

Income Inequality and Technology Diffusion

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Abstract

This paper investigates how household income inequality shapes the diffusion of technologies. A simple demand side model with hierarchical preferences is used to show that after some minimum level of average income relative to the price of the technology is achieved, more consumer inequality hinders the diffusion process for new technologies. Using data on 39 major technologies, the empirical part tests this proposition. It is found that indeed more inequality, as measured by the Gini coefficient, is detrimental to the diffusion of new technology, while a large middle class, measured by quantile shares of income, is conducive to technology diffusion. These effects are stronger for consumer than for producer technologies. Furthermore, there is some evidence that the negative effect of inequality on the diffusion of technologies is more pronounced in rich countries.

JEL Classification: O15, O33

Keywords: Technology Diffusion, Adoption Lags, Inequality

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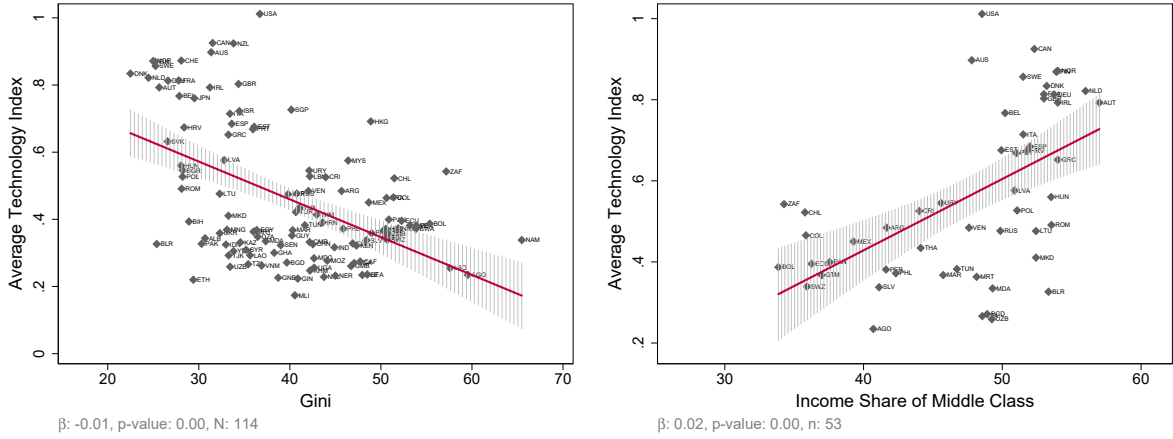
1 Introduction

This paper studies the effect of consumer inequality on the diffusion of technologies. While there is a huge literature explaining how new technology is created, how it relates to total factor productivity and how it spreads across countries, most of these contributions look at technology diffusion through the lens of the production side of the economy. This paper explicitly focuses on how inequality on the demand side (i.e. consumer inequality) might affect the diffusion of new technology. In this sense, this paper tries to combine insights from the literature that examines the effect of inequality on economic growth (e.g. Foellmi and Zweimueller (2006); Foellmi, Wuerbler and Zweimueller (2014)) with findings about the diffusion process of technologies (e.g. Comin, Hobijn and Rovito (2008); Comin and Hobijn (2010)).

In a first part, the paper establishes the link between consumer inequality and technology diffusion by introducing hierarchic preferences and showing that after a technology has passed its initial stage of diffusion, income inequality hinders the diffusion process of the technology. Therefore, the main hypothesis of the paper is that income inequality is detrimental to the intensive margin of technology diffusion.

To test this hypothesis, along with some others, empirically, we collect data on the diffusion of technologies across countries, largely following Comin and Hobijn (2009). We then measure the level of technology diffusion by either its usage per capita or by a measure called "technology adoption lag", which was introduced by Comin, Hobijn and Rovito (2008). This measure basically calculates the backwardness of a country to the United States. Furthermore, to measure inequality, we collect Gini coefficients along with quantile shares of income. Figure 1 gives a first glimpse at the relationship that we will look at in the empirical part. It shows that the Gini Index (in the year 2000) correlates negatively with a measure of technological development in 2000, taken from Comin, Easterly and Gong (2010), while a strong middle class is positively associated with the technology index.

Figure 1: Inequality and Average Technology in 2000



Regression analysis will confirm that inequality indeed has a detrimental effect on the diffusion of technologies. While inequality might be conducive to initial adoption of a country (the extensive margin), it is shown to have significantly adverse effects on the diffusion process (the intensive margin). Furthermore, the effects are shown to hold stronger for rich countries, and as could be expected, the effects are largely driven by consumer technologies, while the effect on producer technologies is much smaller. Nevertheless, assuming that further advances in Information and Communications Technology (ICT) are of increasing importance also for a countries' productivity, it can well be argued that these findings are relevant from a growth (or productivity) perspective as well.

This paper is structured as follows: Section 2 presents the relevant literature for this study. Section 3 elaborates on the shape of technology diffusion curves and introduces optimal consumer demand for technologies assuming hierarchic preferences. In section 4 we will describe the data and provide first descriptive statistics. Section 5 shows results from panel regression, while section 7 concludes. Various robustness checks for the regressions are presented in section 6.

2 Literature Review

The literature investigating technology as a source for economic growth is vast (see, for example Jones (2015)). Especially following the work of Solow (1957), a rich amount of research on

productivity growth as a driver of economic growth emerged. The literature on endogenous growth has put forward the argument that advances in technology, which are a key driver of economic growth, result from investment in research and development (Romer, 1990; Aghion and Howitt, 1992). The work building on Schumpeterian ideas of creative destruction describes the growth process in the light of the idea that growth is generated by innovations. The essence in these models is that entrepreneurs invest in R&D to find innovations because they are motivated by the prospect of a monopoly rent (Aghion, Akcigit and Howitt, 2015, 2014; Aghion and Howitt, 1996). In a more recent contribution, Parente and Prescott (2000) claim that the main part of income differences across countries stems from TFP differences.

Most of this classical literature is concerned with productivity growth at the technology frontier. However, since investment in R&D is concentrated in some rich countries, it cannot be the only source of technological progress (Keller, 2010). Furthermore, technologies do not have the same impact on productivity in all countries (Acemoglu, 2008). The literature exploring drivers of technology diffusion is extensive as well. Stoneman and Battisti (2010) provide a good overview of findings. Parente and Prescott (1994) and Basu and Weil (1998) argue that technology flows stop at national borders because there are (institutional) barriers to technology diffusion. Eaton and Kortum (1999) provide a model with of positive spillovers from inventing countries, while Fagerberg, Srholec and Verspagen (2010) stress the importance of so-called technological capabilities of the adopting country. Keller (2010), noting that foreign sources typically account for a large share of domestic productivity growth, investigates the impact of trade and foreign direct investment on the flow of technological knowledge. Other studies where technology diffuses due to trade or idea flows include Alvarez, Buera and Lucas (2013), where ideas flow through cross-country meetings of business people, and Grossman and Helpman (1991), where technological knowledge flows through R&D spillovers. Packalen and Bhattacharya (2015) examine the effect of geographical proximity and find that it has a considerably positive impact on the adoption of new ideas.

An often-mentioned important driver of technology diffusion is human capital (Nelson and Phelps, 1966; Easterly et al., 1994). Benhabib and Spiegel (2005) and Comin and Mestieri (2014) find a positive impact of human capital on technology diffusion. Comin and Hobijn

(2004) provide further evidence that besides a country's openness, adoption history and type of government, education is a key determinant for the speed of technology adoption. Caselli and Coleman (2001) show that the higher the level of primary schooling, the more computers are imported. Lee (2001) finds that human capital plays a crucial role in the increasing technology gap between developing and advanced countries. As Comin and Mestieri (2014) note, the effects of different potential drivers on technology adoption might vary significantly across different technologies. A country's adoption history was found to be an important driver of diffusion of new technology (Comin and Hobijn, 2004; Comin, Hobijn and Rovito, 2008; Comin and Mestieri, 2014), suggesting that some inputs in the adoption process are transferable. Comin and Mestieri (2014) note that this kind of persistence in adoption, however, might also be the result of some other persistent factor that affects adoption of technology: Similar as for income, such factors might include genetic diversity (such as in Ashraf and Galor (2013)), genetic distance to the technology frontier (Spolaore and Wacziarg, 2009) or stem from differences in the quality of institutions, as put forward by Acemoglu, Johnson and Robinson (2002). Other drivers of technology diffusion that have been identified in recent studies include differences in labor market regulations (Alesina, Battisti and Zeira, 2015), the level of development of the financial system (Cole, Greenwood and Sanchez, 2016), or the role of the business cycle (Comin and Gertler, 2006; Comin and Mestieri, 2010).

A more recent strand of literature which is relevant for this paper looks at the effect of technology advancement on inequality (i.e. the reverse of the research question of this study). Acemoglu (2002) finds that skill biased technological change might lead to increases in inequality. Karabarbounis and Neiman (2013) document a significant decline in the labor share since the early 1980's and attribute this phenomenon to the decrease of the relative price of investment goods due to ICT advances, which induced firms to replace labor with capital. Autor (2014), however, argues that in recent research, the extent of machine substitution has been overrated, while the extent of machine complementary has been ignored. Akerman, Gaarder and Mogstad (2015) find that broadband internet improves outcomes for skilled workers, whereas it worsens outcomes for unskilled workers. Bresnahan (2010) claims that so-called general purpose technologies first lead to a slump (since many resources are required to develop the new technology)

before the adoption of the new technology is finally reflected in a boom and economic growth. There is an ongoing debate between those who are optimistic (e.g. Brynjolfsson and McAfee (2014); Mokyr, Vickers and Ziebarth (2015)) and pessimistic (e.g. Gordon (2012) who worries about secular stagnation and claims that most productivity-enhancing innovations have already been made) about the overall effects of the recent advances in ICT.

All these contributions mainly look at technology diffusion from the production side of the economy. This paper, however, investigates the effect of consumer inequality on the diffusion of technology. Here, the existing literature mainly focuses on the effects of inequality on growth. There is evidence for both, positive as well as negative effects. Foellmi and Zweimueller (2006) show that in an innovation-based growth model with product innovations and hierarchical preferences, inequality fosters economic growth because inequality stimulates R&D. If firms can also undertake process innovation, however, the impact of inequality on economic growth is ambiguous (Foellmi, Wurgler and Zweimueller, 2014). Foellmi and Zweimueller (2016) look at the effect that the productivity gap between innovators and followers has on the relationship between inequality and growth. Kuznets (1955) argues that when individuals in the top bracket of the income distribution have more income, savings in the economy will be higher, since rich individuals save a higher proportion of their income. Hence, inequality might foster growth, because more unequal societies save more. Galor and Moav (2004) also explore the savings channel and argue that during the first stages of industrial revolution, physical capital was the main driver of growth. Therefore, inequality was beneficial to growth, since resources were in the hands of those who saved more. However, as human capital accumulation became the main driver of economic growth, the impact of inequality on growth reversed, since inequality hampers human capital formation (see also Galor and Zeira (1993)). Persson and Tabellini (1994) relate inequality to distributional conflicts, which lead to fiscal inefficiencies and therefore hamper growth. Halter, Oechslin and Zweimueller (2014) explore the time dimension of the impact of inequality on growth. Noting that many of the growth enhancing effects of inequality set in relatively fast, whereas the growth-reducing effects take time to set in, they provide evidence that indeed inequality is growth-enhancing in the short term, but hampers growth in the long run. Voitchovsky (2005) finds that the effect of inequality on economic growth depends on the

part of the income distribution looked at: Inequality at the top is found to be positively related to growth, whereas the converse holds for regions further down the income distribution. Barro (2000) concludes similarly, finding that high inequality is detrimental to economic growth in poor countries, but conducive to growth in rich countries.

3 Inequality and technology diffusion

How does inequality affect technology diffusion? Empirical results on this particular question are rare. Fuchs (2009) estimates the effect of the Gini coefficient on internet access in a cross-section from the year 2005. His work points to a negative estimate of the Gini coefficient, indicating a negative relationship between inequality and technology diffusion. On the other hand, Hyytinen and Toivanen (2011) study the effect of inequality (income share of the top earning deciles) on diffusion of mobile phones in developing countries and estimate positive effects on early diffusion. Note, however, that only developing countries are included and the result only applies to the early stage of the diffusion process. This suggests that more research is needed to uncover the effect of consumer inequality on technology diffusion. Especially for more recent consumer technologies, one could argue that their availability to households is crucial also for a country's productivity. Individual's knowledge in operating modern technologies surely adds to the human capital stock and increases productivity in production, especially for increasingly service-oriented economies. So even though the technologies investigated here are in many cases not production technologies, their accessibility might at least indirectly be related to productivity. Furthermore, the availability of ICT might contribute to Total Factor Productivity (TFP) through yet another channel: One could imagine that ICT intensity increases the speed of diffusion for other (production) technologies. Even though some studies find mixed results about the effect of ICT on productivity (e.g. Acemoglu et al. (2014)), many others find a positive effect of ICT intensity on productivity (e.g. Basu, Fernald and Shapiro (2001); Black and Lynch (2001); Brynjolfsson and Hitt (2000)). Therefore, the fact that individuals' ability to use ICT might be positively related to productivity growth suggests giving special attention to the link between inequality and the diffusion of ICT.

3.1 The shape of technology diffusion curves

How does diffusion of technology look like across countries? A compact overview on the topic is provided in Comin and Mestieri (2014). They argue that diffusion curves typically have two properties: they are concave and their shape looks very similar across countries. Hence, only two parameters (horizontal and vertical shift, reflecting the intensive and the extensive margin, respectively) will be needed to characterize cross-country differences for the diffusion of a given technology. Given that observation, Comin and Mestieri (2014) then conjecture the following approximation for the diffusion curve:

$$y_{\tau,t}^c = \beta_{\tau 1}^c + \beta_{\tau 2} t + \beta_{\tau 3} \log(t - \tau - \beta_{\tau 4}^c) + \epsilon_{\tau t}^c \quad (1)$$

where $y_{\tau,t}^c$ is the log of the output produced with technology τ in period t . Note that here, technologies are denoted by their invention date τ . $\beta_{\tau 1}^c$ captures the vertical shift, whereas $\beta_{\tau 4}^c$ captures the horizontal shift. $\beta_{\tau 2} t$ is a linear time trend and the logarithmic function reflects the fact that diffusion curves look concave. Comin and Hobijn (2010) provide a microfoundation for equation (1), where a similar equation is derived using a model including production and demand for technologies. For both margins of adoption, the literature finds that there is significant variation across countries, economic sectors, and technologies (Comin and Hobijn, 2010; Comin and Mestieri, 2010; Comin, Easterly and Gong, 2010). Newer technologies were adopted much faster than older ones. Comin, Hobijn and Rovito (2008) calculate for each technology-country-pair at each year how many years ago the technology's intensity was the same in the US, calling this measure usage lags. They find that usage lags are large, highly correlated with per capita income and highly correlated across technologies. Comin and Hobijn (2010) and Comin and Ferrer (2013) confirm this finding, concluding that a large fraction of variation in income per capita across countries can be explained by technology adoption, whereas the intensive margin is more decisive than the extensive margin. Recently, adoption lags have converged. But the ongoing divergence in the intensive margin prevents poorer countries to catch up with the Western countries (Comin and Ferrer, 2013; Comin and Mestieri, 2014). Hence, especially investigating the channels that influence the intensive margin seems

to be of great relevance. Therefore, in the empirical part of the paper, we will mainly focus on the intensive margin: We will compare intensity levels of technology diffusion across countries and time, disregarding the point in time when the technology was introduced in a specific country. Then, by comparing the intensity level of a given technology in a given year in two countries, we compare the horizontal distance between their diffusion curves. This is one way of measuring the difference in the intensive margin (or gap in penetration rate), as exposed in Comin and Ferrer (2013), for example.

3.2 Theoretical considerations about the effects of inequality

Section 2 summarized the main findings about the nexus between inequality and growth, highlighting that there arguments for both a positive and a negative effect. Here, we want develop hypotheses about the impact of inequality on technology diffusion. Hence, we first develop a simple household-side model, borrowing heavily from Foellmi and Zweimueller (2008), with non-homothetic preferences to derive a theoretical result about the relationship. Then, we consider past findings of the literature to formulate further hypotheses.

In order to establish a link between consumer inequality and technology diffusion from the demand side, we need to introduce non-homothetic preferences. The approach here follows closely Foellmi and Zweimueller (2008), where here the consumption goods considered are the technologies. These technologies are denoted and ranked by an index i , where lower i correspond to older technologies. We assume that consumers have hierarchic preferences. Consumers first consume basic technologies and once they climb the income ladder they start consuming more advanced technologies. There are, potentially, infinitely many technologies consumers can consume. Denoting the contemporaneous utility as $v(c(i))$ one can then define the consumers preferences as

$$U(c(i)) = \int_0^\infty \xi(i)v(c(i))di, \quad (2)$$

where we assume $v' > 0$ and $v'' < 0$ and $\xi(i)$ denotes the hierarchy function, which is assumed to monotonically decrease in i , $\xi'(i) < 0$, and therefore basic technologies get a higher weight than advanced technologies. This, of course, introduces the desired hierarchy of the technologies in the preferences. To make the hierarchic preferences meaningful, it has to be the case that not

all consumers will buy all technologies, i.e. the non-negativity constraint on consumption will be binding for some goods.

To keep the analysis tractable and allow for an analytic solution, a functional form for both the hierarchy function as well as the contemporaneous utility are assumed. Again, we follow Foellmi and Zweimueller (2008) and assume the weighting function to be a power function, $\xi(i) = i^{-\gamma}$ with $\gamma \in (0, 1)$. This, as shown in Foellmi and Zweimueller (2008), allows the economy to generate the Kaldor facts with balanced growth (in the aggregate) in the dynamic equilibrium and plays a similar role as CRRA preferences in a one-good growth model. Second, we assume instantaneous utility to be quadratic, i.e. $v(c(i)) = 0.5[s^2 - (s - c(i))^2]$. This allows for a binding non-negativity constraint, as marginal utility at zero consumption is finite. Then,

$$U(c(i)) = \int_0^\infty i^{-\gamma} 0.5[s^2 - (s - c(i))^2] di, \quad (3)$$

which consumers maximize subject to a budget constraint given by

$$e = \int_0^\infty p(i)c(i) di \quad (4)$$

and the non-negativity constraints $c(i) \geq 0$. The solution to this maximization problem gives (for goods that are consumed, i.e. $c(i) > 0$)

$$c(i) = s - \lambda i^\gamma, \quad (5)$$

where λ is the Lagrange-Multiplier. Furthermore, for the last good that is consumed N , $c(N) = s - \lambda N^\gamma$. For reasons of continuity, $c(N) = 0$ and therefore $\lambda = s/N^\gamma$. Using this in (5) delivers consumption as a function of i and the total number of goods N .

$$c(i) = s - i^\gamma s N^{-\gamma} = s \left[1 - \left(\frac{i}{N} \right)^\gamma \right] \quad (6)$$

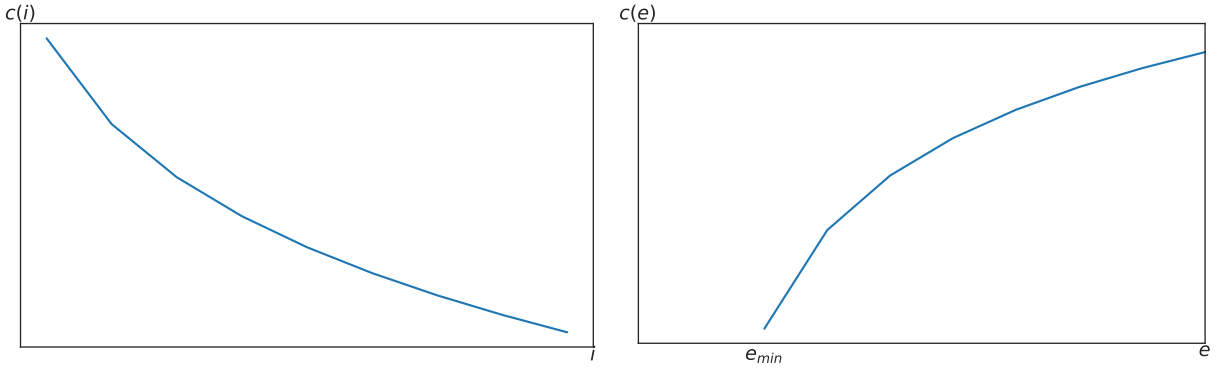
where $i \in [0, N]$. Here one can see the hierarchy of the goods: The quantities consumed depend on the relative position of a good in the hierarchy of needs i/N . $c(i)$ decreases in i , meaning that higher priority goods (indicated by a lower i) are consumed in larger quantities. γ captures

the steepness of this hierarchy.¹ Using the budget constraint, one can then establish that N is proportional to e , and more specifically, $N = ke$, where $k = \frac{1+\gamma}{s\gamma}$. This leads to the individual consumption function:

$$c(i) = s \left[1 - \left(\frac{i}{ke} \right)^\gamma \right] \quad (7)$$

Figure 2 shows individual consumption of good c as a function of i as well as as a function of e . Obviously, $c(i)$ is falling in i , showing the hierarchy of the goods. Furthermore, $c(i)$ is increasing and concave in e .

Figure 2: Individual Consumption as a function of i and e



Note: The left panel of the figure plots equation 7 for given values for $\gamma = 0.1$, $s = 5.0$ and $e = 1.0$. Note that k is given by $\frac{1+\gamma}{s\gamma}$. For i , values from one to ten are used. The right panel of the figure plots equation 7 using the same values for γ and s , but fixes $i = 10.0$ and uses values from one to ten for ke .

Note that since $i \in [0, N]$, and goods are continuous, the last good N is consumed in zero quantity, i.e. $c(N) = 0$. Good zero is consumed in quantity s . Hence, $c(i) \in [0, s]$.

To derive aggregate consumption of good i , i.e. $C(i)$, $c(i)$ needs to be integrated over the distribution of e . Note that the integration boundaries start not at zero but some minimum level $e_{min}(i)$. We assume incomes to be Pareto-distributed, i.e.

$$g(e) = \frac{\alpha e_m^\alpha}{e^{\alpha+1}} \quad (8)$$

with shape-parameter α and and scale-parameter e_m . A nice feature of this distributional form is that one can express the Gini coefficient of the Pareto-distribution in terms of the shape-parameter α , i.e. $G = \frac{1}{2\alpha-1}$, where G is the Gini-coefficient (Kleiber and Klotz, 2003).

¹Note that s is a parameter that will not matter for the results here.

Note that here e_m is the minimum level of income among individuals, while $e_{min}(i)$ denotes the minimum level of income required to consume good i . Integrating (7) over (8) and using the fact that $e_{min}(i)$ sets (7) equal to zero, i.e. $e_{min}(i) = \frac{i}{k}$, leads to

$$C(i) = \frac{\gamma}{\alpha + \gamma} \left(\frac{e_m}{e_{min}(i)} \right)^\alpha \quad (9)$$

Then, since we want to study the effect of a change in inequality on the demand of good i , we need to take the derivative of (9) with respect to α . However, changing α also changes the mean of income in the Pareto distribution.² Since we want to study a mean-preserving inequality change, we have to replace e_m with the mean income, $\bar{e}$. For the Pareto-distribution,

$$e_m = \frac{\alpha - 1}{\alpha} \bar{e} \quad (10)$$

Using this in (9) leads to

$$\frac{\partial C(i)}{\partial \alpha} = \left(\frac{\alpha - 1}{\alpha} \right)^\alpha B^\alpha \frac{\gamma}{\alpha + \gamma} \left[\ln B + \ln \left(\frac{\alpha - 1}{\alpha} \right) + \frac{\gamma + 1}{(\alpha + \gamma)(\alpha - 1)} \right] \quad (11)$$

where $B \equiv \frac{\bar{e}}{e_{min}(i)}$. The term outside the square brackets is clearly positive, while the sign of the term in the square brackets depends on B, γ and α . Hence, we will determine how large B must be in order to make the expression positive³, for different values of γ and α . Table 1 reports these values.

²The mean of the Pareto-distribution is $\frac{\alpha e_m}{\alpha - 1}$ (Kleiber and Klotz, 2003). Therefore, increasing α (i.e. decreasing inequality) lowers the mean of the Pareto-distribution, because $\frac{\partial \frac{\alpha e_m}{\alpha - 1}}{\partial \alpha} = -\frac{e_m}{(\alpha - 1)^2} < 0, \forall \alpha > 1$. Therefore, by increasing α , we would not only decrease inequality in the economy, but also make the economy poorer as a whole.

³Remember, a higher value of α represents a more equal distribution. Hence, whenever (11) is positive, inequality is bad for consumption / diffusion of the technology

Table 1: Minimum values for B such that inequality reduces consumption

α	Gini	γ								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
1.00	1.00	nan	nan	nan	nan	nan	nan	nan	nan	nan
1.25	0.67	0.19	0.18	0.17	0.17	0.16	0.16	0.15	0.15	0.15
1.50	0.50	0.76	0.73	0.71	0.69	0.67	0.65	0.64	0.63	0.62
1.75	0.40	1.06	1.03	1.00	0.98	0.96	0.94	0.93	0.91	0.90
2.00	0.33	1.18	1.16	1.14	1.12	1.10	1.08	1.07	1.05	1.04
2.25	0.29	1.24	1.22	1.20	1.18	1.16	1.15	1.14	1.12	1.11
2.50	0.25	1.26	1.24	1.22	1.21	1.19	1.18	1.17	1.16	1.15
2.75	0.22	1.26	1.25	1.23	1.22	1.21	1.20	1.19	1.18	1.17
3.00	0.20	1.26	1.24	1.23	1.22	1.21	1.20	1.19	1.18	1.18

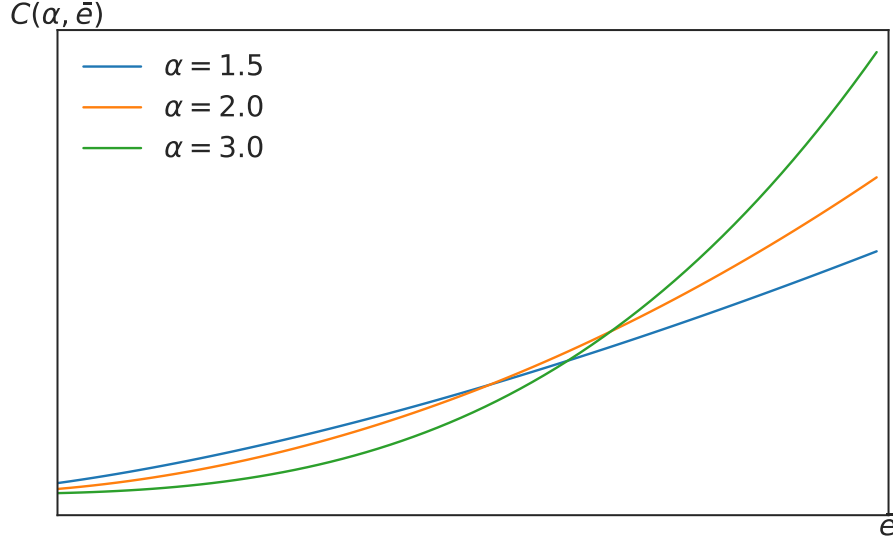
Note: Gini is the Gini-coefficient implied by α

Therefore, for reasonable values of the Gini coefficient and for technologies that are not introduced too recently to the market (i.e. $\bar{e}$ is significantly larger than e_{min}), a higher level of inequality reduces consumption of the technology. This is summarized in proposition 1.

Proposition 1. Higher inequality reduces consumption of a certain technology if the minimum income required to buy a certain technology is not too high compared to the mean of the incomes.

This proposition is illustrated in figure 3, where total consumption is plotted as a function of both the inequality parameter α as well as the mean income of the economy $\bar{e}$. Note that the figure is drawn for a given $e_{min}(i)$. As stated in proposition 1, if $\bar{e}$ is low higher inequality, indicated by a lower value of α , leads to higher consumption levels. However, as the level of $\bar{e}$ goes up, more inequality becomes worse for total consumption, such that for higher values of $\bar{e}$, relative to $e_{min}(i)$, inequality reduces total consumption.

Figure 3: Total Consumption as a function of α and $\bar{e}$



Note: The figure plots total consumption C as a function of $\bar{e}$ and for different values of α , for a given hierarchy-position of the good, $i = 10.0$, steepness parameter $\gamma = 0.1$, and $s = 5.0$ (and hence, $e_{min}(i)$ is fixed). The figure illustrates that for lower values of $\bar{e}$, total consumption is higher for lower values of α , i.e. inequality is good for total consumption. The opposite is true for higher values of $\bar{e}$.

How can this finding be interpreted, and how does it fit into the considerations of section 3.1? First of all, if the technology is very recent (and therefore expensive), higher inequality increases its consumption. Hence, higher inequality is beneficial to the extensive margin of technology diffusion (the adoption lag). If the technology has been on the market for a longer period of time, its price decreases. Then, the technology is purchased by more households if inequality is low. Therefore, lower inequality is beneficial to the intensive margin of technology diffusion. Furthermore, if there is a large middle class that can afford the technology, its diffusion will be faster as well.

These predictions can also be squared with findings in Foellmi and Zweimueller (2006) and Foellmi, Wuergler and Zweimueller (2014). For the initial phase of the technology, the price effect will dominate the market size effect, and a rich class of consumers is required in order to afford the new technology. However, as the technology becomes more mature, process innovation becomes more important and hence the market size effect dominates. A larger income gap between the rich and the poor will hinder diffusion of technology (Foellmi, Wuergler and Zweimueller, 2014). Hence, a strong middle class and lower inequality are beneficial to the intensive margin of technology diffusion. Based on these considerations, the following

hypotheses can be derived:

Hypothesis 1. *Higher inequality decreases the adoption lag. In order to introduce a new technology in a country, a wealthy rich class is needed as potential buyers. Therefore, inequality is beneficial to the extensive margin of technology adoption.*

Hypothesis 2. *Higher inequality lowers the penetration rate. In order for a technology to have high penetration rate, a large share of the population needs to be able to afford the technology when its price has been lowered after the first stages of introduction. This is the case if incomes are distributed more evenly.*

Hypothesis 3. *The size and the relative wealth of the middle class can have important effects on both the adoption lag as well as the penetration rate. Whereas the redistributive effects towards a large and solid middle class can be ambiguous (i.e. dependent on whether redistribution is from the rich or the poor), in general a large middle class is desirable if the median income level is not too low. Such a middle class might both decrease the adoption lag as well as increase the penetration rate.*

Some additional hypotheses can be derived from arguments taken from the existing literature (see section 2). As Halter, Oechslin and Zweimueller (2014) show, inequality might at first be beneficial to growth, while in the long term, the effect tends to be negative. This is due to the fact that the beneficial effects from inequality are purely economic and hence set in relatively fast, while the growth hindering effects are tied to the political process and take time to be effective (Halter, Oechslin and Zweimueller, 2014). Also, since newer technologies diffuse faster (Comin and Hobijn, 2010), time itself is an important explanatory factor. Furthermore, it might also make a difference whether one looks at consumer or producer technologies, since the unit of adoption differs between these two sorts of technology. Intuitively, consumer heterogeneity should have a stronger impact on the diffusion of consumer technologies, since the effect is direct. Lastly, the findings in Barro (2000) and Voitchovsky (2005) suggest that the level of income in the country also affects the effect of inequality on growth and hence the same might be true for technology diffusion. Whereas these contributions suggest that inequality is detrimental to growth in poor countries, while it is conducive in rich countries, for technology

diffusion, building on Foellmi and Zweimueller (2006), we expect the effects to be the opposite. Imagine a rich country, in which the mean consumer can afford a certain technology at time t . If now income is redistributed from the poor to the rich, some consumers that are poorer than the mean but could afford the technology before redistribution can not afford it any longer. At the same time, nothing changes for the consumers that are richer than the average. Hence, redistributing from the poor to the rich is bad for technology diffusion in a rich country. However, in a poor country, where the mean consumer can not afford the technology at time t , redistributing income from the poor to the rich means that now some consumers that are richer than the mean and could not afford the technology before redistribution can now afford it. Hence, redistributing from the poor to the rich is good for technology diffusion in a poor country. These considerations lead to the following additional hypotheses:

Hypothesis 4. *Higher inequality increases technology diffusion in the short run, but decreases diffusion in the long run. The total effect of inequality on technology diffusion is negative.*

Hypothesis 5. *Consumer inequality has a larger impact on the diffusion of consumer technologies than on the diffusion of production technologies, because the effect is direct.*

Hypothesis 6. *The negative effect of inequality on technology diffusion is more pronounced in rich countries. In fact, for poor countries, the effect might even be positive.*

4 Data

The main sources for the data on technology usage are the World Development Indicators provided by The World Bank (2015) and the International Historical Statistics by Mitchell (2013). Generally, data in the The World Bank (2015) dataset start in 1960. Hence, the Mitchell (2013) database is used to generate longer time series for the technology data. Additionally, we take data on some more recent health technologies from OECD (2016). For steel production, we use the data provided by The World Steel Association (2015) and complement them with data from Comin and Hobijn (2009). For data on financial technologies, we use The Bank for International Settlements (2015) along with Comin and Hobijn (2009). Combining these data sources gives me cross-country data on the diffusion of 39 technologies, which are documented

in appendix A (table A.1). For the data not already expressed as a share of population, we divide the usage level by population.

Data on inequality (i.e. Gini coefficients and quantile shares) we collect from four different sources: Deininger and Squire (1996), Solt (2016), The World Bank (2015) and UNU-WIDER (2015). While Deininger and Squire (1996) and UNU-WIDER (2015) have been standard sources for data on Gini coefficients and quantile shares, we complement the data with the The World Bank (2015) data (for quantile shares) and the Solt (2016) data (for Gini coefficients). For the Deininger and Squire (1996) data, we drop all observations for which the reported quality is low, and then combine them with the UNU-WIDER (2015) dataset. For the analysis later we will give priority to the Solt (2016) data for the Gini coefficients (since they are standardized and hence comparable across countries already). In fact, since there are only very few observations available that are not included in Solt (2016), we will only use this database for the Gini coefficients. For the quantile shares, we will combine information from The World Bank (2015), UNU-WIDER (2015) and Deininger and Squire (1996), prioritizing the data stemming from The World Bank (2015).

To control for any additional influences in the regression analysis later, we collect data on political institutions (Freedom House (2016)), GDP (The Maddison-Project (2013); Feenstra, Inklaar and Timmer (2015)), exchange rates, imports, exports, consumption, investment and price levels (all Feenstra, Inklaar and Timmer (2015) i.e. the Penn World Tables).

4.1 Usage Lags

One way to measure technology diffusion is by just looking at per capita levels in a given country. This gives, for example, the share of people having access to the internet. However, since not all technology variables are measured as a percentage of the population, per capita usage levels are difficult to compare across technologies. Therefore, we will borrow a measurement from Comin, Hobijn and Rovito (2008) called technology usage lag. The technology usage lag is the answer to the following question: "How many years before year t did the United States last have a usage intensity of technology x that country c has in year t ?" Hence, for all our

technology variables, we compute

$$\tau_{c,x,t} = \frac{pc_{c,x,t} - pc_{US,x,\underline{s}}}{pc_{US,x,\bar{s}} - pc_{US,x,\underline{s}}}(\bar{s} - \underline{s}) + \underline{s} \quad (12)$$

where $\bar{s}$ is the last time the United States passed level $pc_{c,x,t}$ and $\underline{s}$ is the last time the United States has a usage level lower or equal to $pc_{c,x,t}$. Then, the usage lag for technology x in country c at time t is simply

$$lag_{c,x,t} = t - \tau_{c,x,t} \quad (13)$$

This measure is simple to interpret and has the advantage that it is comparable across technologies. Naturally, the technology usage lag might be negative, indicating that the United States is not the technology frontier for that technology. A potential drawback of the usage lag measure is that there are cases where it is censored. This is the case when either the United States never achieved the usage level of country c or when the United States never had such a low level as country c has in a particular year t .

In order to compare the usage lag across technologies, following Comin, Easterly and Gong (2010), we create a second (standardized) technology variable, where we divide the usage lag by the year minus the invention year of the technology:

$$\widetilde{lag_{c,x,t}} = 100 \times \left(\frac{lag_{c,x,t}}{t - Inventionyear_x} \right) \quad (14)$$

With this measure, we can then compute the average standardized usage lag of a country c in year t :

$$lag_{c,t} = \frac{1}{n} \sum_{x=1}^n \widetilde{lag_{c,x,t}} \quad (15)$$

where n is the number of technologies. This measure will be the main outcome variable in the empirical analysis.

4.2 Descriptive Statistics

After merging the different data, we end up with an unbalanced panel covering over 200 countries, 39 different technologies, various measures of inequality (Gini and quantile shares) and

a rich set of potential covariates. Since inequality data are hardly available prior to 1960, we restrict our sample to observations for years after 1960. Furthermore, we remove observations for geographic entities that are not countries (any more), such as the OECD total or the Ussr. For the technology data, i.e. all usage levels and usage lags, zeros are recoded as missing values. From the original data sources, it is not clear what the difference between a zero and a missing value is. I.e. if the technology is not used in any given country, sometimes this is coded as a missing, while for other technologies it is coded as a zero. We want to harmonize these two cases and decided to recode all zeros as missing. Also, we recode all technology usage lags for the United States as missing: By definition, the usage lags are computed relative to the United States, and therefore having the United States in the sample makes no sense.

All technologies are classified as either consumer- or producer technologies (see table A.1, and the average standardized usage lag formulated in equation (15) are computed for consumer- and producer-technologies separately - along with the measure for all technologies together.

For most parts of this subsection we will restrict ourself to describing two technologies (along with the average standardized usage lag calculated over all technologies), namely electricity production and internet access. Electricity is without doubt one of the most important technologies developed in the past 200 years. Furthermore, it is an interesting case because it is a rather old technology and might reflect an example of an inferior technology for the sample years considered. Internet access, however, is a very recent technology that certainly has not reached its peak in many countries. Additionally, internet access can be viewed an example for a consumer technology, whereas electricity production is likely to be rather a producer technology. Furthermore, we also provide descriptive statistics for the main explanatory variables, i.e. the Gini coefficients and the quantile shares.

4.2.1 Technology data

Tables A.3 and A.4 in appendix A present the basic descriptive statistics for the 39 technology variables. Table A.3 presents descriptive statistics for the technology variables in per capita levels. Obviously we see huge variation in per capita technology variables, deriving from the fact that different years as well as different countries are in the sample. Also, for some technologies

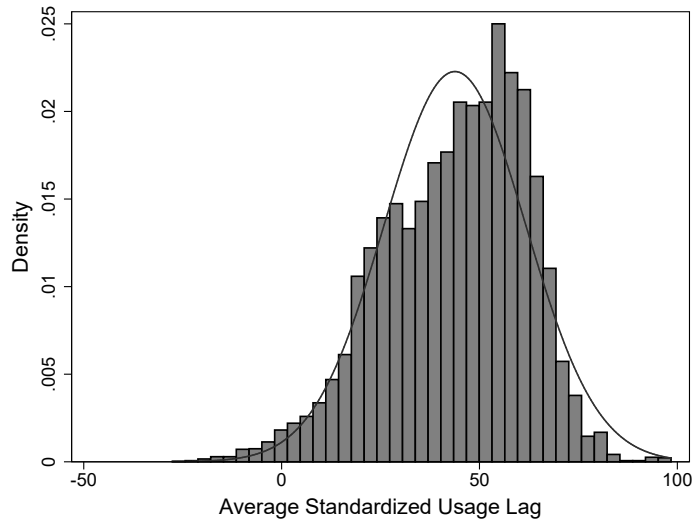
the number of observations is rather small, mostly due to the fact that the technologies are rather recent innovations. In Table A.4, descriptives for the usage lags suggest that for some technologies, the number of observations is very low (due to censoring, see section 4.1). Also, for most of the technologies, the minimum is below zero, meaning that at least for one country-year combination, the United States was not the technology leader. However, in total this is true for only around 3.5% of the observations.

Next we present some graphical representation of some of the technology data (per capita electricity production and internet access). To preserve readability, most of the figures are delegated to appendix B. Figure B.1 plots per capita electricity production for a set of six countries and reveals that usually diffusion curves are concave (see, for example, Comin and Mestieri (2014)). China, which only recently started to develop, is an exception here. Also, for the developed countries, we can see that the technology is phasing out, i.e. the technology might have reached its peak already. For internet access (Figure B.2), a different picture emerges. The technology seems to have diffused very fast (at least in developed countries), suggesting that newer technologies spread faster.

Figure B.3 shows the histogram of the usage lags for electricity production as well as for internet access. For both technologies there are very little observations with a negative usage lag, suggesting that for electricity production and internet access, we can indeed assume that the United States is the technology frontier country. Furthermore, the usage lags are obviously larger for electricity production, because the technology is much older than internet. Therefore, when comparing two technologies with each other, we need to standardize the usage lag, as suggested in section 4.1.

The main outcome variable we will use in the empirical analysis is the average standardized usage lag, as defined in section 4.1. This measure is a summary statistic of technological backwardness against the United States. Figure 4 shows the distribution of these usage lags, calculated using all 39 technologies we collected data for.

Figure 4: Histogram Average Standardized Usage Lags



Note: The histogram shows the distribution of the average standardized usage lags, over all 39 technologies, and over all sample years. The variable is calculated according to equation (15).

In addition to the average standardized usage lags for all technologies, we will also use a standardized usage lags for consumer and producer technologies separately. However, the distributions of these two measures look very similar to the distribution in figure 4. Part III of table A.2 in the appendix provides the descriptive statistics for all three measures.

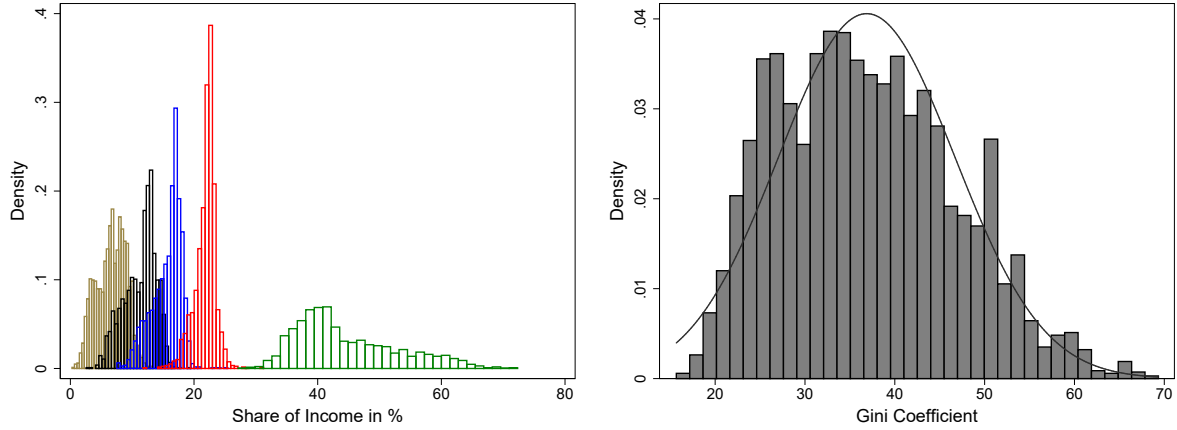
Figure B.4 in the appendix shows the average standardized usage lag in the year 2010 for all countries. Not surprisingly the figure shows that Europe, North America and parts of East Asia lag only little behind the United States, while Africa, Latin America and parts of South Asia are further behind.

4.2.2 Inequality data

Next, we will describe the inequality data. As part I of table A.2 shows, also in the inequality measure, there is quite some variation across countries and time, with the Gini ranging from 15 to 70 and the share of income going to the top 20% anywhere between 27% and over 70%. Figure 5 reveals a well-known fact: The lion's share of income goes to the top 20% of earners. The figure shows the distribution of the quantile shares across countries and years (i.e., the figure has no country and time dimension, such that the data are pooled across years and

countries) on the left. The panel on the right shows the distribution of the other inequality variable, the Gini coefficient.

Figure 5: Histogram of income quantiles and Gini coefficients



Note: The left panel of the figure shows histograms for all five quantile variables, pooled over time. For example, the green bars show the share of income going to the top 20% of earners is distributed. In some country / year combination, this is above 70%. The right panel shows the distribution of the Gini coefficient, pooled across countries and years. A normal density is added for illustrative purpose.

Figure B.5 shows that there is wide variation across countries in inequality, whereas the cross-country mean of the Gini coefficient has remained quite stable over time. Another important aspect is the variation of the Gini coefficient within a country. Examining the data it becomes clear that compared to other factors, the within-country variation in the Gini measure over time is, for many countries, rather small. Hence, when taking out country fixed effects, it is very likely that one cannot find any correlation between technology diffusion over time and measures of inequality.

4.2.3 Covariates

Descriptive statistics for the covariates used in the regression analysis later are provided in part II of table A.2 in the appendix. Real per capita GDP ranges from 190 US Dollar in El Salvador in the year 1950 to over 157'000 US Dollars in Kuwait in 1970. Political rights (Institutions) are scored on a scale from one to seven, one being the best score in the sense of maximum political rights. Many countries achieve the best score of one in many countries, while North Korea, Syria, Cuba but also China are examples of countries scoring the worst score of seven in recent years. Openness is measured by the share of merchandise exports in GDP (EX/GDP).

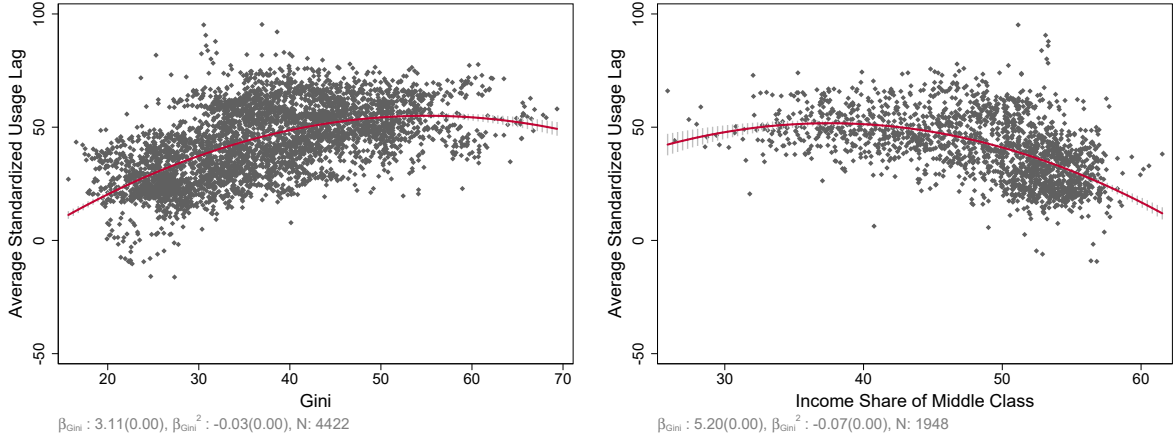
Human Capital is measured as an index based of years of schooling and returns to education. Here, the highest value of 3.62 is achieved by the United States in year 2010, while the lowest value of 1.02 was registered for Nepal in 1960.

4.2.4 Correlation between inequality and technology diffusion

How does electricity production (and internet access, respectively) correlate with inequality? Figure B.6 in the appendix provides some first insights into how inequality and electricity production are related. We conjectured that inequality and technology diffusion are negatively correlated. This seems largely to hold for electricity production. Production levels seem to be higher if the Gini and the top income share are lower, whereas the opposite holds true for the usage lags. Conversely, a solid middle class and a high share of the lowest 20% are correlated positively with technology diffusion. However, Figure B.6 also makes clear that the effects might not be linear. Especially for the share of income going to the middle class, the influence of inequality on technology diffusion seems to be hump-shaped (see two panels in the third row). A similar observation can be made for the one-dimensional measure of the Gini coefficient (top two panels). Figure B.7 repeats the exercise for the technology of internet access. The findings are similar as for electricity production. Indeed, in general, the effects appear to be even stronger for this technology.

Using again the mean of standardized usage lags $lag_{c,t}$, Figure 6 provides a first rough idea how the overall technological development in the sample relates to inequality.

Figure 6: Average Standardized Usage Lag and Inequality



Note: The left panel shows how the Gini coefficient is related the the average standardized usage lag. The regression statistics confirm a hump-shaped relationship, whereas there seems to be a positive relationship in general. The right panel shows the share of income going to the middle class plotted against the average standardized usage lag. Again, the relationship is revealed to be hump-shaped, but here the general relationship seems to be a negative one.

From visual inspection, inequality seems to increase the usage lag, while a strong middle class seems beneficial to technology diffusion.

4.2.5 In illustrative example

To illustrate the claim that inequality affects technology diffusion in a negative way, this subsection briefly compares the development of the main indicators described above for South Korea and the Philippines (two countries that are often taken as an example in studies about inequality). As is evident from Figure B.8, at the beginning of the 1960's both countries had a similar level of development (measured by per capita GDP) and also had similar levels of electricity production. So in these dimensions, both countries are comparable in 1960, except for the fact that the Philippines are much more unequal, as indicated by the bars in the figure. Then over time, the Philippines remain much more unequal, and South Korea experiences rapid growth in its GDP as well as dramatically decreases its lag against the United States in electricity production. For the Philippines, however, GDP remains almost flat, and the country falls further behind the technology frontier in electricity production.

Figure B.9 verifies the findings for the second technology of internet access. We see that while Korea is converging to the United States, the lags in the Philippines seem to increase over time.

In figure B.10 it becomes evident that these observations are also reflected in the main outcome measure used in this paper, the average standardized usage lag. While this measure remains relatively flat over time in the Philippines, one can observe a sharp decrease in the measure for South Korea.

Of course, many other factors might have played a role here. That is why in the next section, we will present results from regression analysis.

5 Regression Analysis

In this section we present results from panel regressions. We use the Gini coefficient and the share of income going to the middle class as inequality measures and investigate their respective effect on the single technologies (measured as the usage level as well as the usage lag). Furthermore, we also use the average over the standardized usage lags, derived in equation (15), as a measure of overall technology level in a given country and year (the average standardized usage lag).

We rely on panel regressions with fixed effects. Since inequality within countries varies very little compared to technology levels over time, country fixed effects cannot be used in this particular setting. Therefore, we use fixed effects for continents along with year fixed effects. To take out the effect that more developed countries tend to be more equal and at the same time more technologically advanced, we control for the countries' income level, measured as the log real GDP per capita (GDP) in most of the specifications. Furthermore, following the literature, (see e.g. Comin and Mestieri (2014)), we also control for differences in human capital (Human Capital), which is an index that combines years of schooling and returns to education, and openness (EX/GDP), where we use the export share of GDP as a proxy. All three series are taken from Penn World Tables (Feenstra, Inklaar and Timmer, 2015). Additionally, a measure of political rights is included (Institutions), again to try to control for some of the unobserved effects. This measure is taken from Freedom House (2016).

The model to estimate, therefore, is

$$\mathbf{y}_{c,t} = \mathbf{Ineq}_{c,t}\boldsymbol{\beta} + \mathbf{X}_{c,t}\boldsymbol{\gamma} + \boldsymbol{\alpha}_c + \boldsymbol{\alpha}_t + \mathbf{u}_{c,t} \quad (16)$$

where $\mathbf{y}_{c,t}$ is a $(ct \times 1)$ outcome (technology) vector, $\mathbf{Ineq}_{c,t}$ the $(ct \times p)$ matrix of regressors for inequality measures (p denoting the number of inequality variables in the regression) and β the $(p \times 1)$ vector of interest. $\mathbf{X}_{c,t}$ is a matrix of control variables, α_c and α_t are region (continent) and time fixed effects. Furthermore, as is standard in the literature, all standard errors are clustered at the country level throughout. Zeros in the technology variables are replaced with N/A values, as was explained in section 4.2.

Tables 2 and 3 show the results for the standardized usage lags, which reflects a country's average technological backwardness against the United States.

Table 2: Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.37 ***	0.26 ***	0.26 ***	0.26 ***	0.06	0.01	0.09	0.09
Human Capital	-17.21 ***	-4.95 ***	-4.09 ***	-2.79 *	-4.18 ***	-2.76 *	-3.68 ***	-2.38
EX/GDP	-5.29	-3.08 ***	-3.49 ***	-3.78 ***	-3.09 ***	-3.22 ***	-3.53 ***	-3.84 ***
Log GDP		-8.46 ***	-8.12 ***	-8.45 ***	-11.98 ***	-13.77 ***	-8.36 ***	-8.81 ***
Institutions			0.59 **	0.54 **	0.45 *	0.36	0.52 *	0.48 *
Gini $\times$ Log GDP					0.10 **	0.14 **		
L5.Gini							0.17 **	0.19 **
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3760	3760	3276	3242	3276	3242	2881	2849
R^2	0.622	0.771	0.775	0.813	0.778	0.818	0.776	0.820

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table 3: Regression Results Q2-Q4

Dependent Variable:	Average Standardized Usage Lags							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.51 ***	-0.34 ***	-0.36 ***	-0.37 ***	-0.11	-0.04	-0.11	-0.16
Human Capital	-17.25 ***	-4.53 ***	-4.15 ***	-2.91 *	-4.23 ***	-2.91 *	-3.82 *	-3.14 *
EX/GDP	-2.38	-3.20 ***	-2.96 ***	-3.31 ***	-2.57 ***	-2.78 ***	-2.66 ***	-3.16 ***
Log GDP		-8.37 ***	-7.80 ***	-8.25 ***	-1.73	0.26	-7.33 ***	-8.33 ***
Institutions			0.55 *	0.34	0.45	0.21	0.63	0.28
Qmid $\times$ Log GDP					-0.12	-0.18 *		
L5.Qmid							-0.22 **	-0.18
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1678	1678	1568	1536	1568	1536	868	841
R^2	0.546	0.725	0.719	0.798	0.721	0.802	0.633	0.782

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Columns (1) to (4) test hypotheses 2 and 3, the main hypotheses of this paper. Columns (5) and (6) test hypothesis 6, while columns (7) and (8) shed light on hypothesis 4.

As expected, a higher level of human capital reduces the lag in technology diffusion, as does, to a lesser extent, openness to trade. Furthermore, the availability of technology significantly increases with income. Finally, and a little surprising, the proxy for institutions seems not to be of great importance here. Its effects, however, might be taken up by human capital and income already. These first results also seem to confirm the main hypotheses: A higher Gini coefficient significantly increases the average standardized usage lag to the United States, whereas having a strong middle class reduces the usage lag. Note that due to how this average usage lag is defined, one cannot make any sensible statement about the size of the effect. However, looking at various individual technologies (appendix D), one can conclude that the effects are moderate: The share of people having access to the internet, for example, increases by 3 to 5 percentage points when the Gini coefficient decreases by 10 points (table D.5). Or, an average country catches up 1.5 years (to the United States) if its Gini drops by 10 points (table D.6).

If the share of income going to the middle class increases by 10 percentage points, then the share of people having access to the internet increases by 3 to 8 percentage points (table D.7). Similar magnitudes of the effects are found for other technologies. Interestingly, for mobile phones, inequality seems to matter less than for other modern ICT. This might indicate that mobile phones are actually an important production good of the poor (Hyytinen and Toivanen, 2011). For the other modern ICT, the results are very robust. This is an important finding, since the spread of modern technology seems to become of ever greater importance, not just for the consumers' side but also for the production side in service-based economies.

More generally, the results found seem to hold stronger for consumer than for producer technologies. We divided, intuitively, all the technologies considered here into technologies that are rather consumer and those that are rather producer technologies (see appendix A). Then, we recalculate the average standardized usage lag using only consumer (producer) technologies and again estimate the effect of inequality on technology diffusion. Tables D.1 to D.4 in appendix D reveal that basically the whole effect is driven by consumer technologies. This is very strong support for hypothesis 5. Furthermore, comparing rail passengers (measured by person-kilometers traveled) to rail freight (measured by ton-kilometers), one finds that while rail passenger transport is significantly and consistently influenced by inequality, this is not at all the case with rail freight. For aviation, this finding holds only to a lesser extent, probably highlighting that air travel is only affordable in better-off countries. Nevertheless, these two examples showcase the finding that inequality influences consumer technologies to a greater extent than producer technologies do.

Does inequality really hinder the diffusion of *new* technology? Many of the technologies in the sample here are not very recent inventions, and also they were not in 1960, the year the panel starts. The only possibilities to shed some more light on this question is by looking into a technology whose production methods have changed over time. This panel includes data on different production methods of steel, and because some are more modern than others (see Comin and Hobijn (2004)), we can investigate how inequality impacts the diffusion of the different methods. As expected, we find that for the more modern production methods, diffusion is significantly influenced by inequality, whereas this is not the case for the older, outdated

technologies. This gives some more backing to the premise that indeed the effect on the diffusion of new technologies is measured.

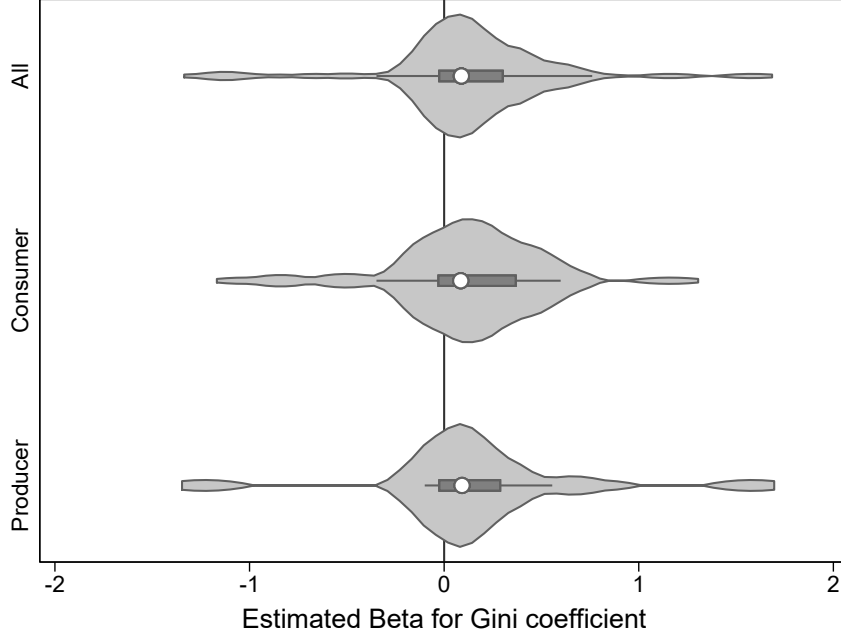
Columns (5) and (6) include the interaction between the inequality variable and GDP. According to hypothesis 6, the expected effect is that the detrimental effect of inequality is more pronounced in rich countries. Tables 2 and 3 show mixed results. The interaction of the Gini coefficient with GDP seems to be important and significant, pointing out that indeed inequality becomes more detrimental in rich countries. However, the point estimates for the Gini coefficient alone are positive and are not statistically significant. Therefore, we cannot conclude that for poor countries, inequality speeds up technology diffusion; only that inequality is more detrimental in developed economies. For the share of income to the middle class, the results are much less clear; the estimates for the interaction between the share going to the middle class and GDP do not seem to be significantly influencing the average standardized usage lag. When only considering the consumer technologies, however, the interaction term becomes strongly statistically significant. Furthermore, for the most recent ICT, the hypothesis can be confirmed, for both the Gini coefficient as well as the share of income going to the middle class. Here, we even find some evidence for the hypothesis that inequality can be good for technology diffusion in poor countries, while with rising GDP inequality becomes detrimental (see tables D.5 to D.12). This might hint to the fact that in poor countries, inequality is conducive to technology diffusion, since a rich upper class is required to be able to afford the new technology: The extensive margin is more important. This is in line with the arguments made in hypothesis 1. The exception again are mobile phones, consistent with the arguments above.

Finally, columns (7) and (8) seem not to confirm hypothesis 4. A lagged value for the inequality variable seems not to be a strong explanatory variable of technology diffusion. Hence, in this setting we fail to distinguish between short- and long-run effects. However, other methods might be required for that purpose (see section 6.2).

To illustrate and give an overview of the estimates for the different individual technologies, figure 7 shows the distribution of the estimates for the Gini coefficient when regressing on the individual technologies' usage lag, using the preferred specification model (4). The figure shows a box plot of the estimated coefficients, surrounded by a kernel density estimate. Also, the

figure shows the distribution of the estimated coefficients for all technologies, for consumer technologies only and for producer technologies only. The figure suggests that the estimates on the Gini coefficients are mostly positive, as we would expect from our hypotheses.

Figure 7: Estimated coefficients for Gini on the individual technologies' usage lag



Note: This figure shows the distribution of the estimated Betas for the Gini coefficients in the regressions (equivalent to model (4) in table 2) with the individual technologies' usage lag as the dependent variables. The white dot is the median of the estimated coefficients, the box represents the interquartile range, and the spikes are the upper- and lower-adjacent values. This box plots is overlaid by a kernel density estimate using the Epanechnikov kernel. The plot shows three plots, including all technologies, only consumer and only producer technologies.

Figure B.11 in the appendix shows some more information on the estimated coefficients for the individual technologies. This figure reports the estimated coefficient for each technology, along with the 95% confidence interval. Again, it can be confirmed that at least for consumer technologies, the estimated effect of the Gini coefficient on the technology lag is positive, and statistically significant for several technologies.

6 Robustness Checks

In this section we provide some robustness checks for the results derived in section 5. An instrumental variable approach will be introduced as a first check. Then, we aggregate the

panel to a 5-year frequency and estimate a dynamic panel to allow for the auto-regressive nature of the technology variable as well as country fixed effects.

6.1 Instrumental variable approach

Since Solt (2016) provides data for both net-Gini coefficients as well as market-Gini coefficients, it is possible to create a measure that proxies the extent of income redistribution in any given country. I.e. one can construct a measure for redistribution policy. Following Solt (2016), we thus construct a measure for (relative) redistribution as:

$$Redistribution_{c,t} = \frac{Gini_{c,t}^{MARKET} - Gini_{c,t}^{NET}}{Gini_{c,t}^{MARKET}} \quad (17)$$

To strengthen the argument that inequality shapes the diffusion of technologies, we then use this redistribution measure to instrument for the Gini-coefficient. The presence of omitted variables, which pose a potential problem to the main specifications because it does not allow to control for country fixed effects, might therefore be alleviated if the exclusion restriction is credible. Also, it is a possible strategy to tackle the problem of reversed causality (i.e. that the diffusion of technology might influence inequality).

The exclusion restriction requires that the only effect of the redistribution measure on the diffusion of technology is through inequality, conditional on the set of control variables. Because it seems likely that more developed countries have stronger preferences for redistributive policies, GDP needs to be controlled for in order to make the exclusion restriction credible. Therefore, we choose to include GDP as a control variable in most specifications, despite the fact that GDP might be endogenous as well, because the diffusion of technology might also influence GDP. We will address this issue further below.

Table 4 summarizes the results for the instrumental variables regressions. The six specifications are the same that were used in section 5.⁴ As a dependent variable, we again use the average standardized usage lags. The results for the first stage indicate that the instrument is strong; a problem with weak instruments does not seem to apply. The lower part of table 4 shows

⁴We do not report results for the specification with the lagged Gini coefficient here. However, as in the main specification, no significant effects result from adding the lagged Gini coefficient as an additional regressor if the contemporaneous Gini is included already.

the results for the second stage. The first 4 columns strengthen the main result found in the last section: More inequality indeed leads to higher usage lags, i.e. it hinders the diffusion of technology.

Contrary to the main results, however, the interaction between the Gini coefficient and the level of GDP do not seem to play any significant role here (columns 5 and 6).

Table 4: IV Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: First Stage Regressions</i>						
Redistribution	-38.07 ***	-41.24 ***	-44.08 ***	-30.93 ***	-17.78 *	-9.93
Human Capital	-3.31 **	-4.72 ***	-4.50 ***	-2.02	-4.91 ***	-2.38 *
EX/GDP	0.64	0.42	-0.03	0.03	0.23	0.25
Log GDP		1.23 *	0.48	0.88	1.36	1.60 *
Institutions			-0.94 ***	-0.45 *	-0.98 ***	-0.50 *
Log GDP $\times$ Redistribution					-9.05 ***	-7.30 **
<i>Panel B: Second Stage Regressions</i>						
Gini	0.99 ***	0.44 ***	0.36 ***	0.33 *	-0.12	0.01
Human Capital	-11.18 ***	-3.68 **	-3.48 **	-2.60 *	-4.49 **	-2.93 *
EX/GDP	-4.85	-3.03 ***	-3.37 ***	-3.73 ***	-2.86 **	-3.41 ***
Log GDP		-8.18 ***	-7.92 ***	-8.43 ***	-14.81 *	-12.39 *
Institutions			0.60 **	0.54 **	0.34	0.41
Log GDP $\times$ Gini					0.17	0.10
Region FE	No	No	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3758	3758	3275	3241	3275	3241
Fstat	72.020	66.979	79.234	24.608	14.226	6.585

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Fstat denotes the F statistic for weak identification.

A further potential endogeneity issue is posed by using GDP as an explanatory variable, i.e. it is reasonable to assume that the diffusion of technology influences GDP, and hence another

reverse causality problem might arise. Hence, especially the results for columns 5 and 6 above should be interpreted with care. This reverse causality problem is much more likely to arise for producer than for consumer technologies: If technology diffusion increases GDP via advances in productivity, this seems to be rather driven by productive production technologies than by consumer technologies used at home. Therefore, we re-estimate (17) again, but this time using the average standardized usage lag calculated over the consumer technologies only, similar to the approach we also followed in section 5, where we divided the technologies into consumer and producer technologies. Table B.1 in the appendix shows the results. The result for the main hypothesis (columns (1)-(4)) remain the same, but now for consumer technologies there is also weak evidence for hypothesis 6: The point estimate for the Gini coefficient is negative, while the interaction term is positive, as expected. Furthermore, the coefficient for the interaction term is significant at the 10% level. Hence, when only looking at consumer technologies, the results from the baseline analysis can be replicated: There is evidence that higher inequality hinders the diffusion of technology, while this effect seems to be more significant in rich countries.

6.2 Dynamic Panel estimation for usage lags

The reason why country fixed effects cannot be introduced in the main specification in section 5 is that there is not enough variation in the Gini-coefficient over the years within a country. One way to tackle this issue is by aggregating the panel to a lower frequency. Hence, we aggregate the data to a 5-year frequency, using the latest available data point for each 5-year period. Furthermore, the results in Comin, Hobijn and Rovito (2008) indicate that technology usage lags can to a large part be explained by their past values. Therefore, it makes sense to include lagged dependent variables as additional regressors. Therefore, the equation to estimate becomes

$$\mathbf{y}_{c,t} = \mathbf{y}_{c,t-1}\boldsymbol{\delta} + \mathbf{Ineq}_{c,t}\boldsymbol{\beta} + \mathbf{X}_{c,t}\boldsymbol{\gamma} + \boldsymbol{\alpha}_c + \boldsymbol{\alpha}_t + \mathbf{u}_{c,t} \quad (18)$$

with $\mathbf{y}_{c,t-1}$ denoting the lag of the dependent variable. In this case, however, random and fixed effect models lead to inconsistent estimates (Cameron and Trivedi, 2005; Nickell, 1981), since the regressors and the error term are correlated by construction. Potential solutions to this problem include estimating the equation by applying the System GMM estimators put forward

by Arellano and Bover (1995) and Blundell and Bond (1998). Alternatively, the fixed effects model estimates can be bias-corrected, as, for example, in Kotschy and Sunde (2017), based on Bruno (2005). Here, we will apply the bias-corrected fixed effects specification and follow closely Kotschy and Sunde (2017).

We will again use the Gini-coefficients as the variable for inequality and the standardized usage lag as the outcome variable. First, tables B.2 and B.3 show the results for a static model, i.e. where δ is restricted to zero in equation (18), applying random and fixed effects, respectively. While for random effects the main hypothesis seems to be confirmed (columns (1) to (3)), this seems not to be the case for the fixed effects specification. Interestingly, in the preferred specification with dynamic fixed effects and bias correction the results are more in line with what we expected, as table 5 shows. In four out of the five specifications, the estimate for the Gini coefficient is significant. Not surprisingly, the lag of the technology usage lag is highly significant in all specifications.

To conclude, using panel data methods, the main results found in section 5 can be replicated with 5-year data. The hypothesis of a heterogeneous effect by different levels of GDP cannot be confirmed here. However, as in the subsection above, this might be due to endogeneity problems of GDP as an explanatory variable.

Table 5: Dynamic, Biased-Corrected FE Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags				
	(1)	(2)	(3)	(4)	(5)
L.Average Standardized Usage Lag	0.66 ***	0.60 ***	0.58 ***	0.58 ***	0.56 ***
Gini	0.11	0.18 **	0.16 **	0.23 **	0.22 **
Human Capital	-2.08	-1.24	-1.96	-2.26	-2.71
EX/GDP	-0.65	0.04	0.27	0.36	1.27
Log GDP		-3.95 ***	-5.27 ***	-3.13	-5.35 ***
Institutions			0.11	0.09	0.08
Gini $\times$ Log GDP				-0.06	
L.Gini					-0.11
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	881	881	805	805	736

Note: Dynamic Fixed Effects model with Bias-correction. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

7 Conclusion

This paper investigates how inequality (measured by the Gini coefficient as well as quantile shares) influences the diffusion of (consumer) technologies. Most of the literature on technology looks at the production side of technology creation. This paper takes another perspective by looking at the demand side of the economy. Using a simple demand-side model with non-homothetic preferences, it is shown that after some minimum level of average income, compared to the minimum level of income required to afford a new technology, is achieved, more consumer inequality hinders the diffusion process of technologies. In line with earlier predictions, this suggests that for the extensive margin of adoption, a higher degree of inequality might be beneficial. However, for the intensive margin (the diffusion of the technology in a given country after its initial adoption has taken place), a lower level of inequality speeds up diffusion.

Using data on the diffusion of 39 major technologies, the paper shows that the hypothesis drawn from this simple demand-side model can not be rejected. By using an aggregate mea-

sure of technological backwardness against the technological frontier, the United States, it is shown that inequality of the households hampers the diffusion of technologies. This result is confirmed when looking at various individual technologies. This results hold for both measures of technology diffusion considered here: The actual usage level (technology usage per capita) as well as a measure that measures the backwardness to the United States. Furthermore, it is found that the effect is much stronger for consumer technologies than for producer technologies. In fact, according to one measure, the whole (total) effect is driven by consumer technologies. This again is in line what was to be expected, since the influence of inequality on the diffusion of consumer technologies is direct, while the (potential) effect on producer technologies is only indirect.

In addition to this main finding, the study also finds limited evidence for the existence of an asymmetric effect regarding the development level of countries. Including an interaction between inequality and real GDP, the results show that inequality is detrimental for the diffusion of new technologies mainly in richer countries. This might be due to the consideration that in rich countries, where the mean consumer can afford the new technology, a mean-preserving redistribution from the rich to the poor makes the marginal consumer of the technology unable to afford the technology, therefore reducing the diffusion level.

This paper adds to the literature in the following way. It is the first paper collecting information about technology diffusion and investigating the influence of household inequality on the diffusion process. In that sense, the paper combines earlier contributions that investigate technology diffusion from a supply-side perspective with the rich literature on the effects of consumer inequality on economic growth. Mainly consumer technologies are considered in this study, but one can well imagine that especially for modern information and communication technologies (ICT), the speed with which these new technologies are spread across a country might (indirectly) influence a countries growth trajectory. With an increasing importance of the services sector, along with the rising importance of skills in the field of the digital economy, the topic and questions asked in this paper might be of growing importance. The fact that the effects found are very robust especially for these new ICT suggests that the importance of inequality remains important also for new technologies in this field. Furthermore, if it is to be

believed that skills in ICT are of ever-growing importance in the labour market, a particular policy implication would be to try to make accessible modern technologies to broad masses of the population. This could be important, as mentioned above, for productivity advances of the economy as a whole. Additionally, this might also be important in order to provide some degree of equality of chances, which can only be guaranteed if all social classes have to ability become familiar with the latest advances in technology.

Investigating the link between the speed of diffusion of modern technologies and increases in productivity (or the stock of human capital) might be an interesting field of study for the future. Establishing a link between consumer inequality, the technology diffusion process and economic growth should be a very interesting task to look into.

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A Data appendix

Table A.1: Technology variables Sources

Label	Main Source	Add. Source
<i>Consumer Technologies</i>		
ATM's	WDI	CHAT
Aviation, passenger KM	Mitchell	
Aviation, passengers carries	WDI	
Broadband internet	WDI	
Cable TV's	CHAT	
Cars	Mitchell	
Payments by credit and debit cards	CHAT	BIS
Card transactions at retailer	CHAT	
Internet access	WDI	
Mails delivers	CHAT	
Mobile phones	WDI	
Newspapers	CHAT	
Personal computers	WDI	
Radios	Mitchell	
Railways, passenger KM	WDI	Mitchell
Railwas, passengers	Mitchell	
Servers	WDI	
Telephones	Mitchell	
Telephones, subscriptions	WDI	
TV sets	Mitchell	
Access to water	WDI	
<i>Producer Technologies</i>		
Aviation, freight	WDI	Mitchell
Commercial vehicles	Mitchell	
Port traffic, containers	WDI	
CT scanners	OECD	
Electricity production	WDI	Mitchell
MRI scanners	OECD	
Patents	WDI	
POS terminals	CHAT	BIS
Rail freight, Mil. Ton KM	WDI	Mitchell
Rail freight, Mil. Metric Tons	Mitchell	
Ships, freight	CHAT	Mitchell
Ships	CHAT	Mitchell
Steel production, BOF	WS	CHAT
Steel production, EAF	WS	CHAT
Steel production, OHF	WS	CHAT
Steel production, total	WS	
Agriculture machineries	WDI	
X-ray scanners	OECD	

Note: WDI refers to The World Bank (2015), CHAT to Comin and Hobijn (2009), Mitchell to Mitchell (2013), BIS to The Bank for International Settlements (2015), WS to The World Steel Association (2015) and OECD to OECD (2016).

Table A.2: Descriptive statistics main variables

Variable	Mean	Std. Dev.	Min.	Max.	N
<i>Part I: Inequality Variables:</i>					
Gini	36.87	9.83	15.68	69.35	4585
Q1	6.65	2.35	0.26	13.37	2017
Q2	11.28	2.58	2.55	19.45	2017
Q3	15.64	2.37	7.51	25.46	2017
Q4	21.86	1.68	11.75	31.25	2017
Q5	44.58	8.24	27.11	72.34	2017
Qmid	48.78	6.21	25.88	61.53	2017
<i>Part II: Economic Variables:</i>					
Human Capital	2.13	0.62	1.02	3.62	6294
EX/GDP	0.23	0.30	-1.01	12.05	7620
Log GDP	1.56	1.25	-1.68	5.06	7620
GDP	9.88	14.10	0.19	157.82	7620
Institutions	3.74	2.23	1.00	7.00	7601
<i>Part III: Main Technology Variables:</i>					
Average Standardized Usage Lag	43.80	17.91	-27.61	98.41	9557
Average Standardized Usage Lag: Consumer Technologies	45.44	19.49	-48.72	98.41	9115
Average Standardized Usage Lag: Producer Technologies	47.51	16.79	-27.58	95.18	8307

Note: Gini measures the net (i.e. after redistribution) Gini coefficient. Q1-Q5 denote the quantile shares, e.g. Q1 measures the share of income going to the bottom 20% of the population. Qmid is the income share of the middle class, i.e. Q2+Q3+Q4. Human capital is an index of human capital and EX/GDP measures openness. GDP is the real GDP per capita in 1'000 (2005) US Dollars. Institutions is an index on Political Rights. The average standardized usage lag is the main outcome variable for this paper; its construction is described in section 4.1.

Table A.3: Descriptive statistics Per capita technology variables

Variable	Mean	Std. Dev.	Min.	Max.	N
ATM's	0.40	0.41	0.00	2.91	2108
Aviation, freight in Mil. Ton KM	0.06	0.52	0.00	16.81	6907
Aviation, Mil. passenger KM	0.69	1.89	0.00	26.63	4896
Aviation, passengers carried	569.48	1452.60	0.11	21887.83	6531
Broadband internet	78.47	108.71	0.00	616.91	2423
Commercial vehicles	24.78	32.41	0.10	319.62	5778
Cable TV's	86.44	111.01	0.00	1545.31	814
Cars	100.15	147.59	0.12	778.72	5860
Port traffic, containers in 20 foot equivalents	362.19	886.96	0.48	6726.92	1284
Payments by credit and debit cards in Mil.	0.04	0.05	0.00	0.23	520
CT scanners	0.02	0.01	0.00	0.10	525
Card transactions at retailer	51615.74	4.4e+05	1.00	6.1e+06	324
Electricity production in gWh	2.53	4.09	0.00	54.72	7719
Internet access	204.39	256.24	0.00	981.60	4069
Mails delivers	0.10	0.11	0.00	0.67	1912
Mobile phones	436.67	491.50	0.00	3212.33	4559
MRI scanners	0.01	0.01	0.00	0.05	476
Newspapers	99.03	130.70	0.03	613.06	4686
Patents	0.13	0.31	0.00	3.19	4031
Personal computers	100.96	158.96	0.00	962.38	2354
POS terminals	7.91	7.28	0.00	33.23	488
Radios	237.45	209.90	0.68	1377.04	2395
Rail freight in Mil. Ton KM	0.96	3.62	0.00	163.55	4651
Rail freight in Mil. Metric Tons	0.00	0.00	0.00	0.14	3566
Railways, Mil. passenger KM	0.35	0.54	0.00	16.08	4615
Railwas, Mil. passengers	0.02	0.10	0.00	1.17	3637
Servers	0.23	0.61	0.00	9.76	2407
Ships, freight in 1000 Tons	1.88	10.99	0.00	162.24	2818
Ships	0.12	0.33	0.00	2.59	1980
Steel production, BOF in Metric Tons	0.20	0.21	0.00	1.32	1714
Steel production, EAF in Metric Tons	0.08	0.12	0.00	1.74	2762
Steel production, OHF in Metric Tons	0.09	0.12	0.00	0.63	909
Steel production, total in Metric Tons	0.21	0.28	0.00	1.95	2581
Telephones	136.63	185.14	0.18	972.76	5761
Telephones, subscriptions	157.87	187.05	0.01	1345.19	8134
Agriculture machineries	5.76	9.95	0.00	59.08	6094
TV sets	150.10	141.37	0.00	879.71	2568
Access to water	842.14	183.38	132.00	1000.00	4851
X-ray scanners	0.01	0.00	0.00	0.03	389

Note: All variables are measured per 1'000 of population. The statistics include the observations of all countries in all years available in the sample, which leads to huge variation in the outcome of the variables. As an example, over the whole sample period and all countries, an average of 20.4% had access to the internet, while the maximum penetration rate of internet access in any given year and country is 98.2%. Also, as stated in the main text, the zeros in the data are replaced by a missing value, since it is unclear from the data whether a zero means the technology has not arrived yet or it has arrived but its usage level is close to zero. The zeros appearing in this table are rounded to zeros and are in fact very small positive numbers.

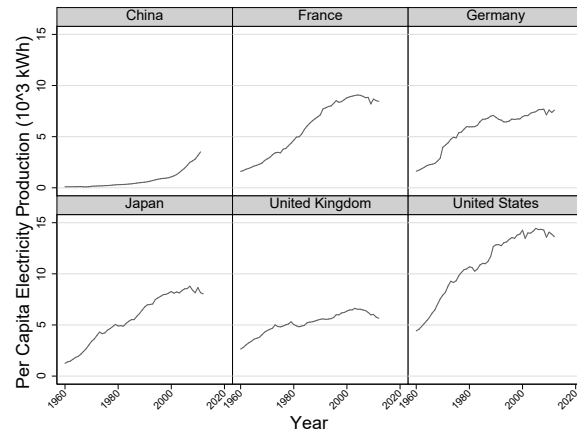
Table A.4: Descriptive statistics Usage Lags

Variable	Mean	Std. Dev.	Min.	Max.	N
ATM's	11.55	5.93	-3.97	25.45	997
Aviation, freight in Mil. Ton KM	32.61	20.02	-30.80	79.64	6297
Aviation, Mil. passenger KM	30.36	15.74	-26.47	76.92	4679
Aviation, passengers carried	16.78	13.50	-33.13	43.74	776
Broadband internet	6.27	4.48	-6.84	15.99	1552
Commercial vehicles	55.58	17.92	-5.15	94.72	5735
Cable TV's	13.17	7.76	-17.95	26.85	317
Cars	61.09	20.87	5.10	102.97	5817
Port traffic, containers in 20 foot equivalents	2.57	4.21	-6.60	12.29	134
Payments by credit and debit cards in Mil.	6.22	5.54	-6.82	21.85	162
CT scanners	3.60	3.68	-7.78	14.23	96
Card transactions at retailer	0.73	5.13	-9.90	11.00	105
Electricity production in gWh	49.56	22.68	-32.33	108.96	6109
Internet access	8.67	5.61	-9.91	23.46	3003
Mails delivered	54.17	21.47	3.98	103.56	807
Mobile phones	6.35	5.71	-10.87	23.00	3730
MRI scanners	8.86	4.90	-10.87	18.45	91
Newspapers	20.33	12.19	0.03	48.41	294
Patents	2.24	18.37	-49.89	40.45	421
Personal computers	13.80	6.53	-3.78	26.89	1643
POS terminals	2.21	5.41	-6.81	18.47	362
Radios	39.79	19.81	-27.98	72.46	1934
Rail freight in Mil. Ton KM	103.67	24.84	-43.27	148.55	2830
Rail freight in Mil. Metric Tons	81.42	32.16	0.60	139.83	1008
Railways, Mil. passenger KM	58.84	31.44	0.08	130.17	2105
Railways, Mil. passengers	61.10	32.88	0.08	123.28	958
Servers	4.59	3.76	-4.70	12.80	345
Ships, freight in 1000 Tons	98.94	64.23	0.79	217.10	897
Ships	15.56	24.02	0.01	117.08	880
Steel production, BOF in Metric Tons	19.42	12.62	-8.36	48.76	1035
Steel production, EAF in Metric Tons	14.26	15.27	-27.49	49.17	1129
Steel production, OHF in Metric Tons	11.21	10.04	0.03	47.83	271
Steel production, total in Metric Tons	8.26	7.16	-0.77	27.61	263
Telephones	68.89	27.18	0.31	126.32	5703
Telephones, subscriptions	19.11	13.42	-13.79	53.74	1739
Agriculture machineries	16.48	11.54	-2.02	42.99	286
TV sets	26.90	13.06	-15.45	50.71	2337
Access to water	-6.70	6.32	-23.00	4.80	74
X-ray scanners	1.60	1.42	-0.17	3.12	4

Note: The usage lag measures the lag in years to the US.

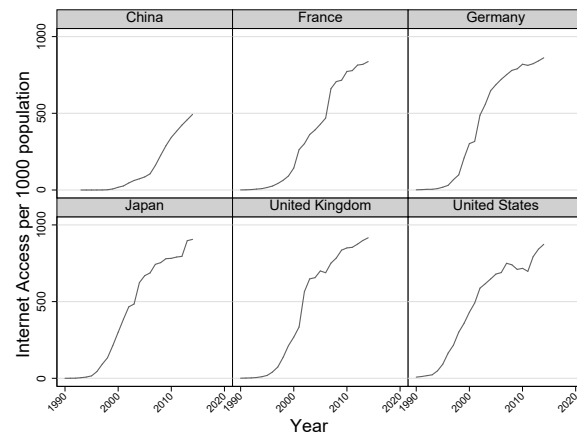
B Additional Tables and Graphs

Figure B.1: Electricity production over time



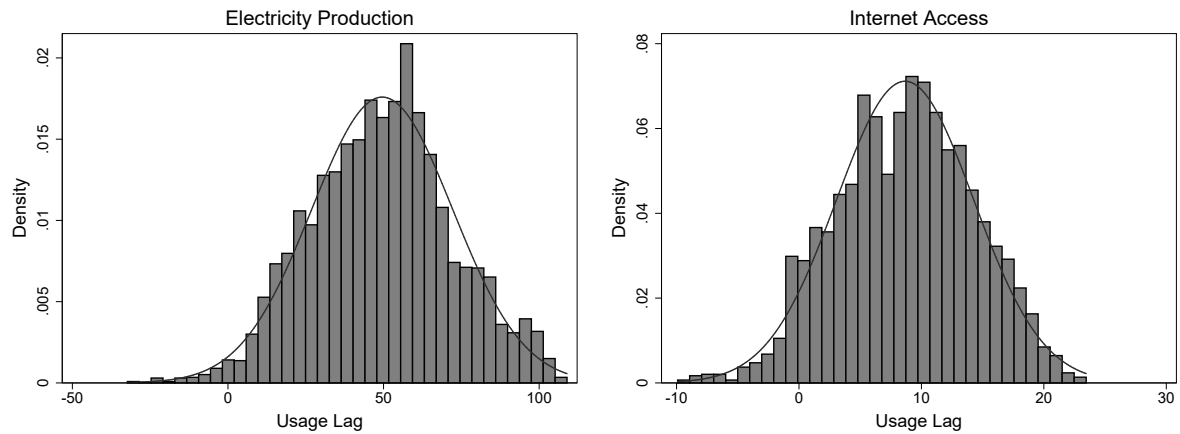
Note: This figure shows per capita electricity production since 1960 in six different countries. While for China there seems to be an upward trend, for the other 5 (developed) economies it seems that production is flattening out.

Figure B.2: Internet access over time



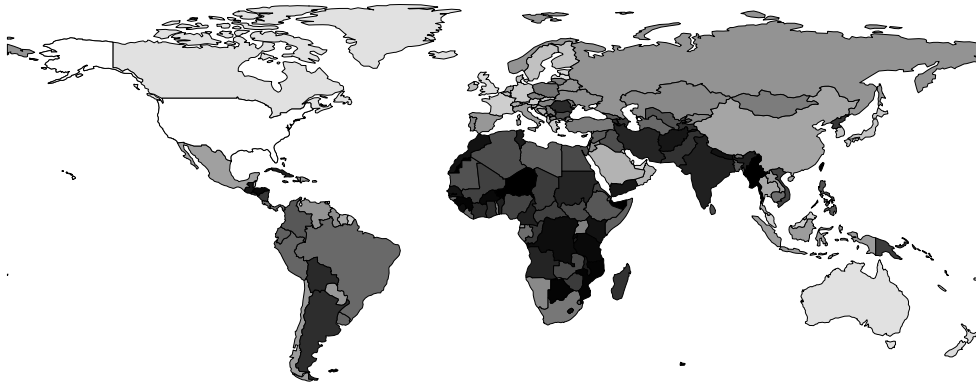
Note: This figure shows the share of people having access to the internet since 1990 for six countries. Internet access seems to be a technology for which the diffusion process happened very quickly.

Figure B.3: Histograms of Usage Lags



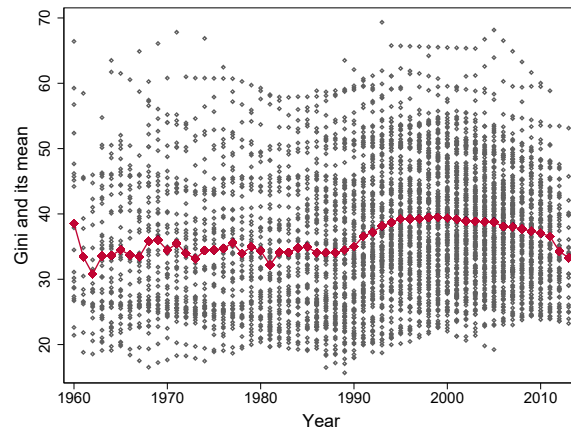
Note: The left (right) panel shows the technology usage lags in years to the United States for electricity production (internet access), along with an added normal density. Obviously, usage lags for electricity production are much larger than for internet access.

Figure B.4: Average Standardized Usage Lags in 2010 around the World



Note: The figure shows the average standardized usage lag for all countries in the year 2010. Darker shaded areas indicate a higher value for the usage lag, i.e. more technological backwardness towards the United States. The United States, as the baseline country, are coloured in white.

Figure B.5: Gini and heterogeneity across years



Note: The figure illustrates the large heterogeneity in inequality across countries. However, over time, the Gini measure seems not to vary too much within countries. This is also highlighted by the cross-country mean of the Gini coefficient over time (in red), which appears quite stable over the years.

Figure B.6: Electricity Production and Inequality

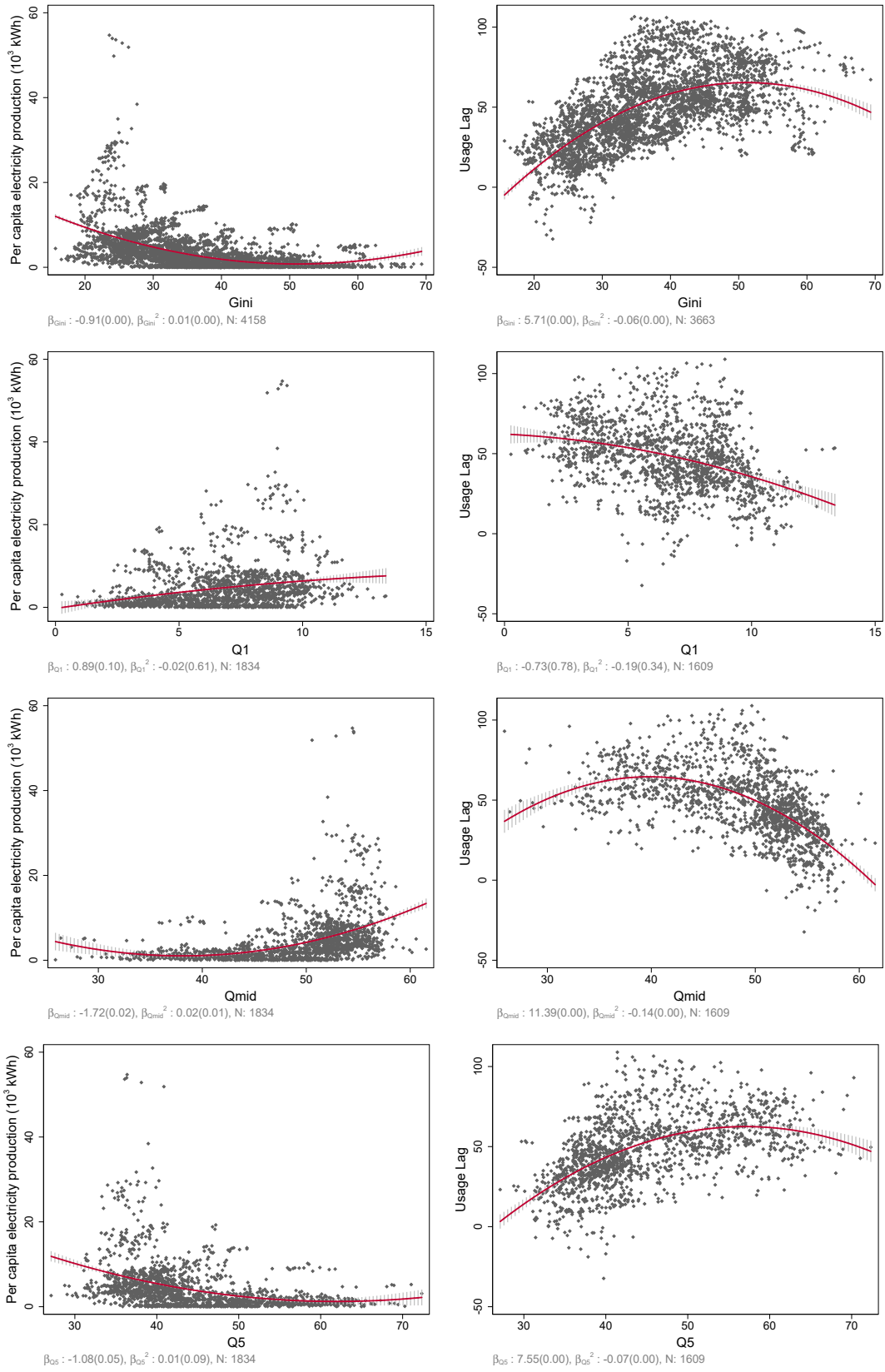


Figure B.7: Internet Access and Inequality

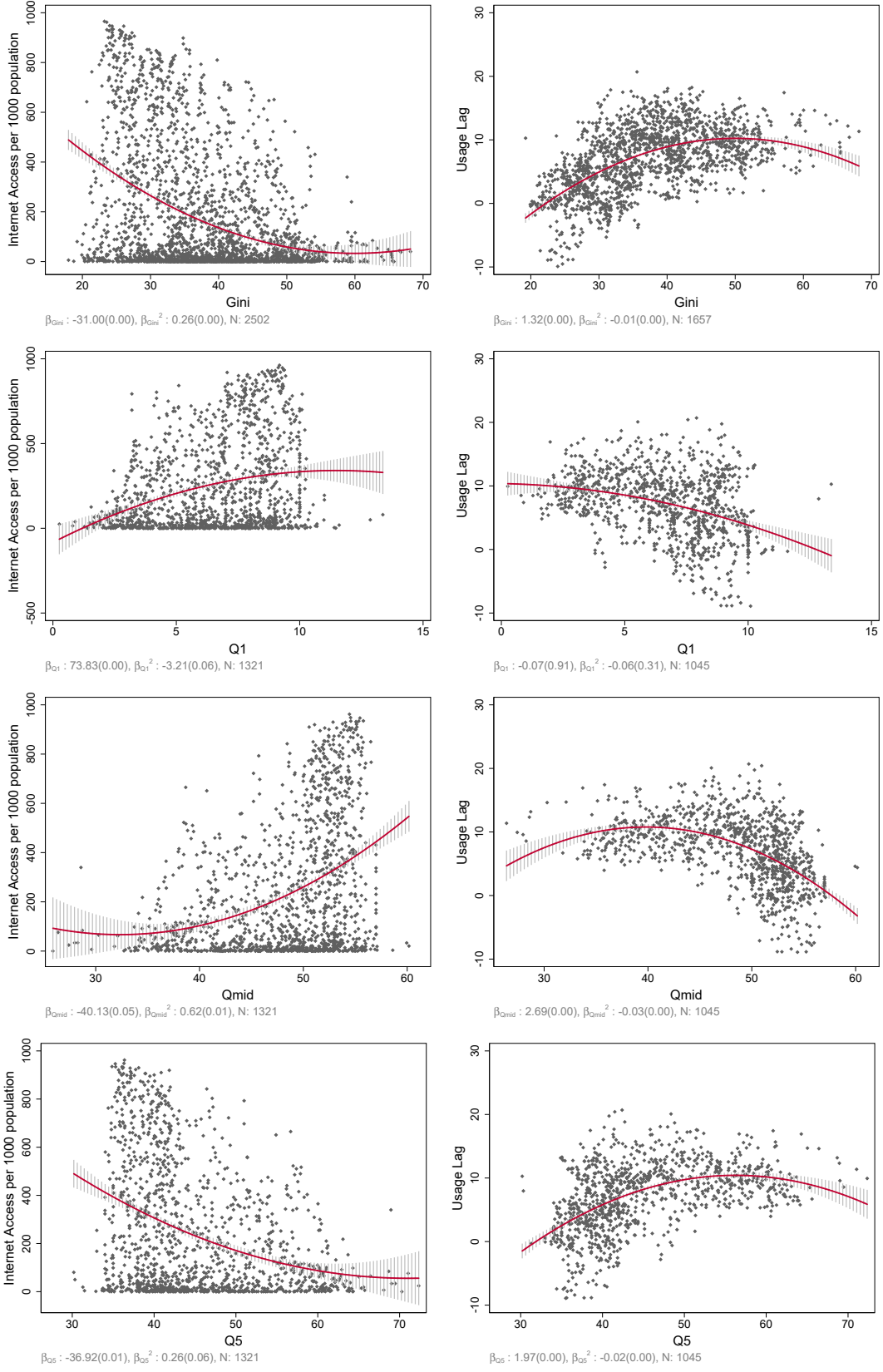


Figure B.8: Electricity Production in South Korea and the Philippines

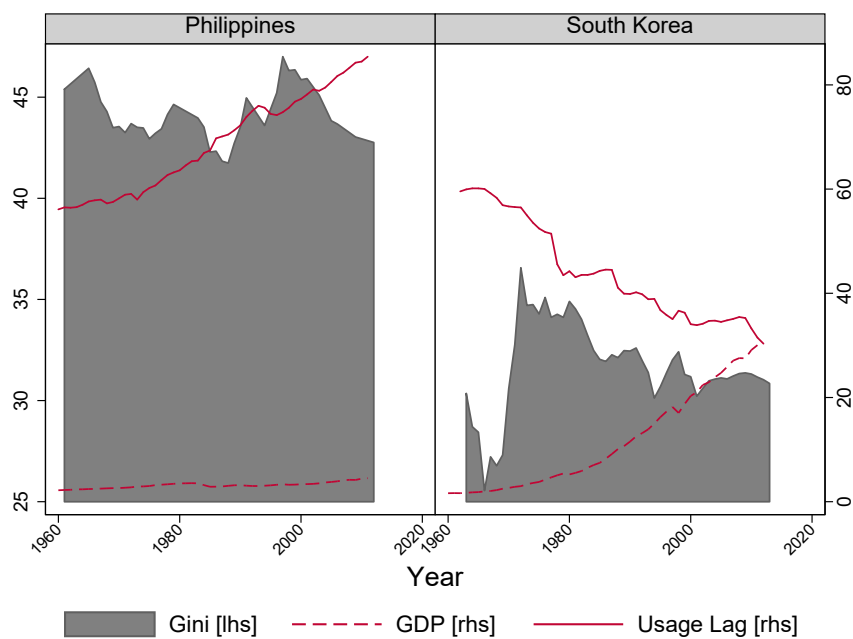


Figure B.9: Internet Access in South Korea and the Philippines

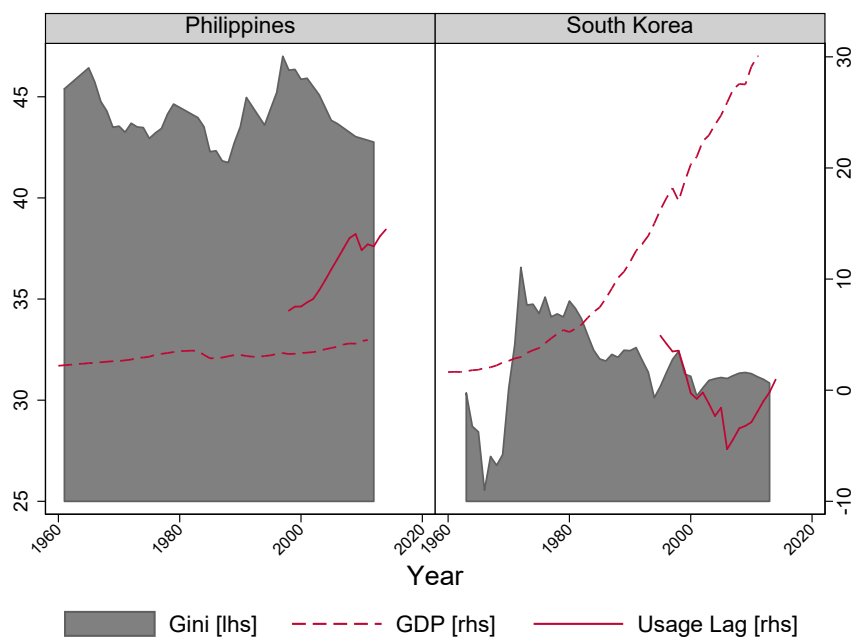


Figure B.10: Average Standardized Usage Lags in South Korea and the Philippines

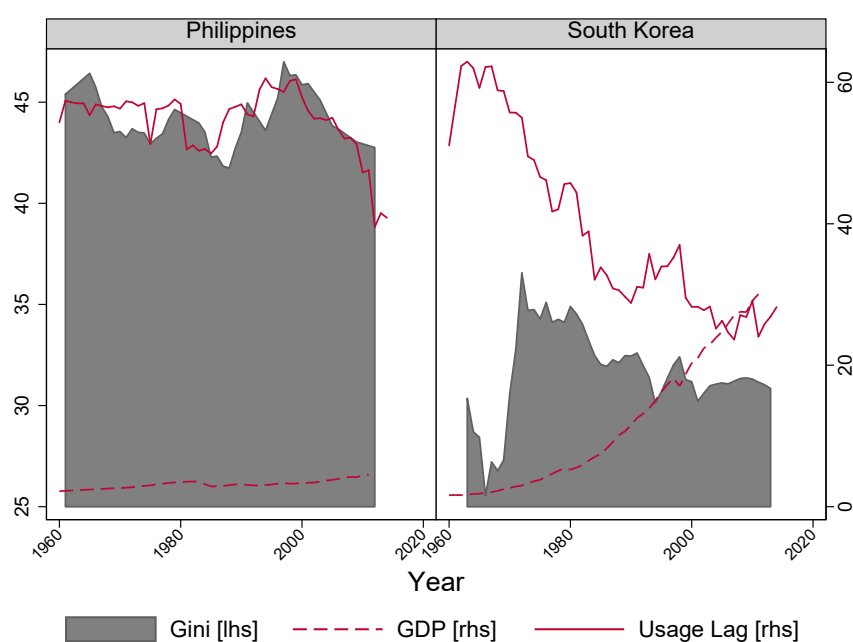
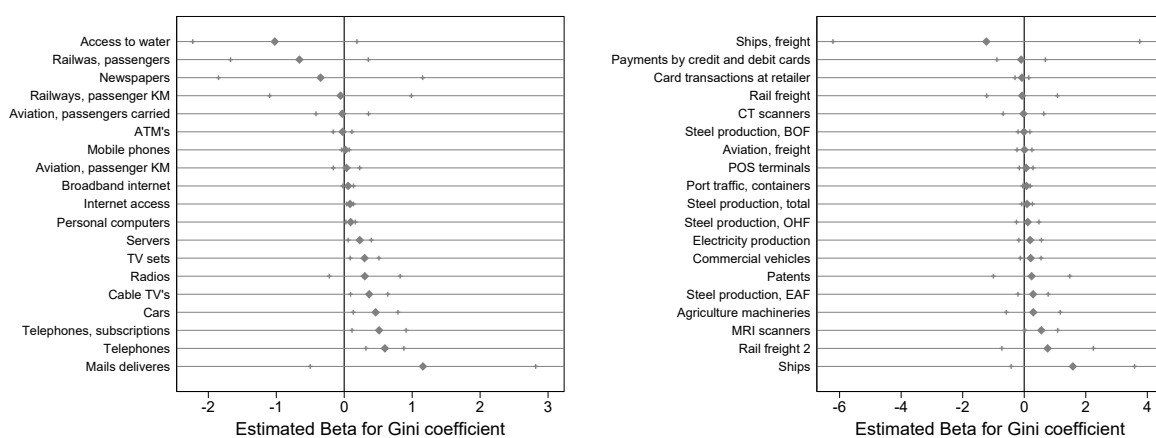


Figure B.11: Estimated coefficients for Gini on the individual technologies' usage lag II



Note: This figure shows the estimated coefficient for the Gini measure when regressed on the individual technologies' usage lag, surrounded by the 95% confidence interval. The estimates are taken from specification / model (4) (see table 2 for the specification). The left panel shows all consumer technologies, while the right panel shows the producer technologies.

Table B.1: IV Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags: Consumer Techs					
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: First Stage Regressions</i>						
Redistribution	-38.82 ***	-42.17 ***	-44.99 ***	-31.41 ***	-17.94 *	-10.51
Human Capital	-3.07 **	-4.55 ***	-4.38 ***	-2.02	-4.82 ***	-2.39 *
EX/GDP	0.62	0.40	-0.02	0.03	0.25	0.25
Log GDP		1.30 *	0.57	0.93	1.48 *	1.65 *
Institutions			-0.93 ***	-0.44 *	-0.98 ***	-0.49 *
Log GDP $\times$ Redistribution					-9.32 ***	-7.25 **
<i>Panel B: Second Stage Regressions</i>						
Gini	1.33 ***	0.71 ***	0.63 ***	0.81 ***	-0.58	-0.34
Human Capital	-10.18 ***	-1.38	-1.02	0.10	-3.51 *	-1.09
EX/GDP	-5.73	-3.73 ***	-3.60 ***	-3.91 ***	-2.34 *	-2.77 ***
Log GDP		-9.39 ***	-8.64 ***	-9.19 ***	-25.86 ***	-23.38 ***
Institutions			1.36 ***	1.30 ***	0.72 *	0.86 ***
Log GDP $\times$ Gini					0.44 *	0.37 *
Region FE	No	No	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3716	3716	3244	3218	3244	3218
Fstat	76.133	73.325	87.567	24.812	14.480	6.690

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***. Fstat denotes the F statistic for weak identification.

Table B.2: RE Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags				
	(1)	(2)	(3)	(4)	(5)
Gini	0.18 **	0.22 ***	0.20 ***	0.07	0.15 *
Human Capital	-15.17 ***	-5.40 ***	-4.88 ***	-4.73 ***	-4.35 ***
EX/GDP	-3.50	-1.78 **	-1.45	-1.41	-2.44 ***
Log GDP		-7.26 ***	-7.17 ***	-10.24 ***	-7.14 ***
Institutions			0.26	0.24	0.29
Log GDP $\times$ Gini				0.08	
L.Gini					0.07
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	942	942	810	810	739

Note: Random Effects model with 5-year panel data. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table B.3: FE Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags				
	(1)	(2)	(3)	(4)	(5)
Gini	0.07	0.17 *	0.15	0.19	0.14
Human Capital	-8.21 **	-5.54 *	-5.53 *	-5.66 *	-5.90 *
EX/GDP	-2.17	-0.27	0.26	0.32	0.17
Log GDP		-8.15 ***	-8.07 ***	-6.76	-8.59 ***
Institutions			0.02	0.01	0.06
Log GDP $\times$ Gini				-0.04	
L.Gini					0.04
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	942	942	810	810	739

Note: Fixed Effects model with 5-year panel data. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

C Derivations and Proofs

Derivation of equation (5)

Utility is

$$U(c(i)) = \int_0^\infty i^{-\gamma} 0.5[s^2 - (s - c(i))^2] di, \quad (19)$$

which is constrained by

$$e = \int_0^\infty p(i)c(i) di \quad (20)$$

and the non-negativity constraints $c(i) \geq 0$. Therefore, the Lagrangian function reads

$$\mathcal{L} = i^{-\gamma} 0.5[s^2 - (s - c(i))^2] - \lambda[p(i)c(i) - e] + \mu c(i), \quad \forall i \quad (21)$$

and leads to the following set of optimality conditions

$$\frac{\partial \mathcal{L}}{\partial c(i)} = i^{-\gamma}(s - c(i)) - \lambda p(i) + \mu = 0 \quad (22)$$

$$\mu c(i) = 0 \quad (23)$$

$$p(i)c(i) = e \quad (24)$$

$$\mu \geq 0 \quad (25)$$

$$c(i) \geq 0 \quad (26)$$

Using (22), multiplying by $c(i)$, and using (23) gives

$$c(i)[i^{-\gamma}(s - c(i)) - \lambda p(i)] = -\mu c(i) = 0 \quad (27)$$

Combining (22) and (25) yields

$$i^{-\gamma}(s - c(i)) - \lambda p(i) = -\mu \leq 0 \quad (28)$$

Then, from (27), for goods that are consumed (i.e. $c(i) > 0$), it follows that $i^{-\gamma}(s - c(i)) = \lambda p(i)$ and, for prices being equal to marginal cost ($p(i) = mc(i) = 1$, where $p(i)$ is chosen as the

numeraire) and assuming symmetry in production, we derive consumption of good i as

$$c(i) = s - \lambda p(i) i^\gamma = s - \lambda i^\gamma \quad (29)$$

Derivation of equation (7)

We know that e equals the total amount of goods consumed, i.e. $e = \int_0^N c(i) di$ from the budget constraint. Using (6), we have

$$e = \int_0^N c(i) \quad (30)$$

$$= \int_0^N s \left[1 - \left(\frac{i}{N} \right)^\gamma \right] di \quad (31)$$

$$= s \int_0^N \left[1 - \left(\frac{i}{N} \right)^\gamma \right] di \quad (32)$$

$$= s \left(i - \frac{i^{\gamma+1}}{\gamma+1} N^{-\gamma} \Big|_0^N \right) \quad (33)$$

$$= s(N - N^{\gamma+1} N^{-\gamma} (\gamma+1)^{-1} - 0) \quad (34)$$

$$= s \frac{\gamma}{\gamma+1} N \quad (35)$$

and therefore

$$N = \underbrace{\frac{1+\gamma}{s\gamma}}_{\equiv k} e \quad (36)$$

So we have

$$c(i) = s \left[1 - \left(\frac{i}{ke} \right)^\gamma \right] \quad (37)$$

Derivation of equation (9)

Aggregate consumption of good i is becomes

$$C(i) = \int_{e_{min}(i)}^{\infty} c(i)g(e)de \quad (38)$$

$$= \int_{e_{min}(i)}^{\infty} s \left[1 - \left(\frac{i}{ke} \right)^{\gamma} \right] \frac{\alpha e_m^{\alpha}}{e^{\alpha+1}} de \quad (39)$$

$$= \frac{\alpha e_m^{\alpha} s}{k^{\gamma}} \int_{e_{min}(i)}^{\infty} e^{-\alpha-1-\gamma} (k^{\gamma} e^{\gamma} - i^{\gamma}) de \quad (40)$$

$$= \frac{\alpha e_m^{\alpha} s}{k^{\gamma}} \left(\int_{e_{min}(i)}^{\infty} e^{-\alpha-1} k^{\gamma} - i^{\gamma} e^{-\alpha-1-\gamma} de \right) \quad (41)$$

$$= \frac{\alpha e_m^{\alpha} s}{k^{\gamma}} \left(k^{\gamma} \int_{e_{min}(i)}^{\infty} e^{-\alpha-1} de - i^{\gamma} \int_{e_{min}(i)}^{\infty} e^{-\alpha-1-\gamma} de \right) \quad (42)$$

$$= \frac{\alpha e_m^{\alpha} s}{k^{\gamma}} \left(\left[-\frac{k^{\gamma}}{\alpha e^{\alpha}} - \frac{i^{\gamma} e^{-\alpha-\gamma}}{-\alpha-\gamma} \right] \Big|_{e_{min}(i)}^{\infty} \right) + Cons \quad (43)$$

$$= \left[-\frac{e_m^{\alpha} s}{e^{\alpha}} - \frac{\alpha e_m^{\alpha} s i^{\gamma} e^{-\alpha-\gamma}}{k^{\gamma}(-\alpha-\gamma)} \right] \Big|_{e_{min}(i)}^{\infty} + Cons \quad (44)$$

$$= \left[\frac{\alpha i^{\gamma} s e^{-\alpha-\gamma} e_m^{\alpha}}{k^{\gamma}(\alpha+\gamma)} - \frac{s e_m^{\alpha}}{e^{\alpha}} \right] \Big|_{e_{min}(i)}^{\infty} + Cons \quad (45)$$

$$= \frac{e_m^{\alpha} s}{e_{min}(i)^{\alpha}} - \frac{\alpha e_m^{\alpha} s i^{\gamma} e_{min}(i)^{-\gamma-\alpha}}{(\alpha+\gamma)k^{\gamma}} + Cons \quad (46)$$

Now, we can use the fact that $k = \frac{1+\gamma}{s\gamma}$. Also, we can determine e_{min} . The minimum income required to consume good i is the level of e makes (7) equal to zero. Hence, $e_{min}(i) = \frac{i}{k} = \frac{is\gamma}{1+\gamma}$.

Using this in (46) gives

$$C(i) = s \left(\frac{e_m(1+\gamma)}{is\gamma} \right)^{\alpha} - \frac{\alpha e_m^{\alpha} i^{\gamma} s (is\gamma)^{-\alpha-\gamma} (1+\gamma)^{\alpha+\gamma}}{(1+\gamma)^{\gamma} (s\gamma)^{-\gamma} (\alpha+\gamma)} \quad (47)$$

$$= e_m^{\alpha} (1+\gamma)^{\alpha} i^{-\alpha} \gamma^{-\alpha} s^{1-\alpha} \left(1 - \frac{\alpha}{\alpha+\gamma} \right) \quad (48)$$

$$= s \frac{\gamma}{\alpha+\gamma} \left(\frac{e_m(1+\gamma)}{i\gamma s} \right)^{\alpha} \quad (49)$$

$$= \frac{\gamma}{\alpha+\gamma} \left(\frac{e_m}{e_{min}(i)} \right)^{\alpha} \quad (50)$$

Derivation of equation (11)

Using (10) in (9) gives

$$C(i) = \underbrace{\frac{\gamma}{\alpha + \gamma}}_{(1)} \underbrace{\left(\frac{\alpha - 1}{\alpha}\right)^\alpha}_{(2)} \underbrace{B^\alpha}_{(3)} \quad (51)$$

where $B \equiv \frac{\bar{e}}{e_{min}(i)}$. Then,

$$\frac{\partial C(i)}{\partial \alpha} = (1)'(2)(3) + (1)(2)'(3) + (1)(2)(3)' \quad (52)$$

due to the chain rule and

$$(1)' = -\gamma(\alpha + \gamma)^{-2} \quad (53)$$

$$(2)' = \left(\frac{\alpha - 1}{\alpha}\right)^\alpha \left[\ln(\alpha - 1) + \frac{\alpha}{\alpha - 1} - \ln \alpha - 1 \right] \quad (54)$$

$$= \left(\frac{\alpha - 1}{\alpha}\right)^\alpha \left[\ln \left(\frac{\alpha - 1}{\alpha}\right) + \frac{1}{\alpha - 1} \right] \quad (55)$$

$$(3)' = B^\alpha \ln B \quad (56)$$

such that

$$\begin{aligned} \frac{\partial C(i)}{\partial \alpha} &= -\frac{\gamma}{(\alpha + \gamma)^2} \left(\frac{\alpha - 1}{\alpha}\right)^\alpha B^\alpha \\ &+ \frac{\gamma}{\alpha + \gamma} B^\alpha \left(\frac{\alpha - 1}{\alpha}\right)^\alpha \left[\ln \left(\frac{\alpha - 1}{\alpha}\right) + \frac{1}{\alpha - 1} \right] \\ &+ \frac{\gamma}{\alpha + \gamma} \left(\frac{\alpha - 1}{\alpha}\right)^\alpha B^\alpha \ln B \end{aligned} \quad (57)$$

$$= \left(\frac{\alpha - 1}{\alpha}\right)^\alpha B^\alpha \frac{\gamma}{\alpha + \gamma} \left[-\frac{1}{\alpha + \gamma} + \ln \left(\frac{\alpha - 1}{\alpha}\right) + \frac{1}{\alpha - 1} + \ln B \right] \quad (58)$$

$$= \left(\frac{\alpha - 1}{\alpha}\right)^\alpha B^\alpha \frac{\gamma}{\alpha + \gamma} \left[\ln B + \ln \left(\frac{\alpha - 1}{\alpha}\right) + \frac{\gamma + 1}{(\alpha + \gamma)(\alpha - 1)} \right] \quad (59)$$

D Selected Regression Outputs

Standardized Usage Lags: Consumer Technologies

Table D.1: Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.51 ***	0.39 ***	0.42 ***	0.39 ***	-0.10	-0.15	0.28 ***	0.27 **
Human Capital	-18.07 ***	-3.65 **	-2.27	-1.00	-2.50 *	-0.93	-2.07	-0.65
EX/GDP	-6.28	-3.81 ***	-3.85 ***	-4.19 ***	-2.83 ***	-2.98 ***	-3.74 ***	-4.13 ***
Log GDP		-9.89 ***	-9.04 ***	-9.30 ***	-19.05 ***	-20.89 ***	-9.39 ***	-9.76 ***
Institutions			1.34 ***	1.32 ***	0.97 ***	0.94 ***	1.30 ***	1.31 ***
Gini $\times$ Log GDP					0.26 ***	0.30 ***		
L5.Gini							0.14	0.14
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3718	3718	3245	3219	3245	3219	2852	2828
R^2	0.623	0.775	0.799	0.809	0.814	0.826	0.816	0.829

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.2: Regression Results Q2-Q4

Dependent Variable:	Average Standardized Usage Lags							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.74 ***	-0.54 ***	-0.59 ***	-0.54 ***	0.02	0.07	-0.24 **	-0.23
Human Capital	-18.66 ***	-3.32 *	-2.92	-1.66	-3.13 *	-1.68	-3.34	-2.55
EX/GDP	-2.97	-3.99 ***	-3.23 ***	-3.68 ***	-2.29 ***	-2.71 ***	-2.63 ***	-3.19 ***
Log GDP		-10.09 ***	-8.84 ***	-9.16 ***	5.99	6.39	-8.50 ***	-9.16 ***
Institutions			1.39 ***	1.25 ***	1.15 ***	1.02 ***	1.54 ***	1.33 ***
Qmid $\times$ Log GDP					-0.31 ***	-0.32 ***		
L5.Qmid							-0.35 ***	-0.32 **
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1666	1666	1556	1532	1556	1532	859	839
R^2	0.582	0.766	0.779	0.794	0.787	0.802	0.779	0.800

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Standardized Usage Lags: Producer Technologies

Table D.3: Regression Results Gini

Dependent Variable:	Average Standardized Usage Lags							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.20 **	0.12 *	0.08	0.07	0.19 **	0.13	-0.05	-0.04
Human Capital	-16.85 ***	-7.11 ***	-6.57 ***	-4.76 **	-6.53 ***	-4.78 **	-6.34 ***	-4.71 **
EX/GDP	-4.33 *	-2.61	-3.74 ***	-3.85 ***	-3.96 ***	-3.98 ***	-3.89 ***	-3.97 ***
Log GDP		-6.71 ***	-6.65 ***	-6.68 ***	-4.51 **	-5.43 **	-6.70 ***	-6.78 ***
Institutions			0.18	-0.01	0.25	0.04	0.11	-0.07
Gini $\times$ Log GDP					-0.06	-0.03		
L5.Gini							0.12	0.10
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3663	3663	3189	3155	3189	3155	2819	2787
R^2	0.563	0.661	0.654	0.683	0.655	0.683	0.651	0.681

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.4: Regression Results Q2-Q4

Dependent Variable:	Average Standardized Usage Lags							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.25 *	-0.12	-0.12	-0.15	-0.06	0.03	-0.10	-0.18
Human Capital	-16.95 ***	-6.85 ***	-6.46 ***	-4.78 **	-6.47 ***	-4.78 **	-4.84 *	-3.89
EX/GDP	-2.47 *	-3.13 ***	-3.32 ***	-3.39 ***	-3.23 ***	-3.09 ***	-3.35 ***	-3.53 ***
Log GDP		-6.65 ***	-6.52 ***	-6.62 ***	-5.15	-1.92	-6.45 ***	-7.09 ***
Institutions			-0.04	-0.35	-0.06	-0.42	-0.16	-0.60
Qmid $\times$ Log GDP					-0.03	-0.10		
L5.Qmid							-0.04	-0.02
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1645	1645	1535	1503	1535	1503	856	829
R^2	0.480	0.596	0.582	0.635	0.582	0.636	0.498	0.587

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Internet Access

Table D.5: Regression Results Gini

Dependent Variable:	Internet Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-5.41 ***	-3.44 ***	-3.38 ***	-3.31 ***	7.49 ***	7.01 ***	1.41	1.43
Human Capital	167.43 ***	8.78	-2.05	-1.49	13.90	8.99	-6.23	-2.69
EX/GDP	56.77	47.93 ***	45.27 **	47.50 **	27.80 *	29.14	47.75 **	50.43 ***
Log GDP		105.96 ***	98.10 ***	101.22 ***	289.32 ***	292.10 ***	102.52 ***	106.25 ***
Institutions			-12.34 ***	-11.00 **	-5.80	-5.56	-12.30 ***	-10.63 **
Gini $\times$ Log GDP					-5.04 ***	-5.06 ***		
L5.Gini							-4.94 ***	-5.53 ***
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2061	2061	2040	2040	2040	2040	1947	1947
R^2	0.629	0.726	0.730	0.734	0.755	0.757	0.742	0.747

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.6: Regression Results Gini

Dependent Variable:	Usage Lags of Internet Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.14 ***	0.08 ***	0.07 ***	0.09 ***	-0.17 ***	-0.16 ***	-0.06	-0.05
Human Capital	-5.18 ***	-1.16 *	-0.80	-0.65	-1.02 *	-0.78	-0.74	-0.61
EX/GDP	-1.16	-1.21 ***	-1.19 ***	-1.23 ***	-0.89 ***	-0.90 ***	-1.25 ***	-1.29 ***
Log GDP		-3.01 ***	-2.83 ***	-2.90 ***	-6.78 ***	-7.03 ***	-2.85 ***	-2.93 ***
Institutions			0.35 ***	0.33 ***	0.23 **	0.24 **	0.32 ***	0.29 ***
Gini $\times$ Log GDP					0.11 ***	0.11 ***		
L5.Gini							0.13 ***	0.15 ***
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1400	1400	1380	1380	1380	1380	1346	1346
R^2	0.584	0.762	0.771	0.775	0.790	0.795	0.774	0.779

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.7: Regression Results Q2-Q4

Dependent Variable:	Internet Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	8.52 ***	3.58 ***	3.99 ***	3.03	-12.96 ***	-12.74 ***	-0.31	-1.33
Human Capital	216.26 ***	24.93	12.70	15.15	32.91	29.64	2.13	14.57
EX/GDP	34.68	59.52 ***	49.42 **	50.07 **	25.16	25.98	48.79 **	49.92 **
Log GDP		132.43 ***	116.35 ***	116.75 ***	-272.19 ***	-260.95 ***	131.88 ***	130.37 ***
Institutions			-20.05 ***	-16.62 ***	-14.57 ***	-13.35 **	-22.33 ***	-24.26 ***
Qmid $\times$ Log GDP					8.00 ***	7.77 ***		
L5.Qmid							5.24 **	3.74
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1113	1113	1109	1109	1109	1109	675	675
R^2	0.631	0.762	0.770	0.773	0.789	0.789	0.801	0.807

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.8: Regression Results Q2-Q4

Dependent Variable:	Usage Lags of Internet Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.20 ***	-0.05	-0.06 *	-0.08	0.31 ***	0.31 ***	0.03	0.02
Human Capital	-5.46 ***	-1.29 *	-0.99	-0.70	-1.31 **	-0.97	-0.98	-1.04
EX/GDP	-0.68	-1.45 ***	-1.24 ***	-1.23 ***	-0.76 **	-0.73 **	-1.17 ***	-1.17 ***
Log GDP		-3.34 ***	-2.96 ***	-2.95 ***	5.52 ***	5.83 ***	-2.96 ***	-2.95 ***
Institutions			0.48 ***	0.41 ***	0.38 ***	0.35 ***	0.57 ***	0.56 ***
Qmid $\times$ Log GDP					-0.17 ***	-0.18 ***		
L5.Qmid							-0.10	-0.09
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	884	884	881	881	881	881	562	562
R^2	0.496	0.720	0.735	0.738	0.755	0.758	0.720	0.723

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Personal Computers

Table D.9: Regression Results Gini

Dependent Variable:	Personal Computers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-4.14 ***	-2.79 ***	-2.92 ***	-3.76 ***	7.37 ***	6.59 ***	-1.63	-1.63
Human Capital	108.44 ***	-7.71	-11.90	-9.35	-0.71	-0.28	-13.02	-10.76
EX/GDP	151.29 ***	95.96 ***	94.55 ***	99.75 ***	66.85 **	70.29 ***	93.96 ***	100.90 ***
Log GDP		85.61 ***	81.49 ***	85.23 ***	263.13 ***	272.81 ***	86.68 ***	90.72 ***
Institutions			-4.71	-6.16	1.58	-0.45	-5.05	-6.94 *
Gini $\times$ Log GDP					-4.78 ***	-4.95 ***		
L5.Gini							-1.32	-2.56 **
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1673	1673	1648	1648	1648	1648	1541	1541
R^2	0.528	0.643	0.639	0.651	0.680	0.692	0.652	0.666

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.10: Regression Results Gini

Dependent Variable:	Usage Lags of Personal Computers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.19 ***	0.08 ***	0.08 ***	0.09 ***	-0.34 ***	-0.34 ***	0.03	0.03
Human Capital	-4.63 ***	-0.89	-0.48	-0.05	-0.79	-0.24	-0.42	-0.01
EX/GDP	-5.39 ***	-3.49 ***	-3.70 ***	-3.92 ***	-2.75 ***	-2.92 ***	-3.67 ***	-3.90 ***
Log GDP		-4.38 ***	-4.21 ***	-4.25 ***	-11.04 ***	-11.23 ***	-4.30 ***	-4.35 ***
Institutions			0.27 **	0.35 ***	0.05	0.17	0.24 *	0.33 **
Gini $\times$ Log GDP					0.18 ***	0.19 ***		
L5.Gini							0.05	0.08 *
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1220	1220	1196	1196	1196	1196	1156	1156
R^2	0.639	0.810	0.814	0.825	0.844	0.855	0.816	0.828

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.11: Regression Results Q2-Q4

Dependent Variable:	Personal Computers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	6.82 ***	3.44 **	3.33 **	5.41 ***	-8.48 **	-6.20 *	2.03	2.72
Human Capital	137.88 ***	-3.04	-0.69	13.00	13.29	24.42	-11.27	-14.05
EX/GDP	128.59	118.01 ***	121.61 ***	127.35 ***	85.10 ***	91.73 ***	131.06 ***	141.75 ***
Log GDP		104.40 ***	106.72 ***	113.09 ***	-174.43 **	-164.42 **	135.43 ***	143.84 ***
Institutions			2.61	-2.03	6.02	0.56	13.18	4.32
Qmid $\times$ Log GDP					5.75 ***	5.67 ***		
L5.Qmid							1.74	4.37 *
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	801	801	797	797	797	797	457	457
R^2	0.496	0.658	0.656	0.676	0.672	0.689	0.693	0.718

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.12: Regression Results Q2-Q4

Dependent Variable:	Usage Lags of Personal Computers							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.31 ***	-0.06	-0.06	-0.11 **	0.50 ***	0.49 ***	-0.09	-0.11
Human Capital	-4.96 ***	-1.10	-0.97	-0.74	-1.50 *	-1.25	0.26	0.87
EX/GDP	-4.51	-4.84 ***	-4.85 ***	-4.97 ***	-3.25 ***	-3.34 ***	-5.16 ***	-5.33 ***
Log GDP		-4.75 ***	-4.69 ***	-4.69 ***	8.16 ***	8.58 ***	-5.17 ***	-5.19 ***
Institutions			0.15	0.21	-0.00	0.11	0.09	0.09
Qmid $\times$ Log GDP					-0.26 ***	-0.27 ***		
L5.Qmid							-0.02	-0.06
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	658	658	654	654	654	654	384	384
R^2	0.588	0.813	0.814	0.822	0.834	0.843	0.810	0.819

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Mobile Phones

Table D.13: Regression Results Gini

Dependent Variable:	Mobiles							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-4.64 ***	-2.00 *	-2.47 **	0.46	-2.55	-0.34	-0.78	0.20
Human Capital	211.66 ***	3.18	-1.70	-19.77	-1.80	-20.27	4.06	-9.92
EX/GDP	125.44 **	110.74 ***	98.10 ***	92.21 ***	98.25 ***	93.69 ***	98.30 ***	91.32 ***
Log GDP		140.31 ***	127.87 ***	118.77 ***	126.31 ***	103.86 ***	133.23 ***	124.32 ***
Institutions			-10.87 *	-6.75	-10.93 *	-7.20	-11.98 *	-7.50
Gini $\times$ Log GDP					0.04	0.39		
L5.Gini							-1.54	0.52
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2352	2352	2319	2319	2319	2319	2182	2182
R^2	0.767	0.820	0.822	0.828	0.822	0.828	0.828	0.835

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.14: Regression Results Gini

Dependent Variable:	Usage Lags of Mobiles							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.09 ***	0.03	0.03	0.02	-0.04	-0.05	0.04	0.03
Human Capital	-5.59 ***	-0.39	-0.05	0.27	-0.10	0.24	-0.15	0.14
EX/GDP	-4.56 ***	-2.95 ***	-2.85 ***	-2.82 ***	-2.62 ***	-2.57 ***	-2.81 ***	-2.76 ***
Log GDP		-3.69 ***	-3.38 ***	-3.33 ***	-4.61 ***	-4.70 ***	-3.48 ***	-3.43 ***
Institutions			0.44 ***	0.40 ***	0.39 ***	0.36 ***	0.44 ***	0.40 ***
Gini $\times$ Log GDP					0.03 *	0.04 *		
L5.Gini							-0.01	-0.02
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2038	2038	2014	2014	2014	2014	1877	1877
R^2	0.571	0.774	0.787	0.789	0.789	0.791	0.789	0.792

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.15: Regression Results Q2-Q4

Dependent Variable:	Mobiles							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	9.17 ***	3.68 **	4.14 **	-2.53	3.91	-1.34	4.71	2.02
Human Capital	236.73 ***	15.16	12.96	-8.17	13.18	-8.96	-27.25	-39.98
EX/GDP	84.19 *	110.65 ***	102.72 ***	97.81 ***	102.38 ***	99.68 ***	96.20 ***	94.02 ***
Log GDP		151.39 ***	142.06 ***	130.40 ***	136.68	159.42	152.68 ***	145.15 ***
Institutions			-7.88	-0.51	-7.80	-0.80	0.77	13.44
Qmid $\times$ Log GDP					0.11	-0.60		
L5.Qmid							3.15	-0.15
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1235	1235	1228	1228	1228	1228	740	740
R^2	0.793	0.846	0.846	0.855	0.846	0.855	0.853	0.859

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.16: Regression Results Q2-Q4

Dependent Variable:	Usage Lags of Mobiles							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.15 ***	-0.03	-0.05 *	0.00	0.09	0.14 *	-0.13 **	-0.11 **
Human Capital	-5.52 ***	0.03	0.26	0.75	0.13	0.66	0.47	0.92
EX/GDP	-3.52 *	-3.85 ***	-3.55 ***	-3.53 ***	-3.14 ***	-3.09 ***	-3.77 ***	-3.74 ***
Log GDP		-3.87 ***	-3.57 ***	-3.47 ***	-0.34	-0.02	-3.89 ***	-3.82 ***
Institutions			0.35 ***	0.29 **	0.31 **	0.25 **	0.15	0.03
Qmid $\times$ Log GDP					-0.07 **	-0.07 **		
L5.Qmid							0.01	0.03
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	965	965	960	960	960	960	520	520
R^2	0.492	0.757	0.763	0.769	0.766	0.772	0.776	0.781

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Cars

Table D.17: Regression Results Gini

Dependent Variable:	Cars							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-5.91 ***	-4.72 ***	-5.00 ***	-4.38 ***	2.79 **	1.80	-2.98 **	-1.61
Human Capital	160.59 ***	48.99	22.69	11.15	12.39	-7.13	24.73	9.36
EX/GDP	-2.36	-13.11	-2.25	2.44	-14.48	-7.92	-3.53	2.99
Log GDP		74.12 ***	68.89 ***	69.83 ***	221.76 ***	211.29 ***	69.71 ***	72.34 ***
Institutions			-20.91 ***	-16.90 ***	-16.15 ***	-13.33 ***	-23.02 ***	-18.47 ***
Gini $\times$ Log GDP					-3.87 ***	-3.49 ***		
L5.Gini							-2.30 *	-3.21 **
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3045	3045	2584	2558	2584	2558	2289	2265
R^2	0.601	0.686	0.756	0.795	0.793	0.819	0.763	0.800

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.18: Regression Results Gini

Dependent Variable:	Usage Lags of Cars							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.85 ***	0.68 ***	0.71 ***	0.46 ***	-0.50 ***	-0.42 ***	0.52 ***	0.19
Human Capital	-21.26 ***	-4.38	-0.59	1.41	1.13	3.89 *	-0.75	1.74
EX/GDP	-1.02	0.48	-0.97	-1.65	0.90	-0.14	-0.71	-1.64
Log GDP		-11.06 ***	-10.20 ***	-9.88 ***	-34.04 ***	-30.09 ***	-10.22 ***	-10.09 ***
Institutions			3.04 ***	2.49 ***	2.31 ***	1.98 ***	3.30 ***	2.65 ***
Gini $\times$ Log GDP					0.60 ***	0.50 ***		
L5.Gini							0.25	0.32 *
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3002	3002	2553	2527	2553	2527	2258	2234
R^2	0.654	0.744	0.805	0.854	0.849	0.878	0.815	0.861

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.19: Regression Results Q2-Q4

Dependent Variable:	Cars							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	10.07 ***	7.19 ***	7.59 ***	7.58 ***	-2.62	-0.61	-0.01	1.50
Human Capital	197.99 ***	55.11	26.62	24.56	22.18	14.46	47.19	32.99
EX/GDP	-7.50	14.46	11.51	14.33	-1.74	4.20	17.87 *	23.69 **
Log GDP		93.32 ***	81.79 ***	83.92 ***	-152.53 **	-117.58 *	90.21 ***	101.11 ***
Institutions			-26.28 ***	-21.52 ***	-22.57 ***	-18.90 ***	-30.23 ***	-23.79 ***
Qmid $\times$ Log GDP					4.92 ***	4.30 ***		
L5.Qmid							6.79 ***	7.73 ***
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1298	1298	1183	1159	1183	1159	661	641
R^2	0.623	0.729	0.775	0.800	0.792	0.811	0.778	0.799

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.20: Regression Results Q2-Q4

Dependent Variable:	Usage Lags of Cars							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-1.51 ***	-1.10 ***	-1.18 ***	-0.69 **	0.67 **	0.67 **	-0.40 *	-0.16
Human Capital	-24.25 ***	-1.81	2.14	3.82	3.28	5.51 *	5.77	7.51 *
EX/GDP	-0.42	-3.93 **	-3.23 **	-3.36 ***	-0.87	-1.68	-3.68 ***	-4.14 ***
Log GDP		-14.09 ***	-12.05 ***	-10.86 ***	30.76 ***	22.63 ***	-12.80 ***	-12.26 ***
Institutions			3.97 ***	3.20 ***	3.31 ***	2.77 ***	4.99 ***	3.94 ***
Qmid $\times$ Log GDP					-0.90 ***	-0.71 ***		
L5.Qmid							-0.98 ***	-0.62 **
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1257	1257	1154	1130	1154	1130	632	612
R^2	0.625	0.761	0.820	0.869	0.850	0.885	0.843	0.884

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Electricity Production

Table D.21: Regression Results Gini

Dependent Variable:	Electricity Production							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	-0.13 ***	-0.11 ***	-0.11 ***	-0.16 ***	0.19 **	0.14 *	-0.05	-0.07
Human Capital	3.66 ***	1.21 **	1.12 *	1.32 **	1.30 **	1.30 **	1.20 *	1.36 **
EX/GDP	1.09	0.64 *	0.70 *	0.78 **	0.11	0.14	0.70 **	0.82 **
Log GDP		1.70 ***	1.64 ***	1.74 ***	7.28 ***	7.93 ***	1.75 ***	1.89 ***
Institutions			-0.18 **	-0.14	0.04	0.08	-0.18 **	-0.14
Gini $\times$ Log GDP					-0.15 ***	-0.16 ***		
L5.Gini							-0.06 *	-0.11 ***
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3685	3685	3202	3182	3202	3182	2830	2812
R^2	0.404	0.469	0.474	0.490	0.536	0.556	0.470	0.492

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.22: Regression Results Gini

Dependent Variable:	Usage Lags of Electricity Production							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Gini	0.43 **	0.26 *	0.22	0.19	0.18	0.15	-0.23	-0.21
Human Capital	-28.04 ***	-13.81 ***	-13.77 ***	-12.09 ***	-13.78 ***	-12.09 ***	-13.51 ***	-11.93 ***
EX/GDP	-4.63	-2.11	-2.84 *	-2.79 **	-2.79 *	-2.71 **	-3.09 **	-3.05 **
Log GDP		-11.44 ***	-11.39 ***	-11.02 ***	-12.04 **	-11.81 **	-11.62 ***	-11.31 ***
Institutions			0.05	-0.36	0.03	-0.39	-0.02	-0.43
Gini $\times$ Log GDP					0.02	0.02		
L5.Gini							0.43 ***	0.42 ***
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3269	3269	2836	2816	2836	2816	2545	2527
R^2	0.690	0.816	0.800	0.807	0.800	0.807	0.809	0.815

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.23: Regression Results Q2-Q4

Dependent Variable:	Electricity Production							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	0.17 ***	0.12 ***	0.12 ***	0.23 ***	-0.41 **	-0.31	0.09	0.18 ***
Human Capital	5.13 ***	1.90 ***	2.03 ***	2.29 ***	2.26 ***	2.37 ***	2.97 ***	2.79 **
EX/GDP	0.75	0.95 **	0.94 **	0.99 **	0.10	0.14	1.21 **	1.27 **
Log GDP		2.17 ***	2.14 ***	2.32 ***	-10.77 **	-11.17 **	2.69 ***	2.91 ***
Institutions			-0.09	-0.05	0.12	0.17	0.04	0.13
Qmid $\times$ Log GDP					0.27 ***	0.28 ***		
L5.Qmid							-0.01	0.07
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1675	1675	1554	1535	1554	1535	876	861
R^2	0.352	0.432	0.428	0.445	0.474	0.493	0.427	0.445

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.

Table D.24: Regression Results Q2-Q4

Dependent Variable:	Usage Lags of Electricity Production							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Qmid	-0.58 **	-0.35 *	-0.32	-0.37	0.03	-0.06	-0.09	-0.20
Human Capital	-28.17 ***	-14.22 ***	-14.37 ***	-11.50 ***	-14.48 ***	-11.67 ***	-11.34 ***	-8.32 **
EX/GDP	-1.23	-2.57 *	-2.79 **	-2.64 ***	-2.29 *	-2.18 *	-2.92 ***	-2.90 ***
Log GDP		-10.71 ***	-10.76 ***	-10.36 ***	-2.55	-2.56	-10.77 ***	-10.71 ***
Institutions			-0.22	-0.86 **	-0.36	-0.99 **	-0.38	-1.06 **
Qmid $\times$ Log GDP					-0.17	-0.16		
L5.Qmid							-0.22	-0.17
Region FE	No	No	No	Yes	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1479	1479	1381	1362	1381	1362	775	760
R^2	0.647	0.788	0.774	0.786	0.775	0.788	0.760	0.770

Note: Standard errors clustered at the country level. Significance at the 10% level is indicated by *, at the 5% level by **, and at the 1% level by ***.