An Exploration of Technology Diffusion

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Abstract

We develop a model that, at the aggregate level, is similar to the one sector neoclassical growth model, while, at the disaggregate level, has implications for the path of observable measures of technology adoption. We estimate our model using data on the diffusion of 15 technologies in 166 countries over the last two centuries. We evaluate the implications of our estimates for aggregate TFP and per capita income. Our results reveal that, on average, countries have adopted technologies 47 years after their invention. There is substantial variation across technologies and countries. Over the past two centuries, newer technologies have been adopted faster than old ones. The cross-country variation in the adoption of technologies accounts for at least a quarter of per capita income differences.

keywords: economic growth, technology adoption, cross-country studies.

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1 Introduction

Most cross-country differences in per capita output are due to differences in total factor productivity (TFP), rather than to differences in the levels of factor inputs.[1] These cross-country TFP disparities can be divided into two parts: those due to differences in the range of technologies used and those due to non-technological factors that affect the efficiency with which all technologies and production factors are operated. In this paper, we explore the importance of the range of technologies used to explain cross-country differences in TFP.

Existing studies of technology adoption are not well suited to answer this question. On the one hand, macroeconomic models of technology adoption (e.g. Parente and Prescott, 1994, and Basu and Weil, 1998) use an abstract concept of technology that is hard to match with data. On the other hand, the applied microeconomic technology diffusion literature (Griliches, 1957, Mansfield, 1961, Gort and Klepper, 1982, among others) involves the estimation of diffusion curves for a relatively small number of technologies and countries. These diffusion curves, however, are purely statistical descriptions which are not embedded in an aggregate model. Hence, it is difficult to use them to explore the aggregate implications of the empirical findings.[2]

In this paper we bridge the gap between these two literatures by developing a new model of technology diffusion. Our model has two main properties. First, at the aggregate level it is similar to the one sector neoclassical growth model. Second, at the disaggregate level it has implications for the path of observable measures of technology adoption. These properties allow us to estimate our model using data on specific technologies and then use it to evaluate the implications of our estimates for aggregate TFP and per capita income.

A technology, in our model, is a group of production methods that is used to produce an intermediate good or service. Each production method is embodied in a differentiated capital good. A potential producer of a capital good decides whether to incur a fixed cost of adopting the new production method. If he does, he will be the monopolist supplying the capital good that embodies the specific production method. This decision determines whether or not a production method is used, which is the extensive margin of adoption.

The size of the adoption costs affects the length of time between the invention and the eventual adoption of a production method, i.e. its adoption lag. Once the production method has been introduced, its productivity determines how many units of the associated capital good are demanded, which reflects the intensive margin

[1] Klenow and Rodríquez-Clare (1997), Hall and Jones (1999), and Jerzmanowski (2004).

[2] Another strand of the literature has also used more aggregate measures of diffusion to explore the determinants of adoption lags (Saxonhouse and Wright, 2000, and Caselli and Coleman, 2001) or the diffusion curve (Manuelli and Seshadri, 2003) for one technology. Our paper differs from these three studies in that (i) we specifically develop an aggregate model to assess the implications of technology adoption differentials for per capita GDP disparities, and (ii) our analysis covers a wide range of technologies and countries.

of adoption. Our model is thus very similar in spirit to the barriers to riches model of Parente and Prescott (1994), which yields endogenous TFP differentials across countries due to different adoption lags.

The endogenous adoption decisions determine the growth rate of productivity embodied in the technology through two channels. First, because new production methods embody a higher level of productivity their adoption raises the average productivity level of the production methods in use. This is what we call the *embodiment effect*. Second, an increase in the range of production methods used also results in a gain from variety that boosts productivity. This is the *variety effect*.

When the number of available production methods is very small, an increase in the number of methods has a relatively large effect on embodied productivity. As this number increases, the productivity gains from such an increase decline. Thus, the variety effect leads to a non-linear trend in the embodied productivity level. Since adoption lags affect the range of production methods used, and thus the variety effect, adoption lags affect the curvature in the path of embodied productivity.

Our model maps this curvature in embodied productivity into similar non-linearities in the evolution of observable measures of technology adoption, such as the number of units of capital that embody a given technology or the output produced with this technology. These measures encompass both the extensive as well as the intensive margin of adoption of these technologies. To identify the adoption lags using these adoption measures, we need to use our model's predictions. In particular, our model determines how the curvature of these measures depends on adoption lags and on economy-wide conditions that determine aggregate demand. By using the structure imposed by our model on these measures of technology diffusion, we can identify the adoption lags for each technology and country.

Our model is broadly consistent with the empirical diffusion literature in that it predicts an S-shape diffusion pattern for conventional adoption measures that only capture the extensive adoption margin. However, the actual diffusion curves implied by the reduced form equations are not S-shaped. This is because our measures incorporate both the extensive and intensive adoption margins. S-shape curves provide a poor approximation to the evolution of technology measures that incorporate the latter.[3]

We use data from Comin, Hobijn, and Rovito (2006) to explore the adoption lags for 15 technologies for 166 countries. Our data cover major technologies related to transportation, telecommunication, IT, health care, steel production, and electricity. We obtain precise and plausible estimates of the adoption lags for two thirds of the 1278 technology-country pairs for which we have sufficient data. There are three main findings that are especially worth taking away from this exploration of technology diffusion.

First, adoption lags are large. The average adoption lag is 47 years. There is, however, substantial variation in these lags, both across countries and across technologies. The standard deviation in adoption lags is 39 years. An analysis of variance yields that 54% of the variance in adoption lags is explained by

[3] See Comin et al. (2008) for a detailed explanation of this argument.

variation across technologies, 18% by cross-country variation, and 11% percent by the covariance between the two. The remaining 17% is unexplained. We also find that newer technologies have been adopted faster than older ones. This acceleration in technology adoption has taken place during the whole two centuries that are covered by our data. Thus, it started long before the digital revolution or the post-war globalization process that have often been cited as the driving forces behind rapid diffusion of technologies in recent decades.

Second, the remarkable development records of Japan in the second half of the Nineteenth Century and the first half of the Twentieth Century and of the, so-called, East Asian Tigers in the second half of the Twentieth Century all coincided with a catch-up in the range of technologies used with respect to industrialized countries. All these development 'miracles' involved a substantial reduction of the technology adoption lags in these countries relative to those in (other) OECD countries.

Third, our model can be used to quantify the aggregate implications of the estimated adoption lags for cross-country per capita income differentials. Doing so yields that cross-country differences in the timing of adoption of new technologies seems to account for at least a quarter of per capita income disparities.

The rest of the paper is organized as follows. Because the focus of our analysis is on technology, we devote the second section of our paper to a detailed explanation of the assumptions we make about the technology structure in our model economy. We then proceed in two directions.

First, in Section 3 we show how our assumptions nest a version of the one-sector neoclassical growth model with adoption lags, we introduce a set of simplifying assumptions about the technology, as well as add preferences, endogenize the technology adoption decision, and show how these assumptions yield the neoclassical growth model.

Second, in Section 4, we discuss how we identify and estimate the adoption lags for the country-technology pairs in our data. In Section 5, we present our estimates, use them for country case-studies, and quantify their implications for cross-country TFP differentials. In Section 6, we conclude by presenting directions for future research. For the sake of brevity, most of the mathematical derivations are relegated to Appendix B.

2 A one sector growth model with endogenous technology adoption

We present our theoretical analysis in the context of a one sector model. When presenting the notion of technology, we make a number of simplifying assumptions for the sake of clarity. We explain how to generalize the model and how the basic results hold in these more general settings. This is important when bringing the model to the data in sections 3 and 4. In what follows, we ommit time subscripts, t, whenever possible.

2.1 Preferences

A measure one of households populate the economy. They inelastically supply one unit of labor every instant, at the real wage rate W, and derive the following utility from their consumption flow

$$U = \int_0^\infty e^{-\rho t} \ln(C_t) dt, \quad (1)$$

where C_t denotes per capita consumption and ρ is the discount rate. The representative household has an initial wealth level of S_0 and cannot run Ponzi schemes. We further assume that capital markets are perfectly competitive and that consumers can borrow and lend at rate r.

The representative consumer's path of consumption is characterized by the following Euler equation

$$\frac{\dot{C}}{C} = r - \rho \quad (2)$$

and lifetime budget constraint:

$$\int_0^\infty (C_s - W_s) e^{-\int_0^s r_{s'} ds'} ds = S_0, \quad (3)$$

where W is the wage rate she earns.

2.2 Technology

In our model economy, final output, Y, is produced competitively by combining a continuum of intermediate goods, Y_v, as follows:

$$Y = \left(\int_{v \in V} Y_{v}^{\frac{1}{\mu}} dv \right)^{\mu}, \text{ with } \mu > 1. \quad (4)$$

Each intermediate good, Y_v, is produced by combining labor and capital, K_v, that embodies a *specific* production method that we call a technology vintage (or vintage) in the following Cobb-Douglas form:

$$Y_v = Z_v L_v^{1-\alpha} K_v^{\alpha}, \quad (5)$$

Productivity growth is embodied in new vintages and is captured by the variable Z_v. The embodied productivity of new vintages grows at a rate γ across vintages. The productivity of a given vintage is constant over time.

$$Z_v = Z_0 e^{\gamma v} \quad (6)$$

Each instant, a new production method appears exogenously. This characterizes the evolution of the world technology frontier. A country does not necessarily use all the capital vintages that are available in the world because, as we discuss below, making them available for production is costly. We denote the set of vintages actually used by $V = (-\infty, t - D]$. Here $D \geq 0$ denotes the *adoption lag*. That is, the amount of time between when the best technology in use in the country became available and when it was adopted.

To economize on notation, all new technology vintages enter symmetrically in the production function (4). In reality, however, there are two different types of innovations. On the one hand, we can think of the introduction of a new version of an old technology (e.g. a new version of the tractor). On the other, the innovation can take the form of a radically new technology (e.g. the first version of the tractor). A priori, it might be important to treat these innovations separately for at least two reasons. First, because the productivity embodied in each of them may be different. Second, because the elasticity of substitution between two intermediate goods, may depend on whether they belong to the same technology.

In Comin and Hobijn (2008), we develop a more general version of the model that allows for these features and that, for all practical purposes, is isomorphic to our model, as we discuss below. However, when bringing the model to the data, it will be important to derive predictions for measures of diffusion at the technology (vs. vintage) level since this is the data available. We close this gap between theory and data by assuming that at pre-specified times, $\underline{v}_\tau$, the vintage that appears is the first vintage associated to a new technology, τ. From that moment on, no more vintages of the old technology appear. The new vintages will be new versions of technology τ, until the next technology arrives at time $\underline{v}_{\tau+1}$.

Under this interpretation, we can rewrite the production function (4) as:

$$Y = \left(Y_{\tau'}^{1/\mu} + Y_{\tau}^{1/\mu}\right)^{\mu}$$

where

$$\begin{aligned} Y_\tau &\equiv \left(\int_{V|v \geq \underline{v}_\tau} Y_v^{1/\mu} dv\right)^{\mu} \\ Y_{\tau'} &\equiv \left(\int_{V|v < \underline{v}_\tau} Y_v^{1/\mu} dv\right)^{\mu} \end{aligned}$$

denote output composite produced with the intermediate goods associated to technology τ, Y_τ, and to all technologies prior to τ, $Y_{\tau'}$.

Capital goods production and technology adoption:

Capital goods are produced by monopolistic competitors. Each of them holds the patent of the capital good used for a particular production method. It takes Q units of final output to produce one unit of capital of any vintage. This production process is assumed to be fully reversible. Q declines at a constant rate q.

By introducing investment-specific technological progress in this way, we allow for a trend in the relative price of capital goods when measured in the particular units used in our data set. For example, when we measure the number of trucks, q_τ reflects the decline in the price per truck relative to the final good price.

The capital goods suppliers rent out their capital goods at the rental rate R_v and capital goods depreciate at rate δ.

2.3 Factor demands

We use the final good as the numeraire good throughout our analysis and, accordingly, normalize its price $P = 1$.

Intermediate goods demand:

The demand for the output produced with vintage v, Y_v, is

$$Y_v = Y\left(P_v\right)^{\frac{-\mu}{\mu-1}}, \text{ where } P = \left(\int_{v\in V} P_v^{-\frac{1}{\mu-1}} dv\right)^{-(\mu-1)}. \tag{7}$$

Labor is homogenous, competitively supplied at the real rate W and perfectly mobile across sectors. Since Y_v is produced competitively, its price equals its marginal cost of production:

$$P_v = \frac{1}{Z_v}\left(\frac{W}{(1-\alpha)}\right)^{1-\alpha}\left(\frac{R_v}{\alpha}\right)^{\alpha}. \tag{8}$$

Capital goods suppliers:

The supplier of each capital good recognizes that the rental price he charges for the capital good, R_v, affects the price of the output associated with the capital good and, therefore, its demand, Y_v. The resulting demand curve faced by the capital good supplier is

$$K_v = YZ_v^{\frac{1}{\mu-1}}\left(\frac{(1-\alpha)}{W}\right)^{\frac{1-\alpha}{\mu-1}}\left(\frac{\alpha}{R_v}\right)^{\epsilon}, \text{ where } \epsilon \equiv 1 + \frac{\alpha}{\mu-1}. \tag{9}$$

Here, ϵ is the constant price elasticity of demand that the capital goods supplier faces. As a result, the profit maximizing rental price equals a constant markup times the marginal production cost of a unit of capital. Because of the durability of capital and the reversibility of its production process, the per-period marginal production cost of capital is Q times the technology-specific user-cost of capital. Thus, the rental price that maximizes the profits accrued by the capital good producer is

$$R_v = R = \frac{\epsilon}{\epsilon-1}Q\left(r+\delta+q\right) = \frac{\epsilon}{\epsilon-1}QUC, \tag{10}$$

where $\frac{\epsilon}{\epsilon-1}$ is the constant gross markup factor.

2.4 Aggregates at the intermediate good level

The lack of data at the capital vintage level makes it impossible to conduct empirical analyses at this level of aggregation. Therefore, we derive the technology-specific aggregates for which data are available.

Technology level output and inputs:

The factor demands for the capital vintage specific output Y_v allow us to express output associated to technology τ in the following Cobb-Douglas form

$$Y_\tau = A_\tau K_\tau^\alpha L_\tau^{1-\alpha}, \tag{11}$$

where

$$K_\tau \equiv \int_{v \in V_\tau} K_{v\tau} dv, \text{ and } L_\tau \equiv \int_{v \in V_\tau} L_{v\tau} dv, \tag{12}$$

and the TFP composite associated with intermediate τ is

$$A_\tau = \left(\int_{v \in V_\tau} Z_{v\tau}^{\frac{1}{\mu-1}} dv \right)^{\mu-1}. \tag{13}$$

Just like for the underlying capital vintage specific outputs, the total wage bill paid to labor used to produce intermediate τ exhausts a constant fraction $(1-\alpha)$ of the revenue generated by the sale of intermediate good τ and the rental costs of capital exhaust the rest. Moreover, the price of the intermediate equals the marginal cost of production

$$P_\tau = \frac{1}{A_\tau} \left(\frac{Y}{L} \right)^{1-\alpha} \left(\frac{R_\tau}{\alpha} \right)^\alpha. \tag{14}$$

By the same tolken, we can derive an expression for aggregate output, Y.

$$Y = A K^\alpha L^{1-\alpha}, \tag{15}$$

where

$$K \equiv \int_{v \in V} K_v dv, \text{ and } L \equiv \int_{v \in V} L_v dv, \tag{16}$$

and TFP is

$$A = \left(\int_{v \in V} Z_v^{\frac{1}{\mu-1}} dv \right)^{\mu-1}. \tag{17}$$

Technology specific TFP and adoption lags:

The endogenous level of TFP in the production of intermediate τ at time t (17) can be expressed as

$$A_\tau = \left(\frac{\mu-1}{\gamma} \right)^{\mu-1} Z_{\underline{v}_\tau} \underbrace{e^{\gamma\left(t - D_{\tau,t} - \underline{v}_\tau\right)}}_{\text{embodiment effect}} \underbrace{\left[1 - e^{-\frac{\gamma_\tau}{\mu-1}\left(t - D_{\tau,t} - \underline{v}_\tau\right)} \right]^{\mu-1}}_{\text{variety effect}} \tag{18}$$

From this equation, it can be seen that our model introduces two mechanisms by which the adoption lags, $D_{\tau,t}$, affect the level of TFP in the production of intermediate τ: (i) the *embodiment effect*; and (ii) the *variety effect*.

First, as newer vintages with higher embodied productivity are adopted in the economy, the level of embodied productivity increases. This mechanism is captured by the 'embodiment effect' term of (18) which reflects the productivity embodied in the best vintage adopted in the economy.

The range of vintages available for production also affects the level of embodied productivity of technology τ. In particular, an increase in the measure of vintages adopted leads to higher productivity through the gains from variety. This is captured by the 'variety effect' term in expression (18).

Capital goods production and technology adoption:

In order to become the sole supplier of a particular capital vintage, the capital good producer must undertake an investment, in the form of an up-front fixed cost. We interpret this investment as the adoption cost of the production method associated with the capital vintage.

The cost of adopting vintage v at instant t is assumed to be

$$\Gamma_{vt} = \overline{V}(1+b)\left(\frac{Z_v}{Z_t}\right)^{\frac{\vartheta}{\mu-1}} P_v Y_v, \text{ where } \vartheta > 0, \text{ and} \tag{19}$$

$$Z_t \equiv Z_{0\tau} e^{\gamma t} \tag{20}$$

denotes the world technology frontier at time t, and $\overline{V}$ is the steady state stock market capitalization to GDP ratio.[4]

We include $\overline{V}$ in the cost function for normalization purposes. The term $(Z_v/Z_t)^{\frac{\vartheta}{\mu-1}}$ captures the idea that it is more costly to adopt technologies the higher is their productivity relative to the productivity of the frontier technology. The parameter b reflects barriers to adoption in the sense of Parente and Prescott (1994). The term $P_v Y_v$ captures the idea that the cost of adoption is increasing in the market size. We choose this functional form because, just like the adoption cost function in Parente and Prescott (1994), it yields the existence of an aggregate balanced growth path. As we shall see below, in this balanced growth path, the adoption lags are constant, and we can separately identify the intensive and extensive margins of adoption. It could of course be the case that the linearity in the adoption cost function is violated for some particular technology for some particular country, without necessarily violating balanced growth, but to the extent that we are documenting adoption lags across many technologies this is perhaps not so critical.

2.5 Optimal adoption

The flow profits that the capital goods producer of vintage v earns are equal to

$$\pi_v = \frac{\alpha}{\epsilon} P_v Y_v = \frac{\alpha}{\epsilon}\left(\frac{Z_v}{A}\right)^{\frac{1}{\theta-1}} Y \tag{21}$$

[4] In particular, $\overline{V} = \frac{\alpha}{\epsilon}\frac{1}{\left\{\rho + \frac{1}{\theta-1}(\chi+\gamma)\right\}}$.

The market value of each capital goods supplier equals the present discounted value of the flow profits. That is,

$$M_{v,t} = \int_t^{\infty} e^{-\int_t^s r_{s'} ds'} \pi_{vs} ds = \left(\frac{Z_v}{Z_t}\right)^{\frac{1}{\theta-1}} \left(\frac{Z_t}{A_t}\right)^{\frac{1}{\theta-1}} V_t Y_t. \tag{22}$$

where

$$V_t = \frac{\alpha}{\epsilon} \int_t^{\infty} e^{-\int_t^s r_{s'} ds'} \left(\frac{A_t}{A_s}\right)^{\frac{1}{\theta-1}} \left(\frac{Y_s}{Y_t}\right) ds \tag{23}$$

is the stockmarket capitalization to GDP ratio.[5]

Optimal adoption implies that, every instant, all the vintages for which the value of the firm that produces the capital good is at least as large as the adoption cost will be adopted. That is, for all vintages, v, that are adopted at time t

$$\Gamma_v \leq M_v \tag{24}$$

This holds with equality for the best vintage adopted if there is a positive adoption lag.[6]

The adoption lag that results from this condition equals

$$D_v = \max\left\{\frac{\theta-1}{\gamma\vartheta}\left\{\ln(1+b) - \ln V + \ln \overline{V}\right\}, 0\right\} = D \tag{25}$$

and is constant across vintages, v. Note also that, since in balance growth $V = \overline{V}$, the adoption lags do not depend, in the steady state. on aggregate TFP or GDP. Further, since the effect of an individual technology τ on aggregate TFP are negligible, D_v is also unaffected by cross-country variation in Z_0 for an specific technology. Intuitively, all of these variables affect the size of the market for the new vintages. Given the specifications of the production function and the cost of adoption, the market size affects symmetrically the benefits and costs of adoption. As a result, variation in market size does not affect the timing of adoption, i.e. the adoption lags. However, as we shall see below, it affects how many units of the specific vintage will be demanded once it has been adopted, i.e. the intensity of adoption.

The resulting aggregate TFP level equals

$$A_t = A_0 e^{\gamma(t-D_t)}, \tag{26}$$

where $A_0 > 0$ is a constant that depends on the model parameters.[7] Hence, aggregate TFP in this model is endogenously determined by the adoption lags induced by the barriers to entry.

Moreover, the total adoption costs across all vintages adopted at instant t equal

$$\Gamma = \overline{V}(1+b)\left(\frac{\gamma}{\theta-1}\right) e^{-\frac{\vartheta}{\theta-1}\gamma D} Y \left(1 - \dot{D}\right), \tag{27}$$

[5] This can be interpreted as the stockmarket capitalization if all monopolistic competitors are publicly traded companies.

[6] If the frontier vintage, t, is adopted, and there is no adoption lag, then $\Gamma_{t\tau} \leq M_{t\tau}$. For simplicity, we ignore the possibility that, for the best vintages, already adopted $\Gamma_{v\tau} > M_{v\tau}$. In that case, no new vintages are adopted. This possibility is included in the mathematical derivations in Appendix B.

[7] In particular $A_0 = Z_0 \left(\frac{\theta-1}{\gamma}\right)^{\theta-1} \left(\left(\frac{\theta-1}{\chi}\right) - \left(\frac{\theta-1}{\chi+\gamma}\right)\right)^{\theta-1}$.

where $\overset{\bullet}{D}$ denotes the time derivative of the adoption lags.

2.6 Equilibrium

The equilibrium path of the aggregate resource allocation in this economy can be defined in terms of the following eight equilibrium variables $\{C, K, I, \Gamma, Y, A, D, V\}$. Just like in the standard neoclassical growth model, the capital stock, K, is the only state variable. The eight equations that determine the equilibrium dynamics of this economy are given by

(i) The consumption Euler equation, (2).

(ii) The aggregate resource constraint[8]

$$Y = C + I + \Gamma. \tag{28}$$

(iii) The capital accumulation equation

$$\dot{K} = -\delta K + I. \tag{29}$$

(iv) The production function, (15), taking into account that in equilibrium $L = 1$.

(v) The adoption cost function, (27).

(vi) The technology adoption equation, (25), that determines the adoption lag.

(vii) The stockmarket to GDP ratio, (23).[9]

(viii) The aggregate TFP level, (26).

In addition to these equations that pin down the equilibrium dynamics, the lifetime budget constraint, (3), pins down the initial level of consumption. We derive the balanced growth path and approximate transitional dynamics of this economy in Appendix B. The growth rate of this economy on the balanced growth path is $\gamma/(1-\alpha)$.

Below the surface:

Underlying these aggregate dynamics, there is a continuum of diffusion curves for the expanding set of vintages and technologies. Where aggregate TFP grows at the constant rate $\chi + \gamma$, the technology-specific TFP level is given by

$$Z_{\tau t} = \left(\frac{\theta - 1}{\gamma}\right)^{\theta - 1} Z_0 e^{\gamma\tau} e^{\gamma(t - D_t - \tau)} \left[1 - e^{-\frac{\gamma}{\theta - 1}(t - D_t - \tau)}\right]^{\theta - 1}. \tag{30}$$

Just like (18), (30) has a variety effect which introduces a non-linearity in Z_τ. This non-linearity is critical for our empirical application.

[8] We assume that adoption costs are measured as part of final demand, such that Y can be interpret as GDP.

[9] The dynamics of V_t are what are considered in the system of equilibrium equations. The law of motion of the stockmarket to GDP ratio is given by $\frac{\dot{V}}{V} = \left\{\alpha \frac{\epsilon-1}{\epsilon} \frac{Y}{K} - \delta + \frac{1}{\theta-1} \frac{\dot{A}}{A} - \frac{\dot{Y}}{Y}\right\} - \frac{\alpha}{\epsilon} \frac{1}{V}$.

As we show below, the evolution of technology-specific TFP governs the speed of diffusion as well as the shape of the diffusion curve of a technology. The variety effect thus drives the non-linearity in the diffusion curve. Since the measure of varieties adopted depends on the diffusion lag, the curvature of the diffusion curve allows us to identify the adoption lags in the data.

GENERALIZATION

continuous

higher elasticity of substitution between vintages within a technology that across technologies.

$\gamma + \chi$

3 Empirical application

The simplifying assumptions that we made for the one-sector growth model are useful because they yield a tractable aggregate production function representation. They do, however, ignore cross-technology variation that might be important in the data. For our empirical investigation, we reintroduce the cross-technology variation by allowing δ_τ, γ_τ, q_τ to be different across technologies. Our aim is to estimate the adoption lags for different technology-country pairs. To make this estimation practically feasible, we assume that the economy is in steady state. This implies that the adoption lags may differ across countries and technologies but are constant over time. In this section, we describe our measures of technology diffusion, derive their reduced form equations and describe the method we use to estimate these equations. Before doing so, however, we relate our measures of diffusion to more traditional measures introduced by Griliches (1957) and Mansfield (1961).

3.1 Measures of diffusion

The empirical literature on technology diffusion has mainly focused on the analysis of the share of potential adopters that have adopted a technology. Such shares capture the extensive margin of adoption. Computing these measures requires micro level data that are not available for many technologies and countries. As a result, over the last 50 years, the diffusion of only relatively few technologies in a very limited number of countries has been documented.[10]

Our model allows us to explore its predictions for alternative measures of technology diffusion for which data is more widely available. In particular, we focus on (i) Y_τ, the level of output of the intermediate good produced with technology τ; (ii) K_τ, the capital inputs used in the production of this output.

[10] The most remarkable finding of the traditional diffusion literature is that, for a majority of the technologies for which it has been possible to construct the diffusion measures, the diffusion curves are S-shaped. As explained in more detailed in Comin and Hobijn (2008), our model is roughly consistent with this finding.

These variables have two advantages over the traditional measures. First, they are available for a broad set of technologies and countries. Second, they capture (directly or indirectly) the number of units of the new technology that each of the adopters has adopted. This intensive margin is important to understand cross-country differences in adoption patterns. For spindles, for example, Clark (1987) argues that this margin is key to explaining the difference in adoption and labor productivity between India and Massachusetts in the Nineteenth century.

In order to see how our measures relate to the traditional diffusion measures consider the following decomposition of K_τ and Y_τ

$$K_\tau = \left(\frac{L_\tau}{L}\right)\left(\frac{K_\tau/L_\tau}{K/L}\right)\left(\frac{K}{Y}\right)Y \tag{31}$$

$$Y_\tau = \left(\frac{L_\tau}{L}\right)\left(\frac{Y_\tau/L_\tau}{Y/L}\right)Y \tag{32}$$

The first component of these expressions measures the share of the labor inputs devoted to technology τ. This captures the extensive margin of adoption, and is similar to the measures most commonly used in empirical microeconomic studies. The second component measures the intensive margin of adoption of the technology τ relative to the economy. In expression (31) this corresponds to the technology-specific capital-labor ratio relative to the economy wide ratio. In expression (32) it is measured by the labor productivity in the production of intermediate τ relative to aggregate labor productivity. This term reflects what Clark (1987) perceived was the difference between Massachusetts and India. Namely, distortions in the adoption of new technologies that caused an inefficiently low intensity of adoption.[11] The third component of (31) is the capital output ratio and reflects the fact that more capital intensive economies tend to have more capital embodying all the technologies, including the new ones. Finally, the last component in both expressions reflects the size of the economy.

These different components are not separately distinguishable in the data. To make further progress in our exploration of technology diffusion, we use our model to derive estimable reduced form equations for K_τ and Y_τ. These reduced form equations relate the paths of the first two components of (31) and (32) to the adoption lags, D_τ. This allows us to relate the technology adoption measures to observable variables and to estimate the adoption lags.

[11] Interestingly , it can easily be shown, that including these distortions in our model is isomorphic to increasing the cost of adopting the new technology. Hence, our estimates of the adoption lags will include the effects of such distortions.

3.2 Reduced form equations

We denote the technology measures for which we derive reduced form equations by $m_\tau \in \{y_\tau, k_\tau\}$. Small letters denote logarithms. By combining the log-linearized versions of the demand equation (**??**)

$$y_\tau = y - \frac{\theta}{\theta - 1} p_\tau, \tag{33}$$

and the intermediate goods price (**??**)

$$p_\tau = -\alpha \ln \alpha - z_\tau + (1-\alpha)(y - l) + \alpha r_\tau, \tag{34}$$

we obtain the reduced form equation (35) for y_τ.[12]

$$y_\tau = y + \frac{\theta}{\theta - 1}\left[z_\tau - (1-\alpha)(y-l) - \alpha r_\tau + \alpha \ln \alpha\right] \tag{35}$$

Similarly, we obtain the reduced form equation for k_τ by combining the log-linear capital demand equation

$$k_\tau = \ln \alpha + p_\tau + y_\tau - r_\tau. \tag{36}$$

with (33) and (34). These expressions depend on the adoption lag D_τ, through the effect the lag has on z_τ.

They also contain the technology-specific capital rental rate, r_τ, for which we do not have data. As mentioned above, the constant adoption lags for each country and technology over time that we estimate implicitly mean that we assume that the economies are close to steady state. This would mean that r_τ is approximately constant over time. Consistent with this, we present our estimates for the case of a constant rental rate, where r_τ is part of the constant term that we estimate.[13]

At this point we could estimate the reduced form equations. However, to a first order approximation γ_τ only affects y_τ and k_τ through the linear trend. More specifically, in Appendix B, we log-linearize (18) around $\gamma_\tau = 0$ to obtain the approximation

$$z_\tau \approx z_{\underline{v}_\tau} + (\mu - 1)\ln(t - T_\tau) - \frac{\gamma_\tau}{2}(t - T_\tau), \tag{37}$$

where $T_\tau = \underline{v}_\tau + D_\tau$ is the time that the technology is adopted.

In this approximation, the growth rate of embodied technological change, γ_τ, only affects the linear trend in z_τ. Intuitively, when there are very few vintages in V_τ the growth rate of the number of vintages, i.e. the

[12] Using the fact that the final output is the numeraire, we can rewrite (35) as

$$y_\tau = y + \frac{\theta}{\theta - 1}((z_\tau - z) + \alpha(r - r_\tau))$$

Intuitively, y_τ depends on aggregate demand and on the technology-specific level of TFP relative to the overall level of TFP and on the relative rental for technology τ capital relative to the aggregate rental rate.

[13] The results are not very sensitive to this assumption. Estimates based on a version of the model that includes a log-linearization of the real interest rate, which results in the addition of the growth rate of per capita income as an explanatory variable to capture the transitional dynamics, yield adoption lags that are almost identical to the ones that we present here.

growth rate of $t - T_\tau$, is very large and it is this growth rate that drives growth in z_τ through the variety effect. Only in the long-run, when the growth rate of the number of varieties tapers off, the growth rate of embodied productivity, γ_τ, becomes the predominant driving force of the variety effect.

This result implies that, in first-order, both γ_τ and q_τ cause a linear trend in our technology measures. Thus, γ_τ, is only separately identified from q_τ through second-order effects, which are small for γ_τ close to zero. Therefore, we present the estimates obtained using the log-linear approximation of z_τ in the estimation, (37), and do not provide estimates of γ_τ.[14]

Then, as we derive in Appendix B, the reduced form equation that we estimate is the same for both capital and output measures and is of the form

$$m_\tau = \beta_1 + y + \beta_2 t + \beta_3 \left((\mu - 1) \ln (t - T_\tau) - (1 - \alpha)(y - l) \right) + \varepsilon_\tau, \tag{38}$$

where ε_τ is the error term. The reduced form parameters are given by the β's. We do not estimate μ and α. Instead, we calibrate $\mu = 1.3$, based on the estimates of the markup in manufacturing from Basu and Fernald (1997), and $\alpha = 0.3$ consistent with the post-war U.S. labor share.[15]

3.3 Identification of adoption lags and estimation procedure

We use the reduced form equations to estimate country-technology-specific adoption lags. For this purpose, we make the following three assumptions: (*i*) Levels of aggregate TFP, relative investment prices, and units of measurement of the technology measures potentially differ across countries; (*ii*) technology-specific growth rates of investment specific technological change, q_τ, embodied technological change, γ_τ, as well as the growth rate of aggregate TFP, are the same across countries; (*iii*) technology parameters are the same except for the adoption lags.

In order to see how these assumptions translate into cross-country parameter restrictions, we consider which structural parameters affect each of the reduced form parameters. The fixed effect, β_1, captures four things (*i*) the units of the technology measure; (*ii*) the level of the relative price of investment goods, Q_τ; (*iii*) different TFP levels across countries, and (*iv*) differences in adoption lags. Because we assume that these things can vary across countries, we let β_1 vary across countries as well. The trend-parameter, β_2, is assumed to be constant across countries because it only depends on the output elasticity of capital, α,[16] and

[14] We have also estimated the reduced form equations using the actual expression for z_τ, (18). Because γ_τ is locally non-identified at zero, this yields imprecise estimates of γ_τ. However, it results in virtually identical estimates of the adoption lags.

[15] Our estimates of the adoption lags are also robust to alternative calibration of μ to a wide range of values both higher and lower than 1.3.

[16] The output elasticity of capital is one minus the labor share in our model. Gollin (2002) provides evidence that the labor share is approximately constant across countries.

on the trends in embodied and investment specific technological change, q_τ and γ_τ. β_3 only depends on the technology parameter, θ, and is therefore also assumed to be constant across countries.

Given these cross-country parameter restrictions, the adoption lags, D_τ, are identified in the data through the non-linear trend component in equation (38), which is due to the variety effect. This is the only term affected by the adoption lag, D_τ. It is also the only term which affects the curvature of m_τ after controlling for the effect of observables such as income and per capita income. Specifically, it causes the trend in m_τ to monotonically decline with the time since adoption. This is the basis of our empirical identification strategy of D_τ. Intuitively, our model predicts that, everything else equal, if at a given moment in time we observe that the trend in m_τ is diminishing faster in one country than another, it must be because the former country has started adopting the technology more recently.

Note that, with this identification scheme, we are not using the level of adoption to identify the adoption lags. The intensive margin of adoption can be measured by the country-technology fixed effect β_1 in (38). This term is determined, among other things, by the productivity of the technology, $Z_{0\tau}$, aggregate TFP and the relative price of capital, $Q_{0\tau}$. Note that, in our model, these factors do not affect the timing of adoption, i.e. the extensive margin, but affect the intensity of adoption. In Appendix B we conduct some comparative statics exercises to illustrate this point with an example.

Because the adoption lag is a parameter that enters non-linearly in (38) for each country, estimating the system of equations for all countries together is practically not feasible. Instead, we take a two-step approach. We first estimate equation (38) using only data for the U.S. This provides us with estimates of the values of β_1 and D_τ for the U.S. as well as estimates of β_2 and β_3 that should hold for all countries. In the second step, we separately estimate β_1 and D_τ, using (38) and conditional on the estimates of β_2 and β_3 based on the U.S. data, for all the countries in the sample besides the U.S.

Besides practicalities, this two-step estimation method is preferable to a system estimation method for two other reasons. First, if we would apply a system estimation method, data problems for one country would affect the estimates for all countries. Since we judge the U.S. data to be most reliable, we use them for the inference on the parameters that are constant across countries. Second, our model is based on a set of stark neoclassical assumptions. These assumptions are more applicable to the low frictional U.S. economic environment than to that of countries in which capital and product markets are substantially distorted. Thus, we think that our reduced form equation is likely to be misspecified for some countries other than the U.S. Including them in the estimation of the joint parameters would affect the results for all countries.

We estimate all the equations using non-linear least squares.[17] This means that the identifying assumption that we make is that the logarithm of per capita GDP is uncorrelated with the technology-specific error, ε_τ.

[17] In Appendix B we conduct a simple Monte Carlo exercise that indicates that the estimates obtained by our estimation procedure are quite precise.

This identifying assumption essentially means that the causation goes from aggregate economic activity to the adoption of a particular technology and not the other way around. This is probably not an unreasonable assumption, since we focus on data for 15 out of the many technologies that drive aggregate economic fluctuations.[18]

Because we derive the reduced form equations from a structural model, the theory pins down the set of explanatory variables. However, even if one takes the theory as given, there are, of course, several potential sources of bias in our estimates. The most important is our assumption that D_τ is constant over time. Because D_τ is identified through the curvature in the data, variations in D_τ over time would be identified by changes in this curvature. There is simply too little variation in the data for this identification scheme. If there is time variation in D_τ then our estimates would be skewed towards the adoption lag at the time of adoption. This is because the variation in the curvature of the non-linear trend is larger right after adoption than later on.

4 Results

We consider data for 166 countries and 15 technologies, that span the period from 1820 through 2003. The technologies can be classified into 6 categories; (*i*) transportation technologies, consisting of steam- and motorships, passenger and freight railways, cars, trucks, and passenger and freight aviation; (*ii*) telecommunication, consisting of telegraphs, telephones, and cellphones; (*iii*) IT, consisting of PCs and internet users; (*iv*) medical, being MRI scanners; (*v*) steel, namely tonnage produced using blast oxygen furnaces; (*vi*) electricity.

The technology measures are taken from the CHAT dataset, introduced by Comin and Hobijn (2004) and expanded by Comin, Hobijn, and Rovito (2006). Real GDP and population data are from Maddison (2007). Appendix A contains a brief description of each of the 15 technology variables used.

Unfortunately, we do not have data for all 2490 country-technology combinations. For our estimation, we only consider country-technology combinations for which we have more than 10 annual observations. There are 1278 such pairs in our data. The third column of Table 1 lists, for each technology, the number of countries for which we have enough data.

For each of the 15 technologies, we perform the two-step estimation procedure outlined above. We divide the resulting estimates up into three main groups: (*i*) plausible and precise, (*ii*) plausible but imprecise, and (*iii*) implausible.

We consider an estimate *implausible* if our point estimate implies that the technology was adopted more

[18] A piece of evidence that supports this assumption is that, while our individual measures of technology are highly non-linear, aggregate measures such as log TFP or log per capita GDP are almost linear.

than 10 years before it was invented. The 10 year cut off point is to allow for inference error. The sixth column of Table 1 lists the number of implausible estimates for each of the technologies. In total, we find implausible estimates in a bit less than one-third, i.e. 394 out of 1278, of our cases.

We have identified three main reasons why we obtain implausible estimates. First, as mentioned above, the adoption year T_τ is identified by the curvature in the time-profile of the adoption measure. However, for some countries the data is too noisy to capture this curvature. In that case, the estimation procedure tends to fit the flatter part of the curve through the sample and infers that the adoption date is far in the past. Second, for some countries the data exhibit a convex technology adoption path rather than the concave one implied by our structural model. This happens in some African countries that have undergone dramatic events such as decolonization or civil wars. Third, for some countries we only have data long after the technology is adopted. In that case $\ln(t - T_\tau)$ exhibits little variation and T_τ is not very well-identified in the data. This can either lead to an implausible estimate of T_τ or a plausible estimate with a high standard error.

Plausible estimates with high standard errors are considered *plausible but imprecise*.[19] The number of plausible but imprecise estimates can be found in the fifth column of Table 1. These are 51 out of the 1278 cases that we consider.

The cases that are neither deemed implausible nor imprecise are considered *plausible and precise*. The fourth column of Table 1 reports the number of such cases for each technology. These represent 65 percent of all the technology-country pairs. Hence, our model, with the imposed U.S. parameters, yields plausible and precise estimates for the adoption lags for two-thirds of the technology-country pairs. In what follows, all our results are based on the sample of 836 plausible and precise estimates.[20]

Included in these plausible and precise estimates are 15 estimates of adoption lags for the U.S. Because we impose restrictions based on U.S. parameter estimates across countries, we plot the fit of our model for the 15 technologies for the U.S. in Figures 1 and 2. As can be seen from these figures, the model captures the curvature in m_τ, which identifies the adoption lags, for all of these technologies well.

Before we summarize the results for these 836 estimates, it is useful to start with an example. Figure 3 shows the actual and fitted paths of m_τ for tonnage of steam and motor merchant ships for Argentina, Japan, Nigeria, and the U.S. The estimated adoption years, T_τ, of steam and motorships for these countries are 1868, 1901, 1959, and 1813, respectively. This means that, on average over the sample period, the pattern of U.S. steam and motor merchant ship adoption is consistent with a 1813 adoption date, according to our model. Given that the first steam boat patent in the U.S. was issued in 1788, we thus estimate that the U.S.

[19] In particular, the cut off that we use is that the standard error of the estimate of T_τ is bigger than $\sqrt{2003 - \underline{v}_\tau}$. This allows for longer confidence intervals for older technologies with potentially more imprecise data.

[20] Results that also include the imprecise estimates are both qualitatively and quantitatively very similar to the ones presented here.

adopted the innovations that enabled more efficient motorized merchant shipping services with an average lag of 25 years.

Given the estimates of β_2 and β_3 based on the U.S. data, the adoption years are identified through the curvature of the path of m_τ. The U.S. path is already quite flat in the early part of the sample. This indicates an early adoption, i.e. a low T_τ, and a short adoption lag. When we compare the U.S. and Argentina, we see that, in most years the path is more steep for Argentina than for the U.S. This is why we find a later adoption date and bigger adoption lag for Argentina than for the U.S. Since Japan's path is even steeper than that of Argentina, the lag for Japan is even larger. A similar analysis reveals why we find the 1959 adoption date for Nigeria.

Comparing the data for Argentina and Japan also reveals another part of our identification strategy. Our focus is on the set of vintages in use and not on how many units of each vintage are in use. In our theoretical framework, the latter, i.e. the intensive margin, is determined by the country-wide level of TFP and capital deepening, not by the adoption cost. A country that uses more units of each vintage will have a higher level of m_τ, which is the case for Japan relative to Argentina in Figure 3.

The R^2's associated with the estimated equations for tonnage of steam and motor merchant ships for Argentina, Japan, Nigeria, and the U.S. are 0.96, 0.14, 0.85, and 0.95, respectively. The R^2 for Japan is very low because our model does not fit the, almost complete, destruction of the Japanese merchant fleet during WWII. The other R^2s are not only high because the model captures the trend in the adoption patters but also because the model captures the curvature.

The last three columns of Table 1 summarize the properties of the R^2's for the 836 plausible and precise estimates. Since we are imposing the US estimates for β_2 and β_3, the R^2 can be negative. The second to last column of Table 1 lists the number of cases for which we find a positive R^2 for each technology.

In total, we find negative R^2's for only 6.8 percent of the cases. Passenger railways and telegraphs are the two where negative R^2's are more prevalent. This means that for those technologies the assumption that the U.S. estimates for β_2 and β_3 apply for all countries seems unrealistic. These are both technologies that have seen a decline in the latter part of the sample for the U.S. Such declines lead to estimates of the trend parameter, β_2, for the U.S. that do not fit the data for countries where these technologies have not seen such a decline (yet). Though present, such issues do not seem to be predominant in our results.

The next to last and last columns of Table 1 list the sample mean and standard deviations of the distributions of positive R^2's for each technology. Overall, the average R^2, conditional on being positive, is 0.81 and the standard deviation of these R^2's is 0.19. Hence, even though we impose U.S. estimates for β_2 and β_3 across all countries, the simple reduced form equation, (38), derived from our model captures the majority of the variation in m_τ over time for the bulk of the country-technology combinations in our sample.

We turn next to the estimates of the adoption lags. The main summary statistics regarding these estimates are reported in Table 2. The average adoption lag in our sample is 47 years with a median lag of 35. This means that the average adoption path of countries in our sample over all technologies is similar to that of a country that adopts the technology 47 years after its invention.

However, there is considerable variation both across technologies and countries. For steam- and motorships as well as railroads we find that it took about a century before they were adopted in half of the countries in our sample. This is in stark contrast with PCs and the internet, for which it took less than 15 years for half of the countries in our sample to adopt them.

Though we do not impose it, we find that the percentiles of the estimated adoption lags are similar for closely related technologies; passenger and freight rail transportation, cars and trucks, passenger and cargo aviation, and even for the upper percentiles of telegraphs and telephones.

Table 3 decomposes the variations in adoption lags into parts attributable to country effects and parts due to technology effects. Let i be the country index and let $D_{i\tau}$ be the adoption lag estimated for country i and technology τ. Table 3 contains the variance decomposition based on three regressions nested in the following specification

$$D_{i\tau} = D_i^* + D_\tau^* + u_{i\tau} \tag{39}$$

where D_i^* is a country fixed effect, D_τ^* is a technology fixed effect, and $u_{i\tau}$ is the residual. The first line of the table pertains to (39) with only country fixed effects. Country-specific effects explain about 30% of the variation in the estimated adoption lags. Technology-specific effects explain about twice as much, namely 66% of the variation. This can be seen from the second row of Table 3, which is computed from a version of regression (39) with only technology fixed effects. The last row of Table 3 shows that country and technology fixed effects jointly explain about 83% of the variation in the estimated adoption lags. Of this, 18% can be directly attributed to country effects, 54% can be directly attributed to technology effects, and the remaining 11% is due to the covariance between these effects that is the result of the unbalanced nature of the panel structure of our data.

Understanding the determinants of adoption lags is beyond the goals of this paper. However, we do consider whether adoption lags tend to have gotten smaller over time. To this end, Figure 4 plots the invention date of each technology, $\underline{v}_\tau$, against the average adoption lag by technology as well as against the technology fixed effects, D_τ^*, obtained from (39). The message from both variables is the same. Newer technologies have diffused much faster than older technologies. In particular, technologies invented ten years later are on average adopted 4.3 years faster.

This finding is remarkably robust. As is clear from Figure 4, the average adoption lags of all 15 technologies covered in our dataset seem to adhere to this pattern. Moreover, the slope before and after 1950 is almost the same. Hence, the acceleration of the adoption of technologies seems to have started long before the digital revolution or the post-war globalization process.

Of course, this trend cannot go on forever. However, it has gone on at this pace for 200 years. If it persists, it will have major consequences for the cross-country differences in TFP due to the lag in technology adoption. In particular, the TFP gap between rich and poor countries due to the lag in technology adoption should be significantly reduced.

4.1 Case studies

Thus far, we have focused on computing a set of broad summary statistics that describe the properties of the estimated adoption lags. In addition to these broad patterns, these estimates also shed some light on a number of debates that focus on particular (groups of) countries and episodes. To see how, consider Table 4. For each technology, it contains the average adoption lag for different (groups of) countries in deviation from the average adoption lag for the technology.

4.1.1 U.S. and the U.K.

The U.S. and the U.K. have been the technological leaders over the last two centuries. Most of the major technologies invented over the last two centuries have been invented either in the U.S. or in the U.K. Table 4 shows that they also have adopted new technologies much faster than the rest of the world. The shorter adoption lags have surely contributed to their high levels of productivity and per capita income.

4.1.2 Japan

Until the Meiji restoration in 1867, Japan had an important technological gap with the western world. This is reflected in the Japanese adoption lag in steam and motor ships which is much longer than that in other OECD countries and is comparable to the lags in Latin America. Technological backwardness, surely, was a significant determinant of the development gap between Japan and other (now) industrialized countries; in 1870, Japan's real GDP per capita was 42 percent of the OECD average.

The industrialization process that was catalyzed by the Meiji restoration closed Japan's technological gap with the western world. This is reflected by Japan's adoption lags for the technologies invented in the 19th century, which are comparable to the lags in other OECD countries. The closing of the technology gap also diminished the development gap. By 1920, per capita GDP in Japan was 56 percent of the OECD average. For those technologies invented in the Twentieth Century, Japan's adoption lag was significantly shorter than for the OECD average and it was comparable to the U.S. and also comparable to, if not shorter than, the U.K.'s. For blast oxygen steel, for example, the adoption lag that we estimate for Japan is 5 years shorter than for other OECD countries. By 1980 Japan's per capita income was about the same as the U.K., 26 percent higher than the OECD average, and 33 percent lower than the U.S.

The estimated adoption lags for Japan thus seem to suggest that a large part of Japan's phenomenal rise in living standards between 1870 and 1980 involved closing the gap between the range technologies Japan used and those used by the world's industrialized leaders.

4.1.3 East Asian Tigers

Japan's phenomenal rise was outdone in the second half of the 20th century by the East Asian Tigers (EATs); Hong Kong, Korea, Taiwan and Singapore. These four countries experienced 'miraculous' growth in per capita GDP between 1960 and 1995 of around 6 percent per year.

There is disagreement about the sources of this growth. Young (1995) claims that factor accumulation is the main source of growth in the EATs, while Hsieh (2002) challenges this view and argues that the TFP growth experienced by the EATs is underestimated by Young (1995).[21]

Whether or not adoption lags show up as TFP or factor accumulation differentials depends on the extent to which capital stock data are quality adjusted. However, what we can say, based on our estimates, is that, just like for Japan, the growth spurt of the EATs has been associated with a substantial reduction in their technology adoption lags.

From Table 4, it is clear that the EATs had long adoption lags for early technologies. In particular, for technologies invented before 1950, the EATs' adoption lags were often longer than in Sub-Saharan Africa (SSA), and almost always longer than in Latin America. For newer technologies, however, the EAT's adoption lags are shorter than in Latin America and Sub-Saharan Africa. In fact, EATs adopted technologies invented since 1950 about as fast as OECD countries.

Young (1992) focuses on the sources of growth in Singapore and Hong Kong and argues that the lower TFP growth rate observed in Singapore reflects its faster rate of structural transformation towards the production of electronics and services, which did not allow agents to learn how to efficiently use older technologies. Some of the post-1950 technologies in our data set such as computers, cellphones, and the internet are surely significant for the production of both electronics and services. Hence, an implication of the Young hypothesis would be that the Singaporean adoption lags in these technologies are shorter than in Hong Kong. As can be seen from Table 5, this is not what we find. Singapore and Hong Kong are estimated to have the same adoption lags in PCs and the internet, 14 and 7 years respectively. Hong Kong is estimated to have adopted cellphones three years earlier than Singapore.

[21] More specifically, According to Hsieh, TFP growth was 2.2% in Singapore (vs. -0.7 for Young), 3.7% in Taiwan (vs. 2.1% for Young), 1.5% in Korea (vs. 1.7% for Young) and 2.3% in Hong Kong (vs. 2.7% for Young).

4.1.4 Latin America

Where the EATs are considered growth 'miracles', Latin American countries are often labeled as growth 'failures'. Some of them, such as Chile and Argentina, were among the richest countries in the world during the late 1800s and the first half of the Twentieth Century (De Long, 1988). This designation is reflected in the fact that for the pre-1950 technologies Latin American countries adopted new technologies faster than the average country. Since World War II, however, they have failed to maintain their position in the development rankings and have been leapfrogged by numerous emerging economies, mostly in Asia. As can be seen from Table 4, this disappointing growth performance since 1950 coincides with longer lags in the adoption of new technologies in Latin American countries than in the average country.

4.1.5 Sub-Saharan Africa

Most Sub-Saharan countries have failed to grow at above average rates despite their low initial per capita income. This performance is consistent with the long lags in technology adoption reported in Table 4. For example, the adoption lags for passenger and freight aviation were, respectively, 22 and 33 years longer than for the average country. The extra lag was 24 years for steam and motor ships, 30 years for the telegraph, and 10 years for the telephone. The most recent technologies have also been adopted more slowly in Sub-Saharan countries than in the rest of the world. However, due to the overall decline in adoption lags, the difference between the lags of Sub-Saharan African countries and the average adoption lags for these technologies are much shorter, i.e. between 1 and 2 years.

4.2 Development accounting

The brief case studies presented above suggest that variation in adoption lags may be associated with both cross-country and time series variation in per capita income. Next, we explore whether the anecdotes described above can be generalized. Specifically, we ask the following question: Are the adoption lags that we estimated a significant potential source of cross-country per capita income differences?

To answer this question, we have to approximate the aggregate effect of the estimated adoption lags for the 15 technologies on per capita GDP levels. We do so by using the equilibrium results of our one-sector growth model. If the only source of cross-country differentials in per capita GDP is adoption lags, then, in steady state, the log difference of country i's level of real GDP per capita with that of the U.S. is given by

$$(y_i - l) - (y_{USA} - l) = \frac{\chi + \gamma}{1 - \alpha} \left(D_{US} - D_i \right), \tag{40}$$

where $(\chi + \gamma)$ is the growth rate of aggregate TFP, which is 1.4% for the U.S. private business sector during the postwar period. We observe the left hand side of (40) in our data and approximate the right hand side in the following way. We use $\chi + \gamma = 0.014$ and $\alpha = 0.3$, consistent with postwar U.S. data. Moreover, we use the country fixed effects from (39) to approximate $D_i \approx D_i^*$. Hence, we assume that the country-specific adoption lags we have estimated for each country using our sample of technologies are representative of the average adoption lags across all the technologies used in production.

Figure 5 plots the data for both sides of (40) for 123 countries in our dataset. The correlation between both sides is 0.51. The solid line is the regression line while the dashed line is the 45°-line. The slope of the regression line is about 0.25, which can be interpreted as that our model and estimates explain about one fourth of the log per capita GDP differentials observed in the data.

The model seems to explain a much larger part of per-capita income differentials for high-income industrialized countries that make up the set of observations in the upper-right corner of the figure.[22] This may result from a downward bias in our estimates of D_i^* for the poor countries in our sample. Specifically, due to lack of data and/or plausible estimates for older technologies in poor countries, these technologies, which tend to be adopted more slowly, do not affect the estimate of D_i^* for poor countries. This may result in a downward bias of the average adoption lag for poor countries and in a lower cross-country dispersion in adoption lags and in TFP differentials due to differences in adoption.

In conclusion, our empirical exploration shows that adoption lags account for a substantial share of cross-country per capita income differences. The share they account for seems to be at least 25%, if not more.

5 Conclusion

In this paper we have built and estimated a model of technology diffusion and growth that has two main characteristics. First, at the aggregate level, it is similar to the one sector neoclassical growth model and has a well-defined balanced growth path. Second, at the disaggregate level, it has implications for the path of observable measures of technology adoption, such as the number of units of capital that embody a given technology or the output produced with this technology.

The main focus of our analysis is on adoption lags. These lags are defined as the length of time between the invention and adoption of a technology. Our model provides a theoretical framework that links the adoption lag of a technology to the level of productivity embodied in the capital associated with it. It also relates the path of the observable technology adoption measures over time to the path of embodied productivity and to economy-wide factors driving aggregate demand. The adoption lag determines the shape of a non-linear trend in embodied productivity as well as in the path of the technology measures. It is this non-linear trend term that allows us to identify adoption lags in the data.

We estimate adoption lags for 15 technologies and 166 countries over the period 1820-2003, using data

[22] The slope for these countries is approximately 1.

from Comin, Rovito, and Hobijn (2006). Our model does a good job in fitting the diffusion curves. For two thirds of the technology-country pairs we obtain precise and plausible estimates of the adoption lags. In light of this result, we conclude that our model of diffusion provides an empirically relevant micro-foundation for a new set of measures of technology diffusion that are more comprehensive and easier to obtain than the measures used in the traditional empirical diffusion literature.

We obtain three key findings. The first is that adoption lags are large, 47 years on average, and vary a lot. The standard deviation is 39 years. Most of this variation is due to technology-specific variation, which contributes more than half of the variance of adoption lags in our sample. Over the two centuries for which we have data the average adoption lag across countries for new technologies has steadily declined.

The second finding is that the growth 'miracles' of Japan and the East Asian Tigers, though more than half a century apart, both coincided with a reduction of the technology adoption lags in these countries relative to those in their OECD counterparts.

Third, when we use our model to quantify the implications of the country-specific variation in adoption lags for cross-country per capita income differentials, we find that differences in technology adoption account for at least a quarter of per capita income disparities in our sample of countries.

Our exploration yields a set of precise estimates of the size of adoption lags across a broad range of technologies and countries. We plan on using these in subsequent work to investigate what are the key cross-country differences in endowments, institutions, and policies that impinge on technology diffusion.

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A Data

The data that we use are taken from two sources. Real GDP and population data are taken from Maddison (2007). The data on the technology measure are from the Cross-Country Historical Adoption of Technology (CHAT) data set, first described in Comin, Hobijn, and Rovito (2006). The fifteen particular technology measures that we consider are:

1. **Steam and motor ships:**

   Definition: Gross tonnage (above a minimum weight) of steam and motor ships in use at midyear.

   Invention year: 1788; the year the first (U.S.) patent was issued for a steam boat design.

2. **Railways - Passengers:**

   Definition: Passenger journeys by railway in passenger-KM.

   Invention year: 1825; the year of the first regularly schedule railroad service to carry both goods and passengers.

3. **Railways - Freight:**

   Definition: Metric tons of freight carried on railways (excluding livestock and passenger baggage).

   Invention year: 1825; same as passenger railways.

4. **Cars:**

   Definition: Number of passenger cars (excluding tractors and similar vehicles) in use.

   Invention year: 1885; the year Gottlieb Daimler built the first vehicle powered by an internal combustion engine.

5. **Trucks:**

   Definition: Number of commercial vehicles, typically including buses and taxis (excluding tractors and similar vehicles), in use.

   Invention year: 1885; same as cars.

6. **Aviation - Passengers:**

   Definition: Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned.

   Invention year: 1903; The year the Wright brothers managed the first succesful flight.

7. **Aviation - Freight:**

   Definition: Civil aviation ton-KM of cargo carried on scheduled services by companies registered in the country concerned.

   Invention year: 1903; same as aviation - passengers.

8. **Telegraph:**

   Definition: Number of telegrams sent.

   Invention year: 1835; year of invention of telegraph by Samuel Morse at New York University.

9. **Telephone:**

   Definition: Number of telegrams sent.

   Invention year: 1876; year of invention of telephone by Alexander Graham Bell.

10. **Cellphone:**

    Definition: Number of users of portable cell phones.

    Invention year: 1973; first call from a portable cellphone.

11. **Personal computers:**

    Definition: Number of self-contained computers designed for use by one person.

    Invention year: 1973; first computer based on a microprocessor.

12. **Internet users:**

    Definition: Number of people with access to the worldwide network.

    Invention year: 1983; introduction of TCP/IP protocol.

13. **MRIs:**

    Definition: Number of magnetic resonance imaging (MRI) units in place.

    Invention year: 1977; first MRI-scanner built.

14. **Blast Oxygen Steel:**

    Definition: Crude steel production (in metric tons) in blast oxygen furnances (a process that replaced bessemer and OHF processes).

    Invention year: 1950; invention of Blast Oxygen Furnace.

15. **Electricity:**

    Definition: Gross output of electric energy (inclusive of electricity consumed in power stations) in KwHr.

    Invention year: 1882; first commercial powerstation on Pearl Street in New York City.

B Mathematical details

Derivation of equation (9):

The demand for capital of a particular vintage is given by the factor demand equation

$$R_{v\tau} K_{v\tau} = \alpha P_{v\tau} Y_{v\tau} \tag{41}$$

Since revenue generated from the output produced with the vintage is determined by the demand function (7), we can write

$$R_{v\tau} K_{v\tau} = \alpha Y_\tau P_\tau^{\frac{\mu}{\mu-1}} P_{v\tau}^{-\frac{1}{\mu-1}} \tag{42}$$

Moreover, the price of the output produced with this vintage is given by the equilibrium unit production cost (8), such that we can write

$$R_{v\tau} K_{v\tau} = \alpha Y_\tau P_\tau^{\frac{\mu}{\mu-1}} Z_{v\tau}^{\frac{1}{\mu-1}} \left(\frac{(1-\alpha)}{W} \right)^{\frac{1-\alpha}{\mu-1}} \left(\frac{\alpha}{R_{v\tau}} \right)^{\frac{\alpha}{\mu-1}} \tag{43}$$

such that

$$K_{v\tau} = Y_\tau P_\tau^{\frac{\mu}{\mu-1}} Z_{v\tau}^{\frac{1}{\mu-1}} \left(\frac{(1-\alpha)}{W} \right)^{\frac{1-\alpha}{\mu-1}} \left(\frac{\alpha}{R_{v\tau}} \right)^{\epsilon} \tag{44}$$

where

$$\epsilon = \frac{\mu}{\mu-1} - \frac{1-\alpha}{\mu-1} = 1 + \frac{\alpha}{\mu-1} \tag{45}$$

which is equation (9).

Derivation of equation (10):

The Lagrangian associated with the dynamic profit maximization problem of the supplier of capital good v for intermediate τ at time t equals

$$\mathcal{L}_{v\tau t} = \int_t^\infty e^{-\int_t^s r_{s'} ds'} H_{v\tau s} ds \tag{46}$$

where $H_{v\tau s}$ is the current value Hamiltonian. We will drop the time subscript s in what follows. Here

$$\begin{aligned} H_{v\tau} \quad = \quad & (R_{v\tau} K_{v\tau} - Q I_{v\tau}) + \\ & \lambda_{v\tau} \left(R_{v\tau} K_{v\tau} - \alpha Y_\tau P_\tau^{\frac{\mu}{\mu-1}} Z_{v\tau}^{\frac{1}{\mu-1}} \left(\frac{(1-\alpha)}{W} \right)^{\frac{1-\alpha}{\mu-1}} \left(\frac{\alpha}{R_{v\tau}} \right)^{\epsilon-1} \right) + \\ & \nu_{v\tau} \left(I_{v\tau} - \delta_\tau K_{v\tau} \right) \end{aligned} \tag{47}$$

Here $\lambda_{v\tau}$ is the co-state variable associated with the demand function that the capital goods supplier faces and $\nu_{v\tau}$ is the co-state variable associated with the capital accumulation equation.

The resulting optimality conditions read

$$\begin{aligned} \text{w.r.t. } R_{v\tau}: &\quad (1+\lambda_{v\tau}) K_{v\tau} + (\epsilon - 1) \lambda_{v\tau} K_{v\tau} = 0 \\ \text{w.r.t. } I_{v\tau}: &\quad \nu_{v\tau} = Q \\ \text{w.r.t. } K_{v\tau}: &\quad (1+\lambda_{v\tau}) R_{v\tau} - \delta \nu_{v\tau} = r \nu_{v\tau} - \dot{\nu}_{v\tau} \end{aligned} \tag{48}$$

The first optimality condition yields that

$$\lambda_{v\tau} = -\frac{1}{\epsilon} \tag{49}$$

while the second and third yield that

$$\begin{aligned} R_{v\tau} &= \frac{1}{(1+\lambda_{v\tau})} Q (r + \delta_\tau + q_\tau) \\ &= \frac{\epsilon}{\epsilon - 1} Q (r + \delta_\tau + q_\tau) \end{aligned} \tag{50}$$

which is (10). Note that the resulting flow profits satisfy

$$\pi_{v\tau} = \frac{1}{\epsilon - 1} Q_\tau \left(r + \delta_\tau + q_\tau\right) K_{v\tau} = \frac{1}{\epsilon} R_{v\tau} K_{v\tau} \tag{51}$$

Derivation of intermediate technology aggregation results:

The factor demands for each of the vintage specific output types satisfy

$$WL_\tau = W \int_{v\in V_\tau} L_{v\tau} dv = (1-\alpha) \int_{v\in V_\tau} P_{v\tau} Y_{v\tau} dv = (1-\alpha) P_\tau Y_\tau \tag{52}$$

and

$$RK_\tau = R \int_{v\in V_\tau} K_{v\tau} dv = \alpha \int_{v\in V_\tau} P_{v\tau} Y_{v\tau} dv = \alpha P_\tau Y_\tau \tag{53}$$

Hence relative factor demands are the same as relative revenue levels

$$\frac{P_{v\tau} Y_{v\tau}}{P_\tau Y_\tau} = \left(\frac{Y_{v\tau}}{Y_\tau}\right)^{\frac{1}{\mu}} = \frac{L_{v\tau}}{L_\tau} = \frac{K_{v\tau}}{K_\tau} \tag{54}$$

which allows us to write

$$\begin{aligned} Y_{v\tau} &= Z_{v\tau} K_{v\tau}^{\alpha} L_{v\tau}^{1-\alpha} = Z_{v\tau} \left(\frac{Y_{v\tau}}{Y_\tau}\right)^{\frac{1}{\mu}} K_\tau^{\alpha} L_\tau^{1-\alpha} \\ &= \left(Z_{v\tau}\right)^{\frac{\mu}{\mu-1}} \left(\frac{1}{Y_\tau}\right)^{\frac{1}{\mu}} \left(K_\tau^{\alpha} L_\tau^{1-\alpha}\right)^{\frac{\mu}{\mu-1}} \end{aligned} \tag{55}$$

Such that we obtain that

$$\begin{aligned} Y_\tau &= \left(\int_{v\in V_\tau} Y_{v\tau}^{\frac{1}{\mu}} dv\right)^{\mu} = \left(\int_{v\in V_\tau} Z_{v\tau}^{\frac{1}{\mu-1}} dv\right)^{\mu} \left(\frac{1}{Y_\tau}\right)^{\frac{1}{\mu}} \left(K_\tau^{\alpha} L_\tau^{1-\alpha}\right)^{\frac{\mu}{\mu-1}} \\ &= \left(\int_{v\in V_\tau} Z_{v\tau}^{\frac{1}{\mu-1}} dv\right)^{\mu-1} \left(K_\tau^{\alpha} L_\tau^{1-\alpha}\right) = Z_\tau K_\tau^{\alpha} L_\tau^{1-\alpha} \end{aligned} \tag{56}$$

The value of the unit production cost follows from the unit production cost of a Cobb-Douglas production function. The aggregation results at the highest level of aggregation can be derived in a similar way.

Derivation of equation (18):

This follows from

$$\begin{aligned} Z_\tau &= \left(\int_{v\in V_\tau} Z_{v\tau}^{\frac{1}{\mu-1}} dv\right)^{\mu-1} = \left(\int_{\underline{v}_\tau}^{t-D_{\tau,t}} \left(Z_{\underline{v}_\tau} e^{\gamma_\tau\left(v-\underline{v}_\tau\right)}\right)^{\frac{1}{\mu-1}} dv\right)^{\mu-1} \\ &= Z_{\underline{v}_\tau} \left(\int_{\underline{v}_\tau}^{t-D_{\tau,t}} e^{\frac{\gamma_\tau}{\mu-1}\left(v-\underline{v}_\tau\right)} dv\right)^{\mu-1} = \left(\frac{\mu-1}{\gamma_\tau}\right)^{\mu-1} Z_{\underline{v}_\tau} \left[e^{\frac{\gamma_\tau}{\mu-1}\gamma_\tau\left(t-D_{\tau,t}-\underline{v}_\tau\right)} - 1\right]^{\mu-1} \\ &= \left(\frac{\mu-1}{\gamma_\tau}\right)^{\mu-1} Z_{\underline{v}_\tau} e^{\gamma_\tau\left(t-D_{\tau,t}-\underline{v}_\tau\right)} \left[1 - e^{-\frac{\gamma_\tau}{\mu-1}\left(t-D_{\tau,t}-\underline{v}_\tau\right)}\right]^{\mu-1} \end{aligned} \tag{57}$$

Derivation of equation (22):

Under the one-sector model assumptions, the price of intermediates produced with capital goods of vintage v and the aggregate price level equal

$$P_{v,\tau} = \frac{1}{Z_{v,\tau}} \left(\frac{W}{1-\alpha}\right)^{1-\alpha} \left(\frac{R}{\alpha}\right)^{\alpha} \text{ and } P = \frac{1}{A} \left(\frac{W}{1-\alpha}\right)^{1-\alpha} \left(\frac{R}{\alpha}\right)^{\alpha} \tag{58}$$

As a consequence, the relative price of output produced with vintage v is given by the relative TFP level, i.e.

$$\frac{P_{v,\tau}}{P} = P_{v,\tau} = \frac{A}{Z_{v,\tau}} \tag{59}$$

From the demand function we obtain that the revenue from output produced with capital goods of vintage v is given by

$$P_{v,\tau} Y_{v,\tau} = \left(\frac{P}{P_{v,\tau}}\right)^{\frac{1}{\theta-1}} Y = \left(\frac{Z_{v,\tau}}{A}\right)^{\frac{1}{\theta-1}} Y \tag{60}$$

The flow profits that the capital goods producer of vintage v makes are equal to

$$\pi_{v,\tau} = \frac{\alpha}{\epsilon} P_{v,\tau} Y_{v,\tau} = \frac{\alpha}{\epsilon} \left(\frac{Z_{v,\tau}}{A}\right)^{\frac{1}{\theta-1}} Y \tag{61}$$

This means that the market value of each of the capital goods suppliers of vintage v, for each of the technologies, at time t equals the present discounted value of the above flow profits. That is,

$$\begin{aligned} M_{v,\tau,t} &= \int_t^{\infty} e^{-\int_t^s r_{s'}ds'} \pi_{vs} ds && (62)\\ &= \left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1}{\theta-1}} \left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} \frac{\alpha}{\epsilon} \int_t^{\infty} e^{-\int_t^s r_{s'}ds'} \left(\frac{A_t}{A_s}\right)^{\frac{1}{\theta-1}} Y_s ds && (63)\\ &= \left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1}{\theta-1}} \left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} \left[\frac{\alpha}{\epsilon} \int_t^{\infty} e^{-\int_t^s r_{s'}ds'} \left(\frac{A_t}{A_s}\right)^{\frac{1}{\theta-1}} \frac{Y_s}{Y_t} ds\right] Y_t && (64)\\ &= \left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1}{\theta-1}} \left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} V_t Y_t && (65) \end{aligned}$$

Derivation of equilibrium adoption lag, (25):

The optimal adoption of technology vintages implies that the best vintage adopted at each instant satisfies

$$\Gamma_{v\tau} = M_{v\tau} \tag{66}$$

The adoption costs satisfy

$$\begin{aligned} \Gamma_{vt} &= \overline{V}(1+b)\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{\vartheta}{\theta-1}} P_{v,\tau} Y_{v,\tau} && (67)\\ &= \overline{V}(1+b)\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1+\vartheta}{\theta-1}} \left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t \end{aligned}$$

Combining this with the market value of the capital goods supplier of capital good (v, τ), we obtain that the vintage that satisfies (66), solves

$$\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{\vartheta}{\theta-1}} = \min\left\{1, \frac{1}{1+b}\left(\frac{V_t}{\overline{V}}\right)\right\} \tag{68}$$

such that

$$\ln Z_{v,\tau} - \ln Z_{t,\tau} = \min\left\{0, -\frac{\theta-1}{\vartheta}\left\{\ln(1+b) - \ln V_t - \ln \overline{V}\right\}\right\} \tag{69}$$

which means that the adoption lag equals

$$D_{t,\tau} = \max\left\{\frac{\theta-1}{\gamma\vartheta}\left\{\ln(1+b) - \ln V_t - \ln \overline{V}\right\}, 0\right\} = D_t \tag{70}$$

and constant across technologies, τ.

Best vintage adopted:

In the main text, we present the equilibrium dynamics of the model for the particular case in which, at every instant, there are some vintages adopted. This does not have to be the case along all equilibrium paths of this economy. Here, in the appendix, we derive the general equilibrium dynamics of the model and subsequently explain how the one main text is a special case.

For these general dynamics, we define $\overline{v}_t$ as the best vintage adopted until time t. This means that if $\overline{v}_t > t - D_t$, then, at instant t, there will be no additional vintages adopted. In the main text, we limited ourselves to the case in which, at any point in time, $\overline{v}_t = t - D_t$.

Derivation of aggregate TFP, (26):

This allows us to write aggregate total factor productivity as

$$\begin{aligned}
A_t &= \left(\int_{-\infty}^{t}\int_{\tau}^{\max\{\overline{v}_t,\tau\}} Z_{v,\tau}^{\frac{1}{\theta-1}}\, dv d\tau\right)^{\theta-1} && (71)\\
&= Z_0\left(\int_{-\infty}^{t} e^{\frac{\chi}{\theta-1}\tau}\int_{\tau}^{\max\{\overline{v}_t,\tau\}} e^{\frac{\gamma}{\theta-1}v}\, dv d\tau\right)^{\theta-1}\\
&= Z_0\left(\int_{-\infty}^{\overline{v}_t} e^{\frac{\chi}{\theta-1}\tau}\int_{\tau}^{\overline{v}_t} e^{\frac{\gamma}{\theta-1}v}\, dv d\tau\right)^{\theta-1}\\
&= Z_0\left(\frac{\theta-1}{\gamma}\right)^{\theta-1}\left(\int_{-\infty}^{\overline{v}_t} e^{\frac{\chi}{\theta-1}\tau}\left[e^{\frac{\gamma}{\theta-1}\overline{v}_t}-e^{\frac{\gamma}{\theta-1}\tau}\right] d\tau\right)^{\theta-1}\\
&= Z_0\left(\frac{\theta-1}{\gamma}\right)^{\theta-1}\left(\int_{-\infty}^{\overline{v}_t} e^{\frac{\chi}{\theta-1}(\tau-\overline{v}_t)}-e^{\frac{\chi+\gamma}{\theta-1}(\tau-\overline{v}_t)} d\tau\right)^{\theta-1} e^{(\chi+\gamma)\overline{v}_t}\\
&= Z_0\left(\frac{\theta-1}{\gamma}\right)^{\theta-1}\left(\left(\frac{\theta-1}{\chi}\right)-\left(\frac{\theta-1}{\chi+\gamma}\right)\right)^{\theta-1} e^{(\chi+\gamma)\overline{v}_t}\\
&= A_0 e^{(\chi+\gamma)\overline{v}_t}
\end{aligned}$$

which, under the assumption that $\overline{v}_t = t - D_t$, equals

$$A_t = A_0 e^{(\chi+\gamma)(t-D_t)} \tag{72}$$

Derivation of aggregate adoption costs, (27):

We derive the aggregate adoption costs at each instant of time by taking the limit of the adoption cost at a period of time of length dt starting at time t for dt going to zero. The total adoption costs between time t and $t+dt$ in the economy are given by

$$\begin{aligned}
\Gamma_t dt &= \int_{-\infty}^{\overline{v}_t}\int_{\overline{v}_t}^{\overline{v}_{t+dt}} \overline{V}(1+b)\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1+\vartheta}{\theta-1}}\left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t dv d\tau && (73)\\
&\quad+\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\int_{\tau}^{\overline{v}_{t+dt}} \overline{V}(1+b)\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1+\vartheta}{\theta-1}}\left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t dv d\tau
\end{aligned}$$

This is solved most easily in two parts. The integral

$$\int_{-\infty}^{\overline{v}_t}\int_{\overline{v}_t}^{\overline{v}_{t+dt}} \overline{V}(1+b)\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1+\vartheta}{\theta-1}}\left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t dv d\tau \tag{74}$$

$$= \overline{V}(1+b)\int_{-\infty}^{\overline{v}_t}\left[\int_{\overline{v}_t}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}} dv\right]\left(\frac{1}{Z_{t,\tau}}\right)^{\frac{1+\vartheta}{\theta-1}}\left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t d\tau \tag{75}$$

$$= \overline{V}(1+b)\left(\frac{1}{Z_0}\right)^{\frac{\vartheta}{\theta-1}} e^{-\frac{\vartheta}{\theta-1}\gamma t}\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}} Y_t \int_{-\infty}^{\overline{v}_t} e^{-\frac{\vartheta}{\theta-1}\chi\tau}\left[\int_{\overline{v}_t}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}} dv\right] d\tau \tag{76}$$

Note that

$$\int_{\overline{v}_t}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}} dv = Z_{\overline{v}_t,\tau}^{\frac{1+\vartheta}{\theta-1}}\frac{1}{\gamma}\frac{\theta-1}{1+\vartheta}\left[e^{\frac{1+\vartheta}{\theta-1}\gamma\left(\frac{\overline{v}_{t+dt}-\overline{v}_t}{dt}\right)dt}-1\right] \tag{77}$$

such that

$$\lim_{dt\downarrow 0}\left[\int_{\overline{v}_t}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}} dv\right]/dt = Z_{\overline{v}_t,\tau}^{\frac{1+\vartheta}{\theta-1}}\dot{\overline{v}}_t \tag{78}$$

This means that

$$\lim_{dt\downarrow 0}\left[\overline{V}(1+b)\left(\frac{1}{Z_0}\right)^{\frac{\vartheta}{\theta-1}} e^{-\frac{\vartheta}{\theta-1}\gamma t}\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}} Y_t\int_{-\infty}^{\overline{v}_t} e^{-\frac{\vartheta}{\theta-1}\chi\tau}\left[\int_{\overline{v}_t}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}}dv\right]d\tau\right]/dt \tag{79}$$

$$= \overline{V}(1+b)\left(\frac{1}{Z_0}\right)^{\frac{\vartheta}{\theta-1}} e^{-\frac{\vartheta}{\theta-1}\gamma t}\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}} Y_t\dot{\overline{v}}_t\int_{-\infty}^{\overline{v}_t} e^{-\frac{\vartheta}{\theta-1}\chi\tau} Z_{\overline{v}_t,\tau}^{\frac{1+\vartheta}{\theta-1}}d\tau$$

$$= \overline{V}(1+b)\,e^{-\frac{\vartheta}{\theta-1}\gamma(t-\overline{v}_t)}\left(\frac{Z_0e^{\gamma\overline{v}_t}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t\dot{\overline{v}}_t\int_{-\infty}^{\overline{v}_t} e^{\frac{1}{\theta-1}\chi\tau}d\tau$$

$$= \overline{V}(1+b)\,\frac{\theta-1}{\chi}e^{-\frac{\vartheta}{\theta-1}\gamma(t-\overline{v}_t)}\left(\frac{Z_0e^{\gamma\overline{v}_t}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t\dot{\overline{v}}_t e^{\frac{1}{\theta-1}\chi\overline{v}_t}$$

$$= \overline{V}(1+b)\,\frac{\theta-1}{\chi}e^{-\frac{\vartheta}{\theta-1}\gamma(t-\overline{v}_t)}\left(\frac{Z_0e^{(\gamma+\chi)\overline{v}_t}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t\dot{\overline{v}}_t$$

Now let's look at the second term

$$\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\int_{\tau}^{\overline{v}_{t+dt}}\overline{V}(1+b)\left(\frac{Z_{v,\tau}}{Z_{t,\tau}}\right)^{\frac{1+\vartheta}{\theta-1}}\left(\frac{Z_{t,\tau}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t dv d\tau \tag{80}$$

$$= \overline{V}(1+b)\,Y_t\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}}\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\left[\int_{\tau}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}}dv\right]\left(\frac{1}{Z_{t,\tau}}\right)^{\frac{\vartheta}{\theta-1}}d\tau$$

Here

$$\left[\int_{\tau}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}}dv\right] = Z_0^{\frac{1+\vartheta}{\theta-1}}\frac{1}{\gamma}\frac{\theta-1}{1+\vartheta}\left[e^{\frac{1+\vartheta}{\theta-1}\chi\tau}e^{\frac{1+\vartheta}{\theta-1}\gamma\overline{v}_{t+dt}} - e^{\frac{1+\vartheta}{\theta-1}(\gamma+\chi)\tau}\right] \tag{81}$$

which allows us to write

$$\overline{V}(1+b)\,Y_t\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}}\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\left[\int_{\tau}^{\overline{v}_{t+dt}} Z_{v,\tau}^{\frac{1+\vartheta}{\theta-1}}dv\right]\left(\frac{1}{Z_{t,\tau}}\right)^{\frac{\vartheta}{\theta-1}}d\tau \tag{82}$$

$$= \overline{V}(1+b)\,Y_t\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}} Z_0^{\frac{1+\vartheta}{\theta-1}}\frac{1}{\gamma}\frac{\theta-1}{1+\vartheta}\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\left[e^{\frac{1+\vartheta}{\theta-1}\chi\tau}e^{\frac{1+\vartheta}{\theta-1}\gamma\overline{v}_{t+dt}} - e^{\frac{1+\vartheta}{\theta-1}(\gamma+\chi)\tau}\right]\left(\frac{1}{Z_{t,\tau}}\right)^{\frac{\vartheta}{\theta-1}}d\tau$$

$$= \overline{V}(1+b)\,Y_t\left(\frac{1}{A_t}\right)^{\frac{1}{\theta-1}}\left(\frac{1}{e^{\frac{\vartheta}{\theta-1}\gamma t}}\right) Z_0^{\frac{1}{\theta-1}}\frac{1}{\gamma}\frac{\theta-1}{1+\vartheta}\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\left[e^{\frac{1}{\theta-1}\chi\tau}e^{\frac{1+\vartheta}{\theta-1}\gamma\overline{v}_{t+dt}} - e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\tau}\right]d\tau$$

Now, we continue by looking at

$$\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\left[e^{\frac{1}{\theta-1}\chi\tau}e^{\frac{1+\vartheta}{\theta-1}\gamma\overline{v}_{t+dt}} - e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\tau}\right]d\tau \tag{83}$$

$$= \frac{\theta-1}{\chi}e^{\frac{1+\vartheta}{\theta-1}\gamma\overline{v}_{t+dt}}\left[e^{\frac{1}{\theta-1}\chi\overline{v}_{t+dt}} - e^{\frac{1}{\theta-1}\chi\overline{v}_t}\right] - \frac{1}{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)}\left[e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\overline{v}_{t+dt}} - e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\overline{v}_t}\right]$$

$$= e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\overline{v}_t}\left\{\frac{\theta-1}{\chi}e^{\frac{1+\vartheta}{\theta-1}\gamma\left(\frac{\overline{v}_{t+dt}-\overline{v}_t}{dt}\right)dt}\left[e^{\frac{1}{\theta-1}\chi\left(\frac{\overline{v}_{t+dt}-\overline{v}_t}{dt}\right)dt}-1\right] - \frac{1}{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)}\left[e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\left(\frac{\overline{v}_{t+dt}-\overline{v}_t}{dt}\right)dt}-1\right]\right\}$$

But this implies that

$$\lim_{dt\downarrow 0}\left[\int_{\overline{v}_t}^{\overline{v}_{t+dt}}\left[e^{\frac{1}{\theta-1}\chi\tau}e^{\frac{1+\vartheta}{\theta-1}\gamma\overline{v}_{t+dt}} - e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\tau}\right]d\tau\right]/dt \tag{84}$$

$$= e^{\left(\frac{1+\vartheta}{\theta-1}\gamma+\frac{1}{\theta-1}\chi\right)\overline{v}_t}\left\{\dot{\overline{v}}_t - \dot{\overline{v}}_t\right\} = 0$$

Hence, the second part of the integral is zero and the aggregate adoption cost at each instant in time are given by

$$\begin{aligned} \Gamma_t &= \overline{V}(1+b)\frac{\theta-1}{\chi}e^{-\frac{\vartheta}{\theta-1}\gamma(t-\overline{v}_t)}\left(\frac{Z_0 e^{(\gamma+\chi)\overline{v}_t}}{A_t}\right)^{\frac{1}{\theta-1}} Y_t\dot{\overline{v}}_t \\ &= \overline{V}(1+b)\left(\frac{\gamma}{\theta-1}\right)^{\frac{1}{\theta-1}}\left(\frac{1}{1-\frac{\chi}{\chi+\gamma}}\right)e^{-\frac{\vartheta}{\theta-1}\gamma(t-\overline{v}_t)}Y_t\dot{\overline{v}}_t \end{aligned} \tag{85}$$

Equilibrium:

Equilibrium in this case consists of the consumption Euler equation

$$\frac{\dot{C}_t}{C_t} = \left(\alpha\frac{\epsilon-1}{\epsilon}\frac{Y_t}{K_t} - \delta - \rho\right) \tag{86}$$

where we have used that the real interest rate is related to the marginal product of capital as follows

$$r_t = \alpha\frac{\epsilon-1}{\epsilon}\frac{Y_t}{K_t} - \delta \tag{87}$$

The resource constraint

$$Y_t = C_t + I_t + \Gamma_t \tag{88}$$

The capital accumulation equation

$$\dot{K}_t = -\delta K_t + I_t \tag{89}$$

The production function

$$Y_t = A_t K_t^{\alpha} \tag{90}$$

The aggregate TFP equation

$$A_t = A_0 e^{(\chi+\gamma)\overline{v}_t} \tag{91}$$

The adoption cost equation

$$\Gamma_t = \overline{V}(1+b)\left(\frac{\gamma}{\theta-1}\right)^{\frac{1}{\theta-1}}\left(\frac{1}{1-\frac{\chi}{\chi+\gamma}}\right)e^{-\frac{\vartheta}{\theta-1}\gamma(t-\overline{v}_t)}Y_t\dot{\overline{v}}_t \tag{92}$$

The adoption lag equation

$$D_t = \max\left\{\frac{\theta-1}{\gamma\vartheta}\left\{\ln(1+b) - \ln V_t - \ln\overline{V}\right\}, 0\right\} \tag{93}$$

And the market value equation

$$V_t = \frac{\alpha}{\epsilon}\int_t^{\infty} e^{-\int_t^s r_{s'}ds'}\left(\frac{A_t}{A_s}\right)^{\frac{1}{\theta-1}}\frac{Y_s}{Y_t}ds \tag{94}$$

which is best written in changes over time

$$\frac{\dot{V}_t}{V_t} = \left\{\alpha\frac{\epsilon-1}{\epsilon}\frac{Y_t}{K_t} - \delta + \frac{1}{\theta-1}\frac{\dot{A}_t}{A_t} - \frac{\dot{Y}_t}{Y_t}\right\} - \frac{\alpha}{\epsilon}\frac{1}{V_t} \tag{95}$$

and the technology adoption equation

$$\dot{\overline{v}}_t = \begin{cases} \max\left\{1-\dot{D}_t, 0\right\} & \text{if} \quad \overline{v}_t = t - D_t \\ 0 & \text{if} \quad \overline{v}_t > t - D_t \end{cases} \tag{96}$$

Because, in the main text we assumed that $\overline{v}_t = t - D_t$ for all t, the dynamic equilibrium equations in the main text are based on the assumption that along the equilibrium paths considered $\dot{\overline{v}}_t = 1 - \dot{D}_t$, and thus that $\dot{D}_t < 1$.

Balanced growth path:

We will consider the balanced growth path in this economy in deviation from the trend

$$\overline{A}_t = A_0 e^{(\chi+\gamma)t} \tag{97}$$

The nine transformed/detrended variables on the balanced growth path are

$$C_t^* = \frac{C_t}{A_t^{\frac{1}{1-\alpha}}},\ Y_t^* = \frac{Y_t}{A_t^{\frac{1}{1-\alpha}}},\ I_t^* = \frac{I_t}{A_t^{\frac{1}{1-\alpha}}},\ K_t^* = \frac{K_t}{A_t^{\frac{1}{1-\alpha}}},\ \Gamma_t^* = \frac{\Gamma_t}{A_t^{\frac{1}{1-\alpha}}},\ \text{and } A_t^* = \frac{A_t}{A_t} \tag{98}$$

as well as

$$D_t,\ V_t,\ \text{and } \overline{v}_t^* = \overline{v}_t - t \tag{99}$$

Derivation of transformed dynamic system:

The resulting dynamic equations that define the transitional dynamics of the economy around the balanced growth path are the following Euler equation

$$\frac{\dot{C}_t^*}{C_t^*} = \left(\alpha \frac{\epsilon - 1}{\epsilon} \frac{Y_t^*}{K_t^*} - \delta - \rho\right) - \frac{1}{1-\alpha}(\chi + \gamma) \tag{100}$$

The resource constraint

$$Y_t^* = C_t^* + I_t^* + \Gamma_t^* \tag{101}$$

The capital accumulation equation

$$\frac{\dot{K}_t^*}{K_t^*} = -\left[\delta + \frac{1}{1-\alpha}(\chi+\gamma)\right] + \frac{I_t^*}{K_t^*} \tag{102}$$

The production function

$$Y_t^* = A_t^* \left(K_t^*\right)^{\alpha} \tag{103}$$

The trend adjusted productivity level

$$A_t^* = e^{(\chi+\gamma)\overline{v}_t^*} \tag{104}$$

The aggregate adoption cost

$$\Gamma_t^* = \overline{V}(1+b)\left(\frac{\gamma}{\theta-1}\right)^{\frac{1}{\theta-1}} \left(\frac{1}{1-\frac{\chi}{\chi+\gamma}}\right) e^{\frac{\vartheta}{\theta-1}\gamma \overline{v}_t^*} Y_t^* \left(\dot{\overline{v}}_t^* + 1\right) \tag{105}$$

The adoption lag

$$D_t = \max\left\{\frac{\theta-1}{\vartheta\gamma}\left\{\ln(1+b) - \ln V_t + \ln \overline{V}\right\}, 0\right\} \tag{106}$$

and the market value transitional equation

$$\frac{\dot{V}_t}{V_t} = \left\{\left[\alpha\frac{\epsilon-1}{\epsilon}\frac{Y_t^*}{K_t^*} - \delta\right] + \frac{1}{\theta-1}\left\{\frac{\dot{A}_t^*}{A_t^*} + (\chi+\gamma)\right\} - \left\{\frac{\dot{Y}_t^*}{Y_t^*} + \frac{1}{1-\alpha}(\chi+\gamma)\right\}\right\} - \frac{\alpha}{\epsilon}\frac{1}{V_t} \tag{107}$$

as well as the adoption law of motion

$$\dot{\overline{v}}_t^* = \begin{cases} \max\left\{-\dot{D}_t, -1\right\} & \text{if} \quad \overline{v}_t^* = -D_t \\ -1 & \text{if} \quad \overline{v}_t > -D_t \end{cases} \tag{108}$$

Steady state equations:

The steady state is defined by the following equations

$$0 = \left(\alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*} - \delta - \rho\right) - \frac{1}{1-\alpha}(\chi+\gamma) \tag{109}$$

The resource constraint

$$\overline{Y}^* = \overline{C}^* + \overline{I}^* + \overline{\Gamma}^* \tag{110}$$

The capital accumulation equation

$$0 = -\left[\delta + \frac{1}{1-\alpha}(\chi+\gamma)\right] + \frac{\overline{I}^*}{\overline{K}^*} \tag{111}$$

The production function

$$\overline{Y}^* = \overline{A}^*\left(\overline{K}^*\right)^{\alpha} \tag{112}$$

The trend adjusted productivity level

$$\overline{A}^{*}=e^{-(\chi+\gamma)\overline{D}} \tag{113}$$

The aggregate adoption cost

$$\overline{\Gamma}^{*}=\overline{V}\left(1+b\right)\left(\frac{\gamma}{\theta-1}\right)^{\frac{1}{\theta-1}}\left(\frac{1}{1-\frac{\chi}{\chi+\gamma}}\right)e^{\frac{\vartheta}{\theta-1}\gamma\overline{\overline{v}}^{*}}\overline{Y}^{*} \tag{114}$$

The steady state adoption lag, assuming that $b\geq0$, equals

$$\overline{D}=\frac{\theta-1}{\vartheta\gamma}\ln\left(1+b\right) \tag{115}$$

and the market value transitional equation

$$0=\left\{\left[\alpha\frac{\epsilon-1}{\epsilon}\frac{Y_{t}^{*}}{K_{t}^{*}}-\delta\right]+\frac{1}{\theta-1}\left(\chi+\gamma\right)-\frac{1}{1-\alpha}\left(\chi+\gamma\right)\right\}-\frac{\alpha}{\epsilon}\frac{1}{\overline{\overline{V}}} \tag{116}$$

as well as

$$\overline{\overline{v}}^{*}=-\overline{D}$$

Steady state solution:

Combining the Euler equation with the market cap to GDP equation, we obtain that

$$0=\left\{\rho+\frac{1}{\theta-1}\left(\chi+\gamma\right)\right\}-\frac{\alpha}{\epsilon}\frac{1}{\overline{\overline{V}}} \tag{117}$$

Such that the steady state market cap to GDP ratio equals

$$\overline{V}=\frac{\alpha}{\epsilon}\frac{1}{\left\{\rho+\frac{1}{\theta-1}\left(\chi+\gamma\right)\right\}} \tag{118}$$

The steady state trend adjusted level of productivity equals

$$\overline{A}^{*}=\left[\left(\frac{1}{1+b}\right)^{\frac{1}{\vartheta}}\right]^{(\theta-1)\frac{(\chi+\gamma)}{\gamma}} \tag{119}$$

When we insert this into the Euler equation, we find that

$$0=\left(\alpha\frac{\epsilon-1}{\epsilon}\left[\left(\frac{1}{1+b}\right)^{\frac{1}{\vartheta}}\right]^{(\theta-1)\frac{(\chi+\gamma)}{\gamma}}\left(\frac{1}{\overline{K}^{*}}\right)^{1-\alpha}-\delta-\rho\right)-\frac{1}{1-\alpha}\left(\chi+\gamma\right) \tag{120}$$

which allows us to solve for the steady state capital stock

$$\overline{K}^{*}=\left[\frac{\alpha\frac{\epsilon-1}{\epsilon}\overline{A}^{*}}{\delta+\rho+\frac{1}{1-\alpha}\left(\chi+\gamma\right)}\right]^{\frac{1}{1-\alpha}}=\left[\frac{\alpha\frac{\epsilon-1}{\epsilon}\left[\left(\frac{1}{1+b}\right)^{\frac{1}{\vartheta}}\right]^{(\theta-1)\frac{(\chi+\gamma)}{\gamma}}}{\delta+\rho+\frac{1}{1-\alpha}\left(\chi+\gamma\right)}\right]^{\frac{1}{1-\alpha}} \tag{121}$$

Such that

$$\begin{aligned}\overline{I}^{*}&=\left[\delta+\frac{1}{1-\alpha}\left(\chi+\gamma\right)\right]\overline{K}^{*} \qquad (122)\\&=\left[\delta+\frac{1}{1-\alpha}\left(\chi+\gamma\right)\right]\left[\frac{\alpha\frac{\epsilon-1}{\epsilon}\left[\left(\frac{1}{1+b}\right)^{\frac{1}{\vartheta}}\right]^{(\theta-1)\frac{(\chi+\gamma)}{\gamma}}}{\delta+\rho+\frac{1}{1-\alpha}\left(\chi+\gamma\right)}\right]^{\frac{1}{1-\alpha}}\end{aligned}$$

and output equals

$$\overline{Y}^{*}=\overline{A}^{*}\left(\overline{K}^{*}\right)^{\alpha}=\left\{\left[\left(\frac{1}{1+b}\right)^{\frac{1}{\vartheta}}\right]^{(\theta-1)\frac{(\chi+\gamma)}{\gamma}}\right\}^{\frac{1}{1-\alpha}}\left[\frac{\alpha\frac{\epsilon-1}{\epsilon}}{\delta+\rho+\frac{1}{1-\alpha}\left(\chi+\gamma\right)}\right]^{\frac{\alpha}{1-\alpha}} \tag{123}$$

while the aggregate adoption cost is

$$\overline{\Gamma}^* = \overline{V}\,(1+b)\left(\frac{\gamma}{\theta-1}\right)^{\frac{1}{\theta-1}}\left(\frac{1}{1-\frac{\chi}{\chi+\gamma}}\right)e^{\frac{\vartheta}{\theta-1}\gamma\overline{\overline{v}}^*}\,\overline{Y}^* \tag{124}$$

and steady state consumption equals

$$\overline{C}^* = \overline{Y}^* - \overline{I}^* - \overline{\Gamma}^* \tag{125}$$

Note that, for steady state consumption to be positive, we need a restriction on the parameters, such that the total adoption costs do not fully exhaust productive capacity.

Transitional dynamics:

The next thing is to linearize the transitional dynamics around the steady state. Note that this model has only one state variable, namely the capital stock K_t. The stock market capitalization to GDP ratio, V_t, is a jump variable and so are the adoption lag, D_t, the best vintage adopted, $\overline{v}_t$, and the trend adjusted productivity level, A_t^*.

The log-linearized equations are the Euler equation

$$\dot{\widehat{C}}_t^* = \alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{Y}_t^* - \alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{K}_t^* \tag{126}$$

as well as the resource constraint

$$0 = \widehat{Y}_t^* - \frac{\overline{C}^*}{\overline{Y}^*}\widehat{C}_t^* - \frac{\overline{I}^*}{\overline{Y}^*}\widehat{I}_t^* - \frac{\overline{\Gamma}^*}{\overline{Y}^*}\widehat{Y}_t^* \tag{127}$$

the capital accumulation equation

$$\dot{\widehat{K}}_t^* = \frac{\overline{I}^*}{\overline{K}^*}\widehat{I}_t^* - \frac{\overline{I}^*}{\overline{K}^*}\widehat{K}_t^* \tag{128}$$

The production function

$$0 = \widehat{Y}_t^* - \widehat{A}_t^* - \alpha\widehat{K}_t^* \tag{129}$$

The trend adjusted productivity level

$$0 = \widehat{A}_t^* - (\chi+\gamma)\left(\overline{v}_t^* - \overline{\overline{v}}^*\right) \tag{130}$$

The adoption lag equation

$$0 = \left(D_t - \overline{D}\right) + \frac{\theta-1}{\vartheta\gamma}\widehat{V}_t \tag{131}$$

The aggregate adoption cost

$$\dot{\overline{v}}_t^* = \widehat{\Gamma}_t^* - \frac{\vartheta}{\theta-1}\gamma\left(\overline{v}_t^* - \overline{\overline{v}}^*\right) - \widehat{Y}_t^* \tag{132}$$

and the market capitalization equation

$$\dot{\widehat{V}}_t = \alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{Y}_t^* - \alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{K}_t^* + \frac{\chi+\gamma}{\theta-1}\dot{\overline{v}}_t^* - (\chi+\gamma)\dot{\overline{v}}_t^* - \alpha\dot{\widehat{K}}_t^* + \frac{\alpha}{\epsilon}\frac{1}{\overline{V}}\widehat{V}_t \tag{133}$$

which simplifies to

$$\dot{\widehat{V}}_t + \left(1 - \frac{1}{\theta-1}\right)(\chi+\gamma)\dot{\overline{v}}_t^* + \alpha\dot{\widehat{K}}_t^* = \alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{Y}_t^* - \alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{K}_t^* + \frac{\alpha}{\epsilon}\frac{1}{\overline{V}}\widehat{V}_t \tag{134}$$

where we have assumed that, all along the equilibrium path $\overline{v}_t^* = -D_t$, such that

$$\dot{\overline{v}}_t^* = \begin{cases} \max\left\{-\frac{\theta-1}{\vartheta\gamma}\dot{\hat{V}}_t, -1\right\} & \text{if} \quad \overline{v}_t^* = -D_t \\ -1 & \text{if} \quad \overline{v}_t > -D_t \end{cases} \tag{135}$$

For our examples, we limit ourselves to the part of the transitional path for which $\overline{v}_t^* = -D_t$ for all t. On that path, the transitional dynamics simplify, because then

$$\overline{v}_t^* - \overline{\overline{v}}^* = -\left(D_t - \overline{D}\right) \tag{136}$$

and

$$\dot{\overline{v}}_t^* = -\dot{D}_t = \frac{\theta-1}{\vartheta\gamma}\dot{\widehat{V}}_t \tag{137}$$

which allows us to write

$$0=\widehat{A}_t^*+(\chi+\gamma)\left(D_t-\overline{D}\right) \tag{138}$$

and

$$\frac{\theta-1}{\vartheta\gamma}\dot{\widehat{V}}_t=\widehat{\Gamma}_t^*+\frac{\vartheta}{\theta-1}\gamma\left(D_t-\overline{D}\right)-\widehat{Y}_t^* \tag{139}$$

as well as

$$\left[1+(\theta-2)\,\frac{\chi+\gamma}{\vartheta\gamma}\right]\dot{\widehat{V}}_t+\alpha\dot{\widehat{K}}_t^*=\alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{Y}_t^*-\alpha\frac{\epsilon-1}{\epsilon}\frac{\overline{Y}^*}{\overline{K}^*}\widehat{K}_t^*+\frac{\alpha}{\epsilon}\frac{1}{\overline{V}}\widehat{V} \tag{140}$$

Derivation of expression for r_τ in balanced growth

Let

$$Q_{\tau,t}=q_{\tau,0}-q_\tau t \tag{141}$$

then, when we evaluate (10) at the steady-state real interest rate $\overline{r}$ and the implied steady-state user cost

$$\overline{uc}_\tau=(\overline{r}+\delta_\tau+q_\tau) \tag{142}$$

we obtain

$$\begin{aligned} r_\tau &= \left[\ln\left(\frac{\epsilon}{\epsilon-1}\right)+\overline{uc}_\tau-\frac{1}{\overline{uc}_\tau}\overline{r}+q_{\tau,0}\right]-q_\tau t \\ &= c_1-q_\tau t \end{aligned} \tag{143}$$

Derivation of equation (37)

Denote the adoption time by $T_\tau=D_\tau+\underline{v}_\tau$. Consider the technology-specific TFP level

$$Z_{\tau t}=Z_{\underline{v}_\tau}\left[\left(\frac{\mu-1}{\gamma_\tau}\right)\left(e^{\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}-1\right)\right]^{\mu-1} \tag{144}$$

We are interested in the behavior of this TFP for $\gamma_\tau\downarrow 0$. In that case, there is no embodied productivity growth and the increase in productivity after the introduction of the technology is all due to the introduction of an increasing number of varieties over time.

For this reason, we consider

$$\lim_{\gamma_\tau\downarrow 0}Z_{\underline{v}_\tau}\left[\left(\frac{\mu-1}{\gamma_\tau}\right)\left(e^{\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}-1\right)\right]^{\mu-1} \tag{145}$$

which, using de l'Hopital's rule, can be shown to equal

$$Z_{\underline{v}_\tau}\left[\lim_{\gamma_\tau\downarrow 0}\left(\frac{\mu-1}{\gamma_\tau}\right)\left(e^{\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}-1\right)\right]^{\mu-1}=Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{(\mu-1)} \tag{146}$$

Taking the first order Taylor approximation around $\gamma=0$ yields that

$$\begin{aligned} Z_{\tau t} \approx\; & Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{(\mu-1)}+ \\ & +Z_{\underline{v}_\tau}\left[\lim_{\gamma_\tau\downarrow 0}\left(\left(\frac{\mu-1}{\gamma_\tau}\right)(t-T_\tau)\,e^{\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}-\left(\frac{\mu-1}{\gamma_\tau}\right)^2\left(e^{\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}-1\right)\right)\right](t-T_\tau)^{(\mu-2)}\gamma_\tau \\ =\; & Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{(\mu-1)}+ \\ & +Z_{\underline{v}_\tau}\left[\lim_{\gamma_\tau\downarrow 0}\left(\frac{\mu-1}{\gamma_\tau}\right)^2\left(\left(\frac{\gamma_\tau}{\mu-1}(t-T_\tau)-1\right)e^{\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}+1\right)\right](t-T_\tau)^{(\mu-2)}\gamma_\tau \\ =\; & Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{(\mu-1)} \\ & +Z_{\underline{v}_\tau}\left[\lim_{\gamma_\tau\downarrow 0}(\mu-1)^2\,\frac{\frac{\gamma_\tau}{(\mu-1)^2}\left(t-T_\tau\right)^2e^{-\frac{\gamma_\tau}{\mu-1}(t-T_\tau)}}{2\gamma_\tau}\right](t-T_\tau)^{(\mu-2)}\gamma_\tau \\ =\; & Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{(\mu-1)}+\frac{1}{2}Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{\mu}\gamma_\tau \\ =\; & Z_{\underline{v}_\tau}\left(t-T_\tau\right)^{(\mu-1)}\left[1+\frac{1}{2}\left(t-T_\tau\right)\gamma_\tau\right] \end{aligned} \tag{147}$$

Hence, for γ_τ close to zero,

$$z_{\tau t} \approx z_{\underline{v}_\tau} + (\mu - 1)\ln(t - T_\tau) + \frac{\gamma_\tau}{2}(t - T_\tau) \tag{148}$$

Derivation of equation (38)

Combining the four log-linearized equations, we obtain for $m_\tau = y_\tau$ that

$$\begin{aligned} y_\tau &= y - \frac{\theta}{\theta-1} p_\tau & (149)\\ &= y - \frac{\theta}{\theta-1}\alpha \ln \alpha + \frac{\theta}{\theta-1} z_\tau - \frac{\theta}{\theta-1}(1-\alpha)(y-l) - \frac{\theta}{\theta-1}\alpha r_\tau \\ &= y + \left[-\frac{\theta}{\theta-1}\alpha\ln\alpha + \frac{\theta}{\theta-1} z_{\underline{v}_\tau} - \frac{\theta}{\theta-1}\alpha c_1 - \frac{\theta}{\theta-1}\frac{\gamma_\tau}{2} T_\tau\right] \\ &\quad + \left[\frac{\theta}{\theta-1}\frac{\gamma_\tau}{2} - \frac{\theta}{\theta-1}\alpha q_\tau\right] t + \frac{\theta}{\theta-1}\left[(\mu-1)\ln(t-T_\tau) - (1-\alpha)(y-l)\right] \\ &= \beta_1 + y + \beta_2 t + \beta_3\left((\mu-1)\ln(t-T_\tau) - (1-\alpha)(y-l)\right) & (150) \end{aligned}$$

Combining the four log-linearized equations, we obtain for $m_\tau = k_\tau$ that

$$\begin{aligned} k_\tau &= y + \ln\alpha - \frac{1}{\theta-1} p_\tau - r_\tau & (151)\\ &= \left[1 + \frac{\alpha}{\theta-1}\right][\ln\alpha - c_1] + \frac{1}{\theta-1}\left[z_{\underline{v}_\tau} + \frac{\gamma_\tau}{2} T_\tau\right] + & (152)\\ &\quad \left[\left[1+\frac{\alpha}{\theta-1}\right] q_\tau + \frac{1}{\theta-1}\frac{\gamma_\tau}{2}\right] t + \frac{1}{\theta-1}\left[(\mu-1)\ln(t-T_\tau) - (1-\alpha)(y-l)\right] & (153)\\ &= \beta_1 + y + \beta_2 t + \beta_3\left((\mu-1)\ln(t-T_\tau) - (1-\alpha)(y-l)\right) & (154) \end{aligned}$$

Simulations

In this section of the Appendix we describe first the comparative statics of our diffusion measures with respect to the adoption lags, D_τ, and the initial productivity, $Z_{0\tau}$. This should clarify further our identification strategy. Then we explore the precision of our estimation procedure with the help of a Monte Carlo exercise.

Comparative Statics:

To illustrate the effects of the adoption lags on our measures of adoption, we compute the evolution of k_τ in two economies that are in balanced growth and which are identical apart from the fact that one has lower adoption costs for technology τ than the other. As a result, the adoption lag of the former are also smaller. As can be seen in Figure, the adoption curve in the economy with lower adoption costs has also a smaller slope at any given moment in time. This variation in the slope of the diffusion curve is the key in our identification of the adoption lags.

In Figure we consider two economies whose only difference is that one presents a lower initial productivity level for technology τ, $Z_{0\tau}$. It is clear from the Figure, that the only effect that $Z_{0\tau}$ has on the adoption pattern is to shift vertically our adoption measure. In particular, $Z_{0\tau}$ does not affect the adoption lag and therefore, it does not affect the curvature of the adoption measures.

Monte Carlo:

To explore the precision of our estimation procedure, we proceed as follows. First, we take the estimates of the adoption lags we have obtained for computers. We use these estimates to calibrate the adoption lags in our simulation. Second, we calibrate, $\gamma = 0.01$, $q_\tau = 0.02$, $\mu = 1.3$ and $\theta = 1.4$. Third, we simulate the log of per-capita income in steady state assuming a long run growth rate of $0.014/0.7$. Finally, we simulate the path for k_τ using equation (36) for 40 yearly periods since the invention date.

Then we apply our estimation procedure to this simulated data set. That is, we first estimate equation (**38**) for the US using the non-linear least squares estimator. Then, we take the US estimates for β_2 and β_3 and fix them for the other countries and reestimate the equation allowing β_1 and T_τ to vary by country. The estimates of the diffusion lag, D_τ, are given by $\hat{T}_\tau - \underline{v}_\tau$.

Figure contains the scatter plot of the calibrated lags and their estimates together with a 45 degree line. The main observation is that the estimates virtually lie in the 45 degree line. The average absolute deviation between the estimates and the adoption lags we have set in the Monte Carlo is 0.04 (i.e. approximately two weeks). Hence, we conclude that the estimation strategy provides precise estimates of the adoption lags.

Table 1: Quality of estimates

	Invention	Number of	Plausible		Implausible	R^2		
Technology	**year ($\underline{v}_\tau$)**	**countries**	**Precise**	**Imprecise**		**$R^2 > 0$**	**mean**	**stdev**
Steam- and motorships	1788	64	54	0	10	54	0.80	0.16
Railways - Passengers	1825	80	60	3	17	40	0.53	0.19
Railways - Freight	1825	85	41	5	39	41	0.81	0.13
Cars	1885	123	76	5	42	65	0.67	0.22
Trucks	1885	109	58	2	49	52	0.67	0.23
Aviation - Passengers	1903	97	50	3	44	50	0.90	0.07
Aviation - Freight	1903	94	29	5	60	29	0.88	0.09
Telegraph	1835	67	44	5	18	32	0.58	0.22
Telephone	1876	142	67	9	66	64	0.85	0.13
Cellphones	1973	85	83	2	0	83	0.90	0.07
PCs	1973	71	70	0	1	70	0.92	0.07
Internet users	1983	60	60	0	0	60	0.94	0.05
MRIs	1977	12	12	0	0	12	0.95	0.05
Blast Oxygen Steel	1950	52	39	3	10	32	0.64	0.27
Electricity	1882	137	93	3	41	93	0.92	0.10
Total		1278	836	45	397	777	0.81	0.19

Table 2: Estimated adoption lags

Technology	Invention	Number	Adoption lags						
	year ($\underline{v}_\tau$)	of countries	mean	stdev	1%	10%	50%	90%	99%
Steam- and motorships	1788	54	118	50	25	56	115	179	180
Railways - Passengers	1825	60	101	25	26	65	104	126	137
Railways - Freight	1825	41	83	33	26	32	91	124	135
Cars	1885	76	46	21	10	19	44	67	102
Trucks	1885	58	40	20	4	16	35	65	89
Aviation - Passengers	1903	50	34	12	17	21	29	53	72
Aviation - Freight	1903	29	44	13	12	24	43	62	74
Telegraph	1835	44	56	33	13	17	48	103	115
Telephone	1876	67	54	32	-7	8	59	100	113
Cellphones	1973	83	15	4	0	10	16	19	20
PCs	1973	70	14	3	3	10	14	17	19
Internet users	1983	60	8	2	0	5	8	11	11
MRIs	1977	12	5	2	3	3	5	7	10
Blast Oxygen Steel	1950	39	16	7	2	9	16	28	33
Electricity	1882	93	57	19	14	25	67	74	107
Total		836	47	39	3	9	35	101	178

Table 3: Analysis of variance

	Total sum of squares = 1287350, N = 833				
	Model SS	**Country effect**	**Technology effect**	**Residual SS**	**Total SS**
Country effect alone	29%	29%		71%	100%
Technology effect	66%		66%	34%	100%
Joint effect	83%	18%	54%	17%	100%

Table 4: Adoption lags for country groups (in deviation from average adoption lag for technology)

Technology	**Invention year ($\underline{v}_\tau$)**	**USA**	**GBR**	**Japan**	**other OECD**	**Asian Tigers**	**Latin America**	**Sub-Saharan Africa**	**Other**
Steam- and motorships	1788	-93	-76	-5	-50	31	-4	24	36
		1	1	1	14	4	10	3	20
Railways - Passengers	1825	-44	5	-36	-27	11	-3	20	13
		1	1	1	15	2	10	9	24
Railways - Freight	1825	-35		-15	-22	1	7	25	18
		1		1	18	2	3	5	16
Telegraph	1835	-21	-40	-17	-22	18	-5	31	23
		1	1	1	17	3	8	2	16
Telephone	1876	-52	-34	-36	-28	25	-15	14	19
		1	1	1	17	4	13	10	29
Electricity	1882	-37	-43	-32	-25	10	-4	12	7
		1	1	1	15	4	15	24	35
Cars	1885	-31	-31	-16	-13	18	-7	2	11
		1	1	1	19	4	13	15	27
Trucks	1885	-20		-10	-12	24	-9	8	13
		1		1	18	4	13	7	16
Aviation - Passengers	1903	-8	-13	-8	-5	19	-5	21	3
		1	1	1	19	3	7	2	19
Aviation - Freight	1903	-15		-3	-2	18	-7	35	-2
		1		1	15	3	2	1	11
Blast Oxygen Steel	1950	-8	-7	-7	-2	8	-1		3
		1	1	1	17	2	6		14
PCs	1973	-6	-4	-3	–1	0	2	0	1
		1	1	1	19	3	10	8	27
Cellphones	1973	-5	-4	-7	-3	-1	2	2	1
		1	1	1	19	4	15	9	35
MRIs	1977	-2			1				-3
		1			10				1
Internet	1983	-3	-2	-1	-2	-1	1	1	2
		1	1	1	19	4	10	3	21

Note: Adoption lags are listed in deviation from the mean adoption lag for each technology. Hence, the smaller the number, the earlier the adoption year.

Table 5: Adoption dates of three recent technologies for EATs

	Singapore	**Hong Kong**	**Korea**	**Taiwan**
PCs	1987	1987	1988	
Cellphones	1987	1984	1986	1988
Internet	1990	1990	1990	1991

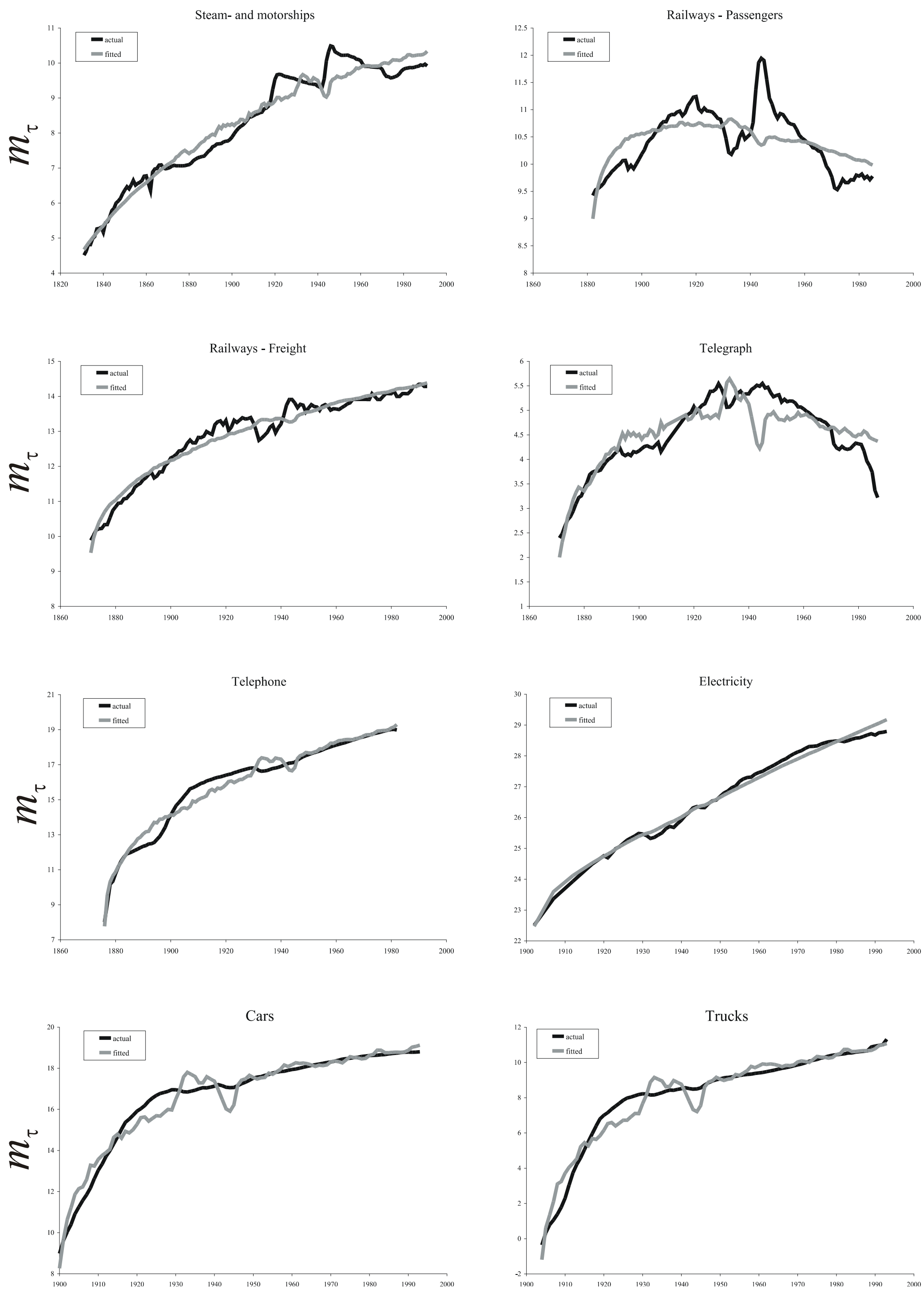

Figure 1: Fit of model to U.S. time series (part 1)

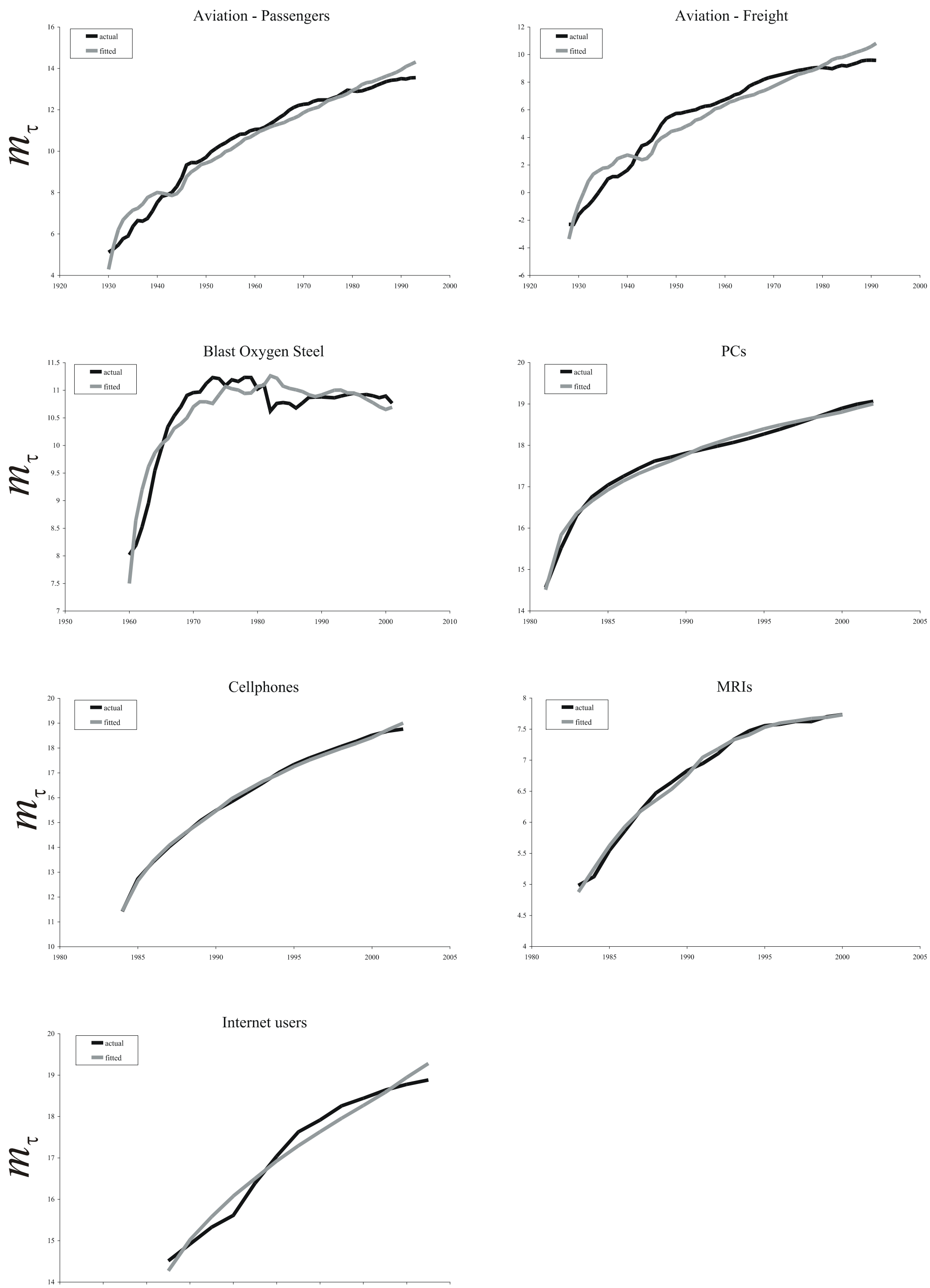

Figure 2: Fit of model to U.S. time series (part 2)

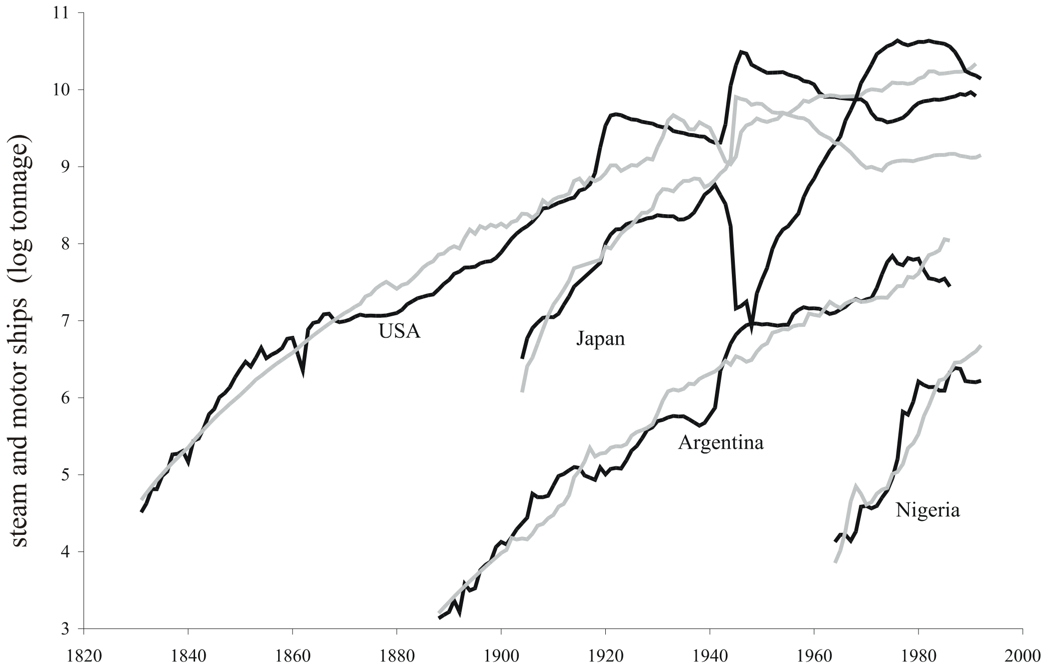

Figure 3: Actual and fitted tonnage of steam and motor ships for four countries

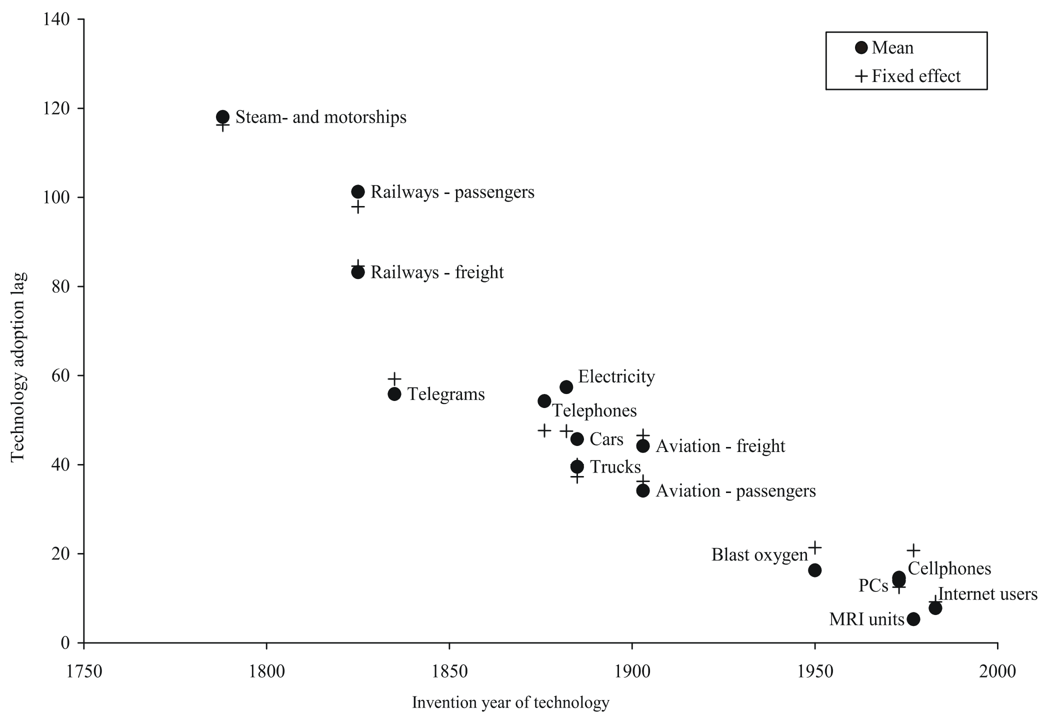

Figure 4: Technology adoption lags decrease for later inventions

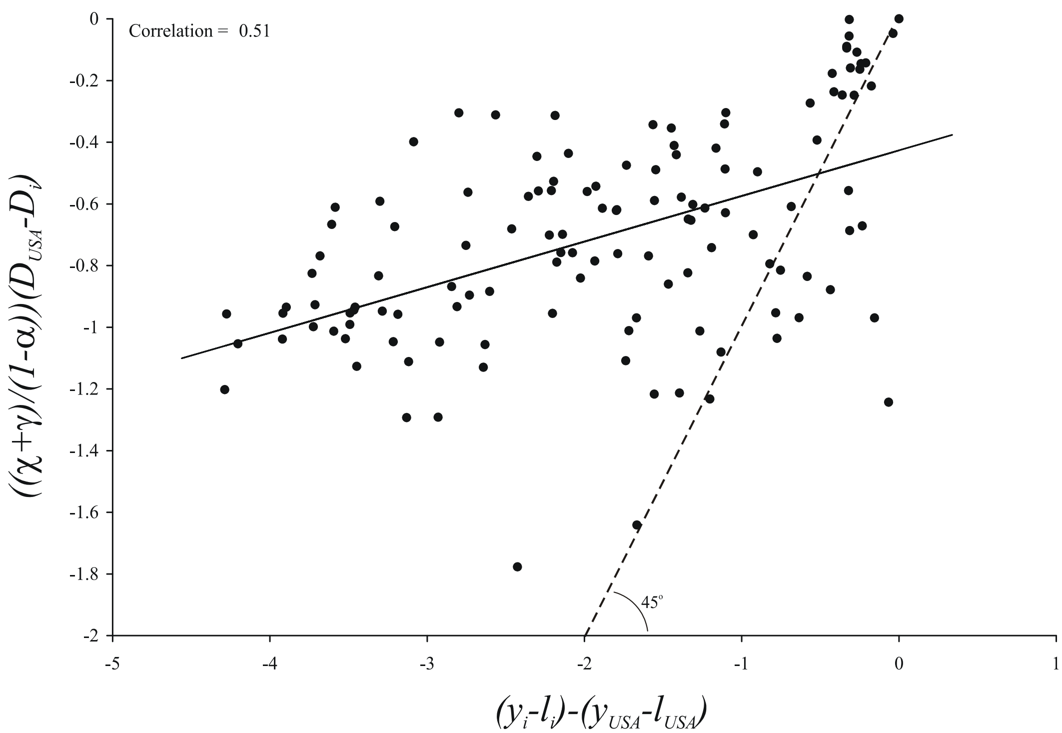

Figure 5: TFP part of technology adoption lags versus real GDP per capita.