Economic Research Working Paper
No. 91/2026

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WIPO

WIPR2026

Working Paper 91

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Abstract

Technology diffusion is central to economic development. This paper examines diffusion patterns for 31 technologies for 139 countries over two centuries, extending existing databases to include recent digital technologies and renewable energy technologies. Using cross-country panel regressions, we find that while adoption lags have declined from 50 years (pre-1950) to 15 years (post-2000), adoption intensity in developing economies remains at 53% of advanced economy levels. We document diverging intensity for older technologies but emerging convergence for post-2000 technologies, suggesting digital innovations may reduce the technology gap. These findings inform policies aimed at accelerating technology diffusion to developing economies.

Keywords: technology diffusion, digital technologies, adoption lag, intensity of use

JEL codes: O33, O47, O57

Acknowledgement: The authors gratefully acknowledge Diego Comin (Harvard University) for invaluable comments and suggestions. We also thank Fabiana Visentin, Ernest Miguelez, Michele Pezzoni, and WIPO colleagues for their helpful feedback during the Innovation Economy Section research seminars. All remaining errors are our own responsibility.

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1. Introduction

Over the past two centuries, humanity has experienced an unprecedented improvement in living standards. Since the Industrial Revolution began more than two hundred years ago, global per capita income has increased more than tenfold. Life expectancy has nearly doubled in many countries, rising from around 40 to over 80 years in developed nations. Communication that once depended on mail carried by horseback now happens instantaneously across continents. Today, generative artificial intelligence (GenAI) can compose symphonies, write poetry, and create artwork that rivals human creativity – capabilities that would have seemed like magic just decades ago.

These remarkable gains reflect the power of innovation and technological progress. At the core of this advancement is creative destruction—the mechanism through which successive waves of innovation replace older technologies and business models, driving long run productivity and growth, as highlighted by Nobel Prize-winning economists Philippe Aghion and Howitt's in their seminal work on the subject (Aghion and Howitt, 1992).

Yet the mere invention of new technologies tells only part of the story. Creating innovative solutions does not automatically translate into economic growth or societal benefits. For new technologies to fulfil their potential, they must be adopted and effectively used by firms and households. This so-called technology diffusion process represents a crucial bridge between invention and impactful innovation. It is neither automatic nor guaranteed.

Technology diffusion faces several challenges that can slow or prevent the spread of beneficial innovations. Users often need to acquire new skills to operate unfamiliar technologies effectively. Breakthrough technologies from the internal combustion engine to information and communication technologies require substantial investments in supporting infrastructure. For instance, consider how the motor car requires not just manufacturing plants, but networks of roads, gas stations, and repair services. Businesses may need to reorganize their operations or develop new management practices. Sometimes they must create entirely new business models to harness technology's full potential.

The arrival of breakthrough technologies typically spurs waves of complementary innovations. These organizational and business model innovations often prove as important as the original technological advance. New ways of organizing work, serving customers, or structuring entire industries can generate major productivity gains that extend far beyond the technology itself. The internet, for example, enabled not just faster communication. It created entirely new forms of commerce, entertainment and social interaction that continue to reshape the global economy.

Multiple factors shape diffusion outcomes, including available skills, competitive dynamics, access to finance, and technical standards and regulations. These factors help explain why technologies do not diffuse seamlessly across economies. These uneven patterns contribute to persistent inequalities in economic development, living standards, health outcomes, and environmental quality.

This paper seeks to shed some light on the technology diffusion process by examining how rapidly and extensively various technologies have spread across the globe, highlighting how diffusion patterns have changed throughout history. Building primarily on Comin and Hobijn, (2010) and Comin and Mestieri (2018), this paper investigates technology diffusion by expanding the sample of technologies proposed by the former to include newer technologies related to the ICT paradigm and sustainable energy sources. We estimate the diffusion model for 31 technologies and 139 countries over the last two centuries.

Consistent with the previous literature, we find that the average estimated adoption lag is 41 years. On average, the intensity of adoption in developing economies is about half (53%) that of advanced economies. We also document substantial heterogeneity across countries and technologies in both adoption lags and adoption intensity. Overall, our results show that adoption lags have declined more sharply over time in developing economies than in advanced economies. By contrast, the intensity of technology use has diverged across countries, although it shows signs of convergence for more recent technologies.

The paper is structured as follows. In Section 2, we review background literature on technology diffusion, focusing on conceptualization, and going through how technology diffusion has been measured. In Section 3, we describe our estimation strategy; Section 4 describes the main findings and Section 5 presents conclusions.

2. Background literature

2.1 Technology diffusion conceptualization

Technology diffusion, the process by which innovations spread from inventors to end users, shapes economic growth, comparative advantage, and societal transformation. Yet despite its importance, this multifaceted process remains challenging to analyze due to its multi-scale nature, spanning individual adoption decisions to industry-wide transformation, and its treatment across diverse disciplinary traditions.

This process represents what Schumpeter identified as the third critical stage of technological progress, after invention and innovation, where economic and social benefits materialize through widespread adoption (Jaffe, 2015). Consequently, technological diffusion has attracted cross-disciplinary attention from agriculture, sociology, economics, and political science (Dosi, 1991; Rogers, 1983), each approaching the phenomenon from different analytical angles. This diversity has offered valuable insights but also resulted in competing definitions and frameworks.

In this paper, technology diffusion refers to the broader spread of new technology across firms, industries, and economies as more users adopt it over time. Diffusion typically follows a recognizable path. Early adopters with greater technical expertise or appetite for risk lead the way. Mainstream users follow once the technology has proven its worth and become more accessible. Even cautious users eventually adopt the technology becomes standard.

While definitions vary across disciplines, this working conception aligns with established scholarship viewing diffusion as a dynamic, time-dependent process involving the transfer of information, knowledge, and innovations across heterogeneous societies and markets (Battisti and Stoneman, 2010; Rogers, 1983). Importantly, diffusion operates simultaneously at multiple scales—international, national, industrial, regional, intrafirm, and household levels—with adoption decisions at one level influencing patterns at others. As Comin and Mestieri (2014) articulate, diffusion emerges as the dynamic consequence of individual adoption decisions, characterized by technology accumulation across adopters and over time.

Several critical insights shape the contemporary understanding of diffusion processes. First, diffusion is inherently time-consuming, regardless of the innovation source, type, or acquisition cost (Dosi, 1991; Lechman, 2015). The path from introduction to widespread adoption spans years or even decades, reflecting the time required for information dissemination, learning, infrastructure development, and institutional adjustment. Second, diffusion depends on multiple interacting factors: the characteristics of both new and incumbent technologies, the structure of adoption incentives, the attributes of potential adopters, available information, and existing technological competence (Dosi, 1991). Third—and perhaps most importantly, intrinsic technological superiority does not guarantee rapid diffusion (Jaffe, 2005). Even demonstrably superior technologies may diffuse slowly due to institutional rigidities, infrastructural gaps, behavioral inertia, and misaligned incentives. The economic significance and social impact of any innovation ultimately depend not on its technical merits alone, but on its acceptance among potential users and the degree to which competitors adopt it (Dosi, 1991).

Understanding these dynamics is essential for analyzing how technologies spread and for identifying the factors that shape diffusion outcomes in specific contexts.

2.2 The evolution of diffusion measurement

2.2.1 Measuring technology diffusion: diffusion curves

The starting point in the theoretical literature on technological diffusion is offered by the work of Zvi Griliches (1957) on the diffusion of hybrid corn seed in the Midwestern United States (US) based on the estimation of S-shaped (or logistic) diffusion curves. Under this framework, measuring diffusion implies measuring the share of potential adopters that have adopted a given technology at a point in time, also known as the extensive margin (Comin et al., 2008).

In this regard, a diffusion curve ranges between two levels of technological adoption: zero adoption and saturation. In other words, in the initial phase of what is typically a logistic curve, only a few early adopters use the new technology and adoption rates remain low (Knez, 2023). The curve has an inflection point; the adoption rates peak, and technology becomes dominant. In the late stage, the laggards are the last to adopt the new technology until it approaches the saturation point and is eventually replaced by the new technology. Within the framework of diffusion curves, differences in technology adoption rates in different countries can be interpreted as a shift in the inflection point, differences in the slope of the logistic curves, and differences in long run technology adoption. Later, Mansfield (1961) uses a similar methodology to examine the diffusion of twelve major innovations in four industries: bituminous coal, iron and steel, brewing, and railroads. Unlike hybrid corn, most of these technologies require the purchase of new equipment, so in each case a significant investment was required to achieve a substantial reduction in costs (Stokey, 2021)

Several theoretical frameworks have been proposed to explain the S-shaped pattern of technology diffusion (Geroski, 2000; Karshenas and Stoneman, 1993). These approaches broadly fall into two groups. On the one hand, rank (or probit) models emphasize firm heterogeneity, linking adoption decisions to characteristics such as size, ownership structure, workforce skills, output growth, and marketing expenditure (Bartoloni and Baussola, 2001). On the other hand, interaction-based models stress that adoption decisions depend on the behaviour of other firms. In this perspective, epidemic models highlight learning and information spillovers that reduce uncertainty over time; stock models point to declining benefits as diffusion increases and competition intensifies; and order models emphasize strategic timing and the incentives to adopt early (Fusaro, 2009).

The traditional diffusion literature has fitted S-shaped diffusion curves (the logistic curve) to diffusion measures such as $Y_t = \frac{m_t}{M}$ (M is the fixed number of potential adopters and m_t is the number of producers that have adopted the technology at time t).

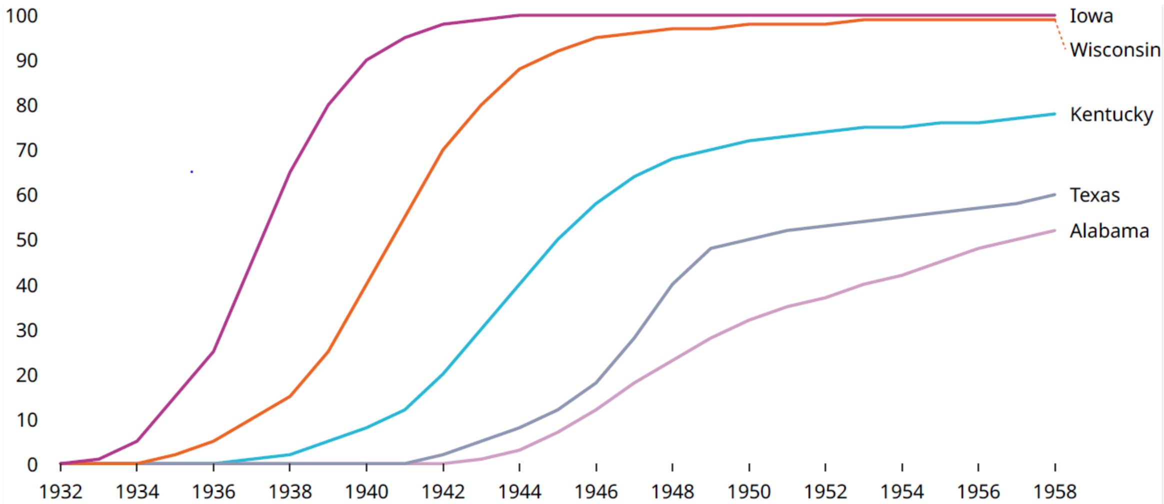
Overall, logistic curves are defined as:

$$Y_t = \frac{\delta_1}{1 + e^{-(\delta_2 + \delta_3 t)}} \qquad (1)$$

Where by t represents time, δ_3 reflects the speed of adoption, δ_2 is a constant of integration that positions the curve on the time scale, and δ_1 is the long run outcome. Two features are worth pointing out. First, adoption shares converge to 0 when t goes to minus infinity and to δ_1 when t goes to infinity. Second, the diffusion curve is symmetric around the inflection point of Y_t=0.5δ_1 which occurs at t=-δ_2/δ_3.

Illustratively, Figure 1, based on data from Griliches (1957), displays the share of hybrid corn in the total area cultivated, that diffuses approximately in an S-shaped manner, and hence reflecting the extensive margin with which modern variety agricultural technologies are used.

FIGURE 1. SHARE OF TOTAL CORN ACREAGE PLANTED WITH HYBRID SEED, SELECTED US



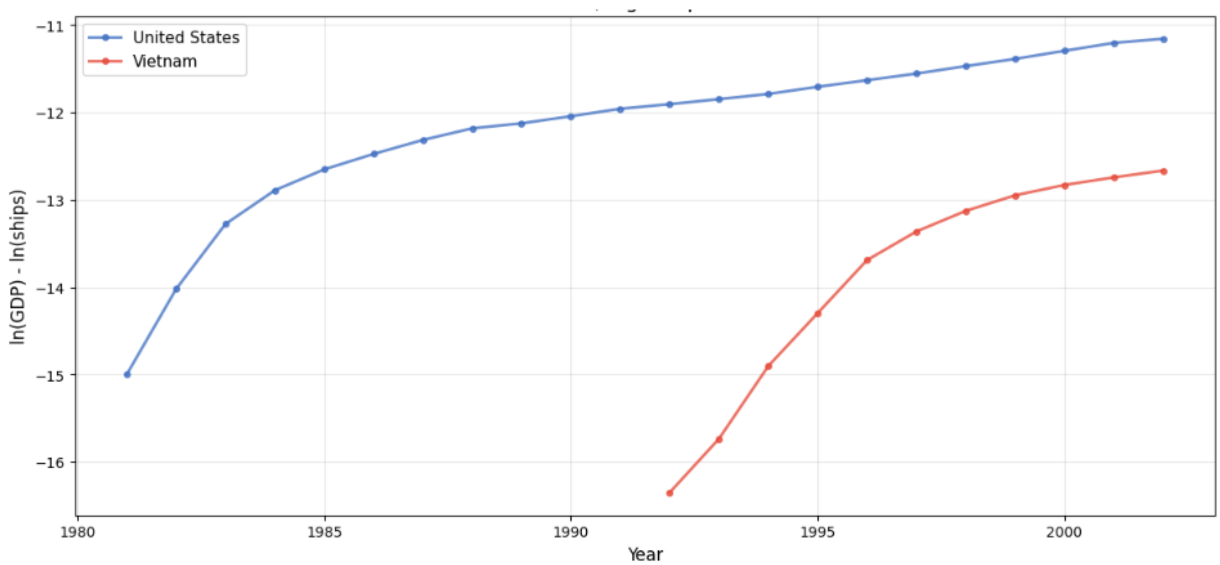
Source: Authors' elaboration based on Griliches, Z. (1957)

2.2.2 Limitations and intensive margin

While S-shaped curves effectively capture the extensive margin of diffusion—the proportion of potential adopters who have adopted a technology—they often fail to adequately represent diffusion patterns for technologies where the intensity of use among adopters is central. In this context, the intensive margin refers to the extent to which a technology is used within adopting economies, measured for example by the number of capital units embodying the new technology (such as telephone installations) or by the volume of output generated using that technology (such as kilowatt-hours of electricity per capita) (Comin and Hobijn, 2010).

For instance, Figure 2 shows the large cross-country dispersion present in diffusion. It indicates that the level of PCs per capita in the US in 1980 was reached by Vietnam in 1994, 14 years later. Following (Comin et al., 2006), these disparities are even higher than the disparities of income levels.

FIGURE 2. DIFFUSION OF PCS, LOG COMPUTERS OVER GDP



Source: Authors' elaboration based on Figure 2 Comin and Mesteri (2018)

Comin et al (2008) using the CHAT[4] dataset, identified that diffusion curves do not provide a good approximation of the diffusion process once the intensive margin—how intensively each adopter uses the technology—is taken into account. They found that the evolution of technology levels in a country does not typically follow a logistic pattern once the intensive margin is taken into consideration.

To capture the intensive margin, it is necessary to use measures of technology in which the numerator depends on the intensity with which each producer or consumer adopts the technology. However, such computation requires hard-to-obtain micro-level data. As a result, the diffusion of only a limited number of technologies for a limited number of countries can be documented using such measures. Traditional measures do not reflect the intensity with which each adopter uses the technology (Comin and Mestieri, 2014).

To address these data challenges and enable cross-country comparisons, subsequent research has developed methodologies based on time lags and usage intensity measures. These approaches, which we detail in the following subsection, allow researchers to quantify not just when countries adopt technologies, but how deeply those technologies penetrate economic activity.

[4] Further information is available in the data description section.

2.2.3 Measuring the intensive margin

This section elaborates on the measurement of the intensive margin introduced above, detailing the methodological innovations that allow researchers to capture technology usage intensity.

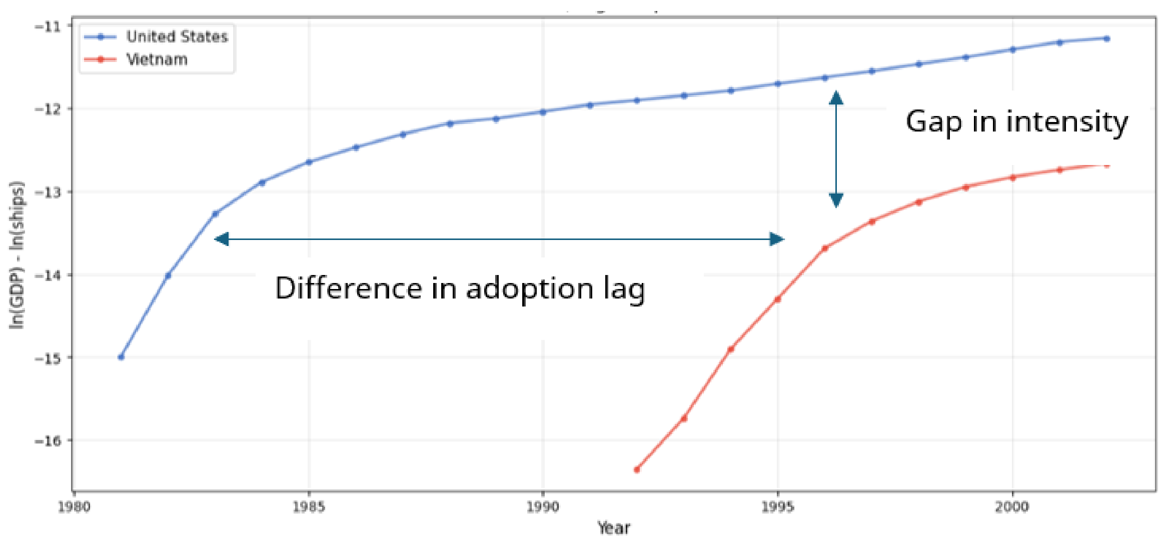
A distinctive feature of these sophisticated models is their assessment of technological disparities across nations in terms of adoption intensity, quantified through time lag measurements (Comin and Mestieri, 2014, 2018). Time lags have the advantage that they have a common unit across technologies (e.g., years). Specifically, the usage lag of technology $x$in country $c$at time $t$is defined as the number of years by which country $c$trails the technological frontier. It answers the following question: how many years prior to year t did the US exhibit the same level of usage intensity of technology x that country $c$exhibits in year t? This methodological advancement offers a more nuanced understanding of how technologies permeate economies at varying rates and with different degrees of implementation depth.

Unlike the logistic diffusion curve, the intensive margin approach characterizes the diffusion curve as follows (Comin and Hobijn, 2010; Comin and Mestieri, 2014, 2018)

$$y_{\tau,t}^{c} = \beta_{\tau1}^{c} + \beta_{\tau2}^{c} t + \beta_{\tau3}^{c} ln(t - \tau - \beta_{\tau4}^{c}) + \varepsilon \tag{2}$$

where $y_{\tau,t}^{c}$ represents the log output from technology τ at time t in country c, the coefficient $\beta_{\tau1}^{c}$ represents the vertical shift in the diffusion curve, $t - \tau$ is the time elapsed since technology τ was invented, the coefficient $\beta_{\tau4}^{c}$ represents the horizontal curve shifter and captures the delay in the arrival date of the technology τ to country c, and $\ln(t - \tau - \beta_{\tau4}^{c})$ captures the curve's concave shape. $\beta_{\tau2}^{c} t$ is a linear time trend that ensures that the technology measure behaves asymptotically log-linearly. Graphically, shifts of the curves can be seen in Figure 3.

FIGURE 3 DIFFERENCE IN ADOPTION LAG AND GAP INTENSITY



Source: Authors elaboration based on Figure 2 Comin and Mesteri (2018)

Furthermore, Comin and Mestieri (2014) argue that richer countries are expected to exhibit greater demand for goods and services that embody or use advanced technologies. The cost of producing such goods and services also tends to rise with the wage level. Hence, the authors include income in the diffusion curve, obtaining the following equation:

$$y_{\tau,t}^{c} = \beta_{t0}^{c} + \beta_{\tau1}^{c} + y_{t}^{c} + \beta_{\tau2}t + \beta_{\tau3}[(\mu-1)ln(t-D_{\tau}^{c}-\tau)-(1-\alpha)(y_{t}^{c}-l_{t}^{c})] + \varepsilon_{\tau t}^{c} \qquad (3)$$

where $\varepsilon_{\tau t}^{c}$ is an error term to account for the discrepancies between the model and the data. The adoption lag $\beta_{\tau4}^{c}$ from Equation (2) is replaced by D_{τ}^{c}, and the parameters are given theoretical interpretations based on the elasticity of substitution (θ) and production function parameters (α, μ).Also, equation 3 shows that $y_{\tau,t}^{c}$ (log of output produced with technology τ) can be expressed as the sum of the following coefficients:

- country time varying term β_{t0}^{c}
- a country-technology specific constant $\beta_{\tau1}^{c}$
- a log linear term in time with coefficient $\beta_{\tau2}^{c}t = \gamma/2$ that captures technology productivity growth.
- the log of output y_{t}^{c}. It is included as the level of aggregate demand affects the demand for technology. This assumption is relaxed by (Comin and Mestieri, 2018) in the robustness checks.

- a nonlinear function of the adoption lag with coefficient $\beta_{\tau 3} = \frac{\theta}{\theta - 1}$

The country-technology intercept $\beta_{\tau 1}^{c}$ is given by:

$$\beta_{\tau 1}^{c} = \beta_{\tau 3}^{c}((\psi - 1)n_{\tau}^{C} - nl\big((1 + \zeta_{\tau x}^{C})\big) + \alpha ln\, \alpha + \left(\chi + \frac{\gamma}{2}\right)\tau - \frac{\gamma}{2}D_{\tau}^{c}) \tag{4}$$

The first two terms of Equation 4 capture the variation in technology τ output associated with the number of producers who use the technology to produce differentiated services and the number of units of technology used per producer. These two components define the intensity of use parameter I_{τ}. The last two terms show the effect on the intercept of the initial level of productivity embodied in technology.

The term β_{t0}^{c} captures the variation in $y_{\tau t}^{c}$ generated by country-wide factors such as exogenous total factor productivity (TFP) growth.

$$\beta_{t0}^{c} = \beta_{\tau 3}(\chi_{t}^{c} - (1 - \alpha)\ln\left(\frac{1 + \zeta_{L}^{C}}{1 - \alpha}\right)) \tag{5}$$

Following (Comin and Mestieri, 2014), equation 3 shows that the adoption lag D_{τ}^{c} is the only determinant of the shifts in the curvature of the diffusion curve. Equation (4) shows that, for a given adoption lag, the only driver of cross-country differences in the intercept $\beta_{\tau 1}^{c}$ is the intensive margin, represented by $((\psi - 1)n_{\tau}^{C} - nl\big((1 + \zeta_{\tau x}^{C})\big)$. According to the authors, a lower level of I_{τ} generates a downward shift of the diffusion curve which, ceteris paribus, leads to lower output associated with technology τ throughout its diffusion and, in particular, in the long run.

The intensive margin measures how intensively a country uses a given technology conditional on adoption. It is constructed from the estimated technology intercepts obtained from country–technology regressions. Intercepts are corrected for long run growth using a common curvature parameter that depends on whether a technology is measured in output or capital units. These corrected intercepts are then normalized by subtracting the corresponding U.S. intercept for each technology, yielding a relative productivity or intensity measure.

To account for quality selection, the relative intercept is further scaled by a factor implied by the model's technology elasticity. The resulting variable captures country–technology intensity of use relative to the US and net of growth and selection effects. Finally, the intensive margin is demeaned with respect to the average intensity of advanced economies so that comparisons are interpreted relative to this reference group.

After constructing the intensive margin, the variable is re-centered by subtracting the mean intensity among developing economies. Specifically, the average of the intensive margin is computed over developing economies and used as the demeaning constant, while the value is set to zero for advanced economies. This normalization implies that the intensive margin has mean zero among developing economies, facilitating interpretation of cross-country differences relative to this benchmark.

3. Empirical strategy

3.1 Estimation

Our empirical strategy mirrors the framework established by (Comin and Mestieri, 2018), making minor adjustments to the code to suit our data structure. While the estimation framework is similar, our study differs in its focus on a distinct dataset, allowing us to extend the existing methodology and provide new insights into more recent technological domains.

We estimate a panel diffusion model of technology intensity using data for country–technology pairs observed over time. The model allows for country–technology–specific adoption lags while flexibly controlling for global diffusion forces and technological progress. Because adoption timing enters the model nonlinearly, we implement an iterative two-step estimation procedure that alternates between linear estimation of fixed effects and nonlinear estimation of adoption lags.

In the first step, conditional on adoption lags, the model is linear and we estimate country–technology fixed effects, technology-specific time trends, and decade fixed effects that differ between advanced and developing economies. In the second step, conditional on these estimated components, we recover adoption lags for each country–technology pair via nonlinear least squares. We iterate between the two steps until convergence.

3.2 Data description

We implement our estimation procedure using data on the diffusion of technologies from the CHAT dataset, along with data on population and income from Maddison (2010). Following Comin and Mestieri (2018), we focus on a subsample of major technologies that are widely adopted across both rich and poor economies and for which the data capture the initial phases of diffusion. Our research extends this dataset by incorporating: (1) clean (green) technologies, including electric vehicles (EVs), wind power generation, and solar energy systems; and (2) digital technologies, comprising second-generation wireless telephone technology (2G), third-generation mobile telecommunications (3G), and fourth-generation broadband cellular network technology (4G). Table 2 presents the newly incorporated technologies, along with their descriptions, data coverage, and time periods.

TABLE 1. DIGITAL AND GREEN TECHNOLOGIES, INVENTIONS, SOURCES AND DESCRIPTIONS

Technology	*Invention*	*Description*	*Source*	*Number of countries*	*Period*
Electric Cars	**1973**: General Motors develops a prototype for an urban electric car, which the company displayed at the First Symposium on Low Pollution Power Systems Development	Stock of electric vehicles (EVs) ("BEV" = battery electric vehicle; "PHEV" = plug-in hybrid electric vehicle)	IEA	26	2010-2023
Solar technologies	**1954**: Creation of the silicon photovoltaic (PV) cell at Bell Labs	Generation Solar (Terawatt hours)	IRENA	62	1983-2023
Wind technologies	**1978**: Inauguration of the first reliable multi-megawatt wind turbine in Tvind (Denmark)	Generation Wind (Terawatt hours)	IRENA	53	1979-2023
2G	**1991**: 2G launched on the Global System for Mobile Communications (GSM) in Finland	People covered by at least a 2G mobile network (ITU+WB)	ITU	110	2000-2023
3G	**2001**: Deployed to the public in Japan by NTT DoCoMo	People covered by at least a 3G mobile network (ITU+WB)	ITU	87	2007-2023
4G	**2009**: Introduced for commercial use in Norway	People covered by at least a 4G mobile network (ITU+WB)	ITU	54	2012-2023

Our dataset covers 31 technologies and covers a wide range of sectors in the economy for 139 countries[5]. The invention dates are spread quite evenly throughout the 200-year period. Overall, the dataset includes 2,233 economies–technology pairs. The average number of technologies per economy is about 16 while 53% of the observations correspond to technologies invented prior to 1900 (See Table 2). Economy-technology pairs corresponding to advanced economies represent 23% of the sample.

TABLE 2. GEOGRAPHIC DISTRIBUTION OF SAMPLE ECONOMIES AND TECHNOLOGIES

Region	Mean technologies per country	Median technologies per country	Standard deviation of technologies per country	Number of countries
Total	16.06	14.00	8.48	139
Advanced economies	29.53	30.00	1.66	17
Asia	13.97	13.50	7.67	36
Latin America	17.16	15.00	7.09	19
Africa	12.42	12.00	4.59	36

GDP per capita is a key conditioning variable in our analysis and is constructed to remain as comparable as possible to the series used in Comin (2018), which relies on the Maddison Project Database (2010 edition). Since the Maddison data provide benchmark levels of GDP per capita and population but do not fully cover the temporal and the economies dimensions required for the present study, we extend these series forward using externally observed growth rates rather than redefining the underlying levels.

Specifically, when GDP per capita or population is missing for a given economy–year but observed in the previous year, we extrapolate the level using the corresponding annual growth rate from the World Development Indicators. This approach preserves the Maddison-based level information while allowing the series to evolve according to observed country-specific growth dynamics. No backward imputation or cross-country interpolation is performed, and observations for which neither lagged levels nor growth rates are available remain missing.

By anchoring GDP per capita and population to the Maddison (2010) benchmarks and extending them only through observed growth rates, this procedure maintains close

[5] They are listed in the Appendix.

comparability with Comin (2018) while enabling the construction of a panel with broader country and time coverage.

4. Results

We consider 139 economies and 31 technologies that span the period 1779 to 2009. Results are divided into 1) plausible and precise, 2) plausible and imprecise, and 3) implausible[6]. The estimations below only consider the estimates of technology-economy pairs that satisfy the plausibility and precision conditions. The plausible and precise criteria are met for 57% of the technology-economy pairs[7].

4.1 Estimated adoption lags

Table 3 presents the estimation results of adoption lags across technologies. The average adoption lag across all the technologies and countries is 41 years. As expected and consistent with previous results from Comin and Hobijn, (2010) and Comin and Mestieri (2014, 2018) that use a slightly different sample of technologies, we find significant variation in the average adoption lags across technologies, ranging from 2 years for 4G to 117 years for spindles. The range for the cross-country standard deviations ranges from 1 year for electric vehicles to 61 for steam and motor ships.

Our findings provide evidence supporting the accelerated adoption of digital technologies. However, green technologies exhibit more heterogeneous patterns. While solar photovoltaic and electric vehicle technologies show notably slower diffusion compared to digital innovations, wind energy demonstrates intermediate adoption rates, suggesting that infrastructure requirements, scalability, and policy support may differentiate renewable energy pathways.

TABLE 1. ESTIMATED ADOPTION LAGS

Technology	Year of Invention	Number of countries	Mean	SD	p1	p10	p50	p90	p99

[6] Implausible estimates are those in which technology was adopted more than ten years before it was invented. Imprecise estimates are those that are not statistically significant at the 5% level (t-statistic ≥ 1.96). Cases that are neither implausible nor imprecise are considered plausible and precise.

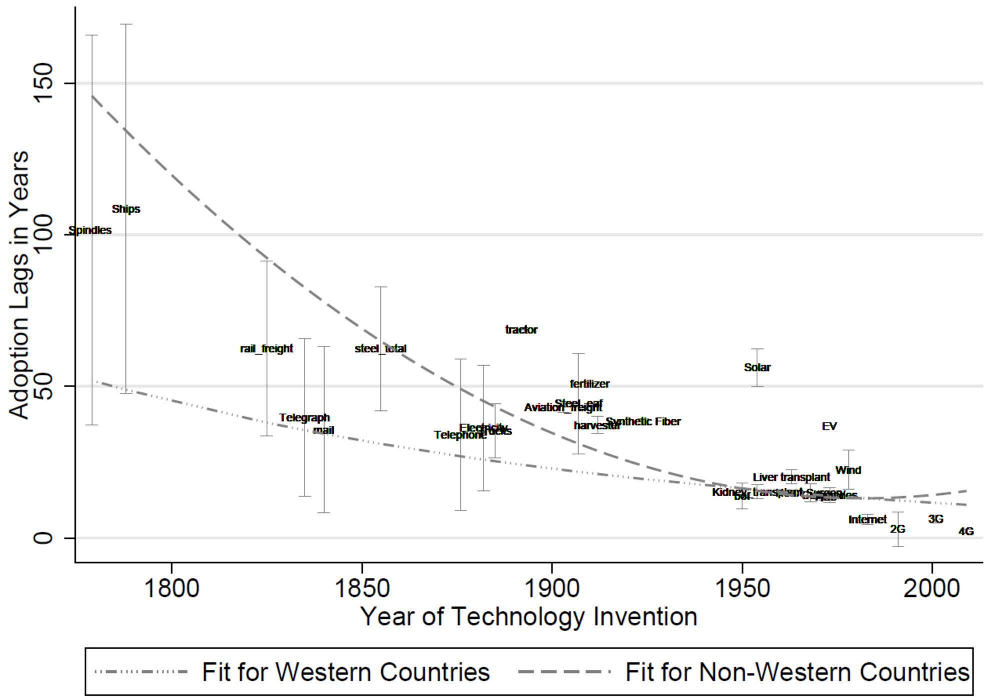
[7] See the quality of the estimates in the Appendix.

Spindles	1779	25	117	61	-3	35	140	171	178
Ships	1788	38	119	61	-7	32	146	180	180
Rail freight	1825	38	75	37	-2	17	77	122	131
Rail passengers	1825	32	78	35	7	37	78	120	134
Telegraph	1835	29	51	35	-7	9	49	91	109
mail	1840	39	51	39	-9	3	52	106	116
steel	1855	41	66	33	-5	12	67	105	122
Telephone	1876	49	51	34	-8	1	54	92	111
Electricity	1882	73	49	21	0	19	54	71	89
Cars	1885	60	39	22	-8	12	34	66	103
Trucks	1885	49	38	22	-4	15	37	67	90
tractor	1892	86	65	11	7	62	69	69	69
Aviation freight	1903	40	41	17	5	17	43	63	75
Aviation passengers	1903	39	28	17	0	6	24	53	71
Steel	1907	45	48	17	9	25	54	65	72
fertilizer	1910	20	48	8	13	45	51	51	51
harvester	1912	69	35	15	-9	9	40	49	55
Synthetic Fiber	1924	46	37	8	-1	28	39	41	45
Blast oxygen	1950	35	14	7	-9	7	14	24	27
Kidney	1954	24	14	6	1	6	14	21	28
Solar	1954	35	56	10	30	39	59	65	68
Liver transplant	1963	19	19	4	13	14	18	25	26
Heart Surgery	1968	16	13	3	8	9	13	18	19
Cellphones	1973	71	14	5	-8	11	16	19	19
EV	1973	21	37	1	33	36	37	38	40
PCs	1973	63	14	2	7	11	14	17	19
Wind	1978	32	23	9	5	13	25	33	38
Internet	1983	43	6	4	-9	1	6	9	10
2G	1991	23	8	3	-3	4	9	11	15
3G	2001	43	7	3	-5	2	7	10	12
4G	2009	32	2	2	-4	-1	3	4	4
All technologies		**1275**	**41**	**35**	**-4**	**7**	**36**	**81**	**176**

Notes: The p10, p50, p90, and p99 refer to the tenth percentile, the median, the ninetieth, and ninety-ninth percentile, respectively.

Figure 4 shows the median adoption lag for each technology among advanced economies and the rest of the world, suggesting that the adoption lags have declined over time, and that the cross-country differences in adoption lags have narrowed.

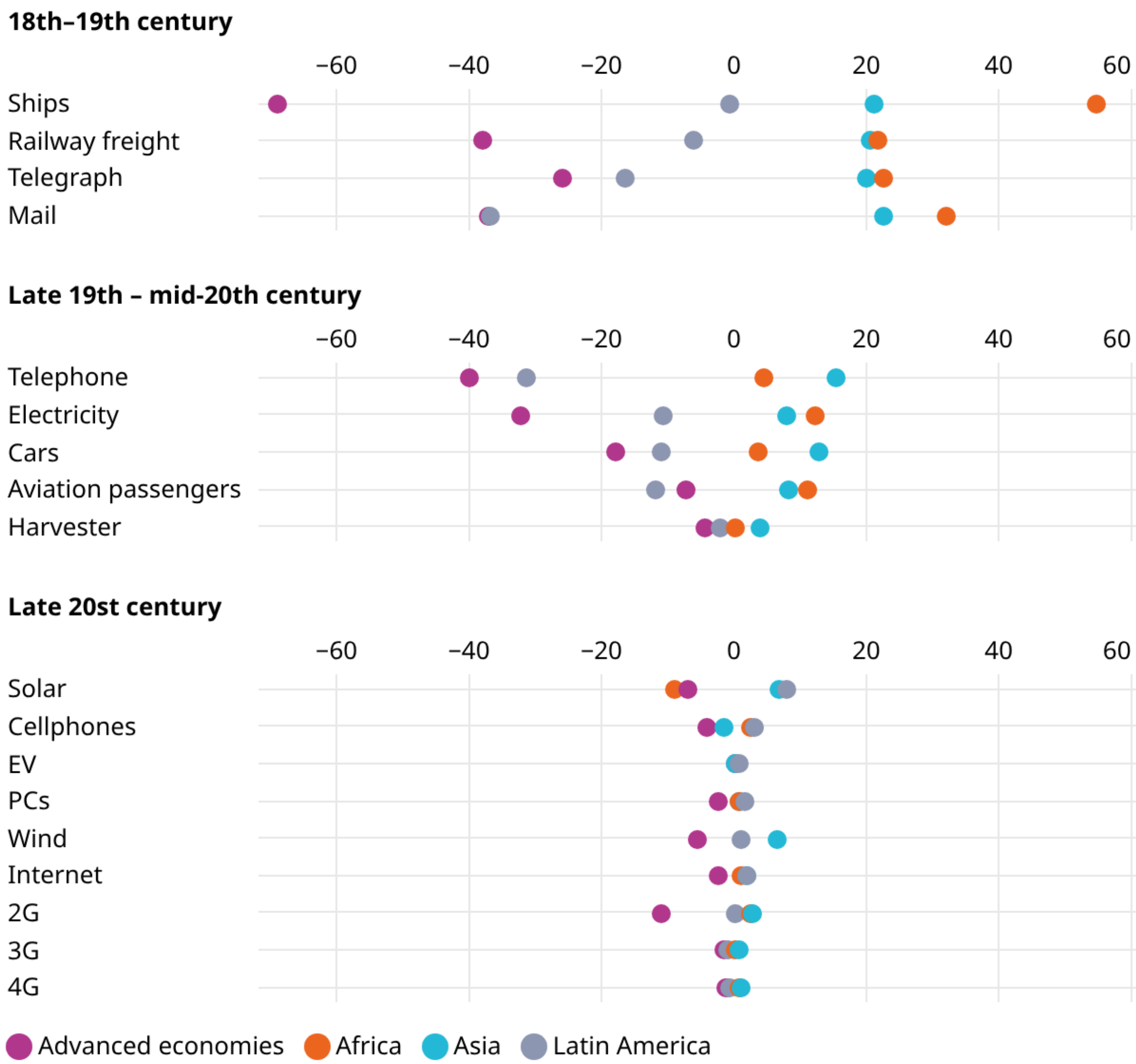
FIGURE 4 CONVERGENCE OF ADOPTION LAGS



Note: Bars show median margins of adoption for advanced versus developing economies.

The adoption lag data also reveals persistent patterns of technological leadership and followership across regions. Advanced economies consistently emerge as early adopters, typically embracing new technologies 20–80 years *before* the global average, while Africa shows the opposite pattern, adopting most technologies 10–50+ years after the global average, while Asia and Latin America show mixed patterns depending on the specific technology (see Figure 5)

FIGURE 5. ADOPTION LAGS FOR ADVANCED ECONOMIES AND SELECTED REGIONS (IN DEVIATION FROM AVERAGE ADOPTION LAG FOR TECHNOLOGY), IN YEARS



Following Comin and Hobijn (2010) we proceed to decompose the variation of the adoption lags into country and technology effects. Table 4 contains the variance decomposition based on three regressions nested in the following specification:

$$D_{TC} = D_T^* + D_C^* + u_{CT}$$

Where D_C^* is a country fixed effect, D_T^* is a technology fixed effect, and u_{CT} is the residual. According to the results of Table 4, country specific effects explain about 28% of the variation in the estimated adoption lags. Technology-specific effects explain about twice as much, around 60%, of the variation. The last row of Table 4 shows that country and technology fixed effects jointly explain about 72% of the variation in the estimated adoption lags. Of this, 14 percent can be directly attributed to country effects, 44 percent can be directly attributed to technology effects, and the remaining 28 percent is due to the covariance between these effects that is the result of the unbalanced nature of the panel structure of our data.

TABLE 2. ANALYSIS OF VARIANCE

	Model SS	Country effect	Technology effect	Residual sum of squares	Total sum of squares
Country effect alone	27.74%	27.74%	0.00%	72.26%	100.00%
Technology effect	58.12%	0.00%	58.12%	41.88%	100.00%
Joint effect	71.67%	13.55%	43.93%	28.33%	100.00%

Total sum squares 1594563.6, N=1275

4.2 Estimated intensive margin

For the intensive margin, we find similar cross-country variation as observed with adoption lags. The average intensity parameter of -0.62 implies that developing economies utilize technologies at approximately 53% of the intensity observed in advanced economies (exp(-0.62) ≈ 0.538), representing a 47 percentage-point gap in utilization intensity. These averages mask considerable heterogeneity across technologies.

Strikingly, mobile communication technologies reverse this pattern. Developing economies exhibit 110% intensity for 2G (exp(0.10) = 1.10), 98% for 3G (exp(-0.02) = 0.98), and 135% for 4G (exp(0.30) = 1.35)—representing a 35% point advantage over advanced economies. This progression provides compelling evidence of technological leapfrogging, where developing countries bypassed fixed-line infrastructure to adopt mobile technologies more intensively than their advanced counterparts.

TABLE 3. ESTIMATES OF THE LOG INTENSITY OF USE PARAMETER RELATIVE TO ADVANCED ECONOMIES

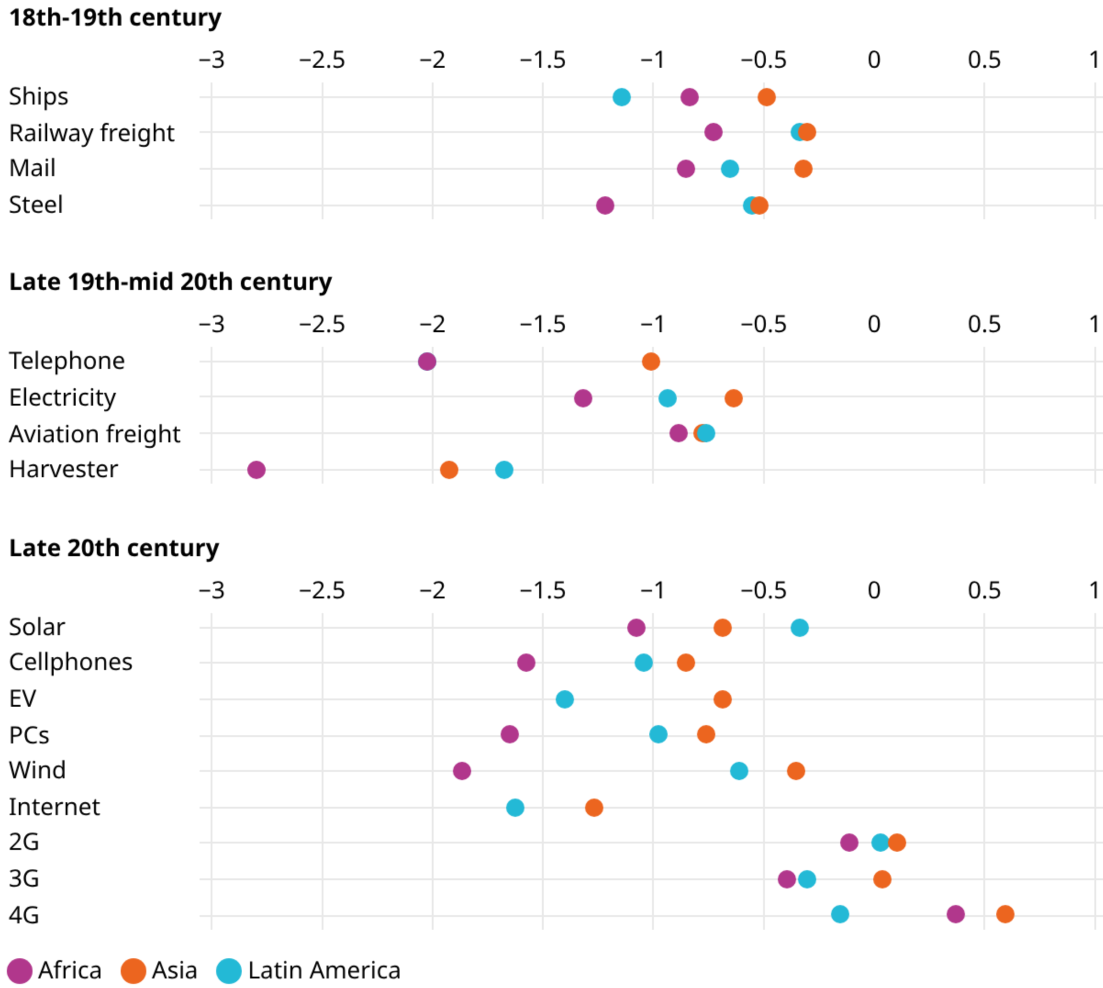
	Year of Invention	Number of countries	Mean	SD	p10	p50	p90	CV	IQR
Spindles	1779	25	-0.15	0.73	-0.98	-0.05	0.76	-4.76	0.82
Ships	1788	38	-0.48	0.84	-1.52	-0.43	0.59	-1.74	1.01
Rail freight	1825	38	-0.3	0.51	-0.84	-0.36	0.41	-1.68	0.65

Rail passengers	1825	32	-0.42	0.51	-1.14	-0.36	0.2	-1.24	0.7
Telegraph	1835	29	-0.33	0.61	-1.14	-0.2	0.27	-1.84	0.76
Mail	1840	39	-0.4	0.54	-1.09	-0.31	0.38	-1.37	0.73
Steel	1855	41	-0.38	0.53	-0.99	-0.31	0.2	-1.41	0.71
Telephone	1876	49	-1.26	1.06	-2.64	-1.12	-0.05	-0.83	1.43
Electricity	1882	73	-0.77	0.64	-1.61	-0.68	-0.04	-0.82	0.97
Cars	1885	60	-1.43	1.38	-2.81	-1.35	0.02	-0.97	2.22
Trucks	1885	49	-1.17	1.17	-2.18	-1.24	0.22	-1	1.23
Tractor	1892	86	-0.57	0.54	-1.41	-0.53	0.01	-0.94	0.74
Aviation freight	1903	40	-0.56	0.71	-1.64	-0.44	0.25	-1.28	1.03
Aviation passengers	1903	39	-0.57	0.82	-1.73	-0.37	0.27	-1.43	1.1
Steel	1907	45	-0.39	0.58	-1.13	-0.22	0.26	-1.49	0.78
fertilizer	1910	20	-0.05	0.22	-0.26	-0.03	0.2	-4.6	0.22
harvester	1912	69	-1.53	1.2	-3.37	-1.44	0.05	-0.78	1.59
Synthetic F	1924	46	-0.49	0.62	-1.42	-0.37	0.2	-1.25	0.83
Blast oxygen	1950	35	-1.02	1.11	-2.68	-0.73	0.1	-1.09	2.17
Kidney transplant	1954	24	-0.27	0.46	-1.09	-0.07	0.12	-1.7	0.64
Solar	1954	35	-0.21	0.55	-0.9	-0.22	0.43	-2.57	0.88
Liver trans	1963	19	-0.51	0.88	-2.22	-0.1	0.17	-1.74	1.02
Heart Surgery	1968	16	-0.53	0.97	-2.16	-0.11	0.24	-1.84	0.72
Cellphones	1973	71	-0.84	0.79	-2.1	-0.65	0.05	-0.94	1.12
EV	1973	21	-0.27	0.54	-0.81	-0.12	0.28	-2	0.62
PCs	1973	63	-0.7	0.68	-1.64	-0.69	0.06	-0.97	1.02
Wind	1978	32	-0.01	0.53	-0.51	-0.02	0.58	-81.43	0.63
Internet	1983	43	-0.83	0.9	-2.03	-0.62	0.09	-1.08	1.49
2G	1991	23	0.1	0.17	-0.11	0.12	0.29	1.69	0.24
3G	2001	43	-0.02	0.34	-0.48	0	0.38	-18.21	0.39
4G	2009	32	0.3	0.49	-0.28	0.2	1.09	1.64	0.63
All technologies		**1275**	**-0.62**	**0.9**	**-1.79**	**-0.4**	**0.24**	**-1.44**	**1.04**

Notes: The p10, p50, p90, and p99 refer to the tenth percentile, the median, the ninetieth and ninety-ninth percentile, IQR refers to the interquartile range, defined as the difference between the third and first quartiles.

As we pointed out in Section 2.3, the average of the intensive margin is computed over developing economies and is used as the demeaning constant, while the value is set to zero for advanced economies. Figure 6 aims to explain how intensively countries use a technology relative to advanced economies and conditional on adoption. Digital innovations like 3G and 4G show a converging use intensity across countries, suggesting that today's digital technologies offer greater opportunities for developing economies to narrow historical gaps. Regional analysis reveals that while Africa exhibits the widest technology use gaps, followed by Latin America and then Asia, all three regions show such gaps narrowing for recent technologies. Figure 6 shows how Asia stands out not only having narrowed technology use gaps substantially, but in some cases even exceeding advanced economy use levels.

FIGURE 6. INTENSITY USAGE COMPARED TO ADVANCED ECONOMIES



4.3 Cross economies evolution of the diffusion process

Understanding whether technology diffusion is accelerating and becoming more equitable is critical for assessing global development trajectories. This section uses econometric analysis to address two questions: First, have adoption lags declined over time and have cross-country differences in these lags narrowed? Second, has the depth of technology use within economies followed a similar convergence pattern, or have disparities persisted even as technologies have spread more quickly.

In the first case, we regress the log of adoption lags on their year of invention and a constant.

$$lnD_t^c = \rho + \omega \cdot (inventionYear_T - 1820) + \varepsilon_T^C \tag{6}$$

In the second case, we regress the intensity of use parameter on the invention year and a constant.

$$lnI_t^c = \rho + \omega \cdot (inventionYear_T - 1820) + \varepsilon_T^C \tag{7}$$

In this regard, ω represents the semi-elasticity of the outcome with respect to technology vintage, that is, the proportional change in adoption lag or intensity associated with each additional year of invention.

Table 6 shows the results of the evolution of adoption lag and intensity use. Columns 2 and Column 3 report the same regression separately for advanced economies and developing economies. To begin, adoption lags are negative and highly significant, indicating that more recently invented technologies diffuse systematically faster. Furthermore, we find that the rate of decline in adoption lags is significantly steeper in developing economies than in advanced economies. Specifically, adoption lags decline by 1.22% per year of invention vintage in developing economies compared to 0.68% per year in advanced economies. This differential implies convergence in adoption speed: the gap in adoption lags between advanced and developing economies narrows by approximately 0.54 percentage points per year of technology vintage ((-0.0122 – (-0.00678)) = 0.00542).

Columns (4)-(6) examine whether technology vintage influences utilization intensity, revealing a starkly different pattern from the adoption lag results. For the global sample (Column 4), the coefficient of 0.00113* indicates a modest positive relationship: each additional year of invention vintage increases intensity by approximately 0.11%. Over a century of technological progress, this translates to an intensity increase of only 12% [exp(0.00113 × 100) ≈ 1.12], compared to the 67% reduction in adoption lags observed over the same period. However, this weak aggregate relationship does not hold within country groups.

Advanced economies (Column 5) exhibit no discernible time trend (coefficient ≈ 0, SE = 0.00032, R^2 = 0.000). The coefficient is not only statistically insignificant but economically negligible in magnitude, indicating that technology vintage plays virtually no role in explaining intensity variation among developed countries. This suggests that advanced economies maintain consistently high utilization rates regardless of whether technologies were invented in the 19th or 21st century—a pattern consistent with uniformly strong absorptive capacity, complementary infrastructure, and institutional quality that enable full exploitation of technologies across vintages.

TABLE 4. EVOLUTION OF THE ADOPTION LAG AND INTENSITY OF USE

Dependent variable		Log (lag)			Log (intensity)	
	(1)	(2)	(3)	(4)	(5)	(6)
	World	Advanced economies	Developing economies	World	Advanced economies	Developing economies
Year-1820	-0.0111***	-0.00678***	-0.0122***	0.00113**	8.40E-09	0.000701
	(-0.0005)	(-0.00058)	(-0.00053)	(-0.00052)	(-0.00032)	(-0.00078)
Constant	4.350***	3.673***	4.538***	-0.623***	-3.56E-07	-0.811***
	(-0.068)	(-0.0867)	(-0.0637)	(-0.0826)	(-0.0492)	(-0.0998)
Observations	1,237	330	907	1,275	347	928
R-squared	0.471	0.199	0.569	0.007	0	0.002

Robust standard errors are in parentheses. Each observation is reweighted so that each technology carries equal weight
*** p<0.01, ** p<0.05, * p<0.1

Table 7 focuses on the evolution of adoption lag by year of invention, comparing pre-1990 and post-1990 technologies across country groups. The results reveal an increase in diffusion speeds for recent innovations. For technologies invented before 1990, adoption lags decline 0.92% annually globally, 0.57% in advanced economies, and 0.97% in developing economies (columns 1, 3 and 5). In contrast, for technologies invented after 1990, the adoption lags exhibit a decline of 5.7% per year globally. This acceleration is evident for advanced economies (6.99%) and developing economies (5.4%) annually.

Our results reveal a striking shift in convergence patterns. For pre-1990 technologies, developing countries exhibit convergence: their adoption lags declined 0.40 percentage points faster per year than advanced economies [(-0.00567) - (-0.00966) = +0.00399]. However, for post-1990 technologies, this reverses to divergence: advanced economies' adoption lags now decline 1.55 percentage points faster per year [(-0.0699) - (-0.0544) = -0.0155]. While both groups adopt post-1990 technologies approximately six times faster than older technologies, advanced economies appear to maintain advantages in adopting cutting-edge innovations. This post-1990 finding should be interpreted cautiously given the limited sample size (n=12) for advanced economies.

TABLE 5. EVOLUTION OF ADOPTION LAG, BY YEAR OF INVENTION

Dependent variable	Log (lag)					
	World		**Advanced economies**		**Developing countries**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Invention pre 1990	Invention post 1990	Invention pre 1990	Invention post 1990	Invention pre 1990	Invention post 1990
Year-1820	-0.00923***	-0.0570***	-0.00567***	-0.0699*	-0.00966***	-0.0544***
	-0.000492	-0.00409	-0.000613	-0.0346	-0.000491	-0.00393
Constant	4.255***	11.96***	3.600***	14.09*	4.427***	11.53***
	-0.0683	-0.748	-0.0889	-6.437	-0.0636	-0.722
Observations	1,147	90	318	12	829	78
R-squared	0.363	0.542	0.153	0.22	0.43	0.572

Robust standard errors are in parentheses. Each observation is reweighted so that each technology carries equal weight
*** p<0.01, ** p<0.05, * p<0.1

Table 8 examines the evolution of the use intensity by year of invention, comparing pre-1990 and post-1990 technologies across country groups. For developing economies with pre-1990 inventions (Column 5), the coefficient of -0.00288** indicates that intensity of use declined by 0.29% per year of invention vintage. Since the intensity of use parameter is measured relative to the mean of advanced economies, this estimate implies a divergence in the intensity of use of new technologies between advanced and developing economies over the last 200 years.

However, for inventions created after 1990 (2G, 3G, 4G) we find a different result. The intensity in the use of new technologies has increased at an annual rate of 1.2%. This positive coefficient implies convergence: developing countries are progressively closing the intensity gap for digital-era technologies. The shift from -0.29% (divergence) to +1.22% (convergence) represents a 1.51 percentage point reversal in trajectory.

TABLE 6. EVOLUTION OF INTENSITY, BY YEAR OF INVENTION

Dependent variable	Log (intensity)

	World		Advanced economies		Developing economies	
	(1)	(2)	(3)	(4)	(5)	(6)
	Invention pre-1990	Invention post 1990	Invention pre-1990	Invention post 1990	Invention pre-1990	Invention post 1990
Year-1820	-0.000538	0.0100**	1.01E-08	6.71E-09	-0.00288***	0.0122***
	-0.000569	-0.00386	-0.0007	-0.00263	-0.000651	-0.0044
Constant	-0.543***	-1.684**	-4.58E-07	-1.47E-06	-0.654***	-2.055***
	-0.0763	-0.664	-0.0486	-0.456	-0.0912	-0.755
Observations	1,177	98	332	15	845	83
R-squared	0.001	0.038	0	0	0.034	0.053

Robust standard errors are in parentheses. Each observation is reweighted so that each technology carries equal weight
*** p<0.01, ** p<0.05, * p<0.1

Table 9 examines the evolution of the use intensity including time and technology interactions.

Column (1) reveals a substantial utilization gap: developing economies operate at 44% of advanced economy intensity (coefficient: -0.811***, exp(-0.811) ≈ 0.444). However, neither country group shows significant time trends, indicating technology vintage plays minimal role when pooling across eras (R^2 = 0.389).

Column (2) examines vintage effects without country heterogeneity. Post-1990 technologies show faster intensity growth (coefficient: 0.0106***, SE = 0.00382), but the dramatically low R^2 (0.063) indicates this specification misses the primary source of variation by ignoring differences between advanced and developing economies.

Column (3) separates pre-1990 from post-1990 technologies and shows completely opposite patterns. For pre-1990 technologies: developing economies show intensity declining by 0.29% per year (coefficient: -0.00288***). This means divergence—developing countries fell further behind in utilizing older technologies as they became more sophisticated. For post-1990 technologies: The triple interaction coefficient (0.00735***) changes everything. Adding this to the pre-1990 coefficient gives: -0.00288 + 0.00735 = +0.00447. This means convergence—intensity now increases by 0.45% per year in developing economies. Advanced economies show no time trend for either era, maintaining stable high utilization throughout.

TABLE 7. EVOLUTION OF INTENSITY, WITH TIME AND TECHNOLOGY INTERACTIONS

	Log (intensity)		
	World	**World**	**World**
	Advanced vs developing economies	Inventions post-1990	Advanced vs developing economies & Inventions post-1990
	(1)	**(2)**	**(3)**
Adv_economies	-3.56E-07		-4.58E-07
	-0.0479		-0.0474
Year-1820# Adv_economies	8.40E-09		1.01E-08
	-0.00031		-0.00031
Developing_economies	-0.811***		-0.655***
	-0.0998		-0.0913
Year-1820# Developing_economies	0.000701		-0.00288***
	-0.00078		-0.00065
Year-1820		-0.00054	
		-0.00057	
Year-1820# Inv-post-1990		0.0106***	
		-0.00382	
Inv-post-1990		-1.142*	
		-0.659	
Year-1820# Adv_economies # Inv-post-1990			-8.90E-09
			-0.00019
Year-1820# Developing_economies # Inv-post-1990			0.00735***
			-0.00053
Constant		-0.543***	
		-0.0764	
Observations	1,275	1,275	1,275
R-squared	0.389	0.063	0.481

Robust standard errors are in parentheses. Each observation is reweighted so that each technology carries equal weight
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions

Technology diffusion is a broad and multifaceted process at the core of economic development and human progress. For technological breakthroughs to drive economic growth, they must spread widely throughout an economy. While the pace of global technology adoption has accelerated dramatically, the benefits of new technologies remain unevenly distributed both within and across countries.

We find that the average estimated adoption lag is 41 years. On average, the intensity of adoption in developing economies is about half (53%) that of advanced economies. We also document substantial heterogeneity across countries and technologies in both adoption lags and adoption intensity. Overall, our results show that adoption lags have declined more sharply over time in developing economies than in advanced economies. By contrast, the intensity of technology use has diverged across countries, although it shows signs of convergence for more recent technologies.

We believe the results of this paper have relevant implications for the study of diffusion of new technologies, particularly digital ones. Technologies such as genAI have spread across the world at unprecedented speed. Early usage was heavily concentrated in the US – more than 70 percent of global traffic at launch – but this dominance faded rapidly. Within one month, the US share had fallen to around 25 percent, and later stabilized near 20 percent, as traffic spread quickly to a wide range of economies. By mid-2023, ChatGPT alone was attracting roughly 500 million unique users a month – equivalent to about 12.5 percent of the global workforce – underscoring the breadth of early international uptake.

Our findings resonate with a broader re-assessment in the economic literature of long run divergence in income and more recent convergence patterns. While much of the historical record points to persistent divergence in income levels across countries, a number of recent contributions document a reversal since the mid-1990s, with poorer economies growing faster than richer ones in absolute terms. In particular, Patel et al (2021) argue that this period marks a "new era" of unconditional convergence in GDP per capita, driven by faster growth among lower-income countries rather than solely by a slowdown at the frontier. Our results suggest a closely related pattern on the technology side: extending the work of Comin and Mestieri, we show that while technology use intensity has historically diverged across countries, newer vintages of technology—especially digital technologies—exhibit markedly stronger convergence since the 1990s. We do not seek to establish a causal link between these two developments. Nevertheless, the parallel timing and direction of convergence in income levels and in the intensity of technology use point to a potentially important connection between the diffusion of digital technologies and the narrowing of cross-country economic gaps, meriting further investigation.

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Appendix

A.1 Number of technologies per economy

Afghanistan	10	Honduras	11	Senegal	13
Albania	10	Hungary	25	Sierra Leone	10
Algeria	24	India	25	Singapore	18
Argentina	25	Indonesia	24	Slovakia	11
Armenia	4	Iran, Islamic Republic of	18	Slovenia	9
Australia	30	Iraq	17	Somalia	11
Austria	31	Ireland	25	South Africa	27
Azerbaijan	7	Israel	25	Spain	31
Bangladesh	16	Italy	30	Sri Lanka	21
Belarus	6	Japan	29	Sudan	15
Belgium	31	Jordan	12	Sweden	30
Bolivia	15	Kazakhstan	7	Switzerland	29
Bosnia and Herzegovina	1	Kenya	16	Syrian Arab Republic	15
Botswana	9	Kuwait	13	Tajikistan	1
Brazil	27	Kyrgyzstan	1	Tanzania	15
Bulgaria	18	Laos PDR	8	Thailand	24
Burkina Faso	10	Latvia	8	Togo	13
Burundi	8	Lebanon	17	Tunisia	20
Cambodia	12	Lesotho	8	Türkiye	25
Cameroon	13	Liberia	8	Turkmenistan	3
Canada	30	Libya	11	Uganda	14
Central African Republic	10	Lithuania	8	Ukraine	7
Chad	10	Madagascar	14	United Arab Emirates	14
Chile	25	Malawi	14	United Kingdom	31
China	27	Malaysia	22	United States of America	31
Hong Kong, China	10	Mali	11	Uruguay	21
Taiwan, Province of China	18	Mauritania	11	Venezuela	19
Colombia	24	Mauritius	14	Viet Nam	8
Congo	11	Mexico	31	Yemen	10
Costa Rica	15	Mongolia	9	Zambia	15
Croatia	9	Morocco	19	Zimbabwe	17
Cuba	16	Mozambique	13		
Czech Republic	9	Namibia	5		
Czechoslovakia	18	Nepal	7		
Denmark	26	Netherlands	30		
Dominican Republic	9	New Zealand	26		

Ecuador	21	Nicaragua	11
Egypt	20	Niger	11
El Salvador	12	Nigeria	16
Equatorial Guinea	3	North Macedonia	1
Estonia	9	Norway	27
Eswatini	6	Oman	13
Finland	30	Panama	9
France	31	Paraguay	12
Gabon	10	Peru	22
Gambia	5	Philippines	25
Georgia	5	Poland	27
Germany	30	Portugal	31
Ghana	18	Republic of Korea	22
Greece	27	Republic of Moldova	4
Guatemala	13	Romania	22
Guinea	10	Russian Federation	17
Guinea-Bissau	4	Rwanda	8
Haiti	7	Saudi Arabia	20

B.1 Quality of the estimates

Year of Invention	Technologies	Total country-technology pairs	Plausible and precise	Implausible and not precise
1779	Spindles	34	25	9
1788	Ships	63	38	25
1825	rail_freight	84	38	46
1825	rail_pass	80	32	48
1835	Telegraph	68	29	39
1840	mail	71	39	32
1855	steel_total	52	41	11
1876	Telephone	139	49	90
1882	Electricity	118	73	45
1885	Cars	121	60	61
1885	Trucks	108	49	59
1892	tractor	118	86	32
1903	Aviation_freight	93	40	53
1903	Aviation_passengers	96	39	57
1907	Steel_eaf	56	45	11

1910	fertilizer	117	20	97
1912	harvester	87	69	18
1924	Synthetic Fiber	47	46	1
1950	Blast oxygen	44	35	9
1954	Kidney_transplant	27	24	3
1954	Solar	62	35	27
1963	Liver transplant	19	19	0
1968	Heart Surgery	17	16	1
1973	Cellphones	73	71	2
1973	EV	26	21	5
1973	PCs	64	63	1
1978	Wind	53	32	21
1983	Internet	45	43	2
1991	2G	110	23	87
2001	3G	87	43	44
2009	4G	54	32	22
	Total	**2233**	**1275**	**958**

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Suggested citation: Fink, C., Menéndez, M., Raffo, J. (2026). How do new technologies diffuse? WIPO Economic Research Working Paper Series, No. 91. World Intellectual Property Organization. https://doi.org/10.34667/tind.59340.

Cover: WIPO Design