If Technology has Arrived Everywhere, why Has Income Diverged?

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Abstract

We study the cross-country evolution of technology diffusion processes. Using data from the last two centuries for twenty-five major technologies, we document two new facts: there has been convergence in adoption lags between rich and poor countries, while there has been divergence in long run penetration rates, once technologies are adopted. We show that the evolution of aggregate productivity implied by these trends in technology diffusion accounts for the bulk of the evolution of the world income distribution in the last two hundred years. In particular, initial cross-country differences in adoption lags account for a significant part of the cross-country income divergence in the nineteenth century. The divergence in penetration rates accounts for the divergence during the twentieth century.

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1 Introduction

At the beginning of the nineteenth century, differences in income per capita between rich and poor countries were relatively small. The average income per capita in 1820 of the seventeen advanced countries denoted by Maddison (2004) as "Western countries" was 1.9 times the average of non-Western countries.[1] For the next 180 years, Western countries grew significantly faster and, by 2000, their per capita income was 7.2 times the average of non-Western countries. This divergence in income is known as the Great Divergence (e.g., Pritchett, 1997 and Pomeranz, 2000), and is one of the great puzzles in economics (Acemoglu, 2011).

More generally, we know little about the drivers of cross-country differences in productivity growth over protracted periods of time. For example, Klenow and Rodríguez-Clare (1997) show that factor accumulation (physical and human capital) accounts only for 10% of cross-country differences in growth between 1960 and 1985. Clark and Feenstra (2003) find similar results for the period 1850-2000. What accounts for the bulk of cross-country differences in the evolution of productivity over long horizons and, in particular, for the Great Divergence?

This paper explores the role that technology has played in the evolution of income growth. To this end, we first study how technology has diffused over the last 200 years. We document significant differences in technology diffusion across countries. Second, we quantify the effect of these differential patterns of diffusion on the evolution of the world income distribution over the last two centuries.

We decompose the contribution of technology to productivity growth into the extensive and intensive margins. The extensive margin captures the range of technologies available, which is given by the lag with which new technologies are adopted. New technologies embody higher productivity. Therefore, a reduction in adoption lags increases the average productivity of technologies adopted, thereby raising aggregate productivity growth. The intensive margin captures the penetration rate of new technologies. The more units of any new technology (relative to income) a country uses, the higher the number of workers or units of capital that can benefit from the productivity gains brought by the new technology.[2] As a result, increases in the penetration of technology raise the growth rate of productivity.

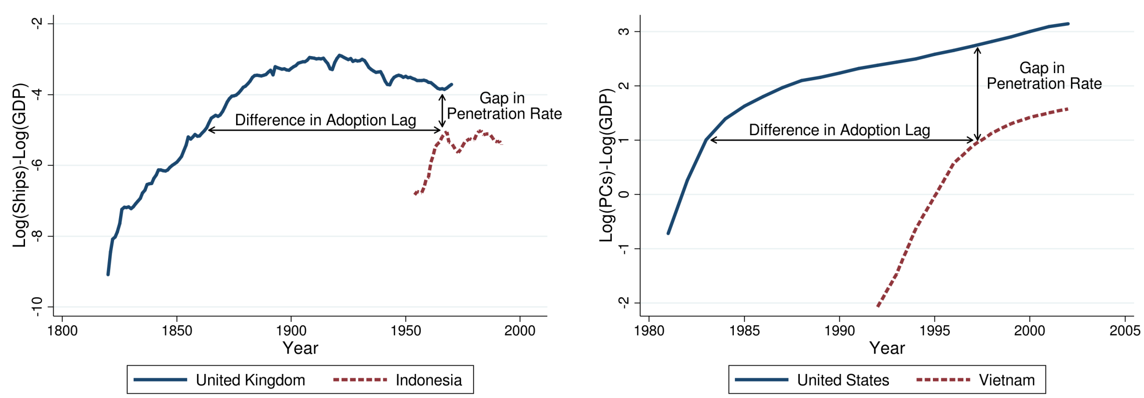
To study the evolution of technology diffusion, first we need to measure these adoption margins from the diffusion curves of individual technologies. We illustrate our strategy to identify the adoption margins in Figure 1. Figures 1a and 1b plot the (log) of the tonnage of steam and motor ships over real GDP in the UK and Indonesia and the (log) number of computers over real GDP for the U.S. and Vietnam, respectively. One feature of these plots is that, for a given technology, the diffusion curves for different countries have similar shapes,

[1] Maddison (2004) defines as Western countries Austria, Belgium, Denmark, Finland, France, Germany, Italy, Netherlands, Norway, Sweden, Switzerland, Untied Kingdom, Japan, Australia, New Zealand, Canada and the United States.

[2] In our context, this is isomorphic to differences in the efficiency with which producers use technology.

Figure 1: Examples of diffusion curves

(a) Diffusion of Steam and Motor ships (b) Diffusion of PCs



but displaced vertically and horizontally. This property holds generally for a large majority of the technology-country pairs. Given the common curvature of diffusion curves, the relative position of a curve can be characterized by only two parameters. The horizontal shifter informs us about when the technology was introduced in the country. The vertical shifter captures the penetration rate the technology will attain when it has fully diffused.

These intuitions are formalized with a model of technology adoption and growth. Crucial for our purposes, the model provides a unified framework for measuring the diffusion of specific technologies and assessing their impact on income growth. The model features both adoption margins, and has predictions about how variation in these margins affect the curvature and level of the diffusion curve of specific technologies. This allows us to take these predictions to the data and estimate adoption lags and penetration rates fitting the diffusion curves derived from our model. We identify the extensive and intensive adoption margins for 25 significant technologies invented over the last 200 years for a sample of 130 countries. Then, we use our estimates to analyze the cross-country evolution of technology diffusion.

We document two new facts. First, cross-country differences in adoption lags have narrowed over the last 200 years. That is, adoption lags have declined more in poor/slow adopter countries than in rich/fast adopter countries. Second, the gap in penetration rates between rich and poor countries has widened over the last 200 years, inducing a divergence in the intensive margin of technology adoption. These patterns are consistent with Figure 1. The horizontal gap between the diffusion curves for steam and motor ships in the UK and Indonesia is much larger than the horizontal gap between the U.S. and Vietnam for computers (131 years vs. 11 years). In contrast, the vertical gap between the curves for ships in the UK and Indonesia are smaller than the vertical gap between the diffusion curves of computers in the U.S. and Vietnam (0.9 vs. 1.6).

After characterizing the patterns of technology diffusion, we evaluate quantitatively their implications for the evolution of the world income distribution. We estimate the evolution of the diffusion margins for various groups of countries. Then, we feed in the estimated diffusion patterns into the aggregate representation of our model economy, and we compare the resulting income dynamics with the data. Note that this approach does not force the estimated adoption margins to fit the actual aggregate productivity dynamics.

We find that initial cross-country differences in the patterns of technology diffusion induce a world income distribution that is very similar to the actual distribution in 1820. Cross-country differences in technology diffusion patterns over the last two centuries account well for the evolution of the world income distribution. The model generates very protracted transitional dynamics, which account better for the dynamics of productivity over longer horizons than the neoclassical growth model.[3] Our simulations show that it took approximately one century since the beginning of the Industrial Revolution for Western economies to reach their Modern long run growth rate of 2%. With respect to the Great Divergence, we observe that differences in the evolution of technology diffusion induce an increase by a factor of 3.2 in the income gap between Western and non-Western countries between 1820 and 2000. This represents 82% of the actual increase in the income gap, which grew by a factor of 3.9.

It is important to emphasize that we use a general equilibrium model. Thus, when evaluating the role of technology for cross-country differences in income, our analysis takes into account that income affects demand for goods and services that embody new technologies. In our baseline model, the restriction that our model has a balanced growth path implies that the income elasticity of technology demand is equal to one. Because this implication of the model may be restrictive, we assess the robustness of our findings to allowing for non-homotheticities in the demand for technology. That is, we allow the income elasticity of technology demand to differ from one. We find that our results are robust to allowing for non-homotheticities.

This paper is related to the literature analyzing the channels driving the Great Divergence. One stream of the literature has emphasized the role of the expansion of international trade during the second half of the nineteenth century. Galor and Mountford (2006) argue that trade affected asymmetrically the fertility decisions in developed and developing economies, due to their different initial endowments of human capital, leading to different evolutions of productivity growth. O'Rourke *et al.* (2012) elaborate on this perspective and argue that the direction of technical change, in particular the fact that after 1850 it became skill-biased (Mokyr, 2002), contributed to the increase in income differences across countries, as Western countries benefited relatively more from them. Trade-based theories of the Great Divergence, however, need to confront two facts. Prior to 1850, the technologies brought by the Industrial Revolution were unskilled-biased rather than skilled-biased (Mokyr, 2002). Yet, incomes

[3]See, for example, Barro and Sala-i-Martin (2003) and King and Rebelo (1993) for a calibration of the neoclassical growth model.

diverged also during this period. Second, trade globalization ended abruptly in 1913. With WWI, world trade dropped and did not reach the pre-1913 levels until the 1970s. In contrast, the Great Divergence continued throughout the twentieth century.

Probably motivated by these observations, another strand of the literature has studied the cross-country evolution of Solow residuals and has found that they account for the majority of the divergence (Easterly and Levine, 2001, and Clark and Feenstra, 2003). Though these authors interpret Solow residuals as a proxy for technology, our paper is the first to use direct measures of technology to document how technology diffusion patterns have evolved in the cross-section over the last two centuries. It is also the first to show the importance that these technology dynamics have had for cross-country income dynamics.[4,5]

Finally, our paper builds upon Comin and Hobijn (2010). They estimate the adoption lags for 15 technologies and quantify how cross-country differences in average adoption lags contribute to differences in current income levels. To do this exercise, they assume all countries are in balanced growth path, growing at a common growth rate.[6] In this paper, we develop a new procedure to estimate not only adoption lags, but also the intensive margin of adoption. In doing so, we build a multi-sectoral model that explicitly accounts for the complementarities across technologies. Second, we study for the first time the cross-country evolution of the intensive and extensive margins of technology adoption over the last two centuries. To our knowledge, we are the first to document the divergence of the intensive margin and the convergence of the adoption lags. Third, this paper studies the transitional dynamics of the model and, most importantly, how technology dynamics have contributed to the evolution of the world income distribution that we have observed over the last 200 years. As emphasized above, this is one of few papers that provides an account of the dynamics of income growth over protracted periods of time.

The rest of the paper is organized as follows. Section 2 presents the model. Section 3 presents the estimation strategy based on the structural model. Section 4 estimates the extensive and intensive margins of adoption and documents the cross-country evolution of both adoption margins. Section 5 quantifies the effect of the technology dynamics on the evolution of the world income distribution. Section 6 concludes.

[4] Our analysis is also related to a strand of the literature that has studied the productivity dynamics after the Industrial Revolution. Crafts (1997), Galor and Weil (2000), Goodfriend and McDermott (1995), Hansen and Prescott (2002) and Tamura (2002) among others, provide complementary reasons why there was a slow growth acceleration in productivity after the Industrial Revolution.

[5] Our paper is also related to Lucas (2000) who studies the evolution of the world income distribution using a model that assumes a negative relationship between the time a country takes off and the TFP growth it experiences during the transition. Lucas (2000) predicts either no growth or a strong convergence.

[6] Gancia *et al.* (2011) also quantify the role of factor endowments and technology on cross-country income.

2 Model

We present a model of technology adoption and growth. Our model serves four purposes. First, it precisely defines the intensive and extensive margins of adoption. Second, it shows how variation in these margins affects the evolution of the diffusion curves for individual technologies. Third, it helps develop the identification strategy of the extensive and intensive margins of adoption. Fourth, because this is a general equilibrium model with an aggregate representation, it can be used to study the dynamics of productivity growth.

2.1 Preferences and Endowments

There is a unit measure of identical households in the economy. Each household supplies inelastically one unit of labor, for which they earn a wage w_t at time t. Households can save in domestic bonds which are in zero net supply. The utility of the representative household is given by

$$U = \int_{t_0}^{\infty} e^{-\rho t} \ \ln(C_t) dt, \tag{1}$$

where ρ denotes the discount rate and C_t, consumption at time t. The representative household maximizes its utility subject to the budget constraint (2) and a no-Ponzi condition (3)

$$\dot{B}_t + C_t = w_t + r_t B_t, \tag{2}$$

$$\lim_{t \to \infty} B_t e^{\int_{t_0}^{t} -r_s ds} \geq 0, \tag{3}$$

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

2.2 Technology

World technology frontier At a given instant of time t, the world technology frontier is characterized by a set of technologies and a set of vintages specific to each technology. Each instant, a new technology τ exogenously appears. We denote a technology by the time it was invented. Therefore, the range of invented technologies at time t is $(-\infty, t]$.

For each existing technology, a new, more productive, vintage appears in the world frontier every instant. We denote vintages of technology τ generically by v_τ. Vintages are also indexed by the time in which they appear. Thus, the set of existing vintages of technology τ available at time t $(> \tau)$ is $[\tau, t]$. The productivity of a technology-vintage pair has two components. The first component, $Z(\tau, v_\tau)$, is common across countries and it is purely determined by technological attributes,

$$Z(\tau, v_\tau) = e^{(\chi+\gamma)\tau+\gamma(v_\tau-\tau)} = e^{\chi\tau+\gamma v_\tau}, \tag{4}$$

where $(\chi+\gamma)\tau$ is the productivity level associated with the first vintage of technology τ and $\gamma(v_\tau-\tau)$ captures the productivity gains associated with the introduction of new vintages $v_\tau \geq \tau$. The second component is a technology-country specific productivity term, a_τ, which we further discuss below.

Adoption lags Economies are typically below the world technology frontier. Let D_τ denote the age of the best vintage available for production in a country for technology τ. D_τ reflects the time lag between when the best vintage in use was invented and when it was adopted for production in the country; that is, the *adoption lag*.[7] The set of technology τ vintages available in this country is $V_\tau = [\tau, t-D_\tau]$.[8] Note that D_τ is both the time it takes for this country to start using technology τ and its distance to the technology frontier in technology τ.

Intensive margin New vintages (τ, v) are incorporated into production through new intermediate goods that embody them.[9] Intermediate goods are produced competitively using one unit of final output to produce one unit of intermediate good.

Intermediate goods are combined with labor to produce the output associated with a given vintage, $Y_{\tau,v}$. Let $X_{\tau,v}$ be the number of units of intermediate good (τ, v) used in production, and $L_{\tau,v}$ be the number of workers that use them. $Y_{\tau,v}$ is given by

$$Y_{\tau,v} = a_\tau Z(\tau, v) X_{\tau,v}^{\alpha} L_{\tau,v}^{1-\alpha}. \tag{5}$$

The term a_τ in (5) captures the effect of factors that reduce the effectiveness of this technology in the country. Thus, in equilibrium, it affects how intensively this technology is used. We refer to a_τ as the *intensive margin*. Differences in the intensive margin may reflect differences in the number of users of the technology and differences in the efficiency with which the technology is used. Our empirical measures of the intensive margin will capture both of these sources of variation.

[7] Adoption lags may result from a cost of adopting the technology in the country that is decreasing in the proportion of not-yet-adopted technologies as in Barro and Sala-i-Martin (1997), or in the gap between aggregate productivity and the productivity of the technology, as in Comin and Hobijn (2010).

[8] Here, we are assuming that vintage adoption is sequential. Comin and Hobijn (2010) and Comin and Mestieri (2010) provide micro-founded models in which this is an equilibrium result rather than an assumption.

[9] In what follows, we omit the subscript τ from the vintage notation and write v when there is no confusion.

There are many potential drivers of the adoption lags D_τ and the intensive margins a_τ.[10] Given that the goal of the paper is to measure the equilibrium adoption margins and assess their contribution to productivity growth, the precise nature of these drivers of adoption is not our focus in this present work. Therefore, we simplify the analysis in the model by treating these margins of adoption as exogenous parameters.[11]

Production The output associated with different vintages of the same technology can be combined to competitively produce sectoral output, Y_τ, according to

$$Y_\tau = \left(\int_\tau^{t-D_\tau} Y_{\tau,v}^{\frac{1}{\mu}} \, dv \right)^{\mu}, \qquad \text{with} \quad \mu > 1. \tag{6}$$

Similarly, final output Y results from aggregating competitively sectoral outputs Y_τ as

$$Y = \left(\int_{-\infty}^{\bar{\tau}} Y_\tau^{\frac{1}{\theta}} d\tau \right)^{\theta}, \qquad \text{with} \quad \theta > 1, \tag{7}$$

where $\bar{\tau}$ denotes the most advanced technology adopted in the economy. That is, the technology τ for which $\tau = t - D_\tau$.

2.3 Factor Demands and Final Output

We take the price of the final good as the numéraire. The demand for output produced with a particular technology is

$$Y_\tau = Y p_\tau^{-\frac{\theta}{\theta-1}}, \tag{8}$$

where p_τ is the price of sector τ output. *Both* the income level of a country, Y, and the price of a technology, p_τ affect the demand of output produced with a given technology. Because of the homotheticity of the production function, the income elasticity of technology τ output is one. Similarly, the demand for output produced with a particular technology vintage is

$$Y_{\tau,v} = Y_\tau \left(\frac{p_\tau}{p_{\tau,v}} \right)^{-\frac{\mu}{\mu-1}}, \tag{9}$$

[10]For example, taxes, risk of expropriation, relative abundance of complementary inputs or technologies, frictions in capital, labor and goods markets, barriers to entry for producers that want to develop new uses for the technology,...

[11]See Comin and Hobijn (2010) and Comin and Mestieri (2010) for ways to endogenize these adoption margins as equilibrium outcomes.

where $p_{\tau,v}$ denotes the price of the (τ, v) intermediate good.[12] The demands for labor and intermediate goods at the vintage level are

$$
\begin{aligned}
(1-\alpha)\frac{p_{\tau,v}Y_{\tau,v}}{L_{\tau,v}} &= w, && (10)\\
\alpha\frac{p_{\tau,v}Y_{\tau,v}}{X_{\tau,v}} &= 1. && (11)
\end{aligned}
$$

Perfect competition in the production of intermediate goods implies that the price of intermediate goods equals their marginal cost,

$$
p_{\tau,v} = \frac{w^{1-\alpha}}{Z(\tau,v)a_\tau}(1-\alpha)^{-(1-\alpha)}\alpha^{-\alpha}. \tag{12}
$$

Combining (9), (10) and (11), the total output produced with technology τ can be expressed as

$$
Y_\tau = Z_\tau L_\tau^{1-\alpha} X_\tau^{\alpha}, \tag{13}
$$

where L_τ denotes the total labor used in sector τ, $L_\tau = \int_\tau^{\max\{t-D_\tau,\tau\}} L_{\tau,v}dv$, and X_τ is the total amount of intermediate goods in sector τ, $X_\tau = \int_\tau^{\max\{t-D_\tau,\tau\}} X_{\tau,v}dv$. The productivity associated with a technology is

$$
\begin{aligned}
Z_\tau &= \left(\int_\tau^{\max\{t-D_\tau,\tau\}} Z(\tau,v)^{\frac{1}{\mu-1}}dv\right)^{\mu-1}\\
&= \left(\frac{\mu-1}{\gamma}\right)^{\mu-1} \underbrace{a_\tau}_{\text{Intensive Mg}} \underbrace{e^{(\chi\tau+\gamma\max\{t-D_\tau,\tau\})}}_{\text{Embodiment Effect}} \underbrace{\left(1-e^{\frac{-\gamma}{\mu-1}(\max\{t-D_\tau,\tau\}-\tau)}\right)^{\mu-1}}_{\text{Variety Effect}}. && (14)
\end{aligned}
$$

Z_τ is affected by the intensive margin, a_τ, and the adoption lag, D_τ. A higher intensive margin increases the sectoral productivity. The adoption lag has two effects on Z_τ. First, the average vintage used is more productive when the adoption lag is lower, resulting in higher aggregate productivity. We denote this the embodiment effect. Second, because there productivity gains from using a broader range of varieties, the shorter the lags, the higher Z_τ is. We denote this is as the variety effect. It follows from (14) that the variety effect is strongest at the early stages of adoption. As additional vintages are added to production, marginal productivity gains decline and, eventually, their impact on the variety effect tends to zero. Hence, this property of the variety effect introduces a curvature in Z_τ that is determined by the adoption lag.

[12] Even though older technology-vintage pairs are always produced in equilibrium, the value of its production relative to total output is declining over time.

The price index of technology τ output is

$$\begin{aligned} p_\tau &= \left(\int_\tau^{t-D_\tau} p_{\tau,v}^{-\frac{1}{\mu-1}} dv \right)^{-(\mu-1)} \\ &= \frac{w^{1-\alpha}}{Z_\tau} (1-\alpha)^{-(1-\alpha)} \alpha^{-\alpha}. \end{aligned} \tag{15}$$

There exists an analogous representation for the aggregate production function in terms of aggregate labor (which is normalized to one),

$$Y = AX^\alpha L^{1-\alpha} = AX^\alpha = A^{1/(1-\alpha)}(\alpha)^{\alpha/(1-\alpha)}, \tag{16}$$

with

$$A = \left(\int_{-\infty}^{\bar{\tau}} Z_\tau^{\frac{1}{\theta-1}} d\tau \right)^{\theta-1}, \tag{17}$$

where $\bar{\tau}$ denotes the most advanced technology adopted in the economy.

2.4 Equilibrium

Given a sequence of adoption lags and intensive margins $\{D_\tau, a_\tau\}_{\tau=-\infty}^{\infty}$, a competitive equilibrium in this economy is defined by consumption, output, and labor allocations paths $\{C_t, L_{\tau,v}(t), Y_{\tau,v}(t)\}_{t=t_0}^{\infty}$ and prices $\{p_\tau(t), p_{\tau,v}(t), w_t, r_t\}_{t=t_0}^{\infty}$, such that

1. Households maximize utility by consuming according to the Euler equation

$$\frac{\dot{C}}{C} = r - \rho, \tag{18}$$

   satisfying the budget constraint (2) and (3).

2. Firms maximize profits taking prices as given (equation 12). This optimality condition gives the demand for labor and intermediate goods for each technology and vintage, equations (10) and (11), for the output produced with a vintage (equation 9) and for the output produced with a technology (equation 8).

3. Labor market clears

$$L = \int_{-\infty}^{\bar{\tau}} \int_{\tau}^{\bar{v}_\tau} L_{\tau,v} dv_\tau d\tau = 1, \tag{19}$$

   where $\bar{v}_\tau$ denotes the last adopted vintage of technology τ.

4. The resource constraint holds

$$Y = C + X, \tag{20}$$

$$C = (1-\alpha)Y. \tag{21}$$

Combining (19) and (10), it follows that the wage rate is given by

$$w = (1-\alpha)Y/L. \tag{22}$$

Combining the Euler equation (18) and the resource constraint (21) we obtain that the interest rate depends on output growth and the discount rate $r = \frac{\dot{Y}}{Y} + \rho$.

Equation (16) implies that output dynamics are completely determined by the dynamics of aggregate productivity, A.To guarantee the existence of a balanced growth path, a sufficient condition, which we take as a benchmark, is that both adoption margins are constant across technologies, $D_\tau = D$ and $a_\tau = a$.[13] If we make the simplifying assumption that $\theta = \mu$, aggregate productivity can be computed in closed form,[14]

$$A = \left(\frac{(\theta-1)^2}{(\gamma+\chi)\chi}\right)^{\theta-1} a\ e^{(\chi+\gamma)(t-D)}. \tag{23}$$

Naturally, a higher intensity of adoption, a, and a shorter adoption lag, D, lead to higher aggregate productivity. Along this balanced growth path, productivity grows at rate $\chi+\gamma$, and output grows at rate $(\chi+\gamma)/(1-\alpha)$.[15]

3 Estimation Strategy

In this section, we describe the estimation procedure used to measure the intensive and extensive margins of adoption for each technology-country pair.

3.1 Estimating Equations

We derive our estimating equation combining the demand for sector τ output (8), the sectoral price deflator (15), the expression for the equilibrium wage rate (22), and the expression for sectoral productivity, Z_τ, (14). Denoting by lowercase the logs of uppercase variables, we obtain the demand equation

$$y_\tau = y + \frac{\theta}{\theta-1}\left[z_\tau - (1-\alpha)(y-l)\right]. \tag{24}$$

We then use the fact that γ takes small values to simplify the expression of sectoral productivity z_τ to its first order approximation in γ (see Appendix B for calculation details),

$$z_\tau \simeq \ln a_\tau + (\chi+\gamma)\tau + (\mu-1)\ln(t-\tau-D_\tau) + \frac{\gamma}{2}(t-\tau-D_\tau). \tag{25}$$

[13] Comin and Mestieri (2010) show in their micro-founded model of adoption that this is a necessary and sufficient condition.

[14] Our empirical analysis in Section 4 suggests that this is a reasonable approximation.

[15] For discounted utility to be bounded, it is required that $(\chi+\gamma)/(1-\alpha) < \rho$.

Substituting (25) in (24) gives our main estimating equation. Explicitly indexing country-specific variables with superscript c and denoting time dependence by a subindex t, the estimating equation is

$$y^c_{\tau t} = \beta^c_{\tau 1} + y^c_t + \beta_{\tau 2} t + \beta_{\tau 3} \left((\mu - 1) \ln(t - D^c_\tau - \tau) - (1 - \alpha)(y^c_t - l^c_t) \right) + \varepsilon^c_{\tau t}, \tag{26}$$

where $\varepsilon^c_{\tau t}$ denotes a country c, technology τ and time t error term. Equation (26) shows that we can express the (log of) output produced with technology τ, $y^c_{\tau t}$, as the summation of a country-specific constant, $\beta^c_{\tau 1}$, various log-linear terms in time and income, and a non-linear function of the adoption lag. The country-technology intercept, β^c_1, which contains the intensive margin a^c_τ, is

$$\beta^c_{\tau 1} = \beta_{\tau 3} \left(\ln a^c_\tau + \left(\chi + \frac{\gamma}{2} \right) \tau - \frac{\gamma}{2} D^c_\tau \right). \tag{27}$$

Aggregate output, y^c_t, enters in (26) because the level of aggregate demand affects the demand for technology in the economy. Everything else equal, countries with higher output will have a higher demand. Note that the coefficient on aggregate output in the estimating equation (26) is one. This is a result of assuming a constant returns to scale aggregate production function (i.e., homothetic), which ensures the existence of a balanced-growth path. Thus, our baseline model imposes that the elasticity of technology with respect to output (i.e., the slope of the Engel curve) must be equal to one. In Section 4.4 we relax this assumption and estimate directly the Engel curve from the data to assess the robustness of our estimates and findings.

Some of the variables in our data set measure the number of units of the input that embody the technology (e.g. number of computers) rather than output. For this case, we derive an estimating equation for input measures. We integrate (11) across vintages to obtain (in logs) $x^c_\tau = y^c_\tau + p^c_\tau + \ln \alpha$. Substituting in for equation (26), we obtain the following expression which inherits the properties from (26),[16]

$$x^c_{\tau t} = \beta^c_{\tau 1} + y^c_t + \beta_{\tau 2} t + \beta_{\tau 3} \left((\mu - 1) \ln(t - D^c_\tau - \tau) - (1 - \alpha)(y^c_t - l^c_t) \right) + \varepsilon^c_{\tau t}. \tag{28}$$

3.2 Identification

The goal of the estimation is to measure the adoption lags and the intensive margins for each technology-country pair. To this end, we assume that the parameters that govern the growth in the technology frontier (γ and χ), and the inverse of the elasticity of demand (θ) are the same across countries, for any given technology. In addition, in our baseline estimation, we calibrate α, μ, and the invention date, τ. We set $\mu = 1.3$ to match the price markups from

[16] Note that there are two minor differences between (26) and (28). The first difference is that in the first equation $\beta_{\tau 3}$ is $\theta / (\theta - 1)$, while in the second it is $1/(\theta - 1)$. The second difference is that, in the second equation, the intercept $\beta^c_{\tau 1}$ has an extra term equal to $\beta_{\tau 3} \ln \alpha$.

Basu and Fernald (1997) and Norbin (1993), $\alpha = .3$ to match the capital income share in the U.S., and τ to the invention date of each technology. Invention dates are detailed in Appendix A.

These restrictions imply that the coefficients of the time-trend, $\beta_{\tau 2}$, and of the non-linear term, $\beta_{\tau 3}$, in (26) and (28) are common across countries. They also imply that cross-country variation in the curvature of (26) and (28) is entirely driven by variation in adoption lags. Specifically, D^c_τ causes the slopes in y^c_τ and x^c_τ to monotonically decline in time since adoption. Everything else equal, if at a given moment in time we observe that the slopes in y^c_τ or x^c_τ are diminishing faster in one country than another, it must be because the former country has started adopting the technology more recently. This is the basis of our empirical identification strategy for D^c_τ. Equivalently, a higher adoption lag D^c_τ shifts the diffusion curve (26) to the right. Thus, countries that for the same income levels have their diffusion curves "shifted to the right" have a longer adoption lag.

As the number of adopted vintages increases, the effect of D^c_τ in the diffusion curve vanishes because the gains from additional varieties become negligible. This implies that y^c_τ asymptotes to the common linear trend in time and (log) income plus the country-specific intercept, $\beta^c_{\tau 1}$. Therefore, after filtering differences in aggregate demand, asymptotic cross-country differences in technology are fully captured by the intercept, $\beta^c_{\tau 1}$. In our model, $\beta^c_{\tau 1}$ reflects the intensive margin, a^c_τ, and differences in the average productivity of the technology due to differences in D^c_τ. The latter effect can be subtracted from $\beta^c_{\tau 1}$ using the estimated adoption lag D^c_τ in equation (27), to obtain an expression for $\ln a^c_\tau$ as

$$\ln a^c_\tau = \frac{\beta^c_{\tau 1}}{\beta_{\tau 3}} + \frac{\gamma}{2} D^c_\tau - \left(\chi + \frac{\gamma}{2}\right)\tau. \tag{29}$$

In order to difference out the technology-specific term $\left(\chi + \frac{\gamma}{2}\right)\tau$ and make the estimates of the intensive margin comparable across technologies (which are measured in different units), we define the intensive margin of adoption of technology τ in country c, $\ln \hat{a}^c_\tau$, relative to the average value of adoption in technology τ for the seventeen Western countries defined in Maddison (2004),

$$\ln \hat{a}^c_\tau \equiv \ln a^c_\tau - \ln a^{\text{Western}}_\tau = \frac{\beta^c_{\tau 1} - \beta^{\text{Western}}_{\tau 1}}{\beta_{\tau 3}} + \frac{\gamma}{2}(D^c_\tau - D^{\text{Western}}_\tau). \tag{30}$$

Since the diffusion curves that we estimate are equilibrium adoption outcomes, they are affected by many possible drivers. For example, the long run level of adoption of a country may be affected by variables such as institutions, geography, policies or endowments. Thus, the estimates of the intensive margin are the collective projection of these drivers on the long run level of the technology in the country. It is important to emphasize, however, that because our model controls for the effect of aggregate demand on technology, cross-country variation in the intensive margin (30) is not driven by aggregate demand. In other words, our framework can separately identify the effect of aggregate demand from the effect of other factors that determine how intensively a technology is used in a country. This is a critical requirement to compute how technology adoption affects aggregate productivity.

3.3 Implementation and further considerations

Next, we discuss the baseline estimation procedure for the diffusion equations (26) and (28).[17] We estimate (26) and (28) in two stages. For each technology, we first estimate the corresponding diffusion equations jointly for the U.S., the U.K. and France, which are the countries for which we have the longest time series.[18] From this estimation, we take the technology-specific parameters $\hat{\beta}_{\tau 2}$ and $\hat{\beta}_{\tau 3}$. Then, in the second stage, for each technology-country pair, we estimate the diffusion curve imposing the values of $\hat{\beta}_{\tau 2}$ and $\hat{\beta}_{\tau 3}$ obtained in the first stage.[19] In this second stage, we obtain a technology-country specific parameters, $\beta^c_{\tau 1}$ and D^c_{τ}. Both of these estimations are conducted using non-linear least squares. Finally, we use the estimated values for $\beta^c_{\tau 1}$, $\beta_{\tau 3}$, D^c_{τ}, and expression (30) to obtain the estimate of the intensive margin for a given country-technology pair.[20]

This two-step estimation method is preferable to a system estimation method for various reasons. First, in a system estimation method data problems for one country can pollute the estimates for all countries. Since we judge the data is most reliable in our baseline countries, we use them for the inference on the parameters that are constant across countries. Second, a precise estimation of the curvature parameter, $\beta_{\tau 3}$, is more likely when exploiting the longer time series we have for our baseline countries. Finally, our model is based on a set of stark neoclassical assumptions. These assumptions are more applicable to the low frictional economic environments of our three baseline countries than to that of countries in which are substantially more distorted. Thus, by estimating the common parameters from the diffusion data in the baseline countries we reduce the likelihood of estimating them with a bias.

[17] In Section 4.4, we discuss alternative approaches, their rationale and the robustness of our baseline estimates.

[18] In the case of railways, we substitute the U.K. for Germany because we lack the initial phase of diffusion of railways for the UK. In the case of tractors, we substitute the U.S. by Germany data for the same reason.

[19] Note that the coefficients $\beta_{\tau 2}$ and $\beta_{\tau 3}$ in (26) are functions of parameters that are common across countries (θ and γ). Therefore their estimates should be independent of the sample used to estimate them. Below we study how sensible is to assume that $\beta_{\tau 3}$ is common across countries.

[20] Consistent with our calibration below, we compute the intensive margin using a value for γ in (30) of $2/3 \cdot 1\%$. In Section 4.4 we conduct robustness analysis of this parametrization.

4 Estimation Results

4.1 Data Description

We implement our estimation procedure using data on the diffusion of technologies from the CHAT data set (Comin and Hobijn, 2009), and data on income and population from Maddison (2004). The CHAT data set covers the diffusion of 104 technologies for 161 countries over the last 200 years. Due to the unbalanced nature of the data set, we focus on a sub-sample of technologies that have a broader coverage over rich and poor countries and for which the data captures the initial phases of diffusion. The twenty-five technologies that meet these criteria are listed in Appendix A and cover a wide range of sectors in the economy (transportation, communication and IT, industrial, agricultural and medical sectors). Their invention dates also span quite evenly over the last 200 years. The number of countries for which we have data for these twenty-five technologies is 130.

The specific measures of technology diffusion in CHAT match the dependent variables in specification (26) or (28). These measures capture either the amount of output produced with the technology (e.g., tons of steel produced with electric arc furnaces) or the number of units of capital that embody the technology (e.g., number of computers). Note that, differently from the traditional diffusion literature that looks at the fraction of adopters (Griliches, 1957), our measures capture the aggregate intensity of use of a technology (see Clark, 1987).

4.2 Estimates

We only use in our analysis the estimates of technology-country pairs that satisfy plausibility and precision conditions. As in Comin and Hobijn (2010), plausible adoption lags are those with an estimated adoption date of no less than ten years before the invention date (this ten year window is to allow for some inference error). Precise are those with a significant estimate of adoption lags D_{τ}^{c} at a 5% level. Most of the implausible estimates correspond to technology-country cases when our data does not cover the initial phases of diffusion. As discussed in Section 3.2, this makes it hard for our estimating equation to identify the adoption lag, since the diffusion curve has no curvature. The plausible and precise criteria are met for the majority of the technology country-pairs (69%). For these technology country-pairs, we find that our estimating equations provide a good fit with an average detrended R^2 of 0.79 across countries and technologies (Table C.1).[21] The fit of the model indicates that the restriction that adoption lags and the intensive margin are constant for each technology-country pair and that the curvature of diffusion is the same across countries are not a bad approximation to the data.

[21] To compute the detrended R^2, we partial out the linear trend component, γt, of the estimation equation and compute the R^2 for the detrended data.

Table 1: Estimates of Adoption Lags

	Invention Year	Obs.	Mean	SD	P10	P50	P90	IQR
Spindles	1779	31	119	48	51	111	171	89
Ships	1788	45	121	53	50	128	180	104
Railway Passengers	1825	39	72	39	16	70	123	63
Railway Freight	1825	46	74	34	31	74	123	49
Telegraph	1835	43	45	32	10	40	93	43
Mail	1840	47	46	37	8	38	108	62
Steel	1855	41	64	34	14	67	105	51
Telephone	1876	55	50	31	8	51	88	51
Electricity	1882	82	48	23	15	53	71	38
Cars	1885	70	39	22	11	34	65	36
Trucks	1885	62	35	22	9	34	62	32
Tractor	1892	88	59	20	18	67	69	12
Aviation Passengers	1903	44	28	16	9	25	52	18
Aviation Freight	1903	43	40	15	26	42	60	19
Electric Furnace	1907	53	50	19	27	55	71	34
Fertilizer	1910	89	46	10	35	48	54	7
Harvester	1912	70	38	18	10	41	54	17
Synthetic Fiber	1924	48	38	5	33	39	41	3
Oxygen Furnace	1950	39	14	8	7	13	26	11
Kidney Transplant	1954	24	13	7	3	13	25	5
Liver Transplant	1963	21	18	6	14	18	24	3
Heart Surgery	1968	18	12	6	8	13	20	4
Pcs	1973	68	14	3	11	14	18	3
Cellphones	1973	82	15	5	11	16	19	6
Internet	1983	58	7	4	1	7	11	3
All Technologies		1306	44	35	10	38	86	45

Table 1 reports summary statistics of the estimates of the adoption lags for each technology using the estimation procedure described in Section 3.3. The average adoption lag across all technologies and countries is 44 years. We find significant variation in average adoption lags across technologies. The range goes from 7 years for the internet to 121 years for steam and motor ships. There is also considerable cross-country variation in adoption lags for any given technology. The range for the cross-country standard deviations goes from 3 years for PCs to 53 years for steam and motor ships.

To compute the intensive margin $\ln \hat{a}^c_\tau$ (equation 30), we calibrate $\gamma = (1-\alpha)\cdot 1\%$, with $\alpha = .3$. We choose this calibration so that half of the 2% long run growth rate of Western countries comes from productivity improvements within a technology (γ) and the other half comes from new technologies being more productive (χ). Section 4.4 conducts the robustness

Table 2: Estimates of the Intensive Margin

	Invention Year	Obs.	Mean	SD	P10	P50	P90	IQR
Spindles	1779	31	-0.02	0.61	-0.85	-0.05	0.75	0.72
Ships	1788	45	-0.01	0.59	-0.58	-0.02	0.74	0.63
Railway Passengers	1825	39	-0.24	0.47	-0.88	-0.17	0.19	0.52
Railway Freight	1825	46	-0.17	0.40	-0.60	-0.19	0.43	0.56
Telegraph	1835	43	-0.26	0.50	-1.00	-0.21	0.29	0.72
Mail	1840	47	-0.19	0.30	-0.63	-0.12	0.13	0.43
Steel	1855	41	-0.22	0.44	-0.71	-0.13	0.20	0.56
Telephone	1876	55	-0.91	0.87	-2.21	-0.84	0.11	1.17
Electricity	1882	82	-0.58	0.57	-1.25	-0.51	0.08	0.90
Cars	1885	70	-1.13	1.14	-2.15	-1.07	0.08	1.62
Trucks	1885	62	-0.86	1.01	-1.66	-0.81	0.13	1.12
Tractor	1892	88	-1.02	0.94	-2.28	-0.91	0.11	1.47
Aviation Passengers	1903	44	-0.45	0.70	-1.33	-0.36	0.23	0.89
Aviation Freight	1903	43	-0.39	0.60	-1.29	-0.16	0.24	0.87
Electric Furnace	1907	53	-0.29	0.53	-0.93	-0.20	0.34	0.79
Fertilizer	1910	89	-0.83	0.79	-1.86	-0.74	0.11	1.29
Harvester	1912	70	-1.10	0.98	-2.66	-0.96	0.16	1.52
Synthetic Fiber	1924	48	-0.52	0.73	-1.57	-0.38	0.23	0.86
Oxygen Furnace	1950	39	-0.81	0.94	-2.31	-0.36	0.10	1.77
Kidney Transplant	1954	24	-0.19	0.35	-0.85	-0.07	0.13	0.35
Liver Transplant	1963	21	-0.33	0.65	-1.62	-0.09	0.10	0.51
Heart Surgery	1968	18	-0.44	0.80	-1.70	-0.11	0.20	0.55
Pcs	1973	68	-0.60	0.58	-1.41	-0.57	0.05	0.92
Cellphones	1973	82	-0.75	0.71	-1.80	-0.58	0.08	1.16
Internet	1983	58	-0.96	1.09	-2.09	-0.80	0.08	1.53
All Technologies		1306	-0.62	0.83	-1.73	-0.40	0.18	1.00

checks of this calibration. We use the value of $\beta_{\tau 3}$ that results from setting the elasticity across technologies, θ, to be the mean across our estimates, which is $\theta = 1.28$. This value is very similar to the estimates of price markups from Basu and Fernald (1997) and Norbin (1993).

Table 2 reports the summary statistics of the intensive margin estimates. The average intensive margin is -.62. This implies that the level of adoption of the average country is 54% (i.e., $\exp(-.62)$) of the Western countries. There is significant cross-country variation in the intensive margin. The range of the cross-country standard deviation goes from 0.3 for mail to 1.1 for cars and the internet. The average 10-90 percentile range in the (log) intensive margin is 1.91, which implies productivity differences by a factor of 17 (i.e., $\exp(1.9/(1-\alpha))$.)

Table 3: Evolution of the Adoption Lag and Intensive Margins

Dep. Var.:	Log(Lag)			Intensive		
	World	Western	Rest	World	Western	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Year -1820	-0.0106	-0.0080	-0.0112	-0.0029	-0.0000	-0.0054
	(0.0004)	(0.0006)	(0.0003)	(0.0005)	(0.0002)	(0.0005)
Constant	4.26	3.67	4.48	-0.32	0.00	-0.39
	(0.06)	(0.07)	(0.05)	(0.05)	(0.04)	(0.07)
Obs.	1274	336	938	1306	350	956
R^2	0.45	0.34	0.53	0.04	0.00	0.13

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

4.3 Cross-country evolution of the diffusion process

To analyze the cross-country *evolution* of the adoption margins in a simple way, we divide the countries in our data set in two groups, as in Maddison (2004): Western countries, and the rest of the world, labeled "Rest of the World"or, simply, non-Western.[22]

Figure 2a plots, for each technology and country group, the median adoption lag among Western countries and the rest of the world. This figure suggests that adoption lags have declined over time, and that cross-country differences in adoption lags have narrowed. Table 3 formalizes these intuitions by regressing (log) adoption lags on their year of invention (and a constant),

$$\ln D_\tau^c = \rho + \omega \cdot (\text{Invention Year}_\tau - 1820) + \varepsilon_\tau^c, \tag{31}$$

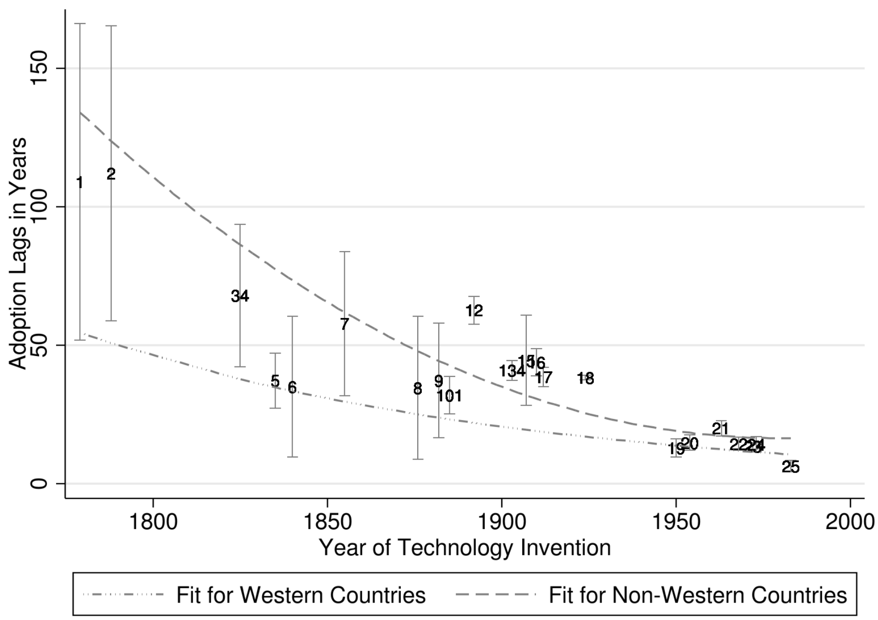
where ε_τ^c denotes an error term. Column (1) reports this regression for the whole sample of countries showing that adoption lags have declined with the invention date. Columns (2) and (3) report the same regression separately for Western and non-Western countries, respectively. We find that the rate of decline in adoption lags is almost a 40% higher in non-Western than in Western countries (1.12% vs. .81%). Hence, there has been *convergence* in the evolution of adoption lags between Western and non-Western countries.

Do we observe a similar pattern for the intensive margin? Figure 2b plots, for each technology and country group the median intensive margin. This figure shows that the gap in the intensive margin between Western countries and the rest of the world is larger for newer than for older technologies. Table 3 studies econometrically this question by regressing the

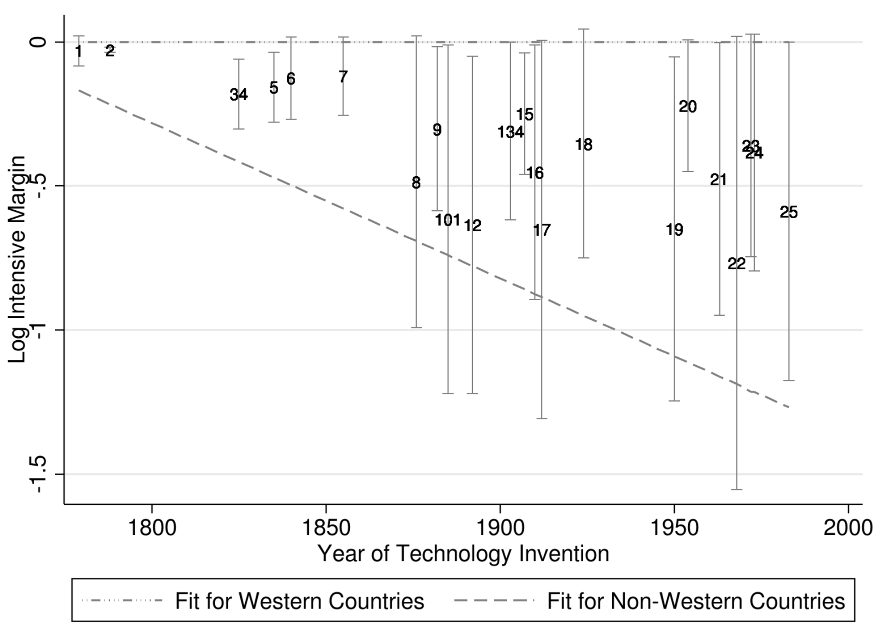
[22]The results are robust to the alternative country groupings described in Section 5.2.

Figure 2: Evolution of Adoption Margins

(a) Convergence of Adoption Lags



(b) Divergence of the Intensive Margin



Note: Bars show median margins of adoption for Western vs. non-Western countries. Technologies: 1. Spindles, 2. Ships, 34. Railway Passengers and Freight, 5. Telegraph, 6. Mail, 7. Steel (Bessemer, Open Hearth), 8. Telephone, 9. Electricity, 101. Cars and Trucks, 12. Tractors, 134. Aviation Passengers and Freight, 15. Electric Arc Furnaces, 16. Fertilizer, 17. Harvester, 18. Synthetic Fiber, 19. Blast Oxygen Furnaces, 20. Kidney Transplant, 21. Liver transplant, 22. Heart Surgery, 23. PCs, 24. Cellphones, 25. Internet.

intensive margin on the invention year and a constant,

$$\ln a_\tau^c = \rho + \omega \cdot (\text{Invention Year}_\tau - 1820) + \varepsilon_\tau^c. \tag{32}$$

Column (6) shows that, for non-Western countries, the intensive margin has declined at an annual rate of .54%.[23] Since the intensive margin is measured relative to the mean of Western countries, this evidence shows a *divergence* in the intensive margin of adoption between Western and non-Western countries over the last 200 years.[24]

4.4 Robustness

We assess the robustness of our estimates and the two cross-country trends in technology diffusion to alternative measurement and estimation approaches.

Curvature The main assumption used in the identification of the adoption margins is that the curvature of the diffusion curve is the same across countries. In our model, this is a consequence of having a common elasticity of substitution between sectoral outputs across countries (i.e., $1/(\theta-1)$). To explore the empirical validity of this assumption, we re-estimate equation (26) allowing $\beta_{\tau 3}$ to differ across countries. Thus, we obtain an estimate $\hat{\beta}_{\tau 3}^c$ for each country-technology pair. Then, we test whether $\hat{\beta}_{\tau 3}^c$ in each country is equal to the baseline estimate $\hat{\beta}_{\tau 3}$. We find that in 74% of the cases, we cannot reject the null that the curvature is the same as for the baseline countries at a 5 percent significance level. Table C.3 in the Appendix reports the results of this test for each technology.

Beyond the statistical validity of the restrictions that our model imposes on $\beta_{\tau 3}$, we would like to assess how relevant this assumption is for our main technology adoption estimates. In the first row of Table 4, we report the correlation between the estimates of the diffusion margins in the baseline and in the unrestricted estimations. The first column reports the unconditional correlation of adoption lags across all technologies, which is .93. Then, we estimate this correlation technology by technology. The second column reports the median correlation within technologies, which is .78. We also report the 25th and 75th percentiles of the within technology correlation which are .60 and .84, respectively. We report the same statistics for the intensive margin. The unconditional correlation is .53 and the median correlation within technologies is .69. Based on these statistics, we conclude that the adoption lags and intensive

[23] For Western countries, column (5) shows that there is no trend in the intensive margin, as by construction the intensive margin is defined relative to Western countries.

[24] One alternative interpretation of Figure 2b is that, rather than a continuous decline in the intensive margin in non-Western countries, there was a structural break around 1860. We find that the linear model provides a better statistical fit as measured by the R^2. In Section 5.3, we examine the implications for income dynamics of modeling the divergence in the intensive margin as a continuous or as a discrete process and show that our results are robust to this modeling choice.

Table 4: Correlation of Baseline Estimates with Alternative Specifications

Alternative Specification	Lags		Intensive Margin	
	Overall	Within Tech.	Overall	Within Tech.
Unrestricted Curvature	0.93	0.78	0.53	0.69
		[0.60, 0.84]		[0.43, 0.75]
Non-homotheticities	0.97	0.96	0.88	0.89
		[0.91, 0.98]		[0.85, 0.93]
Estimated μ	0.84	0.87	0.82	0.90
		[0.78, 0.93]		[0.87, 0.99]
Obsolescence	0.97	0.95	0.85	0.89
		[0.88, 0.98]		[0.86, 0.95]
No correction intensive	-	-	0.99	1.00
				[0.99, 1.00]

Note: Overall refers to the correlation of all estimates in the baseline and in the alternative specification. Within Tech. reports the median correlation of the estimates within technologies. The 25th and 75th percentiles of the correlation within technologies are reported in brackets.

margins that arise under the unrestricted estimation are highly correlated with the baseline estimates.

As important as the robustness of the actual estimates is the robustness of the patterns uncovered for the evolution of the adoption margins. Columns (1) and (2) in Table 5 report the time-trend coefficient of the (log) adoption lag with respect to the invention date for Western and non-Western countries. Column (3) reports the time-trend coefficient for the intensive margin in non-Western countries (recall that by definition is zero for Western countries). For comparison purposes, we report the baseline estimates in the first row of the table. The new estimates confirm that both the convergence of adoption lags and the divergence in the intensive margin are robust to relaxing the restriction of a common curvature across countries. If anything, the new estimates suggest stronger convergence and divergence patterns than the ones reported in the baseline.

Non-homotheticities We investigate the robustness of our estimates and the dynamics of adoption margins once we allow for non-homotheticities in the demand for technology. Non-homotheticities alter our baseline estimating equation (26) by introducing an income elasticity in the demand for technology, $\beta_{\tau y}$, potentially different from one,

$$y_{\tau t}^c = \beta_{\tau 1}^c + \beta_{\tau y} y_t^c + \beta_{\tau 2} t + \beta_{\tau 3}\left((\mu - 1)\ln(t - D_\tau^c - \tau) - (1-\alpha)(y_t^c - l_t^c)\right)) + \varepsilon_{\tau t}^c. \tag{33}$$

A practical difficulty in estimating (33) is the collinearity of the time-trend and log-income, y_t^c. To overcome this problem, we group technologies by their invention date and estimate a

Table 5: Time Trend Coefficient Across Alternative Specifications

Dependent Variable:	Log(Lag)		Intensive
	Western	Rest World	Rest World
	(1)	(2)	(3)
Baseline	-0.0080	-0.0112	-0.0054
	(0.0006)	(0.0003)	(0.0005)
Unrestricted Curvature	-0.0073	-0.0117	-0.0075
	(0.0005)	(0.0004)	(0.0011)
Non-homotheticities	-0.0082	-0.0118	-0.0044
	(0.0006)	(0.0005)	(0.0006)
Estimated μ	-0.0078	-0.0101	-0.0048
	(0.0007)	(0.0006)	(0.0007)
Obsolescence	-0.0081	-0.0113	-0.0062
	(0.0006)	(0.0004)	(0.0007)
No correction intensive	-	-	-0.0042
			(0.0005)

Note: This table reports the coefficient ω on the time trend resulting from regressing the (log) adoption lag and the intensive margin on $\rho + \omega(\text{Invention Year}_\tau - 1820) + \varepsilon^c_\tau$ for the different country groupings. Robust standard errors in parentheses. Each technology observation is weighted so that each technology carries equal weight.

common income elasticity for each group.[25] Accordingly, we divide the technologies in four groups as a function of their invention data denoted by $T = \{\text{pre-1850, 1850-1900, 1900-1950, post-1950}\}$. Then, we proceed similarly to the two-step baseline estimation. In the first step, we jointly estimate the income elasticity, β_{Ty}, along with $\beta_{\tau 2}$, and $\beta_{\tau 3}$ from the diffusion curves of the U.S., UK, and France for each of the four technology groupings. Effectively, this method identifies the income elasticity of technology out of the time series variation in the baseline countries in income and technology. Given that the baseline countries have long time series that for many technologies cover much of its development experience, we consider this to be a reasonable approach.

The estimates of the income elasticity for the technologies invented in the four periods, β_{Ty}, range from 1.58 for $T =$ (pre-1850), to 1.99 for $T =$ (1850-1900).[26] The estimates of the slopes of the Engel curves do not vary much across technology groups and they do not have a clear trend.

Once we have obtained the estimates for the income elasticity, we proceed as in the baseline estimation, but instead of imposing an income elasticity of one as our theoretical model suggests, we impose the estimated income elasticity. We estimate $\beta^c_{\tau 1}$ and D^c_τ for each country-

[25]We have implemented a similar approach grouping the technologies according to the sector rather than the invention date, obtaining similar results.

[26]Table C.2 in the Appendix reports the estimates.

technology pair from the equation

$$y^c_{\tau t} = \beta^c_{\tau 1} + \hat{\beta}_{Ty} y^c_t + \hat{\beta}_{\tau 2} t + \hat{\beta}_{\tau 3}\left((\mu - 1)\ln(t - D^c_\tau - \tau) - (1-\alpha)(y^c_t - l^c_t)\right)) + \varepsilon^c_{\tau t}, \qquad (34)$$

where $\hat{\beta}_{\tau 2}$, $\hat{\beta}_{\tau 3}$ and $\hat{\beta}_{Ty}$ are the values of $\beta_{\tau 2}$, $\beta_{\tau 3}$ and β_{Ty} estimated for the U.S., U.K. and France in the first step.

The estimates of the two margins that we obtain are highly correlated with our baseline estimates. The second line in Table 4 shows that the correlation of adoption lags is .96 and .88 for the intensive margin. Moreover, the patterns of convergence of adoption lags and divergence of the intensive margin remain. The convergence rate (measured as the difference between the coefficients of Western and non-Western countries) is -.44% per year, while in the baseline case it was .31% per year. The divergence rate in the intensive margin is slightly smaller than in the baseline baseline model ($-.44\%$, versus $-.54\%$). However, both trends are statistically and economically robust to allowing for non-homotheticities.

Estimated μ In our baseline estimation, we calibrate the elasticity of substitution between vintages, $\mu/(\mu-1)$, because it is difficult to separately identify $\beta_{\tau 3}$ and μ in the baseline diffusion equation (26). However, it is possible to identify them simultaneously in the structural equation that results from substituting expression (14) for z_τ in (8) rather than its log-linear approximation.

In the third row of Table 4 we compare the adoption margins obtained using this alternative approach with our baseline estimates. Both sets of estimates are similar. Their correlation is .84 for the adoption lags and .82 for the intensive margins. Furthermore, the evolution of the adoption margins across countries quantitatively resembles very much that of our baseline estimates. In fact, we cannot reject the null that the time trends for both adoption lags and the intensive margin are the same as in the baseline estimation.

Obsolescence Some technologies eventually become dominated by others. This is for example the case of the telegraph which was rendered obsolete by the telephone. The obsolescence of technology may affect the shape of the diffusion curves (especially in the long run) and therefore the estimates of our adoption margins. Since our theory just concerns the diffusion process (and is silent about the phase out process) it does not provide any guide on how obsolescence impacts our technology measures. As a robustness check, we re-estimate equation (26) over a time sample where obsolescence dynamics are unlikely to be relevant. For each technology, we censor the sample at the point where the leading country starts to experience a decline in the per capita adoption level.[27] This affects the estimation period in six of the twenty-five technologies in our sample. Table 4 reports the correlation between the estimates

[27] More precisely, we censor all observations that are 90% below the peak level of technology usage for the leading country (after the peak has been attained). This is to allow for some fluctuations in the level of adoption.

of the adoption margins for the censored and uncensored samples. The correlation between the adoption lags is .97, while for the intensive margin it is .85. The evolution of the adoption margins is also robust to controlling for the potential obsolescence of technologies. The rates of decline of the adoption lags for Western and non-Western countries are virtually the same as in the baseline.The divergence in the intensive margin is slightly more pronounced than in our baseline (0.62% vs. 0.54%). Therefore, we conclude that the potential obsolescence of technologies does not affect the trends in adoption patterns we have uncovered.

Measurement of the intensive margin In our baseline estimation, we identify the intensive margin by removing from the intercept $\beta_{\tau 1}$ the productivity gains arising from the timing of adoption. This effect operates through the adoption lag, which we subtract according to (30),

$$\ln \hat{a}_{\tau}^{c} = \frac{\beta_{\tau 1}^{c} - \beta_{\tau 1}^{Western}}{\beta_{\tau 3}} + \frac{\gamma}{2}(D_{\tau}^{c} - D_{\tau}^{Western}).$$

In our theory, correcting for differences in adoption lags in the intercept has a clear interpretation. For the intensive margins to be comparable across countries, they should be computed as if adoption had started at the same time in all countries. This way, any remaining vertical differences in the resulting corrected diffusion curves can be attributed to differences in penetration rates of the technology.

However, in the light of the convergence in adoption lags, one might worry that the divergence in the intensive margin that we find is a mechanical result inherited from the trends in the estimated adoption lags. Alternatively, one can simply report the intercept without correcting for differences in adoption lags as a less structural benchmark. To address these concerns, we compute an alternative measure of the intensive margin under the assumption that the productivity growth of a technology is zero, $\gamma = 0$. Note that, in this case, there is no correction in the intensive margin arising from differences in the timing of adoption. This variation does not affect the estimates of the adoption lags.

The fifth row in Table 4 shows the correlation between these estimates of the intensive margin and our baseline estimates. The overall correlation between these two estimates is .99. The divergence in the intensive margin is also robust to this alternative computation of the intensive margin. In particular, the time trend on the intensive margin for non-Western countries is $-.42\%$, compared to $-.54\%$ in our baseline estimate.

5 Income Dynamics

In this section, we evaluate quantitatively the implications of the cross-country patterns of technology diffusion for the evolution of the world income distribution. We focus on three questions: *(i)* the model's ability to generate pre-industrial income differences, *(ii)* the protractedness of the model's transitional dynamics, and *(iii)* the model's account of the Great Divergence.

5.1 Calibration

To simulate the evolution of productivity growth we use equation (17), which expresses aggregate productivity in terms of the sectoral adoption patterns. This requires specifying the evolution of the technology frontier, calibrating four parameters and specifying the evolution of the adoption margins.

We model the evolution of the technology frontier as a one time increase in the growth rate of the frontier. According to Mokyr (1990) and Crafts (1997), an acceleration in the technology frontier growth captures well the Industrial Revolution. We assume that prior to year $T = 1765$ (year in which James Watt developed his steam engine), the technology frontier grew at 0.2%.[28] This is the growth rate of Western Europe from 1500 to 1800 according to Maddison (2004). After 1765, the frontier growth rate, $\chi + \gamma$, jumps to $(1 - \alpha) \cdot 2\%$ per year. This ensures that Modern growth along the balanced growth path is 2%. As previously discussed, we set $\alpha = .3$. In our baseline simulation, we split evenly the sources of growth in the frontier between γ and χ.[29] Finally, we calibrate the elasticity of substitution in the final good production function, $1/(\theta - 1)$, using the average estimates of $\beta_{\tau 3}$, which implies a value of $\theta = 1.28$.

To specify the adoption margins, which also enter equation (17), we assume that they evolve continuously between 1765 and 1983 as described by equations (31) and (32). Prior to 1765 and after 1983, the adoption margins remain constant.[30] Constant adoption margins at the end and the beginning of the sample ensure that the economies transition between the two balanced growth paths described by equation (23).

5.2 Cross-country evolution of income growth

We consider the implications of technology dynamics for the evolution of income growth for various country classifications. We begin our analysis with the division between Western and non-Western countries. Then, we divide countries by their income in five quintiles to characterize the evolution of the world income distribution more finely. Finally, we classify

[28] Alternatively, we can set, without any significant change to our findings, the beginning of the Industrial Revolution at 1779, year of invention of the first technology in our sample, the mule spindle.

[29] From our reading of the literature, it is unclear what fraction of frontier growth comes from increases in productivity due to new technologies (χ) and new vintages (γ). In Section 4.4 we conduct robustness checks on this division.

[30] We select 1983 as our end date because this is the last invention year in our data (the internet). For the adoption lag, and given that it tends towards zero at the end of the sample, similar results would emerge if we allowed for a continuing trend. For the intensive margin, and given our finding of divergence, allowing for a continuing trend would exacerbate the differences between Western and non-Western countries.

countries by their continent and study the implications of the adoption trends observed in each continent for their evolution of income growth.

We start simulating the evolution of output for Western countries and the rest of the world. As discussed in the calibration section, we feed a (common) one time permanent increase in frontier growth and the estimated evolutions for adoption lags and the intensive margin for each group of countries reported in Table 3.

Prior to the adoption of Modern technologies, both groups of countries are in the pre-Modern balanced growth path. Along the pre-industrial balanced growth path, differences in productivity are entirely due to differences in adoption levels of the pre-Modern era. We assume that pre-Modern levels of adoption coincide with the adoption levels that we estimate for the beginning of our sample. Our estimates from Table 3 imply that the difference between the average adoption lag in the sample of Western countries and the rest of the world is 49 years in 1820. The average gap in the (log) intensive margin is 0.39. Using Maddison's estimates of pre-industrial growth in Western Europe (0.2%) to calibrate the pre-industrial growth rate of the world technology frontier, equation (23) implies an income gap between Western countries and the rest of the world of 90%.[31] This is in line with the results from Maddison (2004), who reports an income gap of the same magnitude.

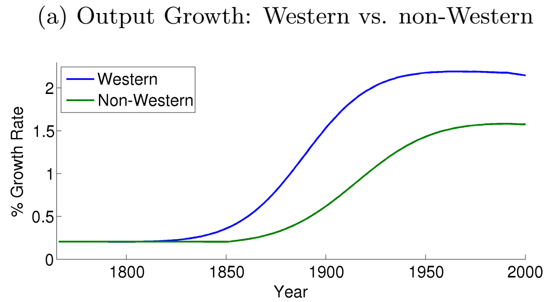
After the increase of frontier growth in 1765, countries can start adopting Modern technologies that embody higher productivity. As a result, they increase their productivity growth and transition to the Modern balanced growth path. We report in Figure 3 the evolution of growth rates for the 1765-2000 period.[32] Figure 3a shows that the model generates sustained differences in the growth rates of Western and non-Western countries for long periods of time. In the Western economy, output growth starts to accelerate around 1830, and it reaches the steady state growth rate of 2% after 1900. The transitional dynamics implied by the model are very protracted: the half-life of the growth rate is a hundred years. Growth in the non-Western economy does not take off until approximately 1870. After that, it accelerates at a slower pace than the average Western economy. By year 2000, it is still 1.5%. As shown in figure 3b, the resulting gap in growth rates between Western and non-Western economies is considerable. The average annual growth rate is 0.65 percentage points lower in non-Western countries over a period of 180 years. The gap peaks around 1913 at 1%. From then on, the gap declines monotonically until reaching 0.6% by 2000.

Table 6 reports the average growth and growth gaps of our simulation and in the Maddison (2004) data. The evolution of productivity growth in both country groups traces quite well

[31] That is, $\exp(.2\% \cdot 49 + .39/(1-\alpha)) = 1.9$.

[32] In the working paper version (Comin and Mestieri, 2013), we characterize analytically the transition after a permanent increase in the growth rate of the technology frontier and after changes in the adoption margins. We show that the path of the growth rate during the transition is S-shaped. We also provide approximate expressions for the half-life of the system during the transition. We show that the half-life depends on both adoption margins, and that it is an order of magnitude larger than in conventional calibrations of the neoclassical model.

Figure 3: World Income Dynamics, 1820-2000



Note: Growth rates of Western countries and the rest of the World obtained imputing the estimated evolution of the intensive and extensive margins using the baseline calibration. Western countries are defined as in Maddison (2004).

the data, though the model slightly underpredicts growth during the nineteenth century.

The sustained cross-country difference in growth rates generated by the model accumulate into a 3.2-fold income gap between the Western countries and the rest of the world from 1820 to 2000. Maddison (2004) reports an actual income widening by a factor of 3.9. Hence, differences in the technology adoption patterns account for 82% of the Great Income Divergence between Western and non-Western countries over the last two centuries. When compounding the increase in the gap with initial income differences in 1820, it follows that differences in technology imply an income gap between Western and non-Western countries of 6.2 ($1.9 \cdot 3.2$) by 2000. This represents 86% of the 7.2-fold gap reported by Maddison (2004).

The simulation does also well in replicating the time series income evolution of each country group separately. For Western countries, Maddison (2004) reports a 18.5-fold increase in income per capita between 1820 and 2000. Approximately 19% of this increase occurred prior to 1913. In our simulation, we generate a 14-fold increase over the same period, and 16% of this increase is generated prior to 1913. For non-Western countries, Maddison (2004) reports an almost 5-fold increase, with around 37% of the increase being generated prior to 1913. Our simulation generates a 4.3-fold increase in the 1820-2000 period with 32% of this increase occurring in pre-1913. The fact that we underpredict the time series increase in output reflects, in our view, that we are not accounting for the accumulation of factors of production over this time period (e.g., human capital), which also contributed to income growth.

Mechanisms at Work We next decompose the mechanisms at work in our simulation: the acceleration of the technological frontier and the evolution of the two adoption margins. We start by simulating the dynamics of our model after a common acceleration of the technology frontier for both countries, keeping constant the adoption margins at their initial levels. Figure 5 shows that these initial conditions are an important source of cross-country income divergence. Longer adoption lags in the non-Western country imply a delay of 80 years to

Table 6: Growth rates of GDP per capita

		Time Period		
		1820-2000	1820-1913	1913-2000
Simulation	Western Countries	1.47%	.84%	2.15%
	Rest of the World	.82%	.35%	1.31%
	Difference West-Rest	.65%	.49%	.84%
Maddison	Western Countries	1.61%	1.21%	1.95%
	Rest of the World	.86%	.63%	1.02%
	Difference West-Rest	.75%	.58%	.93%

Notes: Simulation results and median growth rates from Maddison (2004). We use 1913 instead of 1900 to divide the sample because there are more country observations in Maddison (2004). The growth rates reported from Maddison for the period 1820-1913 for non-Western countries are computed imputing the median per capita income in 1820 for those countries with income data in 1913 but missing observations in 1820. These represent 11 observations out of the total 50. We do the same imputation for computing the growth rate for non-Western countries for 1820-2000. This represents 106 observations out of 145. For the 1913-2000 growth rate of non-Western countries, we impute the median per capita income in 1913 to those countries with income per capita data in 2000 but missing observations in 1913. These represent 67 observations out of the total of 145.

start benefiting from the productivity gains of the Industrial Revolution. As a result, the income gap increases by a factor of 2.3 by year 2000. The transitional dynamics are very protracted. For example, the half-life of the growth rate of Western countries is 141 years. The half-life of output normalized by the long run trend is 114 years, which is an order of magnitude greater than the neoclassical growth model with a conventional calibration, e.g., Barro and Sala-i-Martin (2003).

To assess the role of adoption lags in cross-country growth dynamics, we simulate the evolution of our two economies as in our baseline model, but keeping the intensive margins at pre-industrial levels (i.e., no divergence). Figure 6a presents the results from this simulation. It shows that cross-country differences in adoption lags are an important driver of income divergence during the nineteenth century. By 1900, the income gap between Western and non-Western countries reaches 2.1, as opposed to 2.6 in the full-blown simulation. Thus, the contribution of the divergence in the intensive margin to income divergence during the nineteenth century is rather small. In the twentieth century, the faster reduction in adoption lags in non-Western countries produces a higher growth rate in non-Western countries. Had the intensive margins remained constant at the pre-industrial levels, the relative income between Western and non-Western countries in 2000 would be similar to the level in 1820 and, therefore, there would not have been a Great Divergence.

To analyze the role of the intensive margin, we simulate the evolution of the two economies as in our baseline model, but keeping the adoption lags constant at their pre-industrial levels. Figure 6b presents the dynamics of income growth in each country. In this simulation, the growth acceleration in non-Western countries starts much later than in the baseline (Figure

3). This is a consequence of omitting the productivity gains from a reduction in adoption lags in non-Western countries. Another perspective on this same issue is that the decline in the intensive margin reduces productivity growth by a magnitude that, initially, is equivalent to the gains brought by the industrial revolution to non-Western countries.

We also see in Figure 6b that Western countries grow less than in the baseline, especially during the nineteenth century. This is a reflection of the absence of the productivity gains brought by the reduction in adoption lags. Furthermore, as shown in the bottom panel of Figure 6b, the growth gap between the two groups of countries during the nineteenth century is smaller when we omit the evolution of the adoption lags. Despite that, the growth rate of non-Western countries falls behind during the first half of the twentieth century. This gap does not begin to close until the second half of the twentieth century. In this simulation, the income gap between Western countries and the rest of the world accumulated between 1820 and 2000 is 3.8.

To sum up, the main findings from our simulations are:

1. The model is capable of generating a Great Divergence. Income per capita of Western countries relative to the rest of the world increases by a factor of 3.2 over the last 200 years. This represents 82% of the actual increase in the income gap observed in the data.

2. Our model generates very protracted transitional dynamics. This is due both to the effect of adoption lags and to the fact that it takes time for new technologies to become a significant share of aggregate output. This latter effect is affected by the intensive margin.

3. Large cross-country differences in adoption lags explain much of the income divergence during the nineteenth century between Western countries and the rest of the world.

4. The Great Divergence continued during the twentieth century because of the divergence in penetration rates (i.e., intensive margin of adoption) between Western countries and the rest of the world.

Implications for the World Income Distribution We replicate the exercise we have conducted looking at a finer classification of countries by income quintiles. We consider three years: 1820, 1913 and 2000. At each of these years, we classify countries by income quintiles. For each quintile and date, we estimate the evolution of the adoption margins as in the baseline equations (31) and (32).[33] This gives a total of 15 evolutions for each of the two adoption margins. For each year and income quintile, we feed the estimated technology dynamics and

[33] We conduct the estimation of the evolution using information over the whole sample. The results reported are robust to restricting the time period to prior to 1913 for the years 1820 and 1913.

Table 7: Annual Growth rates of GDP per capita by regions

	Simulation		Maddison	
	1820-1913	1913-2000	1820-1913	1913-2000
USA & Canada	.77%	2.05%	1.63%	1.90%
Western Europe	.62%	1.91%	1.29%	2.16%
Africa	.26%	.75%	.36%	.90%
Asia	.34%	1.37%	.49%	1.70%
Latin America	.37%	1.28%	.59%	1.50%

Note: Annual growth rates of GDP per capita by regions. Simulation results and growth rates from Maddison (2004). For the missing income per capita values in 1820 and 1913, we impute the minimal within group income reported in that year.

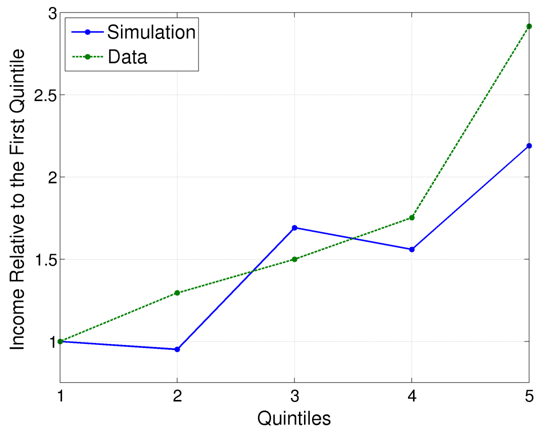
simulate the income growth between 1765 and the year of consideration. Then, we cummulate productivity growth to obtain productivity levels, and scale them by the level of the bottom quintile in each year.

Figure 4 presents the distribution of income generated by the model and the empirical distribution in the data for 1820, 1913 and 2000. Figure 4a shows that for 1820 our simulation underpredicts the relative income at the second, fourth and fifth quintiles relative to the first quintile. This deviation is largest for the top quintile, where our model generates a relative income of 2.2 compared to 2.9 in the data. For the third quintile, we slightly overpredict the relative income, 1.7 compared to 1.5 in the data. For 1913, Figure 4b, the model is on mark for the relative income of the second quintile, slightly overpredicts the relative income of the third (2.5 vs 1.8) and fourth (3.3 vs 2.9) quintiles, and slightly underpredicts income at the top quintile (4.5 vs. 5.7). For 2000, Figure 4c, the model is on mark for the second and third quintiles, and slightly underpredicts the relative income for the fourth (7.7 vs. 9.9) and fifth (26.1 vs. 27.5) quintiles. In sum, we conclude that the evolution of the world income distribution implied by the technology diffusion patterns tracks fairly well the actual evolution of the world income distribution over the last two centuries.

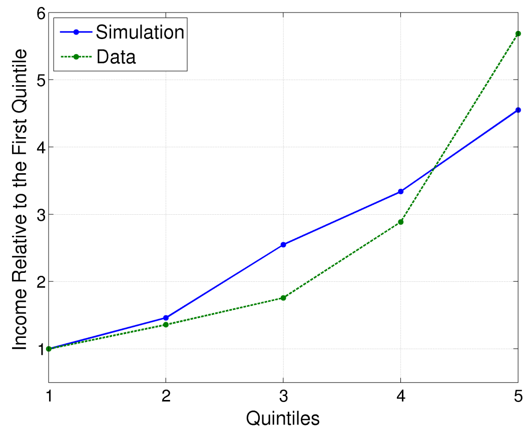
Implications for the Geography of Growth Table 7 reports the results from a similar exercise after grouping countries by continent. For each continent, we estimate the trends in the adoption lags and intensive margin and simulate the evolution of productivity growth since the industrial revolution. This table shows that technology dynamics in each continent have induced income dynamics that resemble those observed in the data over the last two centuries. As in the baseline case, the model tends to slightly underpredict the average growth rates during the nineteenth century. However, the correlation between the actual growth rates across continents between 1820 and 1913 and those predicted by the model is 0.99. For the period 1913-2000, the correlation between actual and predicted income growth is 0.94.

Figure 4: Evolution of the World Income Distribution

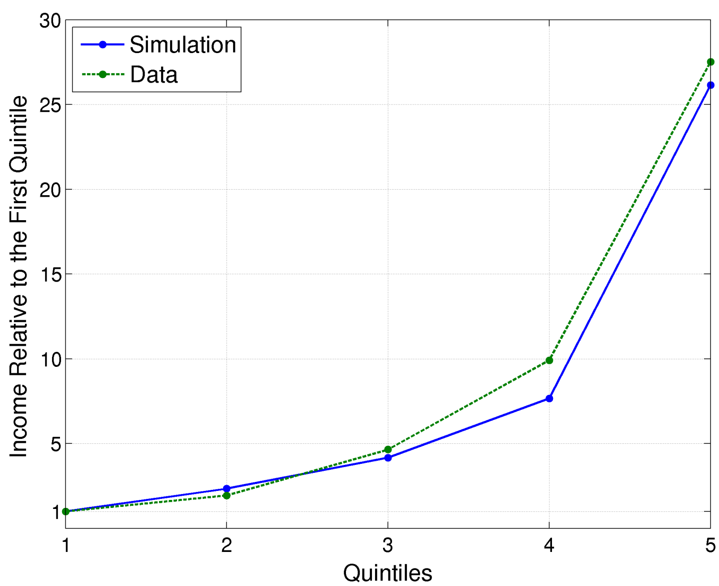
(a) World Income Distribution in 1820



(b) World Income Distribution in 1913



(c) World Income Distribution in 2000



Note: Data refers to the world income distribution computed from Maddison (2004) for the corresponding year. Simulation obtained feeding the diffusion pattern for adoption lags and the intensive margin of the corresponding quintile to the baseline calibration described in Section 5. Quintile groups are computed for each of the three years separately.

Overall, the cross-country evolution of technology adoption patterns can account for a major part of the cross-country evolution of productivity growth over the last two centuries. This conclusion is robust to alternative country groupings based on either initial income levels or on geographical locations.

5.3 Robustness

We conduct three robustness checks to our analysis: *(i)* using the technology dynamics when we allow for non-homotheticities in production, *(ii)* alternative calibrations of γ and χ, and *(iii)* interpreting the divergence of the intensive margin as a structural break instead of a smooth process.

Non-homotheticities in production As shown in Section 4.4, the trends we have identified for the evolution of adoption are robust to the presence of non-homotheticities in the demand for technology. Next, we feed these trends in adoption into our model and quantify their implications for cross-country income growth. We find that the productivity gap between Western and non-Western countries increases by a factor of 2.6 over the period 1800-2000, which represents 67% of the Great Divergence. We conclude, therefore, that both the dynamics of technology diffusion and their implications for the evolution of income growth are robust to allowing for non-homotheticities in demand.

Calibration of γ and χ Our baseline results assumed that the productivity growth after the Industrial Revolution was equally shared between the productivity growth of new technologies (χ) and of new vintages (γ). Given the difficulty of calibrating the contribution of these two sources of growth, we study the robustness of our findings to the relative contributions of new technologies and new varieties to balanced growth. To this end, we redo our baseline simulation under two polar assumptions. Figure C.1a depicts the dynamics of productivity growth when balanced growth comes only from the development of better vintages (i.e., $\chi = 0$), while C.1b shows the polar case, in which all productivity growth comes from the adoption of new technologies (i.e., $\gamma = 0$).

We draw two conclusions from this exercise. First, the main findings of the paper are robust quantitatively and qualitatively to the source of long run growth. In particular, the income gap between Western and non-Western increases by a similar magnitude as in the benchmark (2.9 when growth comes from γ, 3.6 when it comes from χ, and 3.2 in the benchmark). Second, the income gap between Western and non-Western countries is larger when growth comes only from the adoption of new technologies. Intuitively, in this case, for a given technology, all vintages have the same productivity. Hence, the marginal gains from expanding the range of varieties for a given technology are decreasing over time. This implies that the gains from convergence in adoption lags (i.e., vintages of new technologies being adopted at the same rate between Western and non-Western countries) are less important in this case.

Trend vs. structural break in the intensive margin In our estimation, we have assumed that the evolution of the intensive margin follows a linear trend. We analyze an alternative specification in which the the evolution of the intensive margin is modeled as a structural break, rather than as a linear function.[34] Figure C.2 shows that the key features of the cross-country evolution of productivity growth are robust to this modeling choice. The magnitude of the great divergence is relatively similar albeit smaller (increase in the income gap by a factor of 2.4 vs. 3.2), and the predicted timing of the divergence is very similar to what we find in our baseline formulation.

6 Conclusions

What accounts for cross-country variation in income growth over the long term? In this paper we have explored one important factor: differences in the evolution of technology diffusion over the last two centuries. Using a stylized model of adoption that fits well diffusion curves for individual technologies, we have estimated two relevant margins of adoption –adoption lags and the penetration rates– in a panel that covers twenty-five technologies and 130 countries. Analyzing the cross-country evolution of these adoption margins, we have documented two distinct trends over the last two centuries. Adoption lags have converged across countries, while penetration rates have diverged.

To evaluate the significance of the evolution of technology diffusion for productivity growth, we have simulated the aggregate representation of our model economy after feeding in the evolution of technology uncovered in the data. Our simulations have shown that differences in technology diffusion patterns account for a major part of the evolution of the world income distribution over the last two centuries. In particular, differences in the evolution of adoption margins in Western and non-Western countries account for around 80% of the Great Divergence.

Our findings motivate new questions that we plan to pursue in future research. Probably the main one is why has the intensive margin of adoption diverged. Future work shall formulate hypotheses about the nature of the drivers of the intensity of use of technologies and why these drivers have diverged over the last two centuries. We consider that successful explanations of current cross-country differences in productivity will have to properly account for the divergence of the intensive margin of technology. These explorations will complement our analysis towards a fuller understanding of cross-country income dynamics.

[34]The the linear model provides a better statistical fit as measured by the R^2.

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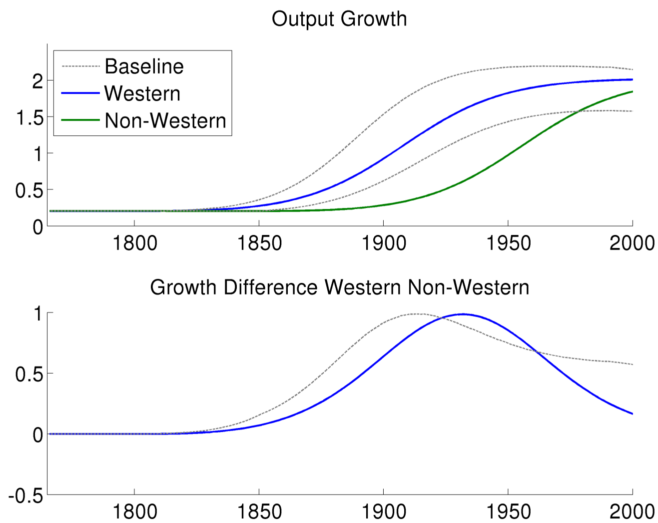
Additional Figures

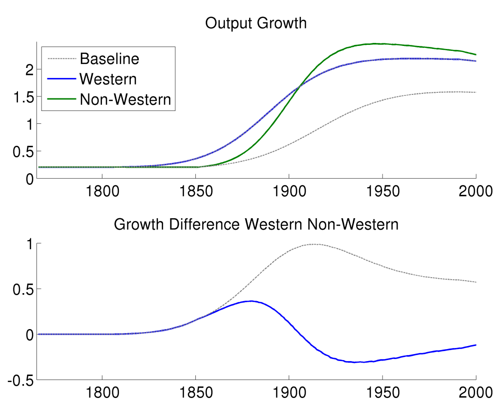
Figure 5: Acceleration of the World Technology Frontier



Growth of Western and non-Western countries with *only* an acceleration of the technology frontier. Both margins of adoption are held constant.

Figure 6: Role played by the different margins of adoption

(a) Dynamics Generated by Adoption Lags



(b) Dynamics Generated by the Intensive Margin