determine the long-run drivers. The fact that we do not observe any convergence or divergence of the two margins by adoption year in table 1 suggests that either our specification may suffer from a selection bias or convergence and divergence already happened before that time period. Moreover, controlling for longer time periods reduces the issue of selection bias. By using the top income share as inequality proxies, longer time periods could be investigated. Leigh (2007) provides evidence that this measure tracks well other measures of inequality.

Another possible extension may be including a measure of GPT, such as electricity of the early twentieth century or internet diffusion later on. Availability of GPTs may facilitate the diffusion of other technologies. A possible competing channel to inequality affecting the adoption, may be government services. If the government supplies GPTs and other technologies as public goods, income inequality may be less important. This channel could be controlled for by an interaction term of GPT diffusion and government spending, through taking government spending as a proxy for services provided by the government.

## 8 Conclusions

In this thesis, we aim to shed light upon the drivers behind the two margins of technology adoption: the adoption lag and the penetration rate. Finding the drivers is relevant because these two margins are crucial for explaining the dynamics of the Great Divergence between Western and non-Western countries. In particular, we investigate whether within-country inequality can explain some of the differences of the two adoption margins. Our first hypothesis suggests that the adoption lag decreases when the rich have a high share of the income and therefore can afford the new luxury products. Also, the adoption lag can fall when a technology is particularly useful to the poor or the middle class. If such groups have a higher income share, we expect a lower adoption lag. The second hypothesis advocates that higher inequality decreases the long-run penetration rate. More specifically, a strong middle class compared to the rich may be important for a high penetration rate. The model of Foellmi, Würzler and Zweimüller (2009) suggests that in the long-run, luxury goods are transformed into mass-products and sold for a lower price to the middle class. Hence, with a high income share of the middle class, the penetration rate is higher. The estimation of the adoption lag and the penetration rate is built upon the theoretical model and estimation strategy of Comin and Mestieri (2010) and Comin and Mestieri (2013a). We do this by approximating the diffusion curves and assuming that they are only horizontally and vertically shifted across countries. These two shifts are the two adoption margins.

We apply a pooled OLS to our sample of 72 countries with 186 observations between 1960 and 1995. Our core specifications may potentially suffer from biased results due to various sources. Potential sources are simultaneity bias, omitted variable bias, measurement error, selection bias, technology specific effects or different returns of inequality on technology diffusion by country groups.

We find that the adoption lag is decreased by distortion-free redistribution of income from the rich to the poor and increased by redistribution from the rich to the middle class. Moreover, increasing the income share of the middle class at the expense of the rich increases the penetration rate. As a consequence, disentangling the effects by quantile income shares is crucial. These findings may help to explain to some extent why the Great Divergence declined, yet still remains. In our dataset, the income share of the rich is on average much higher in non-Western countries compared to the West. However, the middle class is stronger in the West. As a consequence, our results suggest that inequality between the rich and the middle class increased the adoption lags in Western countries and hampered the penetration of technologies in non-Western countries. In our sample, the income share of the poor is higher in the West. In addition to the higher GDP and the better institutions, which are crucial factors in determining the adoption lag, this inequality lowers the lag for the Western countries even more. For the penetration rate, GDP, education and trade openness are important.

We are able to rule out simultaneity bias, measurement error and omitted variable bias, due

to our IV estimation for the penetration rate. The issue of selection bias remains and could cause inconsistent estimates. Additionally, our results are not robust if we control for technology-specific effects. Furthermore, the identified effects may be applicable only to the eight investigated technologies and the examined time period between 1960 and 1995. Further research may be able to show, whether these findings hold for a broader set of technologies and a longer period of time. We find different returns of income inequality on the two margins between Western and non-Western countries. Finally, we allow for heteroskedasticity in our estimation.

In conclusion, the findings of this thesis support our two hypotheses, even if our estimation may suffer from several biases. Further investigating the past 200 years is of particular interest, although the quality of data may be an issue. This interest is based on the fact that much of the variation of the convergence and divergence of the two adoption margins observed by Comin and Mestieri (2013a) stems from that period of time. Nevertheless, our findings may imply fruitful further research in determining the drivers of the two adoption margins and thereby the income dynamics between countries.

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## A Data Description

The technology diffusion data is taken from Comin and Hobijn (2009a), which is the Cross-Country Historical Adoption of Technology (CHAT) dataset. The fifteen technology measures used are described in the following as in Comin and Hobijn (2010):

### *Transportation*

1. **Steam and motor ships:** Gross tonnage (above a minimum weight) of steam and motor ships in use at midyear. Invention year: 1788; the year the first (U.S.) patent was issued for a steam boat design.
2. **Railways - Passengers:** Passenger journeys by railway in passenger-KM. Invention year: 1825; the year of the first regularly schedule railroad service to carry both goods and passengers.
3. **Railways - Freight:** Metric tons of freight carried on railways (excluding livestock and passenger baggage). Invention year: 1825; same as passenger railways.
4. **Cars:** Number of passenger cars (excluding tractors and similar vehicles) in use. Invention year: 1885; the year Gottlieb Daimler built the first vehicle powered by an internal combustion engine.
5. **Trucks:** Number of commercial vehicles, typically including buses and taxis (excluding tractors and similar vehicles), in use. Invention year: 1885; same as cars.
6. **Aviation - Passengers:** Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned. Invention year: 1903; The year the Wright brothers managed the first successful flight.
7. **Aviation - Freight:** Civil aviation ton-kilometers of cargo carried on scheduled services by companies registered in the country concerned. Invention year: 1903; same as aviation - passengers.

### *Communication and IT*

8. **Telegraph:** Number of telegrams sent. Invention year: 1835; year of invention of telegraph by Samuel Morse at New York University.
9. **Telephone:** Number of mainline telephone lines connecting a customers equipment to the public switched telephone network as of year end. Invention year: 1876; year of invention of telephone by Alexander Graham Bell.

10. **Cellphones:** Number of users of portable cell phones. Invention year: 1973; first call from a portable cellphone.

11. **Personal computers:** Number of self-contained computers designed for use by one person. Invention year: 1973; first computer based on a microprocessor.

12. **Internet users:** Number of people with access to the worldwide network. Invention year: 1983; introduction of TCP/IP protocol.

#### *Industrial*

13. **Blast Oxygen Steel:** Crude steel production (in metric tons) in blast oxygen furnaces (a process that replaced Bessemer and OHF processes). Invention year: 1950; invention of Blast Oxygen Furnace.

14. **Electricity:** Gross output of electric energy (inclusive of electricity consumed in power stations) in KwHr. Invention year: 1882; first commercial power-station on Pearl Street in New York City.

#### *Medical*

15. **MRIs:** Number of magnetic resonance imaging (MRI) units in place. Invention year: 1977; first MRI-scanner built.

**Table 5:** Summary Statistics of Adoption Lag of Initial Sample by Comin and Hobijn (2010)

| Technologyname       | Invention Year | Obs        | mean         | sd           | p1          | p10         | p50          | p90          | p99           |
|----------------------|----------------|------------|--------------|--------------|-------------|-------------|--------------|--------------|---------------|
| Ships                | 1788           | 51         | 120.45       | 51.07        | 29.71       | 56.95       | 122.53       | 178.78       | 179.72        |
| Rail - Freight       | 1825           | 42         | 79.59        | 32.67        | 24.92       | 30.93       | 78.99        | 122.95       | 134.54        |
| Rail - Passenger     | 1825           | 60         | 97.32        | 26.43        | 24.98       | 59.90       | 100.96       | 124.70       | 137.29        |
| Telegraph            | 1835           | 44         | 45.61        | 31.06        | -4.17       | 16.94       | 32.93        | 98.27        | 109.20        |
| Telephone            | 1876           | 64         | 51.54        | 32.44        | -7.20       | 7.85        | 57.42        | 94.62        | 113.39        |
| Electricity          | 1882           | 94         | 56.37        | 19.91        | 13.00       | 20.30       | 65.82        | 73.92        | 106.54        |
| Cars                 | 1885           | 73         | 43.68        | 19.09        | 9.66        | 18.78       | 44.19        | 64.68        | 101.85        |
| Trucks               | 1885           | 58         | 39.13        | 19.77        | 4.12        | 16.03       | 35.21        | 64.43        | 89.18         |
| Aviation - Freight   | 1903           | 30         | 43.49        | 13.53        | 11.96       | 24.45       | 41.79        | 60.81        | 73.95         |
| Aviation - Passenger | 1903           | 50         | 33.90        | 12.27        | 16.81       | 21.12       | 29.24        | 52.88        | 71.59         |
| Blast Oxygen Steel   | 1950           | 39         | 16.31        | 7.25         | 2.05        | 8.78        | 15.64        | 27.99        | 32.99         |
| Cellphones           | 1973           | 83         | 14.61        | 3.92         | 0.00        | 9.96        | 15.55        | 18.76        | 19.78         |
| PCs                  | 1973           | 70         | 13.96        | 2.93         | 3.32        | 10.22       | 14.18        | 17.03        | 19.30         |
| MRI                  | 1977           | 12         | 5.30         | 2.29         | 2.62        | 2.87        | 4.68         | 7.38         | 10.14         |
| Internet             | 1983           | 60         | 7.80         | 2.17         | -0.13       | 5.01        | 7.77         | 10.72        | 10.94         |
| <b>Total</b>         |                | <b>830</b> | <b>45.48</b> | <b>38.54</b> | <b>2.62</b> | <b>9.00</b> | <b>32.50</b> | <b>99.26</b> | <b>178.15</b> |

**Table 6:** Adoption Lag of 186 Observations Sample. Adoption Lags in Years.

| Technologyname     | Invention Year | Obs        | mean         | sd           | p1          | p10         | p50          | p90          | p99           | difference of lag to 830 obs sample <sup>3</sup> |
|--------------------|----------------|------------|--------------|--------------|-------------|-------------|--------------|--------------|---------------|--------------------------------------------------|
| Ships              | 1788           | 3          | 177.97       | 1.92         | 175.82      | 175.82      | 178.59       | 179.51       | 179.51        | 57.52                                            |
| Cars               | 1885           | 1          | 90.63        | .            | 90.63       | 90.63       | 90.63        | 90.63        | 90.63         | 46.94                                            |
| Aviation - Freight | 1903           | 2          | 69.39        | 6.45         | 64.83       | 64.83       | 69.39        | 73.95        | 73.95         | 25.90                                            |
| Blast Oxygen Steel | 1950           | 17         | 20.28        | 5.99         | 10.70       | 12.19       | 18.99        | 29.07        | 30.81         | 3.97                                             |
| Cellphones         | 1973           | 59         | 14.37        | 4.16         | 0.00        | 9.81        | 15.46        | 19.10        | 19.78         | -0.24                                            |
| PCs                | 1973           | 46         | 13.64        | 2.36         | 6.71        | 10.84       | 13.91        | 16.28        | 18.88         | -0.32                                            |
| MRI                | 1977           | 10         | 4.61         | 1.68         | 2.62        | 2.75        | 4.37         | 7.03         | 7.17          | -0.69                                            |
| Internet           | 1983           | 48         | 7.57         | 2.09         | 1.00        | 4.53        | 7.72         | 9.96         | 10.87         | -0.23                                            |
| <b>Total</b>       |                | <b>186</b> | <b>16.09</b> | <b>22.96</b> | <b>1.00</b> | <b>5.85</b> | <b>12.79</b> | <b>19.28</b> | <b>178.59</b> |                                                  |

3 Difference of adoption lag in 186 sample and initial sample of 830 observations by Comin and Hobijn (2010)

**Table 7:** Summary Statistics of Penetration Rate of own calculations based on Initial Sample by Comin and Hobijn (2010)

| Technologyname       | Invention Year | Obs        | mean         | sd          | p1           | p10          | p50          | p90         | p99         |
|----------------------|----------------|------------|--------------|-------------|--------------|--------------|--------------|-------------|-------------|
| Ships                | 1788           | 51         | 0.03         | 0.62        | -1.44        | -0.65        | -0.02        | 0.72        | 1.46        |
| Rail - Freight       | 1825           | 42         | -0.59        | 0.34        | -1.22        | -0.99        | -0.63        | -0.03       | 0.12        |
| Rail - Passenger     | 1825           | 60         | 0.07         | 0.30        | -0.53        | -0.32        | 0.06         | 0.53        | 0.71        |
| Telegraph            | 1835           | 44         | -0.47        | 0.51        | -1.70        | -1.24        | -0.38        | 0.08        | 0.70        |
| Telephone            | 1876           | 64         | -0.96        | 0.82        | -4.35        | -2.02        | -0.79        | -0.10       | 0.07        |
| Electricity          | 1882           | 94         | -0.51        | 0.39        | -1.78        | -1.02        | -0.45        | -0.06       | 0.26        |
| Cars                 | 1885           | 73         | -1.78        | 1.26        | -7.01        | -3.05        | -1.68        | -0.37       | 0.30        |
| Trucks               | 1885           | 58         | -1.60        | 1.25        | -7.16        | -2.55        | -1.57        | -0.41       | 0.44        |
| Aviation - Freight   | 1903           | 30         | -0.62        | 0.81        | -2.82        | -1.62        | -0.42        | 0.31        | 0.41        |
| Aviation - Passenger | 1903           | 50         | -0.84        | 0.62        | -2.61        | -1.56        | -0.78        | -0.11       | 0.35        |
| Blast Oxygen Steel   | 1950           | 39         | -0.84        | 0.90        | -2.79        | -2.30        | -0.42        | 0.00        | 0.55        |
| Cellphones           | 1973           | 83         | -1.37        | 1.09        | -3.84        | -3.06        | -1.09        | -0.22       | 0.06        |
| PCs                  | 1973           | 70         | -0.78        | 0.64        | -2.40        | -1.56        | -0.73        | -0.06       | 0.06        |
| MRI                  | 1977           | 12         | -0.54        | 0.49        | -1.81        | -1.14        | -0.37        | -0.11       | 0.00        |
| Internet             | 1983           | 60         | -1.05        | 0.88        | -4.33        | -2.01        | -0.89        | -0.18       | 0.00        |
| <b>Total</b>         |                | <b>830</b> | <b>-0.85</b> | <b>0.97</b> | <b>-3.84</b> | <b>-2.13</b> | <b>-0.60</b> | <b>0.03</b> | <b>0.70</b> |

**Table 8:** Penetration Rate of the 186 Observations Sample. Penetration Rate in Logarithms.

| Technologyname     | Invention Year | Obs        | mean <sup>4</sup> | sd          | p1           | p10          | p50          | p90          | p99         | difference to<br>830 obs sample <sup>5</sup> | difference to<br>CM 2010 sample <sup>6</sup> |
|--------------------|----------------|------------|-------------------|-------------|--------------|--------------|--------------|--------------|-------------|----------------------------------------------|----------------------------------------------|
| Ships              | 1788           | 3          | 0.07              | 0.39        | -0.17        | -0.17        | -0.14        | 0.52         | 0.52        | 3.63                                         | -49.70                                       |
| Cars               | 1885           | 1          | -2.38             | .           | -2.38        | -2.38        | -2.38        | -2.38        | -2.38       | -7.58                                        | -22.07                                       |
| Aviation - Freight | 1903           | 2          | -0.36             | 0.07        | -0.41        | -0.41        | -0.36        | -0.31        | -0.31       | 16.27                                        | 13.26                                        |
| Blast Oxygen Steel | 1950           | 17         | -0.99             | 0.94        | -2.79        | -2.13        | -0.89        | 0.03         | 0.55        | -6.10                                        | -8.10                                        |
| Cellphones         | 1973           | 59         | -1.20             | 1.02        | -3.84        | -2.81        | -0.98        | -0.07        | 0.06        | 4.82                                         | 7.92                                         |
| PCs                | 1973           | 46         | -0.68             | 0.55        | -1.86        | -1.52        | -0.69        | -0.05        | 0.06        | 4.83                                         | -2.69                                        |
| MRI                | 1977           | 10         | -0.52             | 0.49        | -1.81        | -1.22        | -0.37        | -0.15        | 0.00        | 1.03                                         | -5.07                                        |
| Internet           | 1983           | 48         | -0.99             | 0.88        | -4.33        | -2.01        | -0.77        | -0.18        | 0.00        | 2.23                                         | 0.35                                         |
| <b>Total</b>       |                | <b>186</b> | <b>-0.94</b>      | <b>0.87</b> | <b>-3.84</b> | <b>-2.13</b> | <b>-0.70</b> | <b>-0.07</b> | <b>0.52</b> |                                              |                                              |

<sup>4</sup> The means are in logarithms. We take the exponential function of the mean and get the % of penetration compared to the United States.

<sup>5</sup> This is the difference of the mean penetration rate in % in our 186 sample and the mean of our sample with the 830 observations.

<sup>6</sup> This is the difference of the mean penetration rate in % in our 186 sample and the mean of the sample from Comin and Mestieri (2010).

**Table 9:** Overview Technology Diffusion Observations of Western Countries

| Countryname    | Freq.     | Percent    | Cum.   |
|----------------|-----------|------------|--------|
| Australia      | 4         | 6.78       | 6.78   |
| Austria        | 2         | 3.39       | 10.17  |
| Belgium        | 3         | 5.08       | 15.25  |
| Canada         | 5         | 8.47       | 23.73  |
| Denmark        | 4         | 6.78       | 30.51  |
| Finland        | 5         | 8.47       | 38.98  |
| France         | 4         | 6.78       | 45.76  |
| Germany        | 3         | 5.08       | 50.85  |
| Italy          | 4         | 6.78       | 57.63  |
| Japan          | 2         | 3.39       | 61.02  |
| Netherlands    | 3         | 5.08       | 66.10  |
| New Zealand    | 4         | 6.78       | 72.88  |
| Norway         | 3         | 5.08       | 77.97  |
| Sweden         | 4         | 6.78       | 84.75  |
| Switzerland    | 2         | 3.39       | 88.14  |
| United Kingdom | 3         | 5.08       | 93.22  |
| United States  | 4         | 6.78       | 100.00 |
| <b>Total</b>   | <b>59</b> | <b>100</b> |        |

**Table 10:** Overview Technology Diffusion Observations of non-Western Countries

| Countryname        | Freq. | Percent | Cum.  | Countryname     | Freq.      | Percent | Cum.   |
|--------------------|-------|---------|-------|-----------------|------------|---------|--------|
| Algeria            | 2     | 1.57    | 1.57  | Mexico          | 4          | 3.15    | 51.18  |
| Bangladesh         | 1     | 0.79    | 2.36  | Moldova         | 1          | 0.79    | 51.97  |
| Bolivia            | 1     | 0.79    | 3.15  | Morocco         | 1          | 0.79    | 52.76  |
| Brazil             | 4     | 3.15    | 6.30  | Nicaragua       | 1          | 0.79    | 53.54  |
| Bulgaria           | 3     | 2.36    | 8.66  | Panama          | 1          | 0.79    | 54.33  |
| Cambodia           | 1     | 0.79    | 9.45  | Paraguay        | 1          | 0.79    | 55.12  |
| Chile              | 4     | 3.15    | 12.60 | Peru            | 2          | 1.57    | 56.69  |
| China              | 4     | 3.15    | 15.75 | Philippines     | 2          | 1.57    | 58.27  |
| Colombia           | 3     | 2.36    | 18.11 | Poland          | 3          | 2.36    | 60.63  |
| Costa Rica         | 2     | 1.57    | 19.69 | Portugal        | 3          | 2.36    | 62.99  |
| Czech Republic     | 1     | 0.79    | 20.47 | Romania         | 3          | 2.36    | 65.35  |
| Dominican Republic | 1     | 0.79    | 21.26 | Russia          | 1          | 0.79    | 66.14  |
| Ecuador            | 1     | 0.79    | 22.05 | Singapore       | 3          | 2.36    | 68.50  |
| Egypt              | 1     | 0.79    | 22.83 | Slovak Republic | 1          | 0.79    | 69.29  |
| El Salvador        | 1     | 0.79    | 23.62 | Slovenia        | 2          | 1.57    | 70.87  |
| Estonia            | 2     | 1.57    | 25.20 | South Korea     | 6          | 4.72    | 75.59  |
| Ghana              | 1     | 0.79    | 25.98 | Spain           | 5          | 3.94    | 79.53  |
| Greece             | 3     | 2.36    | 28.35 | Sri Lanka       | 3          | 2.36    | 81.89  |
| Guatemala          | 1     | 0.79    | 29.13 | Taiwan          | 3          | 2.36    | 84.25  |
| Hungary            | 5     | 3.94    | 33.07 | Thailand        | 4          | 3.15    | 87.40  |
| India              | 3     | 2.36    | 35.43 | Tunisia         | 3          | 2.36    | 89.76  |
| Indonesia          | 3     | 2.36    | 37.80 | Turkey          | 4          | 3.15    | 92.91  |
| Ireland            | 2     | 1.57    | 39.37 | Ukraine         | 2          | 1.57    | 94.49  |
| Israel             | 2     | 1.57    | 40.94 | Venezuela       | 3          | 2.36    | 96.85  |
| Jordan             | 1     | 0.79    | 41.73 | Vietnam         | 2          | 1.57    | 98.43  |
| Laos               | 1     | 0.79    | 42.52 | Zambia          | 1          | 0.79    | 99.21  |
| Malaysia           | 4     | 3.15    | 45.67 | Zimbabwe        | 1          | 0.79    | 100.00 |
| Mauritius          | 3     | 2.36    | 48.03 |                 |            |         |        |
| <b>Total</b>       |       |         |       | <b>127</b>      | <b>100</b> |         |        |

**Table 11:** Data Description and Sources

| variables        | Description                                                          | Source                                             |
|------------------|----------------------------------------------------------------------|----------------------------------------------------|
| penetration rate | ln of percentage of penetration compared to the United States        | own calculation based on Comin and Mestieri (2010) |
| adoption lag     | ln of difference of invention year and adoption year of a technology | Comin and Hobijn (2010)                            |
| GINI             | 0: equal distribution of income, 100: one person owns everything     | UNU-WIDER (2009)                                   |
| Q1               | income share of poorest 20%                                          | UNU-WIDER (2009)                                   |
| MiddleClass      | income share of 2nd, 3rd and 4th quantile                            | UNU-WIDER (2009)                                   |
| Q5               | income share of richest 20%                                          | UNU-WIDER (2009)                                   |
| lnGDP            | ln of GDP per capita                                                 | Maddison (2007)                                    |
| primary_educ     | percentage of Primary Schooling Attained in Population age 25+       | Barro and Lee (2013)                               |
| secondary_educ   | percentage of Secondary Schooling Attained in Population age 25+     | Barro and Lee (2013)                               |
| tertiary_educ    | percentage of Tertiary Schooling Attained in Population age 25+      | Barro and Lee (2013)                               |
| OPENNESS         | sum of imports and exports as a fraction of GDP, PWT 7.0             | Heston, Summers & Aten (2011)                      |
| INSTITUTIONS     | polity IV dataset: from -10 full autocracy to +10 full democracy     | Marshall & Jaggers (2013)                          |
| Lwheatsugar      | Ratio of arable land of wheat compared to sugar cane                 | Easterly (2007), FAO                               |

**Table 12:** Summary Statistics. Full Sample.

|                  | Observations | mean  | sd    | Min   | Max    |
|------------------|--------------|-------|-------|-------|--------|
| penetration rate | 186          | -0.94 | 0.87  | -4.33 | 0.55   |
| adoption lag     | 186          | 2.45  | 0.87  | -5.35 | 5.19   |
| GINI             | 186          | 37.64 | 10.35 | 20.00 | 64.70  |
| Q1               | 186          | 6.41  | 2.31  | 1.86  | 11.69  |
| MiddleClass      | 186          | 48.22 | 6.93  | 29.58 | 57.67  |
| Q5               | 186          | 45.37 | 8.97  | 31.43 | 68.56  |
| lnGDP            | 186          | 11.71 | 1.48  | 8.30  | 15.48  |
| primary_educ     | 186          | 40.46 | 16.24 | 4.05  | 79.54  |
| secondary_educ   | 186          | 31.29 | 16.64 | 2.50  | 69.00  |
| tertiary_educ    | 186          | 10.75 | 8.30  | 0.33  | 39.07  |
| OPENNESS         | 186          | 62.21 | 47.61 | 6.58  | 344.77 |
| INSTITUTIONS     | 186          | 5.02  | 6.41  | -9.00 | 10.00  |

**Table 13:** Summary Statistics. Western Countries

|                  | Observations | mean  | sd    | Min   | Max    |
|------------------|--------------|-------|-------|-------|--------|
| penetration rate | 59           | -0.21 | 0.19  | -0.57 | 0.55   |
| adoption lag     | 59           | 1.95  | 1.13  | -5.35 | 3.43   |
| GINI             | 59           | 30.68 | 4.75  | 20.70 | 40.21  |
| Q1               | 59           | 7.75  | 1.70  | 4.58  | 10.90  |
| MiddleClass      | 59           | 53.82 | 1.96  | 49.34 | 57.67  |
| Q5               | 59           | 38.43 | 3.32  | 31.43 | 44.73  |
| lnGDP            | 59           | 12.52 | 1.33  | 10.49 | 15.48  |
| primary_educ     | 59           | 39.33 | 18.80 | 6.30  | 79.54  |
| secondary_educ   | 59           | 41.82 | 13.41 | 14.44 | 65.38  |
| tertiary_educ    | 59           | 16.30 | 9.11  | 4.28  | 39.07  |
| OPENNESS         | 59           | 57.02 | 26.24 | 17.27 | 135.44 |
| INSTITUTIONS     | 59           | 9.88  | 0.46  | 8.00  | 10.00  |

**Table 14:** Summary Statistics. Non-Western Countries

|                  | Observations | mean  | sd    | Min   | Max    |
|------------------|--------------|-------|-------|-------|--------|
| penetration rate | 127          | -1.27 | 0.86  | -4.33 | 0.52   |
| adoption lag     | 127          | 2.68  | 0.60  | 0.96  | 5.19   |
| GINI             | 127          | 40.87 | 10.66 | 20.00 | 64.70  |
| Q1               | 127          | 5.79  | 2.29  | 1.86  | 11.69  |
| MiddleClass      | 127          | 45.62 | 6.88  | 29.58 | 56.86  |
| Q5               | 127          | 48.59 | 8.95  | 31.62 | 68.56  |
| lnGDP            | 127          | 11.33 | 1.39  | 8.30  | 14.82  |
| primary_educ     | 127          | 40.98 | 14.95 | 4.05  | 70.84  |
| secondary_educ   | 127          | 26.40 | 15.74 | 2.50  | 69.00  |
| tertiary_educ    | 127          | 8.17  | 6.47  | 0.33  | 34.05  |
| OPENNESS         | 127          | 64.62 | 54.71 | 6.58  | 344.77 |
| INSTITUTIONS     | 127          | 2.76  | 6.63  | -9.00 | 10.00  |

**Table 15:** Two Stage Least Squares. Instrumenting GINI by Lwheatsugar.

| VARIABLES      | (1)<br>GINI           | (2)<br>LAG             | (3)<br>PEN                         |
|----------------|-----------------------|------------------------|------------------------------------|
| Lwheatsugar    | -22.15***<br>(3.570)  |                        |                                    |
| GINI           |                       | -0.00771<br>(0.0164)   | -0.0216 <sup>(*)</sup><br>(0.0135) |
| lnGDP          | 0.314<br>(0.586)      | -0.0820*<br>(0.0440)   | 0.0753**<br>(0.0366)               |
| primary_educ   | 0.0227<br>(0.0659)    | -0.000711<br>(0.00460) | 0.0227***<br>(0.00431)             |
| secondary_educ | -0.184***<br>(0.0545) | -0.00161<br>(0.00649)  | 0.0214***<br>(0.00558)             |
| tertiary_educ  | 0.197**<br>(0.0928)   | -0.00182<br>(0.00591)  | 0.0449***<br>(0.00652)             |
| OPENNESS       | -0.0109<br>(0.0238)   | -0.00150<br>(0.00123)  | -0.000148<br>(0.00295)             |
| INSTITUTIONS   | -0.0493<br>(0.140)    | -0.0359**<br>(0.0140)  | 0.0108<br>(0.00961)                |
| Constant       | 38.26***<br>(7.278)   | 3.704***<br>(0.908)    | -2.376**<br>(0.938)                |
| Time Dummy     | Yes                   | Yes                    | Yes                                |
| Observations   | 175                   | 175                    | 175                                |
| $R^2$          | 0.430                 | 0.258                  | 0.621                              |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1, (\*) p&lt;0.11

Note: We apply a 2SLS instrumental variable approach to a sample of 175 observations, including 67 countries and eight technologies. The instrument is Lwheatsugar, which is the ratio of arable land of wheat compared to sugar cane, applied by Easterly (2007).

**Table 16:** Robustness Check. Excluding Observations of Cars, Ships and Aviation-Freight.

| VARIABLES      | (1)<br>LAG              | (2)<br>LAG              | (3)<br>LAG              | (4)<br>PEN              | (5)<br>PEN              | (6)<br>PEN              |
|----------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| GINI           | 0.00569<br>(0.00471)    |                         |                         | -0.00874*<br>(0.00521)  |                         |                         |
| Q1             |                         | -0.0604<br>(0.0403)     |                         |                         | 0.00166<br>(0.0371)     |                         |
| MiddleClass    |                         | 0.0108<br>(0.0116)      | 0.0712<br>(0.0503)      |                         | 0.0165<br>(0.0138)      | 0.0149<br>(0.0488)      |
| Q5             |                         |                         | 0.0604<br>(0.0403)      |                         |                         | -0.00166<br>(0.0371)    |
| lnGDP          | -0.0839***<br>(0.0300)  | -0.0877***<br>(0.0298)  | -0.0877***<br>(0.0298)  | 0.127***<br>(0.0292)    | 0.118***<br>(0.0289)    | 0.118***<br>(0.0289)    |
| primary_educ   | -0.000262<br>(0.00321)  | 0.000827<br>(0.00313)   | 0.000827<br>(0.00313)   | 0.0188***<br>(0.00417)  | 0.0183***<br>(0.00423)  | 0.0183***<br>(0.00423)  |
| secondary_educ | 0.000237<br>(0.00380)   | 0.00172<br>(0.00415)    | 0.00172<br>(0.00415)    | 0.0196***<br>(0.00470)  | 0.0189***<br>(0.00480)  | 0.0189***<br>(0.00480)  |
| tertiary_educ  | -0.00131<br>(0.00499)   | -0.00349<br>(0.00519)   | -0.00349<br>(0.00519)   | 0.0410***<br>(0.00692)  | 0.0399***<br>(0.00744)  | 0.0399***<br>(0.00744)  |
| OPENNESS       | -0.000852<br>(0.000738) | -0.000825<br>(0.000745) | -0.000825<br>(0.000745) | 0.00387***<br>(0.00110) | 0.00373***<br>(0.00113) | 0.00373***<br>(0.00113) |
| INSTITUTIONS   | -0.0325**<br>(0.0131)   | -0.0344**<br>(0.0135)   | -0.0344**<br>(0.0135)   | 0.00853<br>(0.00946)    | 0.00765<br>(0.00961)    | 0.00765<br>(0.00961)    |
| Constant       | 3.152***<br>(0.567)     | 3.187***<br>(0.606)     | -2.851<br>(4.339)       | -3.355***<br>(0.460)    | -4.348***<br>(0.613)    | -4.182<br>(4.053)       |
| Time Dummy     | Yes                     | Yes                     | Yes                     | Yes                     | Yes                     | Yes                     |
| Observations   | 180                     | 180                     | 180                     | 180                     | 180                     | 180                     |
| $R^2$          | 0.242                   | 0.247                   | 0.247                   | 0.633                   | 0.636                   | 0.636                   |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table 17:** Robustness Check. Including Country Group Dummies.

| VARIABLES       | (1)<br>LAG             | (2)<br>LAG              | (3)<br>LAG              | (4)<br>PEN             | (5)<br>PEN             | (6)<br>PEN             |
|-----------------|------------------------|-------------------------|-------------------------|------------------------|------------------------|------------------------|
| GINI            | -0.00392<br>(0.00672)  |                         |                         | -0.00370<br>(0.00655)  |                        |                        |
| Q1              |                        | -0.124***<br>(0.0461)   |                         |                        | -0.0146<br>(0.0401)    |                        |
| MiddleClass     |                        | 0.0647***<br>(0.0244)   | 0.189***<br>(0.0669)    |                        | 0.0178<br>(0.0166)     | 0.0324<br>(0.0541)     |
| Q5              |                        |                         | 0.124***<br>(0.0461)    |                        |                        | 0.0146<br>(0.0401)     |
| lnGDP           | -0.0712<br>(0.0496)    | -0.0838*<br>(0.0457)    | -0.0838*<br>(0.0457)    | 0.0562<br>(0.0351)     | 0.0534<br>(0.0345)     | 0.0534<br>(0.0345)     |
| primary_educ    | 0.000795<br>(0.00404)  | 0.00183<br>(0.00395)    | 0.00183<br>(0.00395)    | 0.0190***<br>(0.00404) | 0.0188***<br>(0.00414) | 0.0188***<br>(0.00414) |
| secondary_educ  | 0.00141<br>(0.00402)   | 0.00245<br>(0.00429)    | 0.00245<br>(0.00429)    | 0.0210***<br>(0.00490) | 0.0205***<br>(0.00498) | 0.0205***<br>(0.00498) |
| tertiary_educ   | -0.000550<br>(0.00613) | -0.00607<br>(0.00627)   | -0.00607<br>(0.00627)   | 0.0349***<br>(0.00697) | 0.0341***<br>(0.00701) | 0.0341***<br>(0.00701) |
| OPENNESS        | -0.00195*<br>(0.00104) | -0.00191*<br>(0.000987) | -0.00191*<br>(0.000987) | 0.00186<br>(0.00148)   | 0.00186<br>(0.00146)   | 0.00186<br>(0.00146)   |
| INSTITUTIONS    | -0.0108<br>(0.0110)    | -0.0131<br>(0.0111)     | -0.0131<br>(0.0111)     | 0.00327<br>(0.0101)    | 0.00292<br>(0.0101)    | 0.00292<br>(0.0101)    |
| Latin           | 0.524*<br>(0.275)      | 0.858**<br>(0.371)      | 0.858**<br>(0.371)      | -0.326<br>(0.233)      | -0.218<br>(0.224)      | -0.218<br>(0.224)      |
| SubSaharan      | 0.911<br>(0.577)       | 1.114*<br>(0.633)       | 1.114*<br>(0.633)       | -0.296<br>(0.372)      | -0.218<br>(0.369)      | -0.218<br>(0.369)      |
| Tigers          | 0.866**<br>(0.363)     | 0.978***<br>(0.363)     | 0.978***<br>(0.363)     | 0.362*<br>(0.205)      | 0.390*<br>(0.200)      | 0.390*<br>(0.200)      |
| Other Countries | 0.540***<br>(0.184)    | 0.702***<br>(0.224)     | 0.702***<br>(0.224)     | -0.412***<br>(0.149)   | -0.365**<br>(0.152)    | -0.365**<br>(0.152)    |
| Constant        | 3.073***<br>(0.593)    | 0.574<br>(1.352)        | -11.82**<br>(5.483)     | -2.520***<br>(0.535)   | -3.398***<br>(0.840)   | -4.860<br>(4.454)      |
| Time Dummy      | Yes                    | Yes                     | Yes                     | Yes                    | Yes                    | Yes                    |
| Observations    | 186                    | 186                     | 186                     | 186                    | 186                    | 186                    |
| $R^2$           | 0.278                  | 0.315                   | 0.315                   | 0.645                  | 0.648                  | 0.648                  |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table 18:** Adoption Lag. Separate Estimation with Western and non-Western Samples

|                | (1)                   | (2)                       | (3)                  | (4)                       | (5)                  | (6)                       |
|----------------|-----------------------|---------------------------|----------------------|---------------------------|----------------------|---------------------------|
| VARIABLES      | Western               | non-Western               | Western              | non-Western               | Western              | non-Western               |
| GINI           | 0.0244<br>(0.0248)    | -0.00363<br>(0.00420)     |                      |                           |                      |                           |
| Q1             |                       |                           | -0.281**<br>(0.115)  | -0.0406<br>(0.0427)       |                      |                           |
| MiddleClass    |                       |                           | 0.190(*)<br>(0.114)  | 0.0199<br>(0.0168)        | 0.471**<br>(0.216)   | 0.0605<br>(0.0584)        |
| Q5             |                       |                           |                      |                           | 0.281**<br>(0.115)   | 0.0406<br>(0.0427)        |
| lnGDP          | -0.0312<br>(0.103)    | -0.106***<br>(0.0281)     | -0.102<br>(0.0972)   | -0.109***<br>(0.0285)     | -0.102<br>(0.0972)   | -0.109***<br>(0.0285)     |
| primary_educ   | 0.0212<br>(0.0337)    | 0.00185<br>(0.00313)      | -0.00765<br>(0.0282) | 0.00221<br>(0.00317)      | -0.00765<br>(0.0282) | 0.00221<br>(0.00317)      |
| secondary_educ | 0.0165<br>(0.0323)    | 0.00294<br>(0.00362)      | -0.00631<br>(0.0271) | 0.00346<br>(0.00367)      | -0.00631<br>(0.0271) | 0.00346<br>(0.00367)      |
| tertiary_educ  | 0.0187<br>(0.0356)    | -0.00286<br>(0.00783)     | -0.0152<br>(0.0295)  | -0.00435<br>(0.00749)     | -0.0152<br>(0.0295)  | -0.00435<br>(0.00749)     |
| OPENNESS       | 0.00444*<br>(0.00244) | -0.00164***<br>(0.000558) | 0.00393<br>(0.00243) | -0.00170***<br>(0.000572) | 0.00393<br>(0.00243) | -0.00170***<br>(0.000572) |
| INSTITUTIONS   | 0.000347<br>(0.153)   | -0.0109<br>(0.00665)      | -0.0841<br>(0.102)   | -0.0126*<br>(0.00699)     | -0.0841<br>(0.102)   | -0.0126*<br>(0.00699)     |
| Constant       | 0.0772<br>(3.264)     | 3.383***<br>(0.326)       | -3.099<br>(6.190)    | 2.585***<br>(0.563)       | -31.16**<br>(15.42)  | -1.478<br>(4.732)         |
| Time Dummy     | Yes                   | Yes                       | Yes                  | Yes                       | Yes                  | Yes                       |
| Observations   | 59                    | 127                       | 59                   | 127                       | 59                   | 127                       |
| $R^2$          | 0.502                 | 0.440                     | 0.543                | 0.449                     | 0.543                | 0.449                     |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1, (\*) p&lt;0.11

**Table 19:** Penetration Rate. Separate Estimation with Western and non-Western Samples

|                | (1)                     | (2)                     | (3)                     | (4)                     | (5)                     | (6)                     |
|----------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| VARIABLES      | Western                 | non-Western             | Western                 | non-Western             | Western                 | non-Western             |
| GINI           | -0.00817<br>(0.00687)   | -0.00539<br>(0.00636)   |                         |                         |                         |                         |
| Q1             |                         |                         | 0.00307<br>(0.0419)     | -0.0667<br>(0.0551)     |                         |                         |
| MiddleClass    |                         |                         | 0.0186<br>(0.0301)      | 0.0311*<br>(0.0177)     | 0.0155<br>(0.0696)      | 0.0978<br>(0.0706)      |
| Q5             |                         |                         |                         |                         | -0.00307<br>(0.0419)    | 0.0667<br>(0.0551)      |
| lnGDP          | -0.0178<br>(0.0232)     | 0.116**<br>(0.0452)     | -0.0198<br>(0.0302)     | 0.112**<br>(0.0444)     | -0.0198<br>(0.0302)     | 0.112**<br>(0.0444)     |
| primary_educ   | 5.26e-06<br>(0.00810)   | 0.0182***<br>(0.00526)  | 0.000285<br>(0.00903)   | 0.0188***<br>(0.00513)  | 0.000285<br>(0.00903)   | 0.0188***<br>(0.00513)  |
| secondary_educ | 0.000271<br>(0.00842)   | 0.0216***<br>(0.00643)  | 0.000905<br>(0.00898)   | 0.0226***<br>(0.00658)  | 0.000905<br>(0.00898)   | 0.0226***<br>(0.00658)  |
| tertiary_educ  | 0.00764<br>(0.00689)    | 0.0532***<br>(0.0119)   | 0.00771<br>(0.00912)    | 0.0508***<br>(0.0122)   | 0.00771<br>(0.00912)    | 0.0508***<br>(0.0122)   |
| OPENNESS       | -0.000405<br>(0.000988) | 0.00409***<br>(0.00120) | -0.000320<br>(0.000983) | 0.00401***<br>(0.00125) | -0.000320<br>(0.000983) | 0.00401***<br>(0.00125) |
| INSTITUTIONS   | 0.0290<br>(0.0436)      | 0.00440<br>(0.0107)     | 0.0223<br>(0.0388)      | 0.00162<br>(0.0107)     | 0.0223<br>(0.0388)      | 0.00162<br>(0.0107)     |
| Constant       | 0.0842<br>(0.863)       | -3.155***<br>(0.428)    | -1.155<br>(0.990)       | -4.384***<br>(0.728)    | -0.848<br>(4.682)       | -11.05*<br>(5.948)      |
| Time Dummy     | Yes                     | Yes                     | Yes                     | Yes                     | Yes                     | Yes                     |
| Observations   | 59                      | 127                     | 59                      | 127                     | 59                      | 127                     |
| $R^2$          | 0.277                   | 0.469                   | 0.281                   | 0.481                   | 0.281                   | 0.481                   |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table 20:** Robustness Check. Dummy Invention minus year 1820.

|               | (1)                     | (2)                     | (3)                     | (4)                     | (5)                     | (6)                      |
|---------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|--------------------------|
|               | Lag                     | Lag                     | Lag                     | PEN                     | PEN                     | PEN                      |
| VARIABLES     | Full Sample             | Western                 | non-Western             | Full Sample             | Western                 | non-Western              |
| yearminus1820 | -0.0184***<br>(0.00160) | -0.0464***<br>(0.00782) | -0.0162***<br>(0.00114) | -0.00381**<br>(0.00181) | -0.0123***<br>(0.00372) | -0.00614***<br>(0.00170) |
| Constant      | 5.192***<br>(0.241)     | 9.129***<br>(1.262)     | 5.056***<br>(0.172)     | -0.368<br>(0.274)       | 1.690***<br>(0.580)     | -0.371<br>(0.253)        |
| Observations  | 186                     | 59                      | 127                     | 186                     | 59                      | 127                      |
| $R^2$         | 0.318                   | 0.105                   | 0.738                   | 0.014                   | 0.270                   | 0.051                    |

Robust standard errors in parentheses

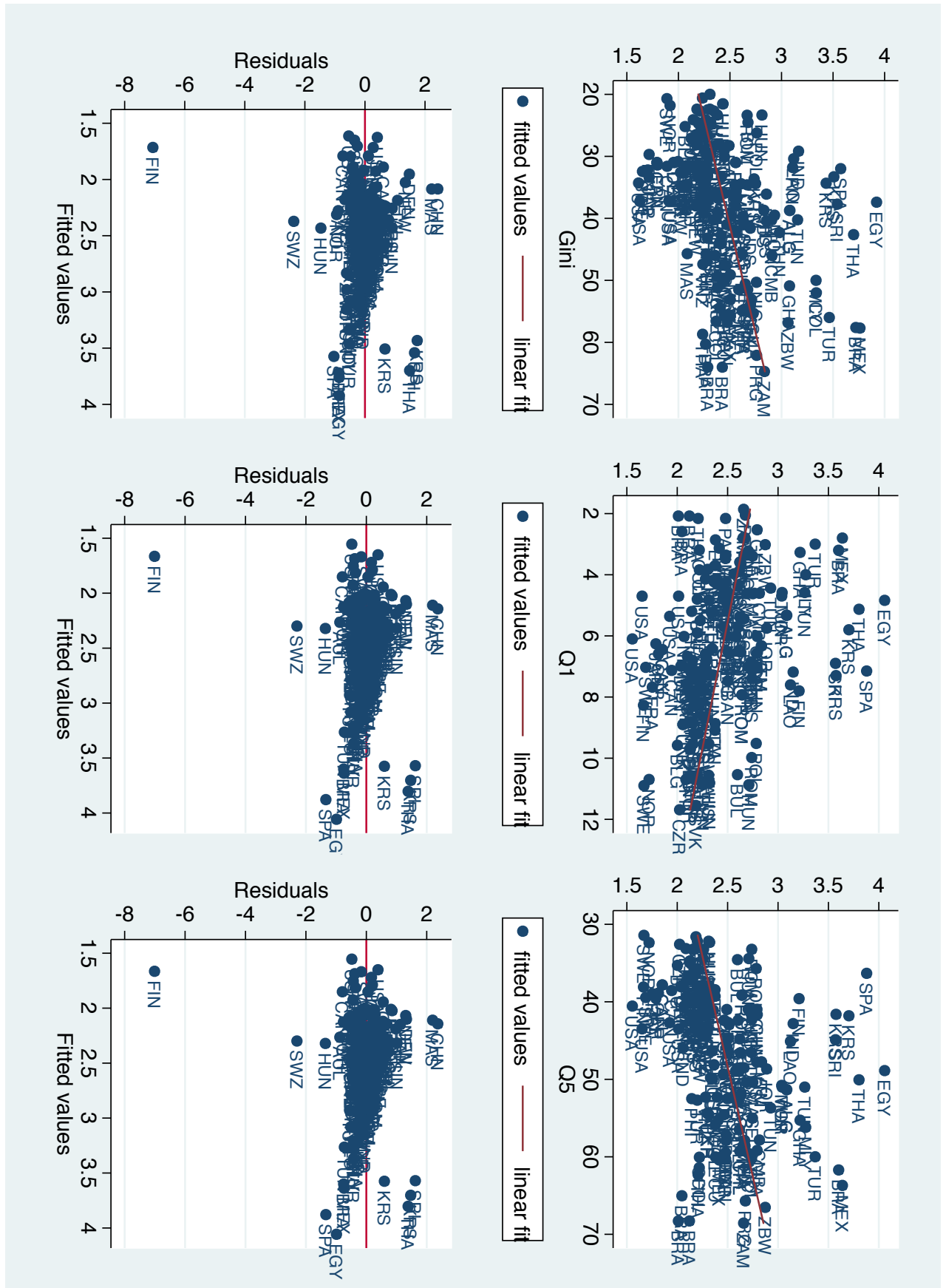
\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1

**Table 21:** Robustness Check. Including Inventionyear Dummy.

| VARIABLES      | (1)<br>LAG              | (2)<br>LAG              | (3)<br>LAG              | (4)<br>PEN               | (5)<br>PEN               | (6)<br>PEN               |
|----------------|-------------------------|-------------------------|-------------------------|--------------------------|--------------------------|--------------------------|
| yearminus1820  | -0.0228***<br>(0.00477) | -0.0225***<br>(0.00472) | -0.0225***<br>(0.00472) | -0.00676***<br>(0.00217) | -0.00638***<br>(0.00208) | -0.00638***<br>(0.00208) |
| GINI           | 0.00610<br>(0.00437)    |                         |                         | -0.00847<br>(0.00515)    |                          |                          |
| Q1             |                         | -0.0350<br>(0.0329)     |                         |                          | -0.00199<br>(0.0376)     |                          |
| MiddleClass    |                         | 0.00480<br>(0.0103)     | 0.0397<br>(0.0420)      |                          | 0.0173<br>(0.0138)       | 0.0192<br>(0.0494)       |
| Q5             |                         |                         | 0.0350<br>(0.0329)      |                          |                          | 0.00199<br>(0.0376)      |
| lnGDP          | -0.0498<br>(0.0318)     | -0.0524*<br>(0.0312)    | -0.0524*<br>(0.0312)    | 0.118***<br>(0.0316)     | 0.109***<br>(0.0314)     | 0.109***<br>(0.0314)     |
| primary_educ   | -0.00288<br>(0.00359)   | -0.00231<br>(0.00347)   | -0.00231<br>(0.00347)   | 0.0192***<br>(0.00413)   | 0.0189***<br>(0.00419)   | 0.0189***<br>(0.00419)   |
| secondary_educ | -0.00286<br>(0.00307)   | -0.00267<br>(0.00324)   | -0.00267<br>(0.00324)   | 0.0199***<br>(0.00472)   | 0.0194***<br>(0.00482)   | 0.0194***<br>(0.00482)   |
| tertiary_educ  | -0.00369<br>(0.00463)   | -0.00454<br>(0.00479)   | -0.00454<br>(0.00479)   | 0.0420***<br>(0.00689)   | 0.0408***<br>(0.00734)   | 0.0408***<br>(0.00734)   |
| OPENNESS       | -0.000264<br>(0.000708) | -0.000250<br>(0.000704) | -0.000250<br>(0.000704) | 0.00401***<br>(0.00110)  | 0.00385***<br>(0.00113)  | 0.00385***<br>(0.00113)  |
| INSTITUTIONS   | -0.0213**<br>(0.0101)   | -0.0223**<br>(0.0105)   | -0.0223**<br>(0.0105)   | 0.0122<br>(0.00906)      | 0.0107<br>(0.00925)      | 0.0107<br>(0.00925)      |
| Constant       | 5.866***<br>(0.651)     | 6.042***<br>(0.745)     | 2.547<br>(3.499)        | -2.418***<br>(0.517)     | -3.472***<br>(0.656)     | -3.670<br>(4.122)        |
| Time Dummy     | Yes                     | Yes                     | Yes                     | Yes                      | Yes                      | Yes                      |
| Observations   | 186                     | 186                     | 186                     | 186                      | 186                      | 186                      |
| $R^2$          | 0.481                   | 0.480                   | 0.480                   | 0.628                    | 0.631                    | 0.631                    |

Robust standard errors in parentheses

\*\*\* p&lt;0.01, \*\* p&lt;0.05, \* p&lt;0.1



**Figure 9:** Above: Fitted Adoption Lags versus Inequality Measures. Below: Residuals versus Fitted Adoption Lags





**Figure 11:** Residuals of Adoption Lags versus Predictor Gini



**Figure 12:** Residuals of Adoption Lags versus Predictor Middle Class

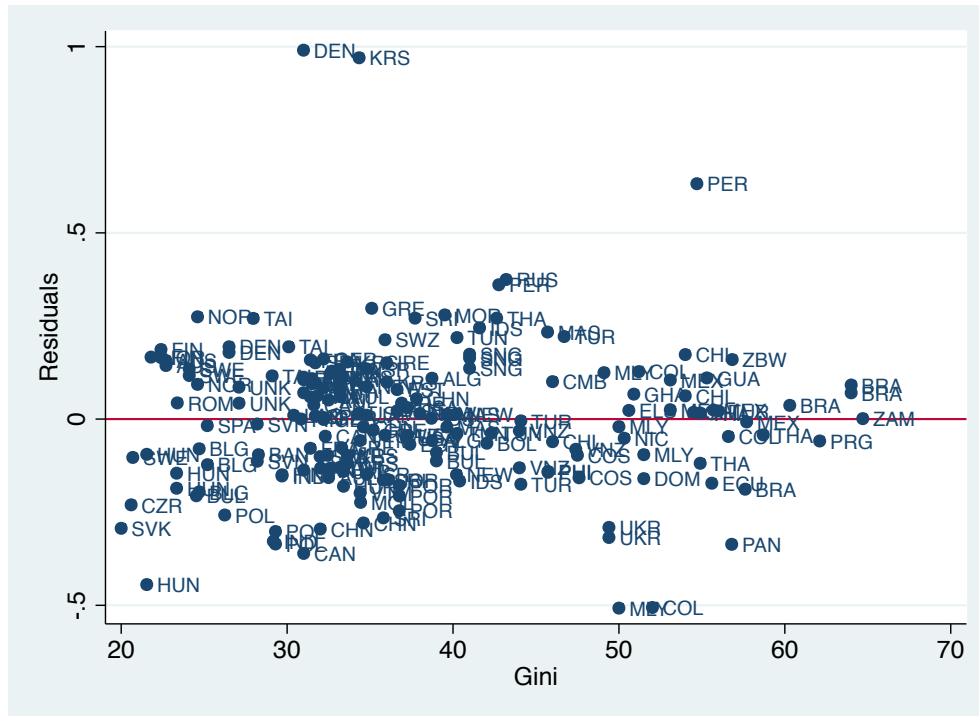


Figure 13: Residuals of Penetration Rates versus Predictor Gini

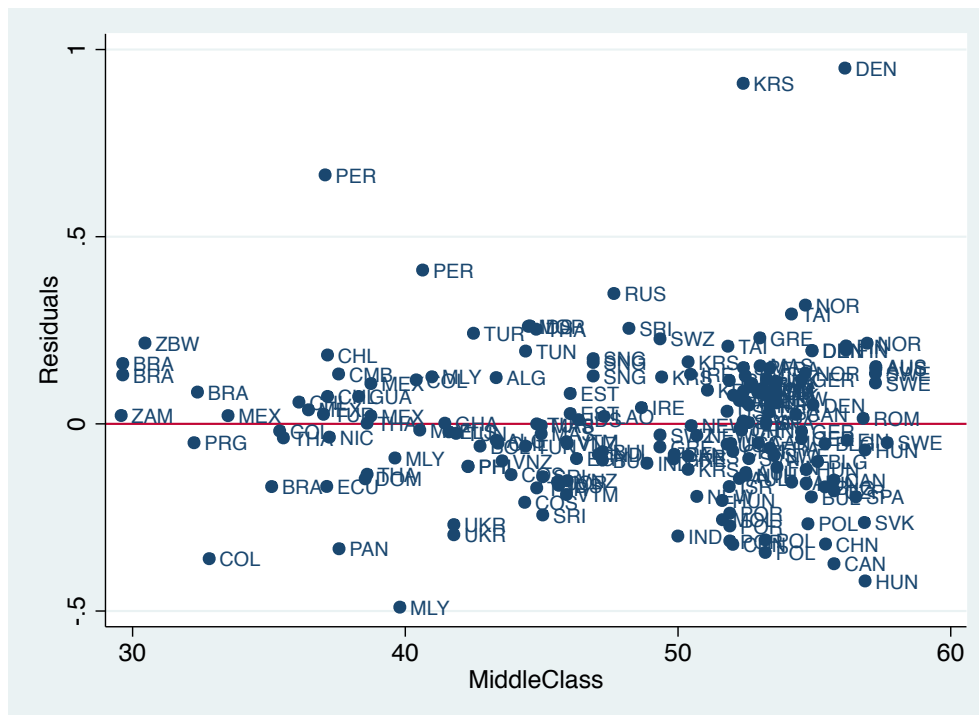


Figure 14: Residuals of Penetration Rates versus Predictor Middle Class

## B Solving the Model

In this appendix, we solve the important steps of the model and spell out the steps in more detail. The goal is to understand how productivity levels of the first and the subsequent vintages affect the productivity on the aggregate total output level. Furthermore, we show the derivation of the intensive and the extensive margin and finally the derivation of our identification strategy.

**Derivation of equation (16):**

By solving equation (14),  $(1 - \alpha) \frac{p_{\tau,v} Y_{\tau,v}}{L_{\tau,v}} = w$ , for  $L_{\tau,v}$  and equation (15),  $\alpha \frac{p_{\tau,v} Y_{\tau,v}}{X_{\tau,v}} = 1$ , for  $X_{\tau,v}$  we get

$$L_{\tau,v} = (1 - \alpha) \frac{p_{\tau,v} Y_{\tau,v}}{w}$$

and

$$X_{\tau,v} = \alpha p_{\tau,v} Y_{\tau,v}.$$

Now we plug  $L_{\tau,v}$  and  $X_{\tau,v}$  into equation (6) which equals  $Y_{\tau,v} = a_{\tau} Z(\tau, v) X_{\tau,v}^{\alpha} L_{\tau,v}^{1-\alpha}$ . This yields

$$Y_{\tau,v} = a_{\tau} Z(\tau, v) (\alpha p_{\tau,v} Y_{\tau,v})^{\alpha} ((1 - \alpha) \frac{p_{\tau,v} Y_{\tau,v}}{w})^{1-\alpha}.$$

First, we simplify to

$$w^{1-\alpha} = a_{\tau} Z(\tau, v) \alpha^{\alpha} (1 - \alpha)^{1-\alpha} p_{\tau,v}.$$

After rearranging, we get

$$p_{\tau,v} = \frac{w^{1-\alpha}}{a_{\tau} Z(\tau, v) (1 - \alpha)^{1-\alpha} \alpha^{\alpha}}. \quad (16)$$

**Derivation of equation (17):**

We start with the following definition

$$p_{\tau} = \left( \int_{\tau}^{t-D_{\tau}} \frac{w^{1-\alpha}}{p_{\tau,v}^{\frac{1}{\mu-1}}} dv \right)^{-(\mu-1)}.$$

We continue by replacing  $p_{\tau,v}$  with (16)  $p_{\tau,v} = \frac{w^{1-\alpha}}{a_{\tau} Z(\tau, v) (1 - \alpha)^{1-\alpha} \alpha^{\alpha}}$  and get

$$p_{\tau} = \left( \int_{\tau}^{t-D_{\tau}} \left( \frac{w^{1-\alpha}}{a_{\tau} Z(\tau, v)} (1 - \alpha)^{-(1-\alpha)} \alpha^{-\alpha} \right)^{-\frac{1}{\mu-1}} dv \right)^{-(\mu-1)}.$$

Now we simplify

$$p_{\tau} = w^{1-\alpha} (1 - \alpha)^{-(1-\alpha)} \alpha^{-\alpha} \left( \int_{\tau}^{t-D_{\tau}} a_{\tau} Z(\tau, v)^{\frac{1}{\mu-1}} dv \right)^{-(\mu-1)}.$$

Finally, we know from equation (9) that  $Z_{\tau} = \left( \int_{\tau}^{\max\{t-D_{\tau}, \tau\}} a_{\tau} Z(\tau, v)^{\frac{1}{\mu-1}} dv \right)^{\mu-1}$ . Thus, we get

$$p_{\tau} = \frac{w^{1-\alpha}}{Z_{\tau}} (1 - \alpha)^{-(1-\alpha)} \alpha^{-\alpha}. \quad (17)$$

**Derivation of equation (18):**

We know from equation (13) that  $Y_{\tau,v} = Y_{\tau} \left( \frac{p_{\tau,v}}{p_{\tau}} \right)^{-\frac{\mu}{\mu-1}}$ . We rearrange the equation and get

$$\frac{p_{\tau,v}}{p_{\tau}} = \left( \frac{Y_{\tau,v}}{Y_{\tau}} \right)^{\frac{1-\mu}{\mu}}.$$

Now we multiply on both sides by  $\frac{Y_{\tau,v}}{Y_{\tau}}$  and receive

$$\frac{p_{\tau,v} Y_{\tau,v}}{p_{\tau} Y_{\tau}} = \left( \frac{Y_{\tau,v}}{Y_{\tau}} \right)^{\frac{1}{\mu}}.$$

We know from equations (14) and (15) that the demands for labor and intermediate goods are  $(1 - \alpha) \frac{p_{\tau,v} Y_{\tau,v}}{L_{\tau,v}} = w$  and  $\alpha \frac{p_{\tau,v} Y_{\tau,v}}{X_{\tau,v}} = 1$ . We rewrite these demands and assume as optimality condition that they are equal. As a consequence, we get

$$p_{\tau,v} Y_{\tau,v} = \frac{w L_{\tau,v}}{1 - \alpha} = \frac{X_{\tau,v}}{\alpha}.$$

On the aggregate level the demands for labor and goods are as well equal due to the optimal condition:

$$p_{\tau} Y_{\tau} = \frac{w L_{\tau}}{1 - \alpha} = \frac{X_{\tau}}{\alpha}.$$

Now we put together what we derived above and get an important expression, showing the relationship between vintage level and aggregate level:

$$\frac{p_{\tau,v} Y_{\tau,v}}{p_{\tau} Y_{\tau}} = \left( \frac{Y_{\tau,v}}{Y_{\tau}} \right)^{\frac{1}{\mu}} = \frac{L_{\tau,v}}{L_{\tau}} = \frac{X_{\tau,v}}{X_{\tau}}.$$

Now we use the production function of the technology vintages:

$$Y_{\tau,v} = a_{\tau} Z(\tau, v) X_{\tau,v}^{\alpha} L_{\tau,v}^{1-\alpha}.$$

We expand this equation on the right hand side by the fraction  $\frac{Z_{\tau} X_{\tau}^{\alpha} L_{\tau}^{1-\alpha}}{Z_{\tau} X_{\tau}^{\alpha} L_{\tau}^{1-\alpha}}$ :

$$Y_{\tau,v} = \frac{a_{\tau} Z(\tau, v) X_{\tau,v}^{\alpha} L_{\tau,v}^{1-\alpha}}{Z_{\tau} X_{\tau}^{\alpha} L_{\tau}^{1-\alpha}} Z_{\tau} X_{\tau}^{\alpha} L_{\tau}^{1-\alpha}.$$

As we know the relationship between the vintage and the aggregate level we can replace  $\frac{L_{\tau,v}}{L_{\tau}}$  and  $\frac{X_{\tau,v}}{X_{\tau}}$  and get

$$Y_{\tau,v}^{\frac{\mu-1}{\mu}} = a_{\tau} Z(\tau, v) \left( \frac{1}{Y_{\tau}} \right)^{\frac{1}{\mu}} X_{\tau}^{\alpha} L_{\tau}^{1-\alpha}.$$

Now we simplify

$$Y_{\tau,v} = \left( a_{\tau} Z(\tau, v) X_{\tau}^{\alpha} L_{\tau}^{1-\alpha} \right)^{\frac{\mu}{\mu-1}} \left( \frac{1}{Y_{\tau}} \right)^{\frac{1}{\mu-1}}.$$

We take the definition of equation (7), which is  $Y_\tau = \left( \int_\tau^{t-D_\tau} Y_{\tau,v}^\mu dv \right)^\mu$ , with  $\mu > 1$ . Here we plug in our expression from above and get

$$Y_\tau = \left( \int_\tau^{t-D_\tau} \left( \left( a_\tau Z(\tau, v) X_\tau^\alpha L_\tau^{1-\alpha} \right)^{\frac{\mu}{\mu-1}} \left( \frac{1}{Y_\tau} \right)^{\frac{1}{\mu-1}} \right)^{\frac{1}{\mu}} dv \right)^\mu$$

Simplifying gives us first

$$Y_\tau^{\frac{\mu}{\mu-1}} = \left( \int_\tau^{t-D_\tau} \left( \left( a_\tau Z(\tau, v) X_\tau^\alpha L_\tau^{1-\alpha} \right)^{\frac{\mu}{\mu-1}} \right)^{\frac{1}{\mu}} dv \right)^\mu$$

and then

$$Y_\tau = \left( \int_\tau^{t-D_\tau} \left( \left( a_\tau Z(\tau, v) X_\tau^\alpha L_\tau^{1-\alpha} \right)^{\frac{\mu}{\mu-1}} \right)^{\frac{1}{\mu}} dv \right)^{\mu-1}.$$

By definition from equation (9) we know that  $Z_\tau = \left( \int_\tau^{\max\{t-D_\tau, \tau\}} a_\tau Z(\tau, v)^{\frac{1}{\mu-1}} dv \right)^{\mu-1}$ . Hence, we take the constants  $X_\tau^\alpha$  and  $L_\tau^{1-\alpha}$  out of the integral, integrate  $Z(\tau, v)$  and get equation (18)

$$Y_\tau = Z_\tau L_\tau^{1-\alpha} X_\tau^\alpha. \quad (18)$$

**Derivation of equation (19):**

We define that

$$Z_\tau = \left( \int_\tau^{\max\{t-D_\tau, \tau\}} a_\tau Z(\tau, v)^{\frac{1}{\mu-1}} dv \right)^{\mu-1}.$$

We know that productivity of a technology-vintage pair consists of two constituents. First,  $Z(\tau, v)$  and second  $a_\tau$ . Furthermore, we defined in equation (5) that  $Z(\tau, v) = e^{(\chi+\gamma)\tau + \gamma(v-\tau)}$ . Hence, we substitute  $Z(\tau, v)$  in and get

$$Z_\tau = \left( \int_\tau^{\max\{t-D_\tau, \tau\}} a_\tau e^{((\chi+\gamma)\tau + \gamma(v-\tau)) \frac{1}{\mu-1}} dv \right)^{\mu-1}.$$

We take out the constant. Moreover, as the constant is the productivity of the first vintage, the integral of the productivity of the new vintages is always bigger than the invention date. Hence, we take away the max and rewrite as

$$Z_\tau = a_\tau e^{(\chi+\gamma)\tau} \left( \int_\tau^{t-D_\tau} e^{\frac{\gamma}{\mu-1}(v-\tau)} dv \right)^{\mu-1}.$$

Now, we integrate and get

$$Z_\tau = \left( \frac{\mu-1}{\gamma} \right)^{\mu-1} a_\tau e^{(\chi+\gamma)\tau} \left( e^{\frac{\gamma}{\mu-1}(t-D_\tau-\tau)} - 1 \right)^{\mu-1}.$$

In the last step we multiply one part of the equation by an exponential term and another part by the exponential term's inverse. It follows

$$Z_\tau = \left( \frac{\mu-1}{\gamma} \right)^{\mu-1} a_\tau e^{(\chi\tau + \gamma \max\{t-D_\tau, \tau\})} \left( 1 - e^{\frac{-\gamma}{\mu-1}(\max\{t-D_\tau, \tau\} - \tau)} \right)^{\mu-1}. \quad (19)$$

**Derivation of equation (20):**

We know from equation (17) that  $p_\tau = \frac{w^{1-\alpha}}{Z_\tau} (1-\alpha)^{-(1-\alpha)} \alpha^{-\alpha}$ . Moreover, the labor market clears at  $L = (\int_{-\infty}^{\bar{\tau}} \int_{\tau}^{\bar{v}_\tau} L_{\tau,v} dv d\tau)$ . Combining the market clearing condition and the wage rate of equation (14), which equals  $(1-\alpha) \frac{p_{\tau,v} Y_{\tau,v}}{L_{\tau,v}} = w$ , gives us the aggregate wage rate  $w = \frac{(1-\alpha)Y}{L}$ . We put the wage rate into  $p_\tau$  and take logarithms

$$p_\tau = -z_\tau + (1-\alpha)(y-l) - \alpha \ln \alpha$$

Equation (12) equals  $Y_\tau = Y p_\tau^{-\frac{\theta}{\theta-1}}$ . First we take logarithms, then we replace  $p_\tau$

$$y_\tau = y - \frac{\theta}{\theta-1} \left[ -z_\tau + (1-\alpha)(y-l) - \alpha \ln \alpha \right]$$

which is equal to

$$y_\tau = y + \frac{\theta}{\theta-1} \left[ z_\tau - (1-\alpha)(y-l) + \alpha \ln \alpha \right]. \quad (20)$$

**Derivation of equation (21):**

We consider a second order approximation of  $Z_\tau$  around  $\Delta t \equiv t - D_\tau - \tau = 0$ . We start with

$$Z_\tau = \left( \frac{\mu-1}{\gamma} \right)^{\mu-1} a_\tau e^{(\chi+\gamma)\tau} \left( e^{\frac{\gamma}{\mu-1} \Delta t} - 1 \right)^{\mu-1}$$

which we derived above. Consequently, we consider the limit of the function, where  $\Delta t \equiv t - D_\tau - \tau = 0$ :

$$\lim_{\gamma \rightarrow 0} \left[ \left( \frac{\mu-1}{\gamma} \right)^{\mu-1} a_\tau e^{(\chi+\gamma)\tau} \left( e^{\frac{\gamma}{\mu-1} \Delta t} - 1 \right)^{\mu-1} \right].$$

Next we apply the l'Hôpital's Rule to show that

$$a_\tau e^{(\chi+\gamma)\tau} \left( \lim_{\gamma \rightarrow 0} \left( \frac{\mu-1}{\gamma} \right) (e^{\frac{\gamma}{\mu-1} \Delta t} - 1) \right)^{\mu-1} = a_\tau e^{(\chi+\gamma)\tau} \frac{\gamma}{\mu-1} \Delta t^{\mu-1}.$$

In the next step we take the first order Taylor approximation around  $\Delta t=0$  and get:

$$Z_\tau \simeq a_\tau e^{(\chi+\gamma)\tau} \left[ \Delta t \left( 1 + \frac{1}{2} \frac{\gamma}{\mu-1} \Delta t \right) \right]^{\mu-1}.$$

Then we simplify the expression of  $\ln Z_\tau$ . To do this we apply the first order Taylor approximation of  $\ln(1+x) \simeq x$ , for small  $x$ . Therefore, we get

$$\ln Z_\tau \simeq \ln a_\tau + (\chi + \gamma)\tau + (\mu-1) \ln \Delta t + \frac{\gamma}{2} \Delta t.$$

From substituting back for  $\Delta t$  follows

$$\ln Z_\tau \simeq \ln a_\tau + (\chi + \gamma)\tau + (\mu-1) \ln (t - D_\tau - \tau) + \frac{\gamma}{2} (t - D_\tau - \tau). \quad (21)$$

**Derivation of equation (22):**

We plug equation (21) into equation (20) and get

$$y_\tau = y + \frac{\theta}{\theta-1} \left[ \left[ \ln a_\tau + (\chi + \gamma)\tau + (\mu-1) \ln (t - D_\tau - \tau) + \frac{\gamma}{2} (t - D_\tau - \tau) \right] - (1-\alpha)(y-l) + \alpha \ln \alpha \right].$$

Next we rearrange

$$y_\tau = y + \frac{\theta}{\theta-1} \left[ \ln a + (\chi + \gamma)\tau + \frac{\gamma}{2}(t - D_\tau - \tau) \right] + \frac{\theta}{\theta-1} ((\mu-1)\ln(t - D_\tau - \tau) - (1-\alpha)(y-l) + \alpha \ln \alpha).$$

To simplify and to close the gap between the theoretical model and the empirical estimation, we define the coefficients. We denote  $\beta_{\tau 3} = \frac{\theta}{\theta-1}$  and  $\beta_{\tau 1} = \beta_{\tau 3}(\ln a + (\chi + \frac{\gamma}{2} + \alpha \ln \alpha)\tau - \frac{\gamma}{2}D_\tau)$ . Furthermore,  $\beta_{\tau 2} = \frac{\theta}{\theta-1} \frac{\gamma}{2}$ . Hence, we get the following estimating equation

$$y_{\tau t}^c = \beta_{\tau 1}^c + y_t^c + \beta_{\tau 2} t + \beta_{\tau 3}((\mu-1)\ln(t - D_\tau^c - \tau) - (1-\alpha)(y_t^c - l_t^c) + \epsilon_{\tau t}^c). \quad (22)$$