Master Thesis

The Role of Inequality in Technology Diffusion

Master of Arts HSG in Economics

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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 the two country groups. Applying pooled OLS, we find that it matters where in the income distribution the inequality appears, which confirms our theoretical predictions. In contrast, overall inequality measured by the Gini coefficient is too broad to be significant. 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 or the poor increases the adoption lag. When it comes to the long run technology penetration rate, we find that lower overall inequality increases the penetration. Increasing the income share of the middle class at the expense of the rich or the poor increases the penetration rate. Our results suggest that a strong middle class increased the adoption lags and penetration rates in Western countries. Therefore, it may account for some of the convergence of adoption lags and divergence of penetration rates between the two country groups.

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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 a factor 5 increase for non-Western countries between 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 in this thesis 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.

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 by 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 lag decreased in all countries, but 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.

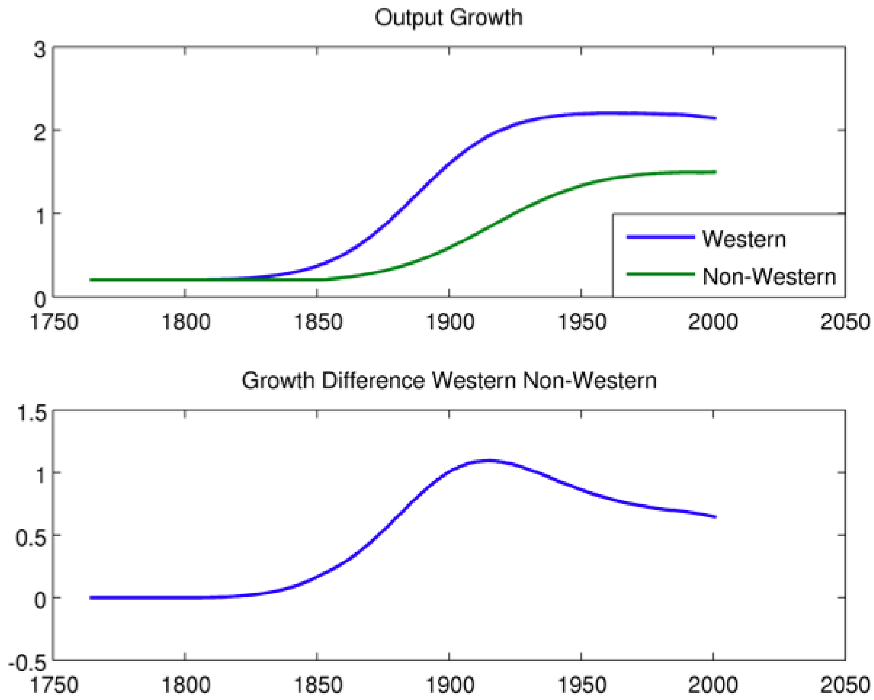

Figure 1: Growth of Western and non-Western countries inputing the estimated evolution of the intensive and extensive margins (Comin and Mestieri, 2013a, p. 42)

In the course of the last century 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.

We suggest that additionally to different demand patterns and economic development 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 Föllmi, Würgler and Zweimüller (2009) who include non-homothetic preferences. They introduced 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 middle class and the poor, due to process innovation. A historic example is the Model T from Ford that made cars available to the middle class. In an unequal society, only the rich can afford the luxuries and the new technologies reach only this restricted 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. In contrast, consider a more equal society where the middle class has a higher income share compared to the rich. Then, incentives for process innovation are higher, 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. Eight technologies, which are ships, cars, aviation - freight, blast oxygen steel, cellphones, PCs, MRI and internet, are included. In our core specifications, we include either the Gini coefficient or quantile income share dummies to control for inequality. Moreover, GDP p.c., education, trade openness and institutions are added as covariates. We find that redistribution from the rich to the poor decreases the adoption lag, while redistribution to the middle class from the rich or the poor increases the adoption lag. For the penetration rate we find that lower overall inequality increases the penetration rate. Furthermore, increasing the income share of the middle class at the expense of the rich or the poor increases the penetration rate as incentives for process innovation are increased. This stresses the importance of a strong middle class. Due to opposing effects of inequality on the adoption lag and penetration rate, 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 technology diffusion and income inequality. Including the model of Comin and Mestieri (2013a) in subsection 2.4 'Model of Technology Diffusion', where the micro foundation for the dependent variables are developed. In section three follows the channels of how inequality affects technology diffusion we form our hypotheses. Section 4 'Estimation Method' presents the empirical framework of our analysis. In section 5 'Data', we describe the identification strategy of the dependent variables as well as an overview over the data sources and definitions is provided. Our results are presented in section 6 'Results', and section 7 'Discussion' summarizes and discusses the implications of our work.

2 Literature Review

In the literature review, we first discuss the importance of technology diffusion for an economy. Then we elaborate the determinants of technology diffusion. In the third part, we discuss channels of income inequality on economic growth. We argue that these channels are relevant for technology diffusion as well. Finally, we discuss the model of Comin and Mestieri (2013a) in detail, as it is relevant for understanding our dependent variables in the estimations.

2.1 Importance of Technology Diffusion

To highlight the importance of investigating 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 describes the fact that the technologies spread to most sectors. Improvement stands for the idea that the GPTs improve over time and lower the users costs. Innovation spawning means that GPTs facilitate the invention and production of products and processes. Figure 2 shows the share of total horsepower generated by different technologies in the period between 1869 to 1954. The period covers the decline in the usage of water wheels, turbines, the increase as well as decrease of steam engines and turbines. Moreover, the symmetry of the decline of steam and the rise of electricity suggests a replacement. It is noteworthy that it took several decades until electricity produced 60% of the total horsepower. Which shows the relevance of investigating the diffusion of technologies additionally to the first time a technology is available. Jovanovic and Rousseau (2005, p. 1186) state that most technologies have to some degree the same characteristics as GPTs [1].

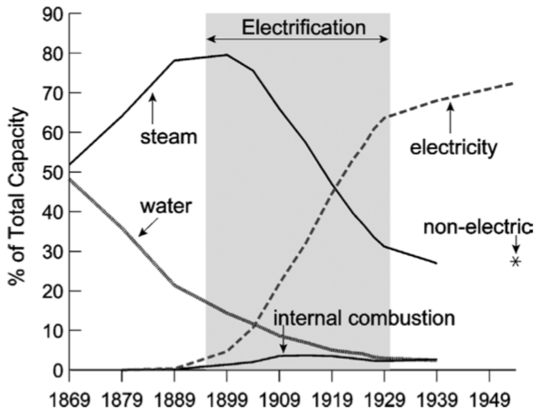

Figure 2: Shares of total horsepower generated by the main sources in U.S. manufacturing, 1869-1954 (Jovanovic and Rousseau , 2005, p. 1188)

[1]In this thesis we do not focus exclusively on GPTs, but our model of technology adoption (described in the subsection 2.4 'Model of Technology Diffusion') features similar characteristics.

Vernon (1966) developed three stages of a product cycle. 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 will become a net importer of a specific good later on. 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. In this thesis, we use the terms Western, non-Western countries as synonyms for the terms North-South. 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. (Föllmi, Hanslin and Kohler, 2012)

2.2 Determinants of Technology Diffusion

In this section, we highlight factors that influence technology diffusion. We assume that the channels described here negatively affect the adoption lag and positively the penetration rate. This review of the determinants of technology diffusion supports the inclusion of trade openness, institutions, education and GDP p.c. as covariates. 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 discuss how economic development affects technology diffusion.

We start by giving an overview over the effects of trade openness and institutions 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. According to their results, the big income disparity between countries is due to differences in adoption barriers. The lower adoption barriers in the Western countries allowed them to grow richer. They assume that a firm has to make an investment in order to upgrade to a higher level of technology. This upgrade depends on two factors: With a higher level of general scientific knowledge in the world, and lower barriers in the firm's country, investments are cheaper. Due to the exogenous growth of the world knowledge, the amount of necessary investment to achieve a higher technology level decreases over time. This implies that the level of development in a country will even increase with unchanged adoption barriers. Hence, Parente and Prescott (1994) point out that greater trade openness can weaken the forces of resistance to technology adoption and make investment in new technologies cheaper.

Comin and Hobijn (2006, p. 17) mention two possible channels for how trade openness can affect the technology adoption lag. First, as proposed by Holmes and Schmitz (2001), a higher foreign competition increases the pressure on domestic firms to adopt technologies 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 as a consequence the adoption lag. Holmes and Schmitz's (2001) main result is that lower tariffs and lower transportation costs shift the relative returns from unproductive to productive entrepreneurship. They define unproductive entrepreneurship as activities that limit competition through the regulatory process. With low tariffs, blocking is not rewarding anymore. Hence, in order to invent or adopt new technologies, firms shift their activities to research. The federalism 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 state B can simply use the more productive technologies to produce more efficiently in Band 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 into their regression an interaction term of different characteristics of institutions with a binary dummy variable, whether a technology has a competing predecessor technology. On the one hand they find a significant negative effect of the dummies with military regime and legislative flexibility on the speed of technology diffusion. On the other hand, democracy and judicial effectiveness increase the pace of technology diffusion. As for example in a democracy lobbying costs are much higher than in a military regime. Thus, lower lobbying costs in these systems lead to higher institutional barriers towards the adoption of new technologies and therefore to a slower diffusion of technologies. Hence, different types of institutions can affect the costs of erecting barriers and thereby influence technology diffusion. From this research we conclude that trade openness and institutions matter for the diffusion of technologies.

In the following, we continue by analyzing the effects of education on technology adoption. According to a model developed by Kiley (1997), education is crucial to the adoption of technologies. The model 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 finding may suggest that a higher share of educated people attracts complementary technology. Then, the attracted technologies induce skill-biased technical change and increases the skill premium. This causes higher inequality. We propose the hypothesis that higher inequality 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. In contrast, de-skilling technologies have the exact opposite effect: They shift capital from fast to slow learning workers and increase absolute and relative wages of slow learners. Consequently, technology-dependent 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 of technology adoption affecting inequality. The instrumental variable estimation method and the data will be described in sections 4 'Estimation Method' and 5 'Data'.

Do two countries use the same technology if it is available in both? 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? No, as only in the US combines are heavily used. 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. Adoption barriers are neglected in this model, and technical improvements made in one country are immediately available all around the world. As a result, technology leaders benefit less from other countries improvements than followers do. However, a follower country can only adopt a new technology after achieving a sufficiently high level of development. The richer and thus closer to the technology frontier a country is, the lower is the cost of adoption. Hence, this model predicts that the higher the relative development is, the faster new technologies are adopted and the higher is the diffusion.

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 developing 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)

2.3 Income Inequality

In this section we introduce channels that account for the effects of inequality on economic growth. Such as the distinction of structural and market inequality, effects of an imperfect credit market and quantile income shares. We build on the ideas of these channels by applying them to technology diffusion. Finally, we discuss the Gini coefficient.

First, Easterly (2007, p. 756) makes a distinction between structural and market inequality: "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, which is scalable, is, the higher the scope for structural inequality. (Easterly, 2007, p. 756) As this measure of factor endowments is exogenously given by the nature, it is well suited for an instrumental variable. We apply this IV as a robustness test. A detailed discussion on the construction of the variable is provided in subsection 5.2.4 'Instrumental Variable'.

Second, in the literature on income inequality effects on economic growth it is an important view that high inequality due to an imperfect credit market is bad for subsequent growth. 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. Föllmi and Oechslin (2008) point out that even with credit market imperfections, higher inequality can be beneficial for the economic performance. Consider a distortion-free redistribution from the richest to the middle class. This equalizes marginal returns of investment opportunities and thus has a positive effect on growth. However, it also increases the demand for capital in the economy and therefore the borrowing rate. With a higher borrowing rate, the poorest suffer from a tighter borrowing constraint and can borrow less. Hence, they remain with high marginal returns, which is bad for the economic performance. Therefore, redistribution from the rich to the middle class is negative and from the rich to the poor is positive for economic growth. Föllmi, Oechslin and Zahner (2011) disentangle these opposing effects by analyzing quantile share inequality data. Given these opposing effects, the Gini coefficient may be too imprecise to discover the relevant effects.

In order 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 3, the x-axis shows the cumulative percentage of the population, starting with the poorest on the left. On the y-axis, the cumulative percentage of income or expenditure that are related to the units on the x-axis is shown. In case of an equal income distribution, we would get the dashed 45-degree line. The more unequal, the more the thick line shifts 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% the Gini coefficient approaches. An advantage of this measure is that neither population size nor GDP matters. A disadvantage is that different Lorenz curves can intersect and hence different distributions can yield the same coefficient. (Deaton, 1997)

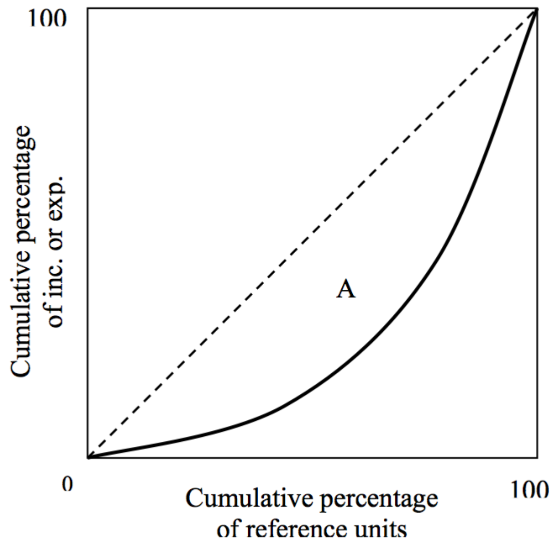

Figure 3: The Lorenz Curve and the Gini coefficient (UNU-WIDER, 2009)

2.4 Model of Technology Diffusion

In the following we start by explaining the shape of diffusion curves, which is relevant for understanding the two margins of technology adoption. These two margins are our dependent variables in the estimation. Secondly, we derive the relevant parts of the model mathematically in order to understand how the two margins affect the level of TFP. This is crucial to understand as this connects the two margins and economic growth theoretically.

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 4 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 particularly 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 4 the x-axis denotes the time. On the y-axis the log of the technology τ at time t in country c is denoted by $y^{c}_{\tau t}$. 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.

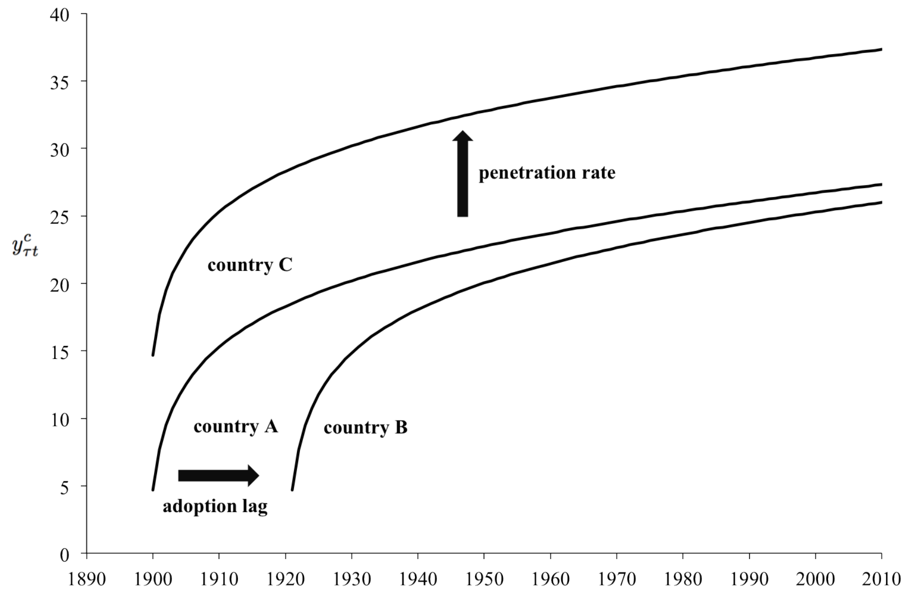

Figure 4: Illustrative Example of the Diffusion Curve

At this point it is only clear what the difference of the shifts between the diffusion curves is. But it is not clear 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

$$y^c_{\tau,t} = \underbrace{\beta^c_{\tau 1}}_{Vtcal\ Shift} + \beta_{\tau 2} t + \beta_{\tau 3} \overbrace{ln(t - \tau - \underbrace{D^c_\tau}_{Hztal\ Shift})}^{Concave\ Shape}. \tag{1}$$

The left hand side is the log-output produced, $y^c_{\tau,t}$, with a technology τ at time t in country c. The variable $\beta^c_{\tau 1}$ 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 subsection 5.1 'Identification Strategy of Dependent Variables'. The expression t-τ represents the time elapsed from the invention date τ to the moment t the technology output is measured. The variable D^c_τ shifts the curve horizontally and therefore captures the adoption lag. The larger D^c_τ, the more is the curve shifted to the right. The term $ln(t-\tau-D^c_\tau)$ is only well defined if $t-\tau-D^c_\tau > 0$. Note that $\beta^c_{\tau 1}$ and D^c_τ 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 5 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.

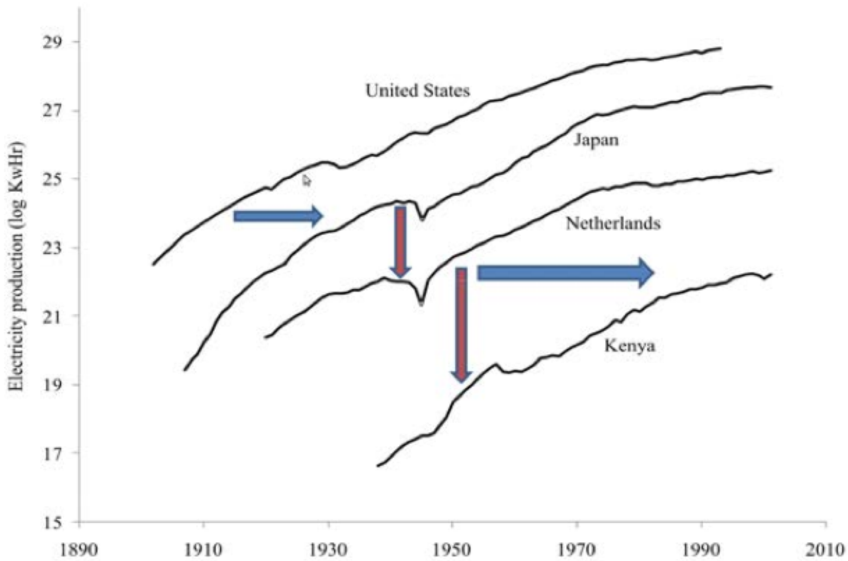

Figure 5: Example of Diffusion Curve (Comin and Mestieri, 2013b, p. 11)

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:

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

C is the abbreviation for consumption and ρ 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):

$$\dot{B}_t + C_t = w_t + r_t B_t \tag{3}$$

$$\lim_{t \to \infty} B_t e^{\int_{t_0}^{t} -r_s ds} \geq 0. \tag{4}$$

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, τ, appears exogenously. Technology is denoted by the time it was invented. Consequently, τ 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-τ are denoted by υ_τ. Vintages are indexed by the time in which they appear. Therefore, at time $t > \tau$ the set of existing vintages of technology-τ available is $[\tau, t]$. The productivity of a technology-vintage pair consists of two constituents. First, $Z(\tau, \upsilon_\tau)$ which is a general measure that is equal across countries. It is determined only by technological attributes

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

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

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

Intensive margin. New intermediate goods embody the new vintages (τ, υ). 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, $Y_{\tau,\upsilon}$. $X_{\tau,\upsilon}$ denotes the number of units of intermediate good (τ, υ) used in production. $L_{\tau,\upsilon}$ is the number of workers that use the intermediate goods. Hence, $Y_{\tau,\upsilon}$ is given by the Cobb-Douglas production function in equation (6):

$$Y_{\tau,\upsilon} = a_\tau Z(\tau, \upsilon) X^\alpha_{\tau,\upsilon} L^{1-\alpha}_{\tau,\upsilon} \tag{6}$$

The important value in equation (6) is a_τ, 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_τ. So, it is the measure for the intensive margin of adoption of a technology in the model. In the estimation strategy the term a_τ is denoted as $\beta^c_{\tau 1}$. 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_τ. We use a CES production function of the following form:

$$Y_\tau = \left(\int_\tau^{t-D_\tau} Y_{\tau,\upsilon}^{\frac{1}{\mu}}\, d\upsilon \right)^\mu, \; with\; \mu > 1. \tag{7}$$

Likewise, final output, Y, is the aggregate of of the sectoral outputs, Y_τ

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

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

$$Z_\tau \;\; = \;\; \left(\int_\tau^{\max\{t-D_\tau,\tau\}} a_\tau Z(\tau,\upsilon)^{\frac{1}{\mu-1}} d\upsilon \right)^{\mu-1}, \tag{9}$$

aggregated labor input L_τ in sector τ as

$$L_\tau = \int_\tau^{t-D_\tau} L_{\tau,\upsilon} d\upsilon, \tag{10}$$

and aggregated intermediate goods X_τ in sector τ as

$$X_\tau = \int_\tau^{t-D_\tau} X_{\tau,\upsilon} d\upsilon. \tag{11}$$

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

$$Y_\tau = Y p_\tau^{-\frac{\theta}{\theta-1}} \tag{12}$$

where p_τ is the price of the output in sector τ. 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 τ output is one. Likewise, the demand for output produced with a given technology vintage is

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

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

$$(1-\alpha)\frac{p_{\tau,\upsilon}Y_{\tau,\upsilon}}{L_{\tau,\upsilon}} \;\; = \;\; w \tag{14}$$

$$\alpha\frac{p_{\tau,\upsilon}Y_{\tau,\upsilon}}{X_{\tau,\upsilon}} \;\; = \;\; 1. \tag{15}$$

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 $X_{\tau,\upsilon}$ and $L_{\tau,\upsilon}$. Then we substitute them into equation (6), solve for $p_{\tau,\upsilon}$ and we get the following:

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

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

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

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

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

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_τ related to a technology, is determined by the intensive and extensive margin. We get the following:

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

In this model the productivity of a technology, Z_τ 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 subsection 5.1 'Identification Strategy of Dependent Variables' this model is used to measure the adoption lag and the penetration rate in the data.

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. These channels are crucial to determine our hypotheses for the estimation. Our contribution lies not only in the review of the literature, but also in the application on the two margins. The relevant literature either discusses the relationship of inequality on technology adoption or on economic growth, but it does not combine the two specific adoption margins. Hence, our contribution in this section is the application of theoretical inequality effects on both margins. We start with the channels for the adoption lag and then proceed with penetration rate.

3.1 Channels of Inequality on the Adoption Lag of a Technology

What is the effect of inequality on the technology adoption lag? On the one hand, consider a society where one individual owns all the resources and buys a new technology at a given price. On the other hand, consider a society with the same mean income and but with an even income distribution. In the latter society, the richest individual's income is lower than in the first. The mean is below a certain threshold of the given price and nobody can afford the new technology. This implies a lower adoption lag in the unequal society and a higher one in the equal society. We focus here on channels that affect the adoption of a new technology in the short run, while in the long-run they 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 income in the upper end of the income distribution, while keeping the mean income constant, leads to a higher short-run penetration and therefore to a shorter adoption lag. Hyytinen and Toivanen (2011) assume taste homogeneity and an initial price at which nobody adopts. A higher income share of the high income segment, decreases the adoption lag after a price reduction. In the second channel, they argue that if mobile phones are an particularly useful production technology for the poor, a higher income in the bottom of the income distribution decreases the adoption lag. As Hyytinen and Toivanan put forward their hypothesis based on anecdotal evidence that many poor in developing countries adopted mobile phones for production purposes and not only consumption purpose like the rich. Assuming that the poor can borrow against their income generated by the mobile-enabled production. Consequently, summing up both channels, increasing the income share of either the poor, the middle class or the rich leads to a lower adoption lag. We may assume taste homogeneity preferences for the first channel, that the rich increase their income share. The second channel suggests taste heterogeneity and thus different preferences between the different quantiles in the income distribution. For the middle class or the poor, the technology may be more useful than for the rich. Therefore, applying quantile shares measures for income inequality allows us to disentangle in which quantile of the distribution inequality matters.

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 from 1985 to 1998. The focus lies 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 used is the above mentioned instrument of suitability of arable land applied by Easterly (2007), which we apply as well as a robustness check.

The crucial difference between Hyytinen and Toivanen (2011) and the 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, discussed in the following section.
Based on the previous discussion, we argue that the adoption lag decreases under the following two conditions:

Hypothesis 1a: First, if the rich increase their income share, the adoption lag decreases, because they can afford the new technologies earlier, assuming taste homogeneity among all individuals.

Hypothesis 1b: Second, when a new technology is particularly useful to the poor or the middle class, they have high preferences for new technologies and are willing to spend a high share of their income on new technologies. In this case, a higher income share of the poor or the middle class would decrease the adoption lag. A complementary explanation may be credit constraints for the poor, which do not allow them to purchase productive new technologies.

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 because the richest can afford the new technology. In to a society with an equal mean income, but where income is evenly distributed the long-run penetration is lower. This is because except for the one rich person, nobody can afford the technology. When lowering the price of the technology due to mass production, initially, 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 review the literature on effects of a strong middle class on a society, as well as 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 particularly focus on the model of Föllmi, Würgler and Zweimüller (2009), which we consider important. Finally, we state some differences between the model of Föllmi, Würgler and Zweimüller (2009) and the one of Comin and Mestieri (2013a). While the first describes the relevant channels of inequality on technology diffusion the latter is our main model in explaining the two margins and their mechanisms in the economy. We describe the mechanisms of the two margins in subsection 2.4 'Model of Technology Diffusion'.

We start with the literature review regarding the middle class. 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. Similar to the argument described above by Easterly (2007) Easterly (2001) suggests that the main causes for these differences are factor endowment and the subsequent inequality due to a small elite capturing the political power.

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 having fewer, healthier and better educated children compared to the poor. Even if they distinguish clear differences between the poor and the middle class, there are many country-specific characteristics. These particular characteristics may exist either due to relative prices, which affect consumption decisions, or due to 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 become 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 due to higher incentives of the firms to innovate by selling to more people. Hence, there is a two-way causality. According to the model, inequality should neither be too high nor too low. If a society is too unequal, technology diffusion stops quickly as the poor cannot afford it. If the society is too equal, the diffusion does not even start because the mean income level is below a certain threshold. Whether redistribution from the upper middle class to the lower middle class has a positive effect on the diffusion is ambiguous. Redistribution may make the products affordable to the lower middle class, but at the same time may 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, such as cars, radios, television sets, washing machines, refrigerators and recently computers, have made this transformation.

In line with the model of Matsuyama (2002), Föllmi, Würgler and Zweimüller (2009) develop their own model, which allows to analyze inequality and the transformation of luxury goods to products of mass consumption. Their model, is motivated by the famous historical example of 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. Ford produced over 15 million Model T's between 1908 and 1927. During this time, the penetration of car ownership rose impressively in the United States. In 1908, 1% of the households owned a car. In 1924, already 50% of the households owned a car (Bowden and Offer, 1994). The mechanism of mass production, described for Ford's Model T, was an important step in the history of manufacturing. Since then, mass production can be observed in developed countries for many products and is getting more important in developing countries in recent years. This 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. (Föllmi, Würgler and Zweimüller, 2009, p. 6-9) We argue that increased incentives for process innovation, increases mass production and hence increases penetration of technologies in an economy. Therefore, the redistribution effects discussed in the following with regards to the incentives of product and process innovations are considered as channels how inequality affect the penetration rate of a technology.

In the following, we describe the important effects of the model in detail, as they are crucial in order to form our hypothesis for the penetration of technologies. In the endogenous growth model of Föllmi, Würgler and Zweimüller (2009) a firm invests in product and process innovation. Product innovation creates new product lines, which are luxury goods. The luxury god is only affordable for the rich, as production costs are high. Once a product innovation is successful, the firm has the option to pursue process innovation. Process innovation reduces cost and quality of the product Costs are reduced more than quality hence results a higher quality-cost ratio. If a firm decides to do only product innovation it is called an exclusive producer and sells only high quality products. In contrast, a firm doing product and process innovation is called a mass producer. A mass producer has several options, which are combinations of supplying high and low quality products for high and low prices to either all or only the rich. (Föllmi, Würgler and Zweimüller, 2009, p. 13)

The effects described in the following are summarized in figure 6. Föllmi, Würgler and Zweimüller (2009, p. 36) conclude in their *baseline model* with only rich and poor that in a more unequal economy, incentives for product innovation are strong (a). Vice versa, in a more egalitarian economy, incentives are high for firms to adopt process innovation and thus mass production (b). Thus, in a more equal economy, the penetration of technologies is higher due to the strong incentives for process innovation. In this model it is important that preferences are non-homothetic. The rich consume more and higher quality products than the poor. As a consequence, the income distribution in the economy affects the relative incentives of the firms, whether to pursue product or process innovation. In the extensions of their model, Föllmi, Würgler and Zweimüller (2009, p. 33-34) include the middle class to discuss the effects of inequality on economic growth. In their baseline model only the rich and the poor exist. In forming our hypothesis the three income classes, including the middle class, are crucial. Therefore, we rely in our analysis on the extended model. With inequality between the rich and the middle class two types of equilibria are distinguished. In the *first type of equilibrium*, the middle class is relatively rich. Hence, the rich buy all high quality products and the middle class some of them. Consider that redistribution from the poor to the middle class (c) in the extended model is the same as redistribution from the poor to the rich in the baseline model. This implies that product innovation incentives are supported, because more products are bought from the exclusive producers and less from the mass producers. In this equilibrium, redistribution from the rich to the middle class (d) reduces incentives for product innovation, as the rich reduce their willingness to pay. Even though the rich still buy all of these products and the middle class buys more of them. In the *second type of equilibrium*, the middle class is less wealthy and cannot afford the goods offered by the exclusive producers. Hence, redistribution from the poor to the middle class (e) increases the middle class' willingness to pay for mass products. As a consequence, the poor buy less of the mass goods, as they have a lower income and prices have increased due to the increased demand. In total, the incentives change in favor of process innovation. Finally, redistribution from the rich to the middle class (f) shifts the innovation incentives in the direction of process innovation as well. Additionally, the increased income of the middle class increases their willingness to pay and hence the prices. This in turn, reduces the poor's demand for these goods. Figure 6 summarizes the effects of redistribution between income classes, based on the theoretical findings of Föllmi, Würgler and Zweimüller's (2009) model. These effects are our hypothesis 2.

Redistribution	Effect on Innovation Incentives	Effect on Penetration Rate
Baseline Model		
a) poor → rich	product innovation ↑	penetration rate ↓
b) rich → poor	process innovation ↑	penetration rate ↑
Extended Model		
Equilibrium 1: relatively rich middle class		
c) poor → middle class	product innovation ↑	penetration rate ↓
d) rich → middle class	process innovation ↑	penetration rate ↑
Equilibrium 2: relatively poor middle class		
e) poor → middle class	process innovation ↑	penetration rate ↑
f) rich → middle class	process innovation ↑	penetration rate ↑

Figure 6: Hypothesis 2: Effects of Inequality on Penetration Rate

Finally, we discuss some differences between the two main models we consider in order to answer our research question. Both models have included product innovation, with new technologies appearing. There is one important difference in the understanding of productivity gains due to new vintages between the models of Föllmi, Würgler and Zweimüller (2009) and Comin and Mestieri (2013a). On the one hand in the former model higher productivity is due to process innovation, even though the quality decreases. On the other hand Comin and Mestieri (2013a) do not explicitly mention process innovation, but they assume continuous reduction in production costs over time for the same quality. As a consequence, they may imply some sort of process innovation, which lowers production costs and makes vintages affordable to more people. In their model, productivity gains stem from the use of more productive vintages and are not necessarily due to improvement of the production process. Another difference is that Comin and Mestieri (2013a) assume homothetic preferences. Föllmi, Würgler and Zweimüller (2009), however, do assume non-homothetic preferences in their model. So, not all individuals in a country have the same preferences. Finally, Föllmi, Würgler and Zweimüller's (2009) model does not embody quality upgrading of existing products. We build our estimation on the model of Comin and Mestieri (2013a), which includes the embodiment effect. This effect represents the idea that new vintages of a technology appear at each instant exogenously. The increase of vintages increases the productivity in a country. We explain this in detail above in subsection 2.4.2 'A Microfoundation for the Diffusion Curve'.

Hypothesis 2: The intensive margin is the long-run penetration rate of an economy. We formulate the hypothesis that higher inequality decreases the penetration rate. In order to achieve a higher penetration in the long-run, particularly a large middle class compared to the rich and compared to the poor may be relevant. The effects of a large middle class on the penetration rate are summarized in figure 6.

4 Estimation Method

In the following subsection we 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.

4.1 Core Specifications

Following the research question and the respective channels in the literature, there are two approaches to estimate the respective effects on the adoption lags and the penetration rate.

Our core specifications for the first specification, the adoption lag, are based on the estimation of Comin and Mestieri (2013a) shown in figure 7. 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 9 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. Then we continue with the necessary assumptions for consistent and efficient estimates. Finally, we discuss the issue of heteroskedasticity.

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 the adoption lag estimation:

$$ln\, D_{t,c,\tau} = \beta_0 + \beta_1\, INEQUALITY_{t,c} + \beta_2\, INSTITUTIONS_{t,c} + \beta_3\ GDP_{t,c} + \beta_4\, EDUC_{t,c} \\ + \beta_5\, OPENNESS_{t,c} + \beta_6\, TD_{t,c} + u_{t,c,\tau} \quad (20)$$

for t=1,...,T, c=1,...,N and τ=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 τ. 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. β_0 is the intercept and starting from β_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 Phelphs (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 quantile shares as measures for inequality. 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 second 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 β. 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:

$$\begin{aligned} ln\, a_{t,c,\tau} = \beta_0 + \beta_1\, INEQ_{t,c} + \beta_2\, INST_{t,c} + \beta_3\ GDP_{t,c} + \beta_4\, EDUC_{t,c} \\ + \beta_5\, OPENNESS_{t,c} + \beta_6\, TD_{t,c} + u_{t,c,\tau} \end{aligned} \tag{21}$$

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 β 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≠t. Assumption POLS.2 is the full rank condition: rank$\left[\sum_{t=1}^{T} E(x'_{t,c}x_{t,c})\right]$ = 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 as well 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 τ=1,...,M, where $\sigma^2 = E(u^2_{t,c,\tau})$ for all t, c and τ; (b) $E(u_{t,c,\tau}u_{s,c,\tau}x'_{t,c}x_{s,c}) = 0$ where s≠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≠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. We plot the residual against the fitted values (in the top row) and against inequality measures (in the bottom row) in figure 11 for the adoption lag and in figure 12 for the penetration rate. From the left to the right, we do this for each of the three sub specifications. The corresponding estimations are shown in table 4. In the top row in figures 11 and 12, the first graph on the left shows the first sub specification for the Gini coefficient, the second and third for the quantile income shares. We discuss the residual plots and heteroskedasticity in detail in subection 6.2 'Robustness Checks'. We conclude that our estimation may suffer from heteroskedasticity. Therefore, we apply heteroskedasticity-robust standard errors. Consequently, if we did not correct the standard errors for heteroskedasticity we would still get consistent estimates. But the estimates were no longer BLUE. Hence, POLS is not the estimation method with the smallest variance and hence the most efficient one among the unbiased methods. Heteroskedasticity causes biased standard errors and therefore biased test statistics and significance levels. 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.

4.2 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 quantiles 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:

$$\begin{aligned} INEQUALITY_{t,c} = \delta_0 + \delta_1\, INSTITUTIONS_{t,c} + \delta_2\, ln\, GDP_{t,c} + \delta_3\, EDUC_{t,c} \\ +\delta_4\, OPENNESS_{t,c} + \theta_1 z_c + \delta_6\, TD_{t,c} + r_{t,c,\tau} \end{aligned} \tag{22}$$

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 (20) and (21).

Instead of INEQUALITY we include the fitted value obtained from the first stage regression:

$$ln\, D_{t,c,\tau} = \beta_0 + \beta_1\, \widehat{INEQUALITY}_{t,c} + \beta_2\, INSTITUTIONS_{t,c} + \beta_3\; GDP_{t,c} + \beta_4\, EDUC_{t,c} \\ +\beta_5\, OPENNESS_{t,c} + \beta_6\, TD_{t,c} + u_{t,c,\tau} \quad (23)$$

$$ln\, a_{t,c,\tau} = \beta_0 + \beta_1\, \widehat{INEQUALITY}_{t,c} + \beta_2\, INSTITUTIONS_{t,c} + \beta_3\; GDP_{t,c} + \beta_4\, EDUC_{t,c} \\ +\beta_5\, OPENNESS_{t,c} + \beta_6\, TD_{t,c} + u_{t,c,\tau} \quad (24)$$

We describe in the following the required assumptions. Assumption 2SLS.1 says that for some 1xL vector z, $E(z_c' u_{t,c,\tau})$=0. 2SLS.2 is the rank condition which says that (a) rank $E(z_c' z_c) = L$; (b) 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 $Var(u_{t,c,\tau}|z_c) = \sigma^2$ 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)

5 Data

5.1 Identification Strategy of Dependent Variables

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 2.4.2 'A Microfoundation for the Diffusion Curve'.

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

$$y_\tau = y + \frac{\theta}{\theta - 1}[z_\tau - (1-\alpha)(y-l) + \alpha\, ln\, \alpha] \tag{25}$$

In equation (19) we can see that, to a first order approximation, γ only affects y_τ through the linear trend. Accordingly, a second-order approximation of log Z_τ around the starting adoption date $(\tau + D^c_\tau)$ can be made:

$$z_\tau \approx ln\, a_\tau + (\chi + \gamma)\tau + (\mu - 1)\, ln\,(t - D_\tau - \tau) + \frac{\gamma}{2}(t - D_\tau - \tau) \tag{26}$$

Now, by substituting (26) into (25) derives the estimating equation:

$$y^c_{\tau t} = \underbrace{\beta^c_{\tau 1}}_{vertical\ shift} + y^c_t + \beta_{\tau 2} t + \beta_{\tau 3}((\mu - 1)\underbrace{ln(t - \overbrace{D^c_\tau}^{horizontal\ shift} - \tau)}_{Concave\ Shape} - (1-\alpha)(y^c_t - l^c_t) + \epsilon^c_{\tau t} \tag{27}$$

where $y^c_{\tau t}$ denotes the log of the output produced with technology τ, y^c_t is the log of output, y^c_t-l^c_t is the log of output per capita and $\epsilon^c_{\tau t}$ is an error term. Equation (27) 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 (27) we do not distinguish between the different measures.

Calibration. In the following paragraphs, the estimation procedure is explained. The estimation of equation (27) gives us the two important measures $\beta^c_{\tau 1}$ and D^c_τ. Where $\beta^c_{\tau 1}$ is essential to calculate the intensive margin and D^c_τ is the extensive margin. For the estimation of equation (27) 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 θ and γ. 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 (χ) and new vintages (γ). 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 θ for the calculation of the intensive margin. The value of θ 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 (27) and use only data for the United States. From this estimation we get values for $\beta_{\tau 1}$ and D_τ^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_τ^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 (27). 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 (27) 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 $\sqrt{2003 - \upsilon_\tau}$. 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 $\beta^c_{\tau 1}$ is calculated for technologies measured by output produced as we show in the following equation:

$$\beta^c_{\tau 1} = \beta_{\tau 3}(ln\, a^c_\tau + (\chi + \frac{\gamma}{2})\tau - \frac{\gamma}{2} D^c_\tau + \alpha\, ln\, \alpha) \tag{28}$$

where $(\chi + \gamma)\tau$ is the productivity level of the first vintage of technology τ. Equation (28) shows that the intensive margin, a^c_τ, is the only driver of cross-country differences in the intercept $\beta^c_{\tau 1}$. 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 (29):

$$ln\, a^c_\tau = \frac{\beta^c_{1,\tau} - \beta^{US}_{1,\tau}}{\beta_{3,\tau}} + \frac{\gamma}{2}(D^c_\tau - D^{US}_\tau) \tag{29}$$

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 7. 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 8 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 10 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) Log(Lag) World	(2) Log(Lag) Western Countries	(3) Log(Lag) Rest of the World
Year-1820	-0.0106	-0.0081	-0.0112
	(0.0004)	(0.0006)	(0.0004)
Constant	4.27	3.67	4.48
	(0.06)	(0.07)	(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 7: Evolution of the Adoption Lag (Comin and Mestieri, 2013a, p. 17)

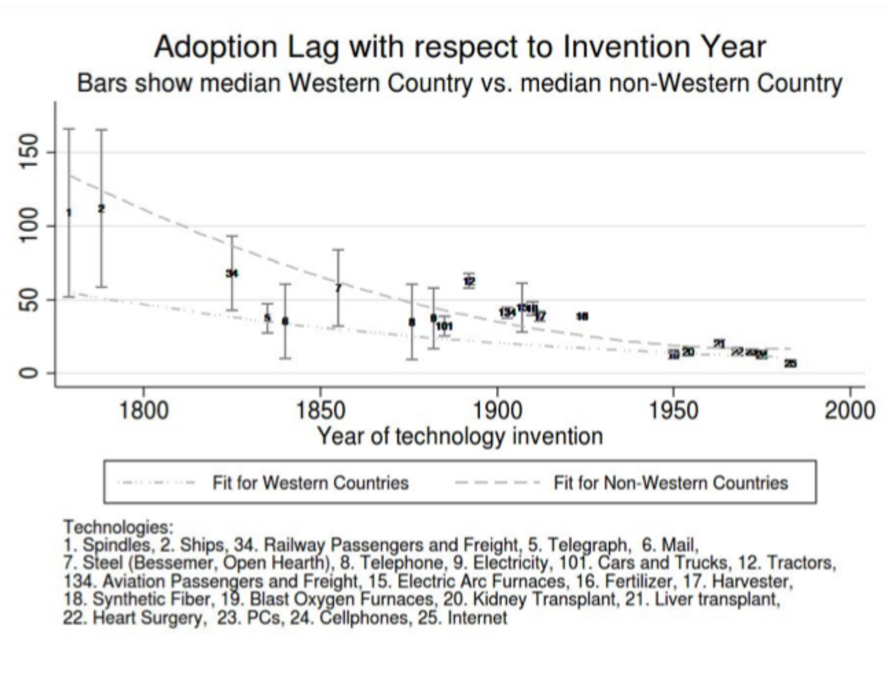

Figure 8: Adoption Lag with respect to Invention Year (Comin and Mestieri, 2013a, p. 17)

Dependent Variable is:	(1) Intensive World	(2) Intensive Western Countries	(3) Intensive Rest of the World
Year-1820	-0.0029	0.0000	-0.0054
	(0.0005)	(0.0002)	(0.0005)
Constant	-0.32	-0.00	-0.39
	(0.05)	(0.06)	(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 9: Evolution of the Intensive Margin (Comin and Mestieri, 2013a, p. 18)

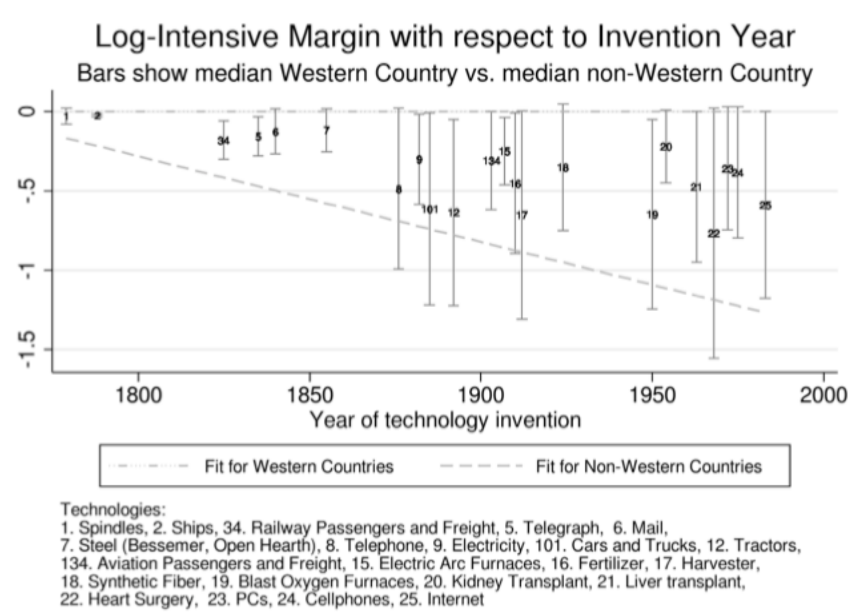

Figure 10: Log-Intensive Margin with respect to Invention Year (Comin and Mestieri, 2013a, p. 18)

5.2 Detailed Description of Dataset

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).

5.2.1 Technology Diffusion Data

We follow Comin and Hobijn (2010) in the selection of a sub-set of technologies. Technology diffusion is measured in three possible ways, as already described above in subsection 2.4.1 'The Shape of Diffusion Curves'. 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. Particularly 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 Descriptidson'. 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 subsection 6.2 '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 (27) 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 subsection 6.2 'Robustness Checks' we exlude 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)[2]. 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.

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
Total	**186**	**100**			

[2]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.

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 we 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 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%
Total	**186**						**22.41%**

5.2.2 Income Inequality Variables

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 quantiles of the distribution to be important for technology diffusion.

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

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%
Total	**186**						**22.41%**

Föllmi, Oechslin and Zahner (2011) in the construction of the dataset.

Föllmi, 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. Föllmi, 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):

$$\bar{Q}^s_{inc} = \sum_{i=1}^{N} \sum_{t=1}^{T} Q^s_{inc,i,t} \tag{30}$$

$$\bar{Q}^s_{exp} = \sum_{i=1}^{N} \sum_{t=1}^{T} Q^s_{exp,i,t} \tag{31}$$

$$\bar{Q}^s_{corr} = Q^s_{exp,i,t} * \frac{\bar{Q}^s_{inc}}{\bar{Q}^s_{exp}} = Q^s_{exp,i,t} * x \tag{32}$$

where s=1,..., 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:

$$z_i = \frac{Q^1_{corr,i,t} + Q^2_{corr,i,t} + Q^3_{corr,i,t} + Q^4_{corr,i,t} + Q^5_{corr,i,t}}{100} \tag{33}$$

$$Q^s_{inc,i,t} = \frac{Q^s_{corr,i,t}}{z_i}. \tag{34}$$

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. (Föllmi, 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 a 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. Thus, the middle class is strong in the West, as the difference to the rich is small and the difference to the poor is big. 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.

5.2.3 Control Variables

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.

5.2.4 Instrumental Variable

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):

$$Lwheatsugar_c = log\left[\frac{(1 + arable\ land\ suitable\ for\ wheat)}{(1 + arable\ land\ suitable\ for\ sugar\ cane)}\right] \tag{35}$$

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.

6 Results

In the following, we first describe our results of the core specifications. Second, we describe some robustness checks, which 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.

We start by analyzing the effects of inequality on the adoption lag. Our main findings are that higher inequality, measured by the Gini coefficient, does not have a significant effect on the adoption lag. The Gini coefficient is positive. This is the opposite of the expected sign, however, the magnitude of the coefficient is small. The regressions in columns (2) and (3) with quantile income shares are statistically significant on the 10% level, except for the redistribution from the rich to the middle class in column (2). However, this effect is borderline significant with 11.4%. Hence, we reject the Null hypothesis that inequality has no effect on the adoption lag. We find that distortion-free redistribution from the rich to the poor decreases the adoption lag. This emphasizes the channel that the poor have different preferences than the rich, which makes new technologies particularly useful to them. Alternatively, credit constraints prevent them from affording the new technologies, which is why increasing their income share decreases the adoption lag. These findings supports hypothesis 1b for the poor but not for the middle class. Moreover, hypothesis 1b as well is supported for the poor by the results in column (3). Increasing the income share of the rich compared to the poor increases the adoption lag, and thus the rich can afford the new luxuries later. Even though the effect in column (2) for redistribution from the rich to the middle class is only borderline significant, we find that it increases the adoption lag. In column (3), too, we find that increasing the income share of the middle class compared to the poor increases the adoption lag. Hence, we find two opposing effects of the income distribution on the adoption lag. On the one hand, higher top-end inequality decreases the adoption lag. But, on the other hand, higher overall inequality (between rich and poor) and higher low-end inequality (between middle class and 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. Finally, due to the finding that a strong middle class increases the adoption lag we conclude that the importance of a strong middle class cannot be supported. A strong middle class even hampers the arrival of technologies.

We continue by analyzing the effects of inequality on the penetration rate. Again, the Gini coefficient is not significant and of very small magnitude. The result is shown in column (4). For the quantile income shares in columns (5) and (6), we find statistically significant effects on the

5% level. In line with our predictions of hypothesis 2, we see in both columns that redistribution from the rich to the poor decreases the penetration rate, and redistribution from the poor to the rich it increases the penetration rate. This finding confirms the predictions of the baseline model of Föllmi, Würgler and Zweimüller (2009). It supports the channel described by them that lower (higher) overall inequality increases the incentives for product (process) innovation, which decreases (increases) the penetration rate. With regards to the middle class, the theoretical model predicts two different types of equilibria. In the first type of equilibrium, the middle class is relatively rich and consumes luxury goods. In the second type, it is relatively poor and consumes mass products. The result in columns (5) and (6) suggest that distortion-free redistribution from the poor or the rich to the middle class both increases the penetration rate. From that we conclude that on average, the middle classes are relatively poor, which makes us end up in the second type of equilibrium. This suggests that increasing the relative income of the middle class increases their willingness to pay for mass products, and thus increases incentives for process innovation. Interestingly, the penetration rate increases even though the poor consume less in both cases. Redistribution from the rich and the poor to the middle class increases prices and hence lowers the demand of the poor. Again, we find opposing effects. On the one hand, redistributing from the poor to the rich increases overall inequality. On the other hand redistributing from the rich to the middle class decreases overall inequality. But both effects increase the penetration rate. Thus, the Gini coefficient seems to be a too broad measure again. These effects with regards to the penetration rate support the literature emphasizing the importance of a strong middle class.

Assuming that there is no omitted variable bias, we can interpret all regressors. To answer the 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, whose discussion would go beyond the scope of this thesis. For these reasons, all interpretations should be considered cautiously.

In the following, we discuss the covariates in the core specification. In accordance with what the literature suggested, we find negative effects of GDP p.c. on the adoption lag and positive effects on the penetration rate. These effects are highly statistically significant on the 5% and 1% level, respectively. As expected, the high magnitudes indicate the importance of GDP p.c.. Primary and secondary education is only significant for the penetration rate, but not the adoption lag. A higher education level increases the penetration level, as expected by the literature reviewed. Following from the literature review, Acemoglu (1998) states that the educated workers attract complementary technology, which increases the penetration of the technologies. Interestingly, this effect is not significant for tertiary education. This may suggest that a secondary education already enables the operation of all technologies. Openness has no statistically significant effect on any of the two dependent variables. Institutions are only statistically significant for the adoption lag. As expected, good institutions decrease the adoption lag.

The R^2 is below 25% for the adoption lag, which is not very high. This means that the included control variables are able to explain 23% of the variation of the adoption lag. For the penetration rate, in contrast, we can explain much more, with a R^2 of above 78%. By including time dummies, we account for time-specific effects that otherwise may drive our results. In addition to time-specific effects, these dummies can account for measurement errors in income inequality measures resulting from worldwide changes in the calculation of the income share. Interestingly, time dummies for the adoption lag are only significant in the years 1965 and 1970. This is the time period 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 of the observations in the early period, where the bias is most severe.

In conclusion, we find partial support for our hypothesess 1a and 1b. For 1a we find support with regards to an increased income share of the rich compared to the middle class, which decreases the adoption lag. However, the lag does not decrease when the rich increase their income share compared to the poor. From this finding we derive that hypothesis 1b as well is partially true, because increasing the share of the poor compared to the middle class or the rich decreases the adoption lag. Hence, new technologies seem particularly useful to the poor, which suggests taste heterogeneity among the income classes. With regards to the penetration rate, we find support for our hypothesis 2. Redistribution from the poor to the rich as well as redistribution from the poor or the rich to the middle class increases the penetration rate. Hence, we end up in the second type of equilibrium. The Gini coefficient might be too general for both dependent variables, as it is not able to capture opposing effects within the income distribution.

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

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LAG	LAG	LAG	PEN	PEN	PEN
GINI	0.00226			-0.000721		
	(0.00532)			(0.00381)		
Q1		-0.0769*			-0.0797**	
		(0.0459)			(0.0322)	
MiddleClass		0.0263	0.103*		0.0309**	0.111**
		(0.0165)	(0.0609)		(0.0122)	(0.0433)
Q5			0.0769*			0.0797**
			(0.0459)			(0.0322)
lnGDPpcMAD	-2.217**	-2.188**	-2.188**	6.143***	6.193***	6.193***
	(0.890)	(0.895)	(0.895)	(0.575)	(0.569)	(0.569)
primary_educ	0.000995	0.00189	0.00189	0.00993***	0.0108***	0.0108***
	(0.00407)	(0.00387)	(0.00387)	(0.00347)	(0.00345)	(0.00345)
secondary_educ	0.00291	0.00346	0.00346	0.0120***	0.0128***	0.0128***
	(0.00423)	(0.00448)	(0.00448)	(0.00344)	(0.00352)	(0.00352)
tertiary_educ	0.00338	-0.000252	-0.000252	0.0108**	0.00652	0.00652
	(0.00806)	(0.00816)	(0.00816)	(0.00514)	(0.00541)	(0.00541)
OPENNESS	0.00141	0.00148	0.00148	-0.000335	-0.000281	-0.000281
	(0.000977)	(0.00102)	(0.00102)	(0.000573)	(0.000560)	(0.000560)
INSTITUTIONS	-0.0226*	-0.0256*	-0.0256*	-0.00721	-0.0107	-0.0107
	(0.0130)	(0.0135)	(0.0135)	(0.00742)	(0.00737)	(0.00737)
Constant	4.723***	3.945***	-3.743	-8.554***	-9.671***	-17.64***
	(1.013)	(0.943)	(4.940)	(0.673)	(0.660)	(3.639)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	186	186	186	186	186	186
R^2	0.238	0.247	0.247	0.784	0.796	0.796

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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 Middle Class consists of the quantiles Q2, Q3 and Q4. Q1 are the poorest and Q5 are the richest 20% of a country. GDP per capita 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 and selection bias and to check the validity of our core specifications results. First, we start by discussing the IV regression to check for 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 do separate estimates for Western and non-Western countries. Fifth, we include the dummy (Invention Year-1820) into the estimation, these results are shown in figures 7 and 9 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 statistically significant on the 1% level, with a huge magnitude on the Gini coefficient. In column (2), we see that the IV estimate neither has a significant effect on the adoption lag nor on the penetration rate, like the Gini coefficient in the core specification in table 4. It might be that the Gini is not significant due to opposing effects in the income distribution on both dependent variables. Nevertheless and as we expected, the IV estimate on the adoption lag is negative. Accordingly, it is possible that endogeneity leads to an upward bias of the adoption lag in the core specification. The magnitude of the IV of both estimates is more negative than our estimates in the core specification 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 rather causes an upward bias in our coefficients. In case of an attenuation bias due to measurement error, the estimate is biased towards zero. This may be the case here for the penetration rate, as the IV estimate is more negative than the Gini coefficient in our core specification. We cannot reject the Null hypothesis that structural inequality, accounted for by the IV, is relevant for the adoption lag or the penetration rate. Furthermore, for both the adoption lag and the penetration rate, there is a potential upward bias.

Second, we check whether our sample suffers from selection bias. Due to the fact that we restrict our sample to observations made from 1960 onwards, of old technologies with an early invention year, only observations of countries with a long adoption lag are included. As discussed in section 5 'Data', the technologies for which this selection bias is most severe are cars, ships and aviation - freight. As a consequence, we exclude these observations, which sum up to only six. The countries of the excluded observations are China, Mauritius, South Korea, Sri Lanka and Thailand. Interestingly, China, South Korea and Mauritius are identified as outliers in the analysis of the residual plots below in the seventh robustness check. In table 16, we show the estimation output of the smaller sample, finding no significant results of the inequality measures on the adoption lag anymore. The standard errors are similar, but the magnitudes drop, while 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 that the magnitudes for all quantile income estimates drop. Accordingly, we interpret that there may also be a selection bias for the penetration rate, which triggers an upward bias. Another possible explanation is that the effects are driven by technology-specific effects. This can be verified by including technology dummies.

Third, we check for technology-specific effects. Including technology dummies gives us no significant results for any income inequality measure on adoption lags anymore. For the penetration rate estimation, we now get statistically significant results for the quantile income shares even on the 1% level. The signs are equal as in the core estimation, but the magnitudes dropped. The technology dummies are ordered by invention date and interpreted against the technology Cars. We see that the two first technologies, Ships and Aviation Freight, significantly increase the penetration rate compared to the Cars. The technologies from Blast Oxygen Steel to the Internet, which are all invented from 1950 onwards, have a significant negative effect on the adoption lags. This effect increases with a more recent invention date. This may account, additional to the time dummies, for the faster adoption of newer technologies due to globalization. We show these results in table 17. We conclude that particularly technology-specific factors are important, which we have neglected in our specification of the adoption lags. For the penetration rate, the technology dummies do not change our conclusion from the core specification. Overall, we have relatively few observations for each technology. With a bigger sample it would be interesting to disentangle the different effects. The small size of our sample 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 Western and non-Western samples. We start by including country group dummies into the core specifications. Following the classification of Comin and Hobijn (2010), we create five groups: OECD, Latin, Sub Saharan, Tigers and Other Countries. In table 18, we show the results of the estimation. For both dependent variables, we find the same effects for quantile income shares as in the core specification. Interestingly, for the adoption lag, the quantile income shares estimates are much more significant now due to an increase in the magnitudes of the coefficients. Now, the Gini coefficient has a positive effect on the penetration rate, which is the opposite of the expected sign. The region dummies are interpreted against OECD, which is excluded. We observe significant and positive effects in the adoption lag specifications for all country group dummies. Consequently, these regions have higher adoption lags on average compared to the OECD countries. For the penetration rates, we find the Tiger countries having higher penetration rates on average. Consequently, the Tiger countries seem to have longer lags and higher penetration compared to OECD countries. This is counterintuitive. Analyzing the summary statistics of the inequality measures for the Tigers, which are not shown, 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 shares for the rich increase the adoption lag and high income shares for the middle class increase the penetration rate. In tables 19 and 20, we show the estimations for the samples of Western and non-Western countries separately. We find the same signs for the inequality measures as in the core estimation. However, in Western countries, only the estimates for the adoption lag are significant. The magnitudes are much higher than in the core specification for these results.

The smaller the difference in the income shares of the middle class to the poor or the rich, the more important is the middle class. We analyze the difference in the summary statistics in tables in tables 13 and 14. We see that the difference between the average income shares of the middle class relative to the poor is bigger and to the rich is smaller in Western countries than in non-Western countries. This suggests that a strong middle class relatively to the poor and the rich. This hampers the initial adoption and therefore increases the adoption lag in the West. This may explain part of the convergence in adoption lags. Moreover, the high income share of the middle class in Western countries increases the penetration rate and leads to divergence of the penetration rates between the two groups.

We conclude that there is some support for the convergence of adoption lags and divergence of penetration rates between Western and non-Western countries. Nevertheless, it is possible that we look at the wrong time period or not at the relevant drivers. A further interesting robustness test would be including an interaction term of Western countries, in order to check whether the returns of inequality differ between the two country groups.

Fifth, in table 21 we include 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 is, the lower the adoption lag and the penetration rate are. 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 Western countries and compared to the US the penetration rate decreases faster in the West than in non-Western countries. Even when excluding the possible sample selection bias, we still get the same results. This suggests that convergence and divergence may not be driven by the specific technologies included in our sample. Alternatively, we may have too many observations of technologies with a recent and similar 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 22, in order to determine whether we account for the relevant variables that drive the margins over time. We find highly significant estimates for the variable 'difference of years to invention year'. However, no inequality measures have a statistically significant effect on the adoption lag. The quantile income shares have still a statistically significant on the 5% level on the penetration rate.

Finally, we discuss the residual plots and the issue of heteroskedasticity. Heteroskedasticity is present if the variance of the error varies with different values of a control variable. In figures 11 to 16, we show the residual plots for our core specification estimations. In figures 11 and 12, we show in the three graphs 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. Thus, in the top row on the left is the estimation with the Gini coefficient, in the middle with the exclusion of the rich and on the right the exclusion of the poor quantile income shares. For both margins we find in the top row the majority along the linear fit however, there are few observations that have some deviation. In the bottom row of figures 11 and 12 we show the residual plots for the adoption lag and penetration rate. Again, from left to the right, are the graphs corresponding to the three rows in the core estimation. In figure 11 and 12, we find few big deviations for some observations of the fitted values from the actually observed ones and thus high residual values for the adoption lag. We find China and Mauritius above a deviation of two and the countries Finland and Switzerland below minus two. Finland is a huge outlier with a deviation of -6.94. 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 higher as well compared to the penetration rate. In figure 12, we find in the residual plots in the bottom row four countries that are below or above one deviation point for the penetration rate estimation. While South Korea is above, Algeria, Hungary and Colombia are below. In figures 13 to 16, we show the residual plots of the dependent variables versus the inequality measures. Again, we see a similar picture with the same countries as outliers. Overall, we find that the outliers for the adoption lag are further away than for the penetration rate. Consequently, due to some outliers we conclude that there are indications for heteroskedasticity. Without correcting the standard errors for heteroskedasticity, we would still have consistent estimates and therefore we could interpret the coefficients. But as the estimates are no longer BLUE, POLS is not the estimation method with the smallest variance and therefore not the most efficient method 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 thereby gives the highest weight to the observations with the largest error terms. With the heteroskedasticity-robust error terms, we weight the observations far away from the regression line less, because we consider them less relevant to give us information about the true regression line. Hence, instead of equally weighting all observations, we give more weight to those close to our regression line.

7 Discussion

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

Altogether, we find support for our hypotheses. 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 reject the Null hypothesis that a higher Gini coefficient decreases the adoption lag. Due to opposite effects in the quantile income shares, this overall inequality measure may be too broad to be significant. For the penetration rate we find as well opposite effects. Redistribution from the poor to the rich and from the rich to the middle class increases the penetration rate, even though the former increases and the latter decreases overall inequality. Hence, the Gini coefficient is too general again. Furthermore, we find that redistribution from the poor to the middle class increases the penetration rate. These findings stress the importance of a strong middle class with regards to the penetration rate.

We perform six different robustness checks to examine whether our core specifications suffer from a bias. First, from our IV estimation we find no support that overall inequality affects the adoption lag or the penetration rate. If our core estimates are biased due to measurement error, simultaneity bias, or omitted variable bias due to hidden preferences, this rather causes an upward bias in our coefficients. The sample may suffer from a selection bias which causes upward biased estimates, particularly for the adoption lag estimation. For the penetration rate, may as well contain a selection bias. This may be an upward bias and is rather small. Including technology-dummies results in non-significant estimates for the adoption lags. As there may be some underlying factors, we cannot observe, we should be cautious about our findings. Omitted variables may cause our estimates to be biased or the marginal effects for the technologies to be different. For the penetration rate, the results are robust to the inclusion of the technology dummies. Moreover, we also control for country groups and find robust effects for quantile income shares on both dependent variables. In particular for the adoption lags, we find that all included regions (Latin, Sub Saharan, Tigers and Other Groups) have higher adoption lags compared to the OECD countries. We find support for the convergence of the adoption lags and divergence of the penetration rates between Western and non-Western countries by analyzing the summary statistics. The relatively high income share of the middle class in Western countries increases the adoption lag and the penetration rate in Western countries. Nevertheless, it is possible that investigating an earlier time period for this pattern would be more relevant. In contrast to Comin and Mestieri (2013a), when estimating for the two country groups separately we only find support for increasing penetration in Western countries due to the relatively strong middle class. Furthermore, the 'difference of years to invention year' dummy is highly significant and causes the quantile income share dummies to be insignificant for the adoption lag. This suggests that we have not controlled for some hidden but relevant factors and hence suffer from omitted variable bias. Finally, in the residual plots we observe some outliers. By applying heteroskedasticy-robust standard errors we get correct standard errors and therefore, more efficient results. In conclusion, we find support for our two hypotheses. Nevertheless, some findings of our robustness checks call for a cautious interpretation of our results. Particularly the results for the adoption lags seem not to be very robust. More precisely, we cannot rule out simultaneity bias, and there remain doubts about measurement error and omitted variable bias. Measurement error may arise due to bad quality of inequality data while omitted variable bias may be caused by a selection bias or technology-specific factors.

In conclusion, the robustness of our estimations can be confirmed. We highlight the importance of applying quantile income shares. Without such a detailed inequality measure, we would not be able to detect the relevant effects on both dependent variables. Furthermore, our results may only be relevant for the eight technologies we were able to match to our covariates. These technologies are ships, cars, aviation - freight, blast oxgen steel, cellphones, PCs, MRI and the internet. Further research may investigate whether the effects are equal for the diffusion of other technologies.

Further research could address various aspects, such as improving the dataset or controlling for further channels that compete with our hypotheses or including an additional variable we have not controlled for. The dataset could be improved with regard to technology data. By including more technologies, it may be possible to control better for technology-specific effects or to discover different marginal returns of the covariates on the diffusion of different technologies. For example by Caselli (1999), proposes that different kinds of technologies have different effects on the wage. Accordingly, the simultaneity bias may be hidden due to these possibly opposing effects. Furthermore, it would be important to investigate a longer time period, rather than the relatively short period from 1960 to 1995. It is possible that this period is either too short or not relevant determining 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 suffer from a selection bias or convergence and divergence have already happened before that period of time. 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 is as well suited to track other measures of inequality.

Another possible extension is the inclusion of a measure of general purpose technologies (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 possibly competing channel to inequality affecting the adoption lag are government services. If the government supplies GPTs and other complementary 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.

Furthermore, an interesting channel worth investigating is the influence of politics. Possibly, it is not the income of the middle class that directly increases penetration rate through incentives for process innovation. A stronger middle class may as well demand more services from their politicians, who then facilitate the diffusion of technologies.

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 hypothesis 1a suggests that the adoption lag decreases when the rich have a high share of the income and therefore can afford the new luxury products. Hypothesis 1b states that new technologies are particularly useful to the poor or the middle class and hence if they increase their income the adoption lag decreases.

The model of Föllmi, Würgler 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 and poor. Hence, with a high income share of the poor, the penetration rate is higher as incentives for process innovation are increased. Therefore, redistribution from the rich to the poor decreases overall inequality and increases the penetration rate. With regards to the middle class we find two theoretically possible equilibria. Our hypothesis depends on whether the middle class is relatively rich or relatively poor. In case that the middle class is relatively rich we are in the first type of equilibrium. Then redistribution from the poor to the middle class increases product innovation as the relatively rich buy high quality products. In the second type of equilibrium the redistribution from the poor to the middle class increases process innovation as they cannot afford the high quality products and buy the mass products. In both equilibria redistribution from the rich to the middle class reduces product innovation incentives and hence increases incentives for process innovations. Therefore, this leads to a higher penetration rate.

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 can confirm both, hypothesis 1a and 1b, to some extent. We find that the adoption lag is decreased by distortion-free redistribution of income from the middle class to the poor as well as to the rich. Hence, this confirms partially hypotheses 1a and 1b. As the rich and poor buy earlier the new goods. Hence, for the poor new technologies seem to be particularly useful but not for the middle class. The effect that new technologies are more useful to the poor seems to dominate the income effect of the rich. As redistribution from the rich to the poor decreases the adoption lag, too.

For the penetration rate the results suggest, as predicted by hypothesis 2, that lower overall inequality increases the penetration rate. Furthermore, the importance of the middle class is stressed by the results. Our estimation results suggest a relatively rich middle class and hence the second type of equilibrium. As a strong middle class compared to the rich as well as compared to the poor is important for a high penetration rate.

Moreover, for both the adoption lag and the penetration rate opposite effects within the income distribution are relevant. A weak middle class but high income shares for the poor and the rich decrease he adoption lag. For the penetration rate a strong middle class compared to the poor and rich increases the penetration rate. As a consequence, disentangling the effects by quantile income shares is crucial, which is not possible with the broad Gini coefficient. We may stress that we only analyze how distortion-free redistribution affects our dependent variables. But not how this redistribution is applicable in practice. As probably any intervention will distort some incentives.

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 middle class compared to the rich is smaller and compared to the poor is bigger in Western than in non-Western countries. Our estimation results suggest that this leads to a higher adoption lag and a higher penetration rate. We conclude that a strong middle explains some of the convergence of adoption lags and divergence of penetration rates between Western and non-Western countries. In addition to the higher GDP and more openness is important in order to decrease adoption lags. For the penetration rate GDP and education are relevant.

We are not able to rule out simultaneity bias, measurement error and omitted variable bias, due to our IV estimation, which is not significant for both dependent variables. The issue of selection bias remains and could cause inconsistent estimates. Additionally, our results are not robust for adoption lags 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 non conclusive results for income inequality on the two margins when separating 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 though 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 income dynamics between countries.

9 References

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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
Total		**830**	**45.48**	**38.54**	**2.62**	**9.00**	**32.50**	**99.26**	**178.15**

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** [3]
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
Total		**186**	**16.09**	**22.96**	**1.00**	**5.85**	**12.79**	**19.28**	**178.59**	

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
Total		**830**	**-0.85**	**0.97**	**-3.84**	**-2.13**	**-0.60**	**0.03**	**0.70**

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

Technologyname	Invention Year	Obs	mean[4]	sd	p1	p10	p50	p90	p99	difference to 830 obs sample [5]	difference to CM 2010 sample [6]
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
Total		**186**	**-0.94**	**0.87**	**-3.84**	**-2.13**	**-0.70**	**-0.07**	**0.52**		

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

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

6 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
Total	**59**	**100**	

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				
				Total	**127**	**100**	

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)
lnGDPpcMAD	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
lnGDPpcMAD	186	1.19	0.10	0.81	1.39
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
Lwheatsugar	175	0.16	0.20	-0.33	0.54

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
lnGDPpc	59	1.28	0.04	1.22	1.35
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
Lwheatsugar	59	.27	0.16	0.02	0.54

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
lnGDPpc	127	1.15	0.10	0.81	1.24
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
Lwheatsugar	116	0.10	0.19	-0.33	0.47

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

	(1)	(2)	(3)
VARIABLES	GINI	LAG	PEN
lwheatsugar	-20.34***		
	(3.475)		
GINI		-0.00977	-0.0112
		(0.0189)	(0.00954)
lnGDPpcMAD	-20.84**	-2.819**	5.532***
	(9.548)	(1.168)	(0.614)
primary_educ	0.0637	0.00403	0.0127***
	(0.0645)	(0.00358)	(0.00331)
secondary_educ	-0.135**	0.00307	0.0122***
	(0.0529)	(0.00551)	(0.00420)
tertiary_educ	0.303***	0.0124	0.0153***
	(0.0901)	(0.00989)	(0.00560)
OPENNESS	-0.0170	0.000781	-0.00234**
	(0.0199)	(0.00147)	(0.00113)
INSTITUTIONS	0.00958	-0.0294**	-0.00249
	(0.146)	(0.0124)	(0.00762)
Constant	62.31***	5.729***	-7.521***
	(11.26)	(1.901)	(0.956)
Time Dummy	Yes	Yes	Yes
Observations	175	175	175
R^2	0.445	0.284	0.787

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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. Exluding Observations of Cars, Ships and Aviation-Freight.

VARIABLES	(1) LAG	(2) LAG	(3) LAG	(4) PEN	(5) PEN	(6) PEN
GINI	0.00396			0.00116		
	(0.00461)			(0.00332)		
Q1		-0.0398			-0.0545**	
		(0.0408)			(0.0244)	
MiddleClass		0.00521	0.0451		0.0196**	0.0740**
		(0.0117)	(0.0509)		(0.00831)	(0.0313)
Q5			0.0398			0.0545**
			(0.0408)			(0.0244)
lnGDPpcMAD	-1.337**	-1.269*	-1.269*	6.718***	6.704***	6.704***
	(0.648)	(0.657)	(0.657)	(0.482)	(0.486)	(0.486)
primary_educ	0.00121	0.00188	0.00188	0.00815**	0.00875***	0.00875***
	(0.00295)	(0.00288)	(0.00288)	(0.00327)	(0.00325)	(0.00325)
secondary_educ	0.00115	0.00229	0.00229	0.00933***	0.00975***	0.00975***
	(0.00387)	(0.00419)	(0.00419)	(0.00310)	(0.00316)	(0.00316)
tertiary_educ	0.00440	0.00261	0.00261	0.00830*	0.00575	0.00575
	(0.00692)	(0.00709)	(0.00709)	(0.00498)	(0.00522)	(0.00522)
OPENNESS	0.000796	0.000825	0.000825	-0.000669	-0.000616	-0.000616
	(0.000801)	(0.000815)	(0.000815)	(0.000488)	(0.000486)	(0.000486)
INSTITUTIONS	-0.0288**	-0.0301**	-0.0301**	-0.00782	-0.00998	-0.00998
	(0.0126)	(0.0130)	(0.0130)	(0.00664)	(0.00664)	(0.00664)
Constant	3.708***	3.729***	-0.256	-9.145***	-9.720***	-15.17***
	(0.770)	(0.766)	(4.403)	(0.561)	(0.556)	(2.783)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	180	180	180	180	180	180
R^2	0.236	0.239	0.239	0.834	0.839	0.839

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 17: Robustness Check. Including Technology Dummies.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LAG	LAG	LAG	PEN	PEN	PEN
GINI	0.00413			0.000701		
	(0.00307)			(0.00292)		
Q1		-0.0253			-0.0602***	
		(0.0262)			(0.0226)	
MiddleClass		0.00241	0.0277		0.0217***	0.0819***
		(0.00643)	(0.0318)		(0.00726)	(0.0288)
Q5			0.0253			0.0602***
			(0.0262)			(0.0226)
lnGDPpcMAD	-0.546*	-0.535*	-0.535*	6.801***	6.794***	6.794***
	(0.294)	(0.303)	(0.303)	(0.420)	(0.418)	(0.418)
primary_educ	-0.00162	-0.00117	-0.00117	0.00725***	0.00799***	0.00799***
	(0.00195)	(0.00175)	(0.00175)	(0.00249)	(0.00245)	(0.00245)
secondary_educ	-0.000926	-0.000501	-0.000501	0.00837***	0.00906***	0.00906***
	(0.00195)	(0.00222)	(0.00222)	(0.00254)	(0.00263)	(0.00263)
tertiary_educ	-0.000522	-0.00128	-0.00128	0.00894*	0.00596	0.00596
	(0.00332)	(0.00355)	(0.00355)	(0.00509)	(0.00516)	(0.00516)
OPENNESS	0.000693**	0.000723**	0.000723**	-0.000689	-0.000625	-0.000625
	(0.000301)	(0.000309)	(0.000309)	(0.000573)	(0.000567)	(0.000567)
INSTITUTIONS	-0.00127	-0.00195	-0.00195	-0.00287	-0.00535	-0.00535
	(0.00485)	(0.00505)	(0.00505)	(0.00623)	(0.00610)	(0.00610)
Ships	0.264	0.239	0.239	2.165***	2.139***	2.139***
	(0.672)	(0.684)	(0.684)	(0.374)	(0.347)	(0.347)
Aviation - Freight	-0.455	-0.438	-0.438	1.001**	1.027**	1.027**
	(0.371)	(0.375)	(0.375)	(0.469)	(0.462)	(0.462)
Blast Oxygen Steel	-2.083***	-2.081***	-2.081***	0.394	0.468	0.468
	(0.695)	(0.692)	(0.692)	(0.278)	(0.287)	(0.287)
Cellphones	-4.933***	-4.936***	-4.936***	-0.186	-0.114	-0.114
	(1.610)	(1.610)	(1.610)	(0.210)	(0.212)	(0.212)
PCs	-4.835***	-4.838***	-4.838***	0.258	0.332	0.332
	(1.576)	(1.576)	(1.576)	(0.208)	(0.209)	(0.209)
MRI	-5.187***	-5.186***	-5.186***	-0.0253	0.0558	0.0558
	(1.396)	(1.394)	(1.394)	(0.261)	(0.258)	(0.258)
Internet	-5.764***	-5.761***	-5.761***	-0.102	-0.0243	-0.0243
	(1.580)	(1.577)	(1.577)	(0.226)	(0.225)	(0.225)
Constant	5.029***	5.181***	2.652	-9.580***	-10.33***	-16.35***
	(0.794)	(0.842)	(2.515)	(0.482)	(0.517)	(2.543)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	186	186	186	186	186	186
R^2	0.734	0.734	0.734	0.873	0.879	0.879

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 18: Robustness Check. Including Country Group Dummies.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	LAG	LAG	LAG	PEN	PEN	PEN
GINI	-0.00945			0.00859*		
	(0.00625)			(0.00465)		
Q1		-0.0977**			-0.0815***	
		(0.0468)			(0.0296)	
MiddleClass		0.0625**	0.160**		0.0216*	0.103**
		(0.0245)	(0.0678)		(0.0123)	(0.0399)
Q5			0.0977**			0.0815***
			(0.0468)			(0.0296)
lnGDPpcMAD	-1.689**	-1.559**	-1.559**	6.216***	6.319***	6.319***
	(0.797)	(0.780)	(0.780)	(0.484)	(0.491)	(0.491)
primary_educ	0.00265	0.00300	0.00300	0.0109***	0.0118***	0.0118***
	(0.00380)	(0.00368)	(0.00368)	(0.00335)	(0.00339)	(0.00339)
secondary_educ	0.00258	0.00288	0.00288	0.0128***	0.0136***	0.0136***
	(0.00417)	(0.00435)	(0.00435)	(0.00335)	(0.00344)	(0.00344)
tertiary_educ	0.00855	0.00295	0.00295	0.00470	0.00198	0.00198
	(0.00724)	(0.00740)	(0.00740)	(0.00486)	(0.00515)	(0.00515)
OPENNESS	5.94e-05	0.000167	0.000167	-0.00233***	-0.00222***	-0.00222***
	(0.000962)	(0.000972)	(0.000972)	(0.000618)	(0.000628)	(0.000628)
INSTITUTIONS	-0.00790	-0.00991	-0.00991	-0.00310	-0.00393	-0.00393
	(0.0114)	(0.0114)	(0.0114)	(0.00807)	(0.00806)	(0.00806)
Latin	0.620***	0.925***	0.925***	-0.337**	-0.162	-0.162
	(0.230)	(0.335)	(0.335)	(0.136)	(0.141)	(0.141)
Sub Saharan	1.092**	1.302**	1.302**	-0.263	-0.136	-0.136
	(0.508)	(0.562)	(0.562)	(0.212)	(0.229)	(0.229)
Tigers	0.750**	0.847**	0.847**	0.704***	0.765***	0.765***
	(0.356)	(0.361)	(0.361)	(0.189)	(0.176)	(0.176)
Other Groups	0.521***	0.684***	0.684***	-0.136	-0.0517	-0.0517
	(0.157)	(0.196)	(0.196)	(0.0880)	(0.0961)	(0.0961)
Constant	4.260***	1.263	-8.505	-8.848***	-9.282***	-17.44***
	(0.970)	(1.111)	(5.375)	(0.584)	(0.672)	(3.413)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	186	186	186	186	186	186
R^2	0.284	0.315	0.315	0.828	0.834	0.834

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 19: 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	0.0230	-0.00263				
	(0.0311)	(0.00420)				
Q1			-0.289**	-0.0503		
			(0.129)	(0.0428)		
MiddleClass			0.192*	0.0195	0.482**	0.0697
			(0.114)	(0.0163)	(0.225)	(0.0580)
Q5					0.289**	0.0503
					(0.129)	(0.0428)
lnGDPpcMAD	0.381	-1.351**	3.489	-1.379**	3.489	-1.379**
	(4.497)	(0.629)	(4.311)	(0.648)	(4.312)	(0.648)
primary_educ	0.0211	0.00215	-0.00508	0.00255	-0.00508	0.00255
	(0.0301)	(0.00314)	(0.0276)	(0.00317)	(0.0276)	(0.00317)
secondary_educ	0.0158	0.00526	-0.00452	0.00644	-0.00452	0.00644
	(0.0292)	(0.00409)	(0.0264)	(0.00422)	(0.0264)	(0.00422)
tertiary_educ	0.0194	0.00357	-0.0149	0.00199	-0.0149	0.00199
	(0.0353)	(0.00858)	(0.0330)	(0.00835)	(0.0330)	(0.00835)
OPENNESS	0.00493**	0.000150	0.00431**	0.000155	0.00431**	0.000155
	(0.00207)	(0.000683)	(0.00198)	(0.000710)	(0.00198)	(0.000710)
INSTITUTIONS	0.0108	-0.00555	-0.0729	-0.00736	-0.0729	-0.00736
	(0.151)	(0.00727)	(0.104)	(0.00747)	(0.104)	(0.00747)
Constant	-0.826	3.807***	-8.982	3.112***	-37.91**	-1.915
	(5.610)	(0.684)	(5.761)	(0.819)	(18.05)	(4.710)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59	127	59	127	59	127
R^2	0.501	0.420	0.542	0.429	0.542	0.429

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 20: Penetration Rate. Separate Estimation with Western and non-Western Samples

VARIABLES	(1) Western	(2) non-Western	(3) Western	(4) non-Western	(5) Western	(6) non-Western
GINI	-0.00459	-0.00522				
	(0.00759)	(0.00435)				
Q1			-0.0170	-0.0520		
			(0.0450)	(0.0526)		
MiddleClass			0.0245	0.0268	0.0415	0.0788
			(0.0298)	(0.0179)	(0.0722)	(0.0695)
Q5					0.0170	0.0520
					(0.0450)	(0.0526)
lnGDPpcMAD	1.548	6.717***	1.863	6.667***	1.863	6.667***
	(0.929)	(0.572)	(1.241)	(0.589)	(1.241)	(0.589)
primary_educ	0.00242	0.0126***	0.00154	0.0131***	0.00154	0.0131***
	(0.00778)	(0.00433)	(0.00818)	(0.00431)	(0.00818)	(0.00431)
secondary_educ	0.00302	0.0105**	0.00280	0.0112**	0.00280	0.0112**
	(0.00799)	(0.00418)	(0.00810)	(0.00441)	(0.00810)	(0.00441)
tertiary_educ	0.00750	0.00934	0.00554	0.00763	0.00554	0.00763
	(0.00679)	(0.00702)	(0.00893)	(0.00714)	(0.00893)	(0.00714)
OPENNESS	-0.000844	-0.000323	-0.000834	-0.000340	-0.000834	-0.000340
	(0.000841)	(0.000530)	(0.000817)	(0.000545)	(0.000817)	(0.000545)
INSTITUTIONS	0.0218	-0.00772	0.0116	-0.00984	0.0116	-0.00984
	(0.0444)	(0.00812)	(0.0361)	(0.00827)	(0.0361)	(0.00827)
Constant	-2.270	-9.041***	-3.833*	-10.12***	-5.532	-15.32***
	(1.571)	(0.677)	(2.101)	(0.736)	(6.500)	(5.696)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59	127	59	127	59	127
R^2	0.318	0.728	0.332	0.737	0.332	0.737

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 21: Robustness Check. Dummy Invention minus year 1820.

VARIABLES	(1) Lag Full Sample	(2) Lag Western	(3) Lag non-Western	(4) PEN Full Sample	(5) PEN Western	(6) PEN non-Western
yearminus1820	-0.0184***	-0.0464***	-0.0162***	-0.00381**	-0.0123***	-0.00614***
	(0.00160)	(0.00782)	(0.00114)	(0.00181)	(0.00372)	(0.00170)
Constant	5.192***	9.129***	5.056***	-0.368	1.690***	-0.371
	(0.241)	(1.262)	(0.172)	(0.274)	(0.580)	(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<0.01, ** p<0.05, * p<0.1

Table 22: Robustness Check. Including Inventionyear Dummy.

VARIABLES	(1) LAG	(2) LAG	(3) LAG	(4) PEN	(5) PEN	(6) PEN
yearminus1820	-0.0227***	-0.0225***	-0.0225***	-0.0103***	-0.00967***	-0.00967***
	(0.00463)	(0.00455)	(0.00455)	(0.00161)	(0.00138)	(0.00138)
GINI	0.00526			0.000633		
	(0.00435)			(0.00333)		
Q1		-0.0219			-0.0561**	
		(0.0338)			(0.0244)	
MiddleClass		0.00115	0.0231		0.0201**	0.0763**
		(0.0106)	(0.0432)		(0.00842)	(0.0315)
Q5			0.0219			0.0561**
			(0.0338)			(0.0244)
lnGDPpcMAD	-0.797	-0.814	-0.814	6.785***	6.782***	6.782***
	(0.521)	(0.529)	(0.529)	(0.479)	(0.484)	(0.484)
primary_educ	-0.00198	-0.00159	-0.00159	0.00858***	0.00930***	0.00930***
	(0.00341)	(0.00326)	(0.00326)	(0.00315)	(0.00314)	(0.00314)
secondary_educ	-0.00231	-0.00228	-0.00228	0.00963***	0.0103***	0.0103***
	(0.00307)	(0.00328)	(0.00328)	(0.00304)	(0.00309)	(0.00309)
tertiary_educ	-0.000339	-0.000589	-0.000589	0.00917*	0.00637	0.00637
	(0.00589)	(0.00596)	(0.00596)	(0.00502)	(0.00524)	(0.00524)
OPENNESS	0.000760	0.000801	0.000801	-0.000629	-0.000570	-0.000570
	(0.000661)	(0.000675)	(0.000675)	(0.000497)	(0.000488)	(0.000488)
INSTITUTIONS	-0.0187*	-0.0191*	-0.0191*	-0.00543	-0.00784	-0.00784
	(0.0101)	(0.0105)	(0.0105)	(0.00640)	(0.00643)	(0.00643)
Constant	6.181***	6.437***	4.247	-7.895***	-8.602***	-14.22***
	(0.861)	(0.887)	(3.561)	(0.580)	(0.558)	(2.789)
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Observations	186	186	186	186	186	186
R^2	0.479	0.478	0.478	0.833	0.838	0.838

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

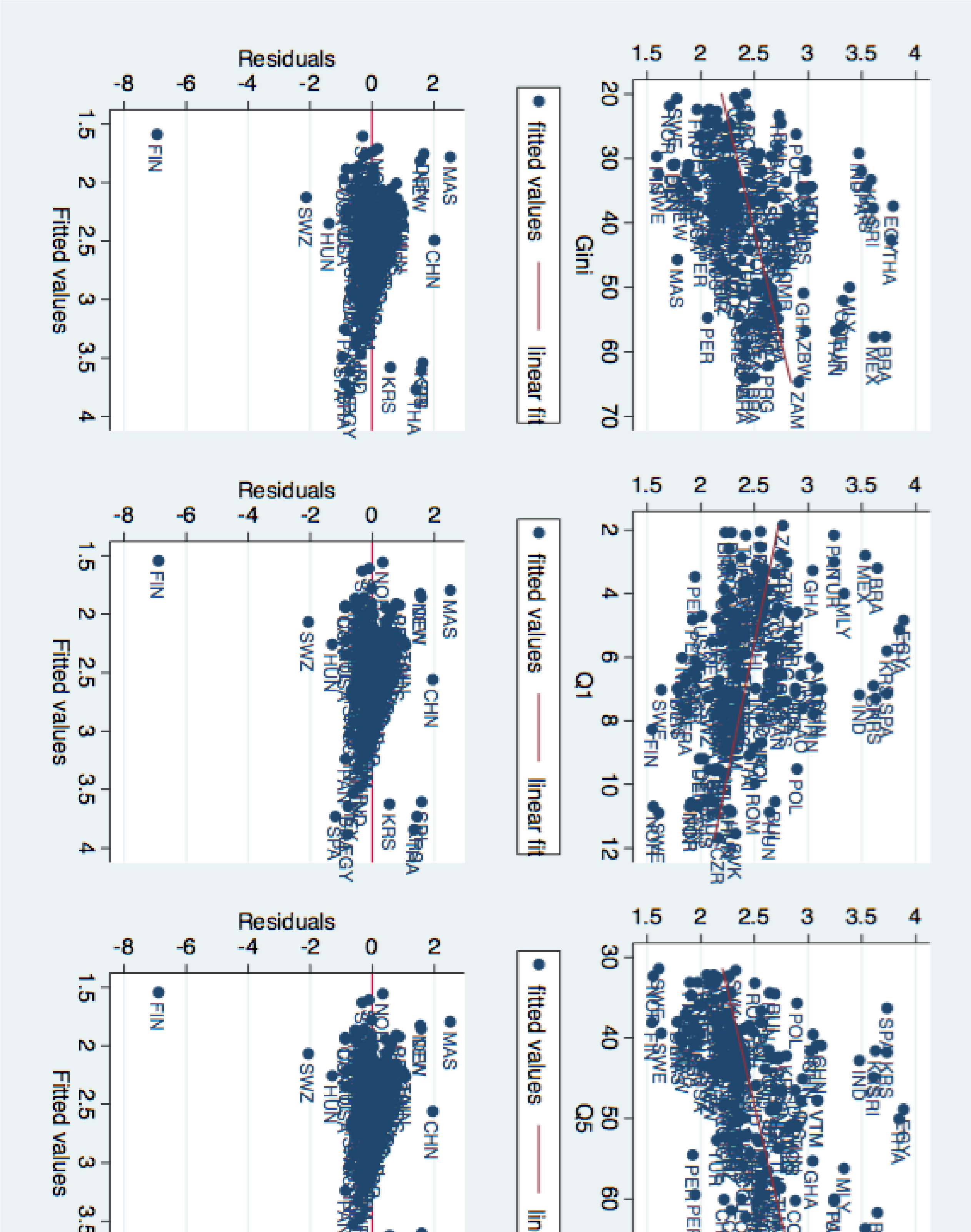

Figure 11: Adoption Lags. Above: Fitted Adoption Lags versus Inequality Measures. Below: Residuals versus Fitted Adoption Lags. For sub specifications 1-3 in table 4.

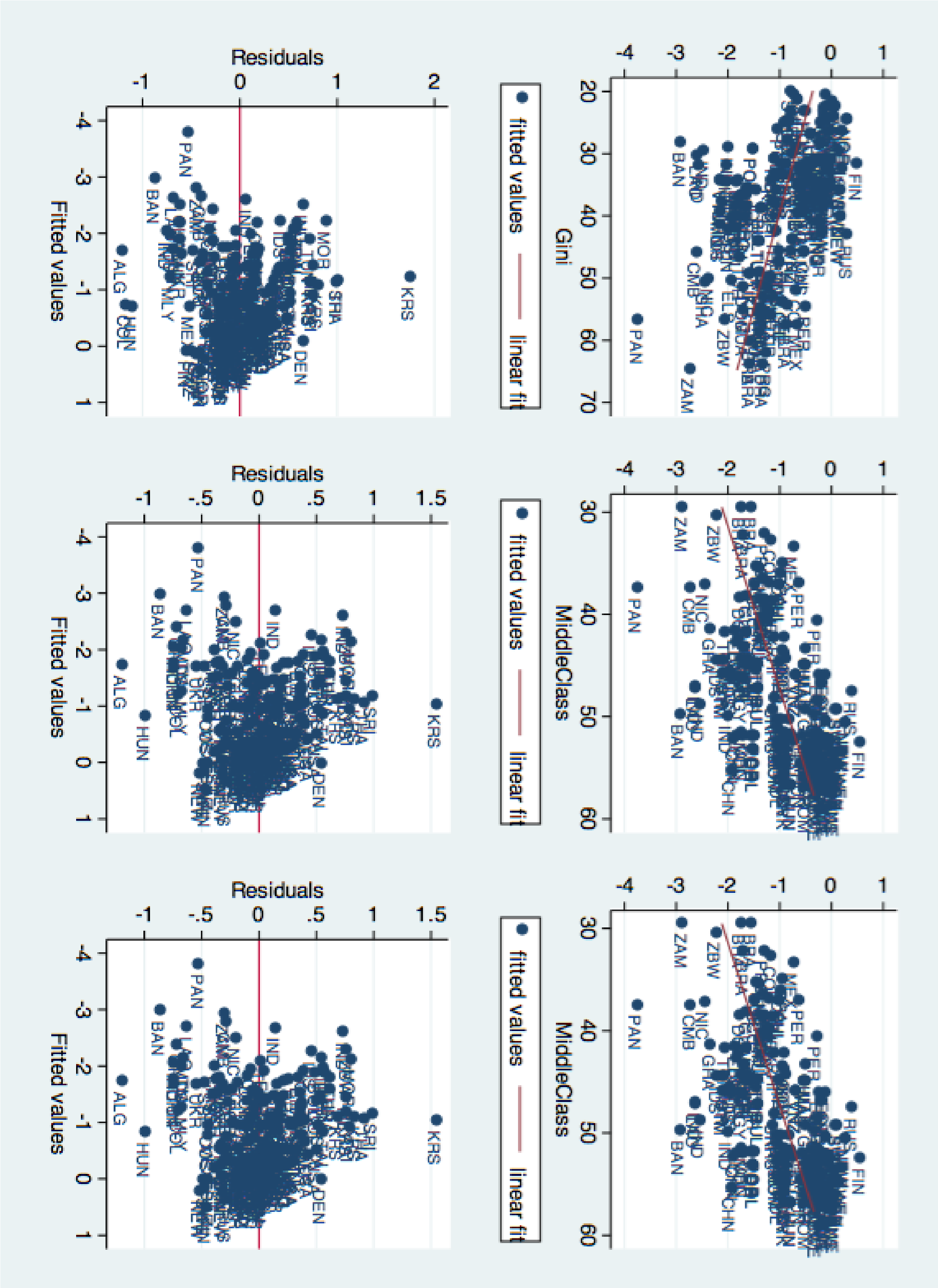

Figure 12: Penetration Rates. Above: Fitted Penetration Rates versus Inequality Measures. Below: Residuals versus Fitted Penetration Rates. For sub specifications 4-6 in table 4.

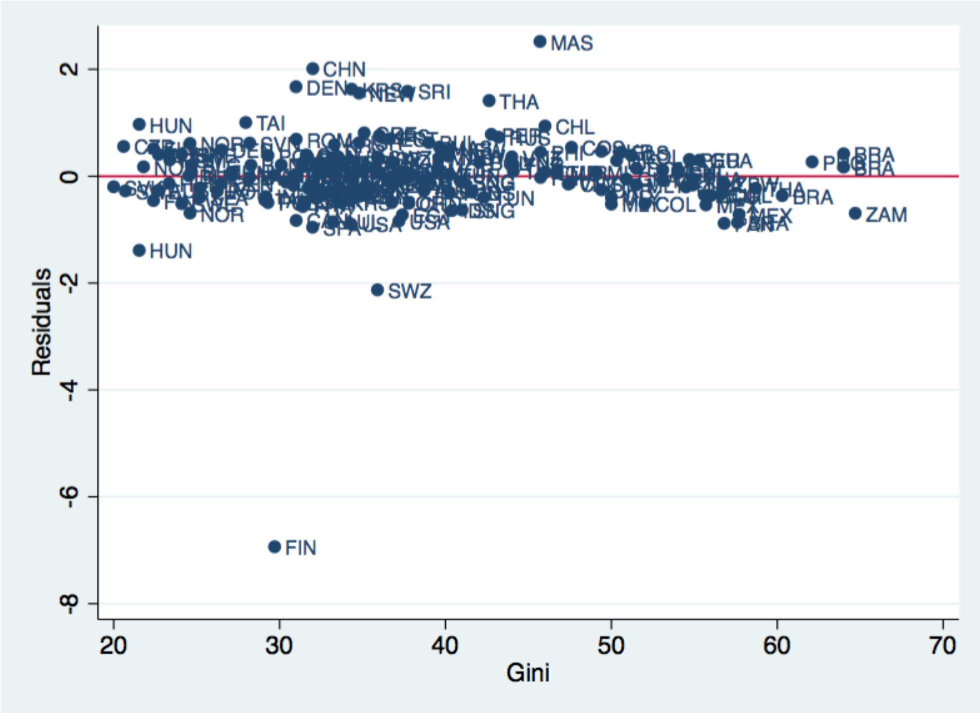

Figure 13: Residuals of Adoption Lags versus Predictor Gini. Based on sub specification 1 in table 4.

Figure 14: Residuals of Adoption Lags versus Predictor Middle Class. Based on sub specification 2 in table 4.

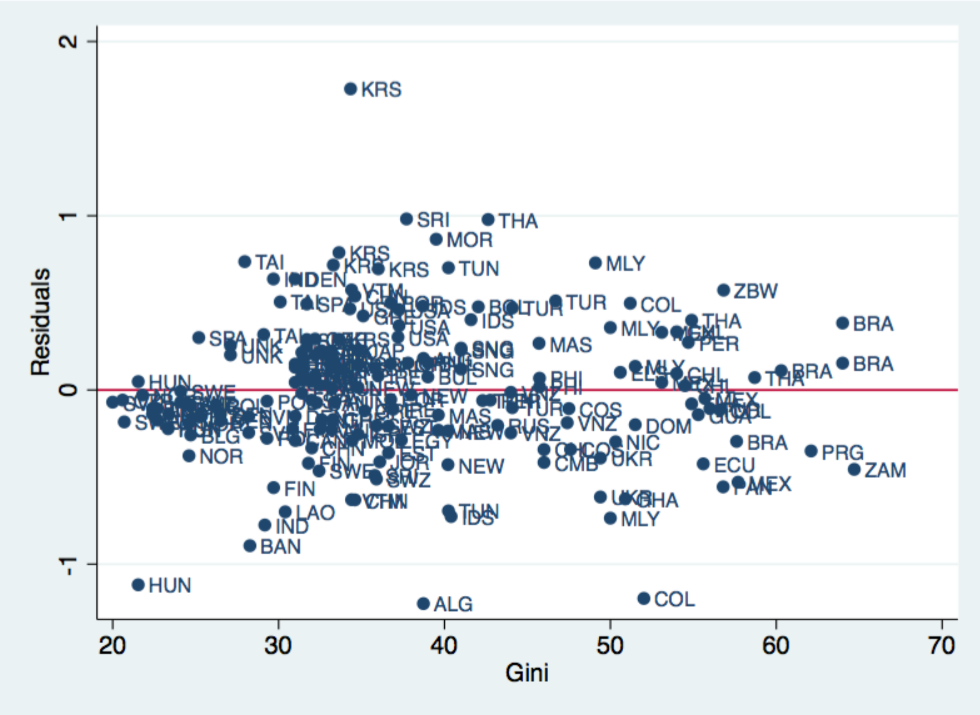

Figure 15: Residuals of Penetration Rates versus Predictor Gini. Based on sub specification 4 in table 4.

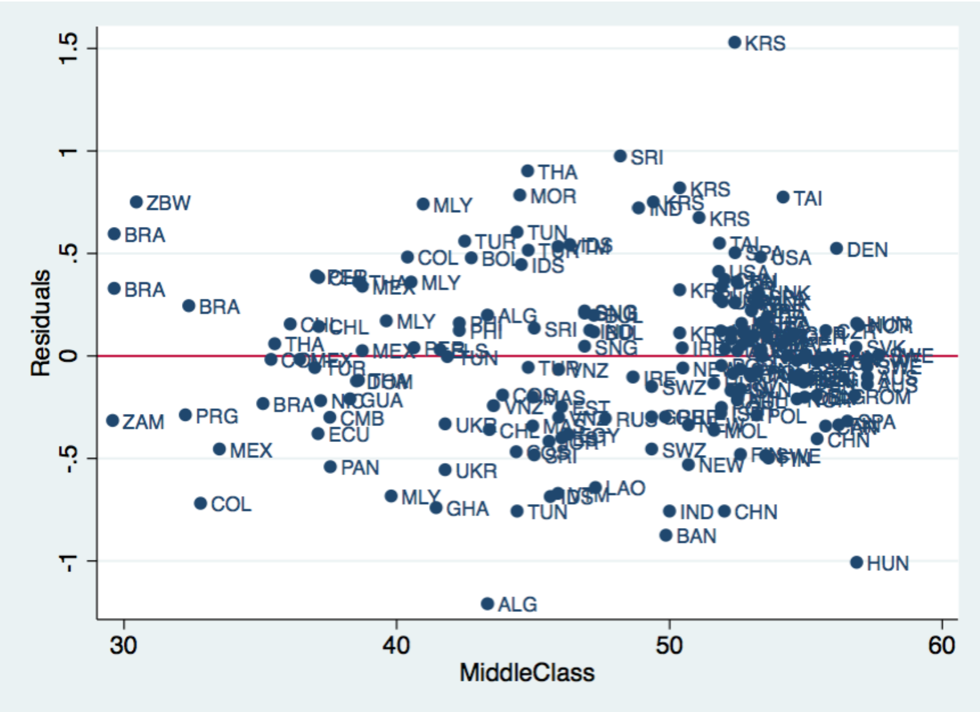

Figure 16: Residuals of Penetration Rates versus Predictor Middle Class. Based on sub specification 5 in table 4.

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

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

and

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

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

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

First, we simplify to

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

After rearranging, we get

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

Derivation of equation (17):
We start with the following definition

$$p_\tau = \left(\int_\tau^{t-D_\tau} p_{\tau,\upsilon}^{-\frac{1}{\mu-1}}\,d\upsilon\right)^{-(\mu-1)}.$$

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

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

Now we simplify

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

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

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

Derivation of equation (18):

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

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

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

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

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

$$p_{\tau,\upsilon}Y_{\tau,\upsilon} = \frac{wL_{\tau,\upsilon}}{1-\alpha} = \frac{X_{\tau,\upsilon}}{\alpha}.$$

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

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

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

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

Now we use the production function of the technology vintages:

$$Y_{\tau,\upsilon} \quad = \quad a_\tau Z(\tau,\upsilon)X^\alpha_{\tau,\upsilon}L^{1-\alpha}_{\tau,\upsilon}.$$

We expand this equation on the right hand side by the fraction $\frac{Z_\tau X^\alpha_\tau L^{1-\alpha}_\tau}{Z_\tau X^\alpha_\tau L^{1-\alpha}_\tau}$:

$$Y_{\tau,\upsilon} \quad = \quad \frac{a_\tau Z(\tau,\upsilon)X^\alpha_{\tau,\upsilon}L^{1-\alpha}_{\tau,\upsilon}}{Z_\tau X^\alpha_\tau L^{1-\alpha}_\tau} Z_\tau X^\alpha_\tau L^{1-\alpha}_\tau.$$

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

$$Y_{\tau,\upsilon}^{\frac{\mu-1}{\mu}} = a_\tau Z(\tau,\upsilon)\left(\frac{1}{Y_\tau}\right)^{\frac{1}{\mu}} X^\alpha_\tau L^{1-\alpha}_\tau.$$

Now we simplify

$$Y_{\tau,\upsilon} = \left(a_\tau Z(\tau,\upsilon)X^\alpha_\tau L^{1-\alpha}_\tau\right)^{\frac{\mu}{\mu-1}} \left(\frac{1}{Y_\tau}\right)^{\frac{1}{\mu-1}}.$$

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

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

Simplifying gives us first

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

and then

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

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

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

Derivation of equation (19):

We define that

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

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

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

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

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

Now, we integrate and get

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

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

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

Derivation of equation (25):

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 $L = (\int_{-\infty}^{\bar{\tau}} \int_{\tau}^{\bar{\upsilon}_\tau} L_{\tau,\upsilon} d\upsilon d\tau))$. Combining the market clearing condition and the wage rate of equation (14), which equals $(1-\alpha)\frac{p_{\tau,\upsilon}Y_{\tau,\upsilon}}{L_{\tau,\upsilon}} = w$, gives us the aggregate wage rate $w = \frac{(1-\alpha)Y}{L}$. We put the wage rate into p_τ 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_τ

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

which is equal to

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

Derivation of equation (26):

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

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

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

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

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

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

In the next step we take the first order Taylor approximation around Δt=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_τ. 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 Δt follows

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

Derivation of equation (27):

We plug equation (26) into equation (25) and get

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

Next we rearrange

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

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

$$y^c_{\tau t} = \beta^c_{\tau 1} + y^c_t + \beta_{\tau 2}t + \beta_{\tau 3}((\mu-1)ln(t - D^c_\tau - \tau) - (1-\alpha)(y^c_t - l^c_t) + \epsilon^c_{\tau t}. \qquad (22)$$

C Declaration of Authorship

”I hereby declare

- that I have written this thesis without any help from others and without the use of documents and aids other than those stated above,
- that I have mentioned all the sources used and that I have cited them correctly according to established academic citation rules,
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Dimitri Lenzin