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ABSTRACT

We develop and estimate a model where technology diffusion depends on the level of productivity embodied in capital and where this is, in turn, determined by two key mechanisms: the rate at which the quality embodied in new technology vintages increases (embodiment) and the gains from varieties induced by the introduction of new vintages (variety). In our model, these two effects are related to technology adoption decisions taken at two different levels. The capital goods suppliers' decisions of when to adopt a given vintage determines the embodiment margin. The workers' decisions of which of the adopted vintages to use in production determines the variety margin.

Estimation of our model for a sample of 19 technologies, 21 countries, and the period 1870-1998 reveals that embodied productivity growth is large for many of the technologies in our sample. On average, increases in the variety of vintages available is a more important source of growth than the increases in the embodiment margin. There is, however, substantial heterogeneity across technologies. Where adoption lags matter, they are largely determined by lack of educational attainment and lack of trade openness.

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1 Introduction

Most cross-country differences in levels of output per capita are due to differences in the level of total factor productivity (TFP), rather than differences in the levels of factor inputs.[1] These cross-country TFP disparities can be divided into two parts: productivity differences from countries using different ranges of technologies and different levels of efficiency with which technologies are operated.

In this paper, we assess the relative importance of the economic mechanisms that influence the range of technologies a country uses. In particular, we answer the following two questions: 'What are the key economic aspects that differ across technologies that influence the speed of diffusion?' and 'What are the key cross-country differences in endowments, institutions, and policies that impinge on technology diffusion?'

We answer these questions by developing and estimating a model of one of the key determinants of technology diffusion, the level of productivity embodied in the capital goods associated with a technology. In our model, agents adopt technologies at two different levels. First, a capital good producer decides whether to incur the fixed cost of adopting a capital good that embodies a new vintage of the particular technology (e.g. the Pentium as a new vintage of microprocessor). As in Parente and Prescott (1994), the size of the adoption costs determine the adoption lag at the country level.

In addition, each worker that uses a given technology (e.g. microprocessors) decides which of the vintages, associated with this technology and available in the country, to use in production (i.e. Pentium vs. Intel IV). Heterogeneity across workers in the productivity of each vintage introduces a smooth adoption of new vintages at the micro level.

These adoption decisions endogenously determine the level and evolution of productivity embodied in the technology. The introduction of vintages with higher embodied productivity raises the overall level of productivity. It also increases the range of vintages available for production. As this range increases, workers obtain a gain from variety, which also raises the average level of productivity embodied in capital.

When the number of available vintages is very small, an increase in the number of varieties has a relatively large effect on embodied productivity. As this number increases, the productivity gains from such an increase decline. This leads to curvature in the embodied productivity level.

This curvature in embodied productivity translates into similar non-linearities in the evolution of available measures of technology, such as the number of units of capital that embody a given technology or the output produced with these units. For each of these technologies, this allows us to estimate the growth rate of productivity embodied in new vintages, as well as the determinants of the costs of adopting new vintages that generate adoption lags.

We estimate the model taking advantage of the historical data set on technology measures from Comin and Hobijn (2004). This data set covers 19 types of technologies, for 21 industrialized countries, over the

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

period 1870 - 1998.

To explore the determinants of adoption lags, we assume that the costs of adopting new vintages are functions of the following variables: human capital, in line with Nelson and Phelps (1966) and Chari and Hopenhayn (1991), the degree of trade openness, as emphasized by Coe and Helpman (1995) and Holmes and Schmitz (2001), the degree of democracy, as proposed by Hall and Jones (1999) and Acemoglu, Johnson, and Robinson (2005), as well as income per capita as a proxy for relative factor endowments, consistent with Basu and Weil's (1998) appropriate technology hypothesis.

We find that for several of our technologies, such as computers, robots, planes, electricity and steel, new vintages embody significantly more productivity than old vintages. In terms of the determinants of the adoption lags, we find that technologies such as PC's, robots and electricity are complementary to human capital in the sense that human capital reduces the adoption lags for these technologies. Trade openness tends to reduce the adoption lags of transportation technologies, such as passenger and cargo aviation as well as sail and motor shipping. Other factors, such as the degree of democracy, do not seem to be very important for explaining the variation in the range of vintages used, but might still affect the intensity with which technologies are used.

Our model of endogenous embodied productivity generates a diffusion path that fits the data quite closely for most of the technologies in our sample. The R^2s are high, even after filtering out the exogenous trends, country fixed effects and interest rate effects that the technology adoption mechanism in our model does not account for.

We find that the average growth rate of embodied productivity over the periods studied is large for most of the technologies in our sample. The relative importance of the two adoption margins, however, varies substantially across technologies. This heterogeneity in the results emphasizes the importance of the multi-technology character of our analysis. On average, the increase in the number of available varieties is a more important source of growth in embodied productivity than the actual productivity embodied in the best adopted vintages.

This paper is related to various strands of the literature. It is closely related to the empirical diffusion literature (Griliches 1957, Mansfield, 1961, Gort and Klepper 1982, among others) which has estimated logistic diffusion curves for a relatively small number of technologies and countries. Our model is consistent with this micro evidence because the workers adoption decisions generate a (quasi) logistic diffusion pattern at the micro level.

The logistic diffusion curve in our model differs from that in the empirical literature because it results from the optimizing behavior of agents. There are two other important factors that differentiate our paper from this literature. First, our approach only requires the use of widely available aggregate data to estimate the diffusion processes. Therefore, our analysis covers more technologies and countries than if we had to rely on scarce micro data.[2] Second, by embedding the micro adoption decisions in a macro model, we can explore their aggregate implications.

This paper is also related to the macro technology adoption literature (i.e. Parente and Prescott 1994, and Basu and Weil, 1998). Contrary to our model, these studies are not based on models of adoption that are sufficiently rich to be brought to the data. As a result, empirical analyses conducted with these models are restricted to calibration exercises.

The rest of the paper is organized as follows. Next we present the model and derive analytical expressions for the diffusion curves that we estimate. Section 3 contains the empirical analysis. Section 4 summarizes our findings and presents directions for future research. For the sake of brevity, many of the mathematical derivations are relegated to the Appendix.

2 Model

The aim of our model is to explain the paths of aggregate measures of capital and output associated with particular types of embodied technologies. For this purpose, we develop a model of endogenous technology in which adoption occurs at two different levels. First, capital goods producers determine when to adopt and start producing capital goods that embody a given level of productivity. Second, workers decide which of the adopted capital goods to use in production.

The model incorporates the following notion of technology. Each type of technology is used to produce a particular good or service. For example, sail ships are used to provide sail shipping services. Of course, not all sail ships are the same. Some sail ships, like clippers, belong to a more advanced technological vintage than others, like schooners. Goods or services produced with similar technologies are aggregated into sectoral output. For example, merchant shipping services are the result of the shipments provided with sail ships, as well as steam and motor ships.

In terms of notation, workers are indexed by l, technology vintages are inxed by v, technology types are indexed by τ, sectors are indexed by s, and time is indexed by t. For example, $Y_{l,t}^{(v)}$ denotes the output worker l produces using technology vintage v at time t, $Y_{v,t}^{(\tau)}$ is the level of output of technology vintage v of technology type τ, $Y_{\tau,t}^{(s)}$ is the output produced with technology type τ in sector s, and $Y_{s,t}$ is the output of sector s, Y_t is aggregate output (i.e. GDP).

We structure the presentation of the model as follows. First, we set up and solve the technology choice problem of the worker. Then we analyze the adoption decision of the capital goods suppliers. Next we

[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 shape of technology diffusion (Manuelli and Seshadri, 2004) for one technology. Our paper differs from these three studies in that (i) it develops a different approach to modeling and estimating the forces that shape technology diffusion and (ii) it covers a wider range of technologies and countries.

explore the aggregate implications of these technology adoption decisions. Finally, we derive the reduced form equations that we estimate and describe our identification strategy.

2.1 Worker's technology choice

A worker that uses technology type τ has to choose which of the available vintages, v, of that type to use. Output is homogenous across vintages of the same technology type. Because this technology choice is essentially a discrete choice, we base our model on the discrete choice problem that is used as the microfoundation of the multinomial logit model. [3]

Let the set of technology vintages among which the worker can choose be given by $v \in \left[\underline{v}_{\tau}^{(s)}, v_{\tau,t}^{(s)}\right] = V_t^{(\tau)}$. Here, $\underline{v}_{\tau}^{(s)}$ reflects the first vintage of technology type τ that was ever introduced and $v_{\tau,t}^{(s)}$ reflects the most recent and modern vintage of technology type τ provided to workers at time t. Let the level of output that worker l would produce using vintage v at time t equal

$$Y_{l,t}^{(v)} = \left(Z_v^{(\tau)} e^{\varepsilon_{l,t}^{(v)}}\right)^{1-\alpha} \left(K_{l,t}^{(v)}\right)^{\alpha}, \text{ where } 0 < \alpha < 1 \tag{1}$$

where $K_{l,t}^{(v)}$ is the number of units of the vintage specific capital good, $Z_v^{(\tau)}$ is the level of productivity embodied in capital of vintage v and $\varepsilon_{l,t}^{(v)}$ is an idiosyncratic, time, worker, and vintage specific productivity shock.

Capital goods of vintage v are rented at the rental rate $R_{v,t}^{(\tau)}$ and the technology type specific price of output is given by $P_{\tau,t}^{(s)}$. Conditional on the productivity shock $\varepsilon_{l,t}^{(v)}$, the technology level, $Z_v^{(\tau)}$, the rental rate, $R_{v,t}^{(\tau)}$, and the output price, $P_{\tau,t}^{(s)}$, a worker using technology vintage v chooses the level of the capital input, $K_{l,t}^{(v)}$, to maximize revenue minus rental expenses, which we denote by

$$\Pi_{l,t}^{(v)} = P_{\tau,t}^{(s)} Y_{l,t}^{(v)} - R_{v,t}^{(\tau)} K_{l,t}^{(v)} \tag{2}$$

The profit-maximizing level of the capital input is such that rental expenditures exhaust a fraction α of revenue.

Therefore, the surplus that the worker produces when he uses technology vintage v (i.e. $\Pi_{l,t}^{(v)}$) is a fraction $(1-\alpha)$ of total revenue. Hence, the worker will choose that technology that maximizes revenue. The worker's technology choice is assumed to not affect the equilibrium price level, so this is equivalent to choosing the technology vintage that maximizes output.

Mathematically, this means that, conditional on the sequence of productivity shocks $\left\{\varepsilon_{l,t}^{(v)}\right\}_{v \in V_t^{(\tau)}}$, the vintage productivity levels and rental rates $\left\{Z_v^{(\tau)}, R_{v,t}^{(\tau)}\right\}_{v \in V_t^{(\tau)}}$, and the output price $P_{\tau,t}^{(s)}$, a worker l employed in technology type τ chooses the vintage v that satisfies

$$Y_{l,v}^{(v)} \geq Y_{l,v'}^{(v')} \text{ for all } v' \in V_t^{(\tau)} \tag{3}$$

[3] This is commonly referred to as the ARUM, or Additive Random Utility Model (Anderson, de Palma, and Thisse, 1992).

This implies that the worker-specific productivity shock for the technology that the worker chooses, i.e. v, has to satisfy

$$\overline{y}^{(\tau)}_{v',t} + \varepsilon^{(v')}_{l,t} \leq \overline{y}^{(\tau)}_{v,t} + \varepsilon^{(v)}_{l,t} \text{ for all } v' \in V^{(\tau)}_t \tag{4}$$

where

$$\overline{y}^{(\tau)}_{v,t} = \frac{\alpha}{1-\alpha}\ln\alpha + \frac{\alpha}{1-\alpha}p^{(s)}_{\tau,t} - \frac{\alpha}{1-\alpha}r^{(\tau)}_{v,t} + z^{(\tau)}_{v} \tag{5}$$

and small letters denote natural logarithms. $\overline{Y}^{(\tau)}_{v,t}$ is the worker's supply function at $\varepsilon^{(v)}_{l,t} = 0$.

The actual distribution of choices made depends on the distribution of the shocks. We assume that the worker-specific technology shocks are identically distributed for all workers, vintages, and points in time, according to a double exponential distribution. That is,

$$F(x) = \Pr\left[\varepsilon^{(v)}_{l,t} \leq x\right] = \exp\left(-\exp\left(-\frac{x}{\mu}\right)\right), \text{ where } \mu > 0 \tag{6}$$

where the variance of the shocks is increasing in μ.

The probability that vintage v satisfies (4) and that the associated productivity shock equals $\varepsilon^{(v)}_{l,t}$ is

$$\pi\left(v, \varepsilon^{(v)}_{l,t}\right) = \frac{1}{\mu}\exp\left[-\frac{\varepsilon^{(v)}_{l,t}}{\mu} - \exp\left(-\frac{\varepsilon^{(v)}_{l,t}}{\mu}\right)\int_{v'\in V^{(\tau)}_t}\exp\left(-\frac{\overline{y}^{(\tau)}_{v,t} - \overline{y}^{(\tau)}_{v',t}}{\mu}\right)dv'\right] \tag{7}$$

Because there is a continuum of vintages, this is not a proper probability but can better be interpreted as our continuous vintage approximation to the finite number of vintages case.[4]

This interpretation gives the probability that a worker will choose technology v as

$$S^{(\tau)}_{v,t} = \int_{-\infty}^{\infty}\pi\left(v, \varepsilon^{(v)}_{l,t}\right)d\varepsilon^{(v)}_{l,t} = \frac{\left(\overline{Y}^{(\tau)}_{v,t}\right)^{\frac{1}{\mu}}}{\int_{v'\in V^{(\tau)}_t}\left(\overline{Y}^{(\tau)}_{v,t}\right)^{\frac{1}{\mu}}dv'} \tag{8}$$

By the law of large numbers, this probability equals the share of workers using technology τ who choose vintage v, which is why we denote it by $S^{(\tau)}_{v,t}$. These share equations are the same as those implied by the optimal demand of each technology vintage when the production function is a CES aggregate of the continuum of vintages.[5]

In this context, $1/\mu$ can be interpreted as the elasticity of substitution of technology vintages. Intuitively, the smaller the variance of the idiosyncratic productivity shocks, the more the demand responds to changes in the relative average productivity level $\overline{Y}^{(\tau)}_{v,t}$ of vintage v and the more quickly workers substitute away toward other technology vintages in response to a change in $\overline{Y}^{(\tau)}_{v,t}$ relative to that of other vintages.

[4]In practical applications, discrete choice models consider the choice over a finite number of choices, and the choice for which the random utility is maximized is well-defined. Because we aim to implement the worker's technology choice decision into a more general equilibrium framework, our model is such that the set of available vintages contains a continuum of choices and, because of that, in principle, the worker obtains an unbounded level of productivity.

[5]In this sense, we are using the production function equivalent of the result that aggregate CES preferences can be interpreted as the result of underlying individual agents facing a discrete choice problem. See Feenstra (1995) and Anderson, de Palma, and Thisse (1992) for both applications and derivations of this result on the consumer side.

Let $L^{(s)}_{\tau,t}$ be the number of workers who use technology type τ in sector s at time t. The number of workers that use vintage v is then given by

$$L^{(\tau)}_{v,t} = S^{(\tau)}_{v,t} L^{(s)}_{\tau,t} \tag{9}$$

The corresponding level of output produced with vintage v is

$$Y^{(\tau)}_{v,t} = C L^{(s)}_{\tau,t} \left(\overline{Y}^{(\tau)}_{v,t}\right) \left(S^{(\tau)}_{v,t}\right)^{1-\mu} \tag{10}$$

where the constant C depends only on μ.

As we show in Appendix A, output produced using a particular technology type is represented by a CES production function in the sense that

$$\begin{aligned} Y^{(s)}_{\tau,t} &= \left(C L^{(s)}_{\tau,t}\right) \left[\int_{v \in V^{(\tau)}_t} \left(\overline{Y}^{(\tau)}_{v,t}\right)^{\frac{1}{\mu}} dv\right]^{\mu} \\ &= \alpha^{\frac{\alpha}{1-\alpha}} \left(C L^{(s)}_{\tau,t}\right) \left(P^{(s)}_{\tau,t}\right)^{\frac{\alpha}{1-\alpha}} \left[\int_{v \in V^{(\tau)}_t} \left(Z^{(\tau)}_v \Big/ \left(R^{(\tau)}_{v,t}\right)^{\frac{\alpha}{1-\alpha}}\right)^{\frac{1}{\mu}} dv\right]^{\mu} \end{aligned} \tag{11}$$

This equation illustrates the three sources of productivity growth in our model: (i) The increasing number of varieties, as in Romer (1990), is reflected by the size of the set of technology vintages, $V^{(\tau)}_t$, adopted in the country; (ii) investment specific technological change, similar to Greenwood, Hercowitz, and Krusell (1997)[6], is reflected by the increases in output due to declines in $R^{(\tau)}_{v,t}$; and (iii) embodied technological change is reflected in the different levels of total factor productivity for different vintages, $Z^{(\tau)}_v$.

2.2 Adoption at the aggregate level

Every instant, a constant number of new technology vintages is invented in the world. The most recently invented vintage, which we denote by $\overline{v}^{(s)}_{\tau,t}$, is the world technology frontier. Without loss of generality we assume that $\overline{v}^{(s)}_{\tau,t} = t$. As in Johansen (1959) and Solow (1960), newer vintages are technologically superior to older ones. In particular, the productivity embodied in vintage v is

$$Z^{(\tau)}_v = Z^{(\tau)}_{\underline{v}_\tau} \exp\left(\gamma^{(s)}_\tau \left(v - \underline{v}^{(s)}_\tau\right)\right), \tag{12}$$

where $\gamma^{(s)}_\tau > 0$ denotes the growth rate of embodied productivity.

A newly invented vintage is not available for production in the economy until a capital good supplier adopts it. Let $v^{(s)}_{\tau,t}$ be the most advanced vintage adopted, then the adoption lag in technology τ is

[6] Under the assumptions in Greenwood, Hercowitz, and Krusell (1997), embodied technological change and investment-specific technological change are not separately identifiable, and capital can be defined in terms of quality-adjusted units such that there is only investment specific technological change. Because we measure particular types of units of capital, like cars, telephones or merchant ships, such quality adjustment assumptions are not applicable to our empirical analysis. Therefore, we will explicitly distinguish between these two types of technological progress in our model.

$$D_{\tau,t}^{(s)} = t - v_{\tau,t}^{(s)} \geq 0 \tag{13}$$

and the set of vintages available for production is

$$V_t^{(\tau)} = \left[\underline{v}_\tau^{(s)}, v_{\tau,t}^{(s)}\right]. \tag{14}$$

Producers of capital goods have a patent on the technology that enables them to produce a particular vintage of capital good, v, at the unit production cost $Q_{v,t}^{(\tau)}$. This production process is assumed to be reversible. We assume that the production cost, $Q_{v,t}^{(\tau)}$, is the same across technology vintages and that $Z_{v,t}^{(\tau)}$ distinguishes these vintages. More specifically, we assume that

$$Q_{v,t}^{(\tau)} = Q_{\tau,t}^{(s)} \text{ and } \dot{Q}_{\tau,t}^{(s)}/Q_{\tau,t}^{(s)} = -q_\tau^{(s)} \tag{15}$$

The producers choose the path of rental rates $R_{v,t}^{(\tau)}$ to maximize the present discounted value of their profits, which equals

$$\int_t^\infty e^{-\int_t^s r_{s'}ds'} \left(R_{v,s}^{(\tau)} K_{v,s}^{(\tau)} - Q_{\tau,s}^{(s)} I_{v,s}^{(\tau)}\right) ds \tag{16}$$

subject to the capital accumulation equation

$$\dot{K}_{v,t}^{(\tau)} = I_{v,t}^{(\tau)} - \delta_\tau^{(s)} K_{v,t}^{(\tau)} \tag{17}$$

and the demand function for $K_{v,t}^{(\tau)}$ implied by the capital input decisions made by the workers that use technology type τ.

As we show in Appendix A, the monopolist chooses a rental price that equals a gross markup times the technology-vintage-specific user cost of capital. That is, the capital good supplier sets

$$R_{v,t}^{(\tau)} = \frac{1+\eta}{\eta} Q_{\tau,s}^{(s)} UC_{\tau,s}^{(s)}, \text{ where } \eta = \frac{1}{\mu}\frac{\alpha}{1-\alpha} \text{ and } UC_{\tau,t}^{(s)} = \left(r_t + \delta_\tau^{(s)} + q_\tau^{(s)}\right) \tag{18}$$

Here, $1/\eta$ is the net markup of the rental price over the vintage-specific user cost.[7]

The resulting market value of the patent holder for a capital good of vintage v for technology τ at time t is

$$M_{v,t}^{(\tau)} = \frac{1}{\eta} \int_t^\infty e^{-\int_t^s r_{s'}ds'} K_{v,s}^{(\tau)} Q_{\tau,s}^{(s)} UC_{\tau,t}^{(s)} ds = \left(Z_v^{(\tau)}\right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)} \tag{19}$$

where $\widetilde{M}_{\tau,t}^{(s)}$ is technology type but not vintage specific and is derived in Appendix A.

The rental cost decision of the capital good supplier allows us to simplify (11) and write

$$Y_{\tau,t}^{(s)} = \left(Z_{\tau,t}^{(s)} L_{\tau,t}^{(s)}\right)^{1-\alpha} \left(K_{\tau,t}^{(s)}\right)^\alpha \tag{20}$$

where

$$Z_{\tau,t}^{(s)} = C\left[\int_{v \in V_t^{(\tau)}} \left(Z_v^{(\tau)}\right)^{\frac{1}{\mu}} dv\right]^\mu \tag{21}$$

[7] The user cost, $UC_{\tau,t}^{(s)}$, is the same as that derived in Jorgenson (1963).

Thus, we obtain an aggregate Cobb-Douglas production function for the output produced using technology type τ in sector s.[8] The random productivity model at the worker level yields a factor of labor augmenting technological progress $Z^{(s)}_{\tau,t}$ that is a CES aggregate of the underlying vintage specific productivity levels.

2.3 Entry into sector

The idiosyncratic productivity shocks cause uncertainty about an individual worker's labor productivity. Firms act as insurers that insure the workers' idiosyncratic labor productivity risk.by offering a continuum of workers a contract at the competitive wage W_t. Because the firm employs a continuum of workers, it pools their idiosyncratic risks and thus faces no risk over the average labor productivity. Free entry of firms into the sector implies that, in equilibrium, the competitive wage rate equalizes the average profit per worker. That is

$$W_t = (1-\alpha)\frac{P^{(s)}_{\tau,t}Y^{(s)}_{\tau,t}}{L^{(s)}_{\tau,t}} \tag{22}$$

Combining this free entry condition with (20), we find that the implied price level of output of technology type τ in sector s satisfies

$$P^{(s)}_{\tau,t} = \left(\frac{1}{Z^{(s)}_{\tau,t}}\frac{W_t}{(1-\alpha)}\right)^{1-\alpha}\left(\frac{R^{(s)}_{\tau,t}}{\alpha}\right)^{\alpha} \tag{23}$$

which corresponds to the unit production cost function of the Cobb-Douglas production function with factor prices W_t for labor and $R^{(s)}_{\tau,t}$ for capital and a level of labor augmenting technological change equal to $Z^{(s)}_{\tau,t}$.

2.4 Aggregation

To consider the relationship between the adoption of the technologies in our sample and aggregate economic conditions, we need to make some assumptions about how output produced with various technologies aggregates into sectoral output and how sectoral output aggregates into aggregate output. We assume a CES production function for sectoral output, $Y_{s,t}$.[9] That is

$$Y_{s,t} = \left[\sum_{\tau=1}^{n}\left(Y^{(s)}_{\tau,t}\right)^{\frac{\theta_s-1}{\theta_s}}\right]^{\frac{\theta_s}{\theta_s-1}}, \text{ where } \theta_s > 1 \tag{24}$$

Given the technology type production functions that we derived before, we can write the unit production cost of sectoral output as

$$P_{s,t} = \left[\sum_{\tau=1}^{n}\left(\frac{1}{P^{(s)}_{\tau,t}}\right)^{(\theta_s-1)}\right]^{-\frac{1}{(\theta_s-1)}} = \left(\frac{W_t}{(1-\alpha)\,Z_{s,t}}\right)^{1-\alpha}\left(\frac{R_{s,t}}{\alpha}\right)^{\alpha} \tag{25}$$

[8]This is an application of the result in Fisher (1965), who proves the existence of an aggregate capital stock in case of an underlying vintage specific Cobb-Douglas production function.

[9]Note that we could have derived this from first principles as we have done for the technology type production function. This would yield a nested logit.

where

$$Z_{s,t} = \left[\sum_{\tau=1}^{n} \left(Z_{\tau,t}^{(s)} \right)^{(1-\alpha)(\theta_s - 1)} \right]^{\frac{1}{(1-\alpha)(\theta_s-1)}}, \; R_{s,t} = \frac{1+\eta}{\eta} Q_{s,t} UC_{s,t}, \tag{26}$$

and $UC_{s,t}$ and $Q_{s,t}$ are similar CES aggregates.

The second aggregation level determines how sectoral output is related to aggregate output. We assume that aggregate output, is produced using a constant returns to scale production function with the outputs of each of the individual sectors as inputs. We also assume that demand for output of sector s is characterized by a constant elasticity of substitution with respect to aggregate output. That is, the demand function is of the form

$$Y_{s,t} = \left(\frac{P_{s,t}}{P_t} \right)^{-\rho_s} Y_t = P_{s,t}^{-\rho_s} Y_t \tag{27}$$

where ρ_s is the elasticity of substitution, and the price of aggregate output, P_t, has been normalized to 1.

Cost minimization and free entry in the production of the final good implies that, in equilibrium, final good producers make zero profits and total revenue of the final good producers equals their costs of buying sectoral output as intermediate inputs. Because the share of labor equals $(1-\alpha)$ for each intermediate input, so does the aggregate share of labor. As a result,

$$W_t = (1-\alpha) \frac{Y_t}{L_t}. \tag{28}$$

2.5 Equilibrium technology adoption

Technology adoption in our model occurs at two levels. The first is at the aggregate level. That is, capital goods suppliers face a cost of adopting a technology vintage and only choose to incur this cost when the present discounted value of their flow profits is greater than or equal to the adoption cost.

At time t, the present discounted value of the capital good monopolist supplying vintage v is given by (19). We denote the cost of adopting technology vintage v at time t by $A_{v,t}^{(\tau)}$ and assume they are equal to

$$A_{v,t}^{(\tau)} = \left(1 + b_{\tau,t}^{(s)} \right) \left(\frac{Z_v^{(\tau)}}{Z_{\overline{v}_{\tau,t}^{(s)}}} \right)^{\frac{1+\nu}{\mu}} \left(Z_{\overline{v}_{\tau,t}^{(s)}} \right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)}, \text{ where } b_{\tau,t}^{(s)}, \nu > 0 \tag{29}$$

This formulation of the adoption costs contains four terms. The second and third terms reflect the higher cost of adopting technologies that are more sophisticated both relative to the world technology frontier and in absolute terms. The fourth term, $\widetilde{M}_{\tau,t}^{(s)}$, is related to the market value for the technology type and makes the model tractable. For our purposes, the most important term is the first. It reflects additional factors that affect the cost of adopting new technology vintages.

When estimating the model, we make $b_{\tau,t}^{(s)}$ a function of several variables that have been proposed in the literature as important determinants of the size of adoption barriers at the aggregate level. By identifying how $b_{\tau,t}^{(s)}$ depends on these variables, we can understand how these variables affect both the cross-country and the time series costs of technology adoption.

As we show in Appendix A, the best vintage for which $A_{v,t}^{(\tau)} \leq M_{v,t}^{(\tau)}$, which is the best vintage that will be adopted by a capital good supplier at time t is given by

$$\underline{v}_{\tau,t}^{(s)} = \overline{v}_{\tau,t}^{(s)} - D_{\tau,t}^{(s)} = t - D_{\tau,t}^{(s)}, \text{ where } D_{\tau,t}^{(s)} = \frac{\mu}{\nu\gamma_{\tau}^{(s)}} \ln\left(1 + b_{\tau,t}^{(s)}\right) \tag{30}$$

Hence, if $b_{\tau,t}^{(s)} = 0$ then technology type τ is operated at the world technology frontier. The higher $b_{\tau,t}^{(s)}$, the further the adoption of technology type τ lags behind the frontier.[10]

The second level of technology adoption is the technology choice is the individual worker's technology decision. As we derive in Appendix A, in equilibrium, the share of workers who use vintages that are more advanced than $v \geq \underline{v}_{\tau}^{(s)}$ in technology τ equals

$$\Sigma_{v,t}^{(\tau)} = \frac{\Psi\left(t - D_{\tau,t}^{(s)} - \underline{v}_{\tau}^{(s)}; \frac{\gamma_{\tau}^{(s)}}{\mu}\right)}{\Psi\left(t - D_{\tau,t}^{(s)} - v; \frac{\gamma_{\tau}^{(s)}}{\mu}\right)}, \text{ where } \Psi\left(t; g\right) = \frac{1}{1 - e^{-g\max\{t,0\}}} \tag{31}$$

when

$$\underline{v}_{\tau}^{(s)} \leq t - D_{\tau,t}^{(s)} \tag{32}$$

and zero otherwise.

This is an approximately logistic adoption curve at the individual worker level. The difference between this and an actual logistic adoption curve is the starting date term in our curve

$$\Psi\left(t - D_{\tau,t}^{(s)} - v; \frac{\gamma_{\tau}^{(s)}}{\mu}\right) \tag{33}$$

which implies that the share of workers who use the technology before it is invented is zero. This term is absent in an actual logistic curve.

An actual logistic adoption curve, therefore, cannot be the reduced form adoption curve from this model, since it implies that the adoption share is positive at any point in time (it asymptotes to zero for $t \to -\infty$). This would counterfactually imply that technologies are adopted before they are actually invented.[11]

The measure $\Sigma_{v,t}^{(\tau)}$ is very similar to the adoption share measures that are commonly studied in empirical technology adoption studies, like Griliches (1957), Mansfield (1961), Gort and Klepper (1982) and Skinner and Staiger (2005). The crucial difference is that, while the logistic curves used in empirical applications are assumed, the (quasi) logistic evolution of $\Sigma_{v,t}^{(\tau)}$ results from the optimizing behavior of workers confronted with a technology choice.

[10]This formulation does not preclude a corner solution where $\partial \underline{v}_{\tau,t}^{(s)}/\partial t < 0$. This would mean that the best vintage adopted at time t is actually determined by the best vintage adopted before time t and not by $\underline{v}_{\tau,t}^{(s)}$. We abstract from this case and assume that $b_{\tau,t}^{(s)}$ is such that in every period $\partial D_{\tau,t}^{(s)}/\partial t = (\mu/\nu\gamma_{\tau}^{(s)}(1 + b_{\tau,t}^{(s)}))(\partial b_{\tau,t}^{(s)}/\partial t) < 1$.

[11]Comin, Hobijn, and Rovito (2006) estimate logistic adoption curves for many technologies and countries and find that the implied 1% adoption date is often before the actual invention date of the technologies.

2.6 Measures of technology diffusion

The main goal of this paper is to estimate $\gamma_\tau^{(s)}$ and the determinants of $D_{\tau,t}^{(s)}$ to obtain a better understanding of what the key economic mechanisms that influence the diffusion of technology are and what consequences this has for growth and development. Attempts to answer this question using the share measures developed in the empirical diffusion literature and in (31) are likely to be unsuccessful because there is no cross-country data set that reports these measures for a significant number of technologies.

Our approach to estimating $\gamma_\tau^{(s)}$ and $D_{\tau,t}^{(s)}$ instead takes advantage of the model's implications for other measures of technology for which we have data. In particular, we have two technology measures: the number of units of capital goods of a particular technology type, $K_{\tau,t}^{(s)}$, and the amount of output produced with a particular technology type, $Y_{\tau,t}^{(s)}$.

As we derive in Appendix A, our model yields that the logarithms of these measures satisfy

$$\begin{aligned} y_{\tau,t}^{(s)} &= c_y^{(s)} + \theta_s \left((1-\alpha)\, z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)} \right) \\ &\quad + (\rho_s - \theta_s)\left((1-\alpha)\, z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right) \\ &\quad - (1-\alpha)\,\rho_s\,(y_t - l_t) + y_t \end{aligned} \tag{34}$$

and

$$\begin{aligned} k_{\tau,t}^{(s)} &= c_k^{(s)} + (\theta_s - 1) \left((1-\alpha)\, z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)} \right) - q_{\tau,t}^{(s)} - u c_{\tau,t}^{(s)} \\ &\quad + (\rho_s - \theta_s)\left((1-\alpha)\, z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right) \\ &\quad - (1-\alpha)\,(\rho_s - 1)\,(y_t - l_t) + y_t \end{aligned} \tag{35}$$

where $c_y^{(s)}$ and $c_k^{(s)}$ are measure- and sector-specific constants.

These equations are driven by the technology-type-specific levels of embodied productivity, $z_{\tau,t}^{(s)}$, investment-specific technological change, $q_{\tau,t}^{(s)}$, and the user costs, $uc_{\tau,t}^{(s)}$. Our model of adoption presents mechanisms that endogenize $z_{\tau,t}^{(s)}$ and relate it to the terms we want to estimate (i.e. $\gamma_\tau^{(s)}$ and $D_{\tau,t}^{(s)}$). The other two driving forces in equations (34) and (35) are exogenous from the perspective of our model.

In equilibrium, the log-level of embodied productivity in technology type τ in sector s at time t equals

$$z_{\tau,t}^{(s)} = c_{\tau,z}^{(s)} + z_{\underline{v}_\tau^{(s)}}^{(\tau)} + \underbrace{\gamma_\tau^{(s)} \left(t - D_{\tau,t}^{(s)} - \underline{v}_\tau^{(s)} \right)}_{Embodiment} + \underbrace{\mu \ln \left[1 - e^{-\frac{\gamma_{z,\tau}^{(s)}}{\mu}\left(t - D_{\tau,t}^{(s)} - \underline{v}_\tau^{(s)}\right)} \right]}_{Variety} \tag{36}$$

At the heart of our analysis are two mechanisms by which the agents' adoption decisions affect the level of embodied productivity, $z_{\tau,t}^{(s)}$. These are represented by the third and fourth terms in (36). First, as newer vintages with higher embodied productivities are adopted in the economy, the level of embodied productivity increases. The *Embodiment* term in (36) reflects the productivity embodied in the best vintage adopted in the economy. Second, as the range of technology vintages available for production increases, workers are more likely to sample a high ideosyncratic productivity shock, which raises the average level of productivity embodied in capital. The *Variety* term in (36) reflects this variety effect. This term is central to our estimation and identification strategy because it governs the curvature in the embodied productivity level and in the observable measures of technology.

To better understand the different natures of the embodiment and variety effects, it is worthwhile to consider Figure 1. It depicts the profile of vintage productivity levels $z_v^{(\tau)}$ available on the world technology frontier. Of these vintages, only $\underline{v}_\tau^{(s)}$ through $v_{\tau,t}^{(s)}$ have actually been adopted at time t. The embodiment loss is the percentage difference between the productivity of the best vintage available in the world (i.e. $\overline{v}_{\tau,t}^{(s)} = t$) and the productivity embodied in the best adopted vintage (i.e. $v_{\tau,t}^{(s)}$). The effect on $z_{\tau,t}^{(s)}$ of increasing the number of adopted vintages is represented by triangle (a, b, c). The effect of increasing the number of varieties on the world technology frontier is triangle (a, d, e). Hence, the productivity loss from the non-adopted varieties is given by $1 - [area\,(a, b, c)\,/area\,(a, d, e)]$ and is the graphical equivalent of the variety loss.[12]

It is important to note that, for a given adoption lag, the contribution of the variety term to embodied productivity is larger at the initial stages of diffusion. Initially, there are no vintages of a particular technology type available, so the number of varieties grows infinitely fast at the moment of adoption of the first vintage of type τ. As time goes on, the newly adopted vintages make up a smaller and smaller part of the total set of available vintages. Therefore, the growth rate of the variety term declines over time. In the long run, the loss in the variety term from an adoption lag goes to zero, and the only effect that the lag has on productivity is through the reduction in the embodied productivity of the last vintage adopted. The evolution of the importance of the variety effect is what determines the curvature of the productivity embodied in the technology type.

The exogenous variables in (34) and (35), $uc_{\tau,t}^{(s)}$ and $q_{\tau,t}^{(s)}$, evolve as follows: the logarithm of the user cost equals and can be approximated by

$$uc_{\tau,t}^{(s)} = \ln\left(r_t + \delta_\tau^{(s)} + q_\tau^{(s)}\right) \approx \overline{uc}_\tau^{(s)} + \frac{r_t}{\left(\overline{r} + \delta_\tau^{(s)} + q_\tau^{(s)}\right)} \tag{37}$$

while the level of investment specific technological change evolves according to

$$-q_{\tau,t}^{(s)} = -q_{\tau,\underline{v}_\tau^{(s)}}^{(s)} + q_\tau^{(s)}\left(t - \underline{v}_\tau^{(s)}\right) \tag{38}$$

2.7 Reduced form equations

One approach to estimating $\gamma_\tau^{(s)}$ and the determinants of $D_{\tau,t}^{(s)}$ is to substitute (36), (37) and (38) into equations (34) and (35) and estimate $D_{\tau,t}^{(s)}$ and $\gamma_\tau^{(s)}$ for all τ in sector s directly. This approach is overly

[12] In Figure 1, $\gamma_\tau^{(s)}$ is the slope of the world technology frontier. What follows from the figure is that, for a given adoption lag, an increase in $\gamma_\tau^{(s)}$ leads to a higher loss in the embodiment, as well as the variety, effects.

complex, however, because $D_{\tau,t}^{(s)}$ and $\gamma_\tau^{(s)}$ enter these equations non-linearly and because $z_{s,t}$ is a highly non-linear function of the parameters that we would like to estimate.[13]

In order to estimate $\gamma_\tau^{(s)}$ and the determinants of $D_{\tau,t}^{(s)}$ we proceed as follows. We avoid the problem with $D_{\tau,t}^{(s)}$ and $\gamma_\tau^{(s)}$ by linearizing (36) around the immediate adoption path in which $D_{\tau,t}^{(s)} = 0$ for all t. Doing so yields

$$z_{\tau,t}^{(s)} \approx \widetilde{c}_{\tau,z}^{(s)} + \gamma_\tau^{(s)} \left(t - \underline{v}_\tau^{(s)}\right) - \mu\psi\left(t - \underline{v}_\tau^{(s)}; g_\tau^{(s)}\right) - \Psi\left(t - \underline{v}_\tau^{(s)}; g_\tau^{(s)}\right) \gamma_\tau^{(s)} D_{\tau,t}^{(s)}, \text{ where } g_\tau^{(s)} = \frac{\gamma_\tau^{(s)}}{\mu} \tag{39}$$

where $\Psi(t;g)$ is as defined in (31) and $\psi(t;g)$ is its logarithm. Here $-\mu\psi(t;g)$ reflects the immediate adoption path around which we log-linearize at every point in time and the adoption lag term reflects the approximate deviation from that path.

We deal with the complications introduced by $z_{s,t}$ in two different ways, depending on whether various technologies are close substitutes in a sector or not.

For some technologies, we have no data on other technologies that are close substitutes. These technologies are interpreted as belonging to a sector with just one technology type. In that case $z_{\tau,t}^{(s)} = z_{s,t}$, $q_{\tau,t}^{(s)} = q_{s,t}$, and $uc_{\tau,t}^{(s)} = uc_{s,t}$, so (34) simplifies to

$$\left(y_{\tau,t}^{(s)} - y_t\right) = c_y^{(s)} + \rho_s \left((1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha uc_{\tau,t}^{(s)} - (1-\alpha)(y_t - l_t)\right) + y_t \tag{40}$$

As we show in Appendix A, the equation for capital, (35), simplifies similarly in this case.

For technologies for which we have data on close substitutes we difference $z_{s,t}$ out of our reduced form equations. If we have two technology types, τ and τ', that we consider close substitutes and therefore belonging to the same sector, s, then (34) implies that

$$\left(y_{\tau,t}^{(s)} - y_{\tau',t}^{(s)}\right) = \theta_s \left[\left((1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha uc_{\tau,t}^{(s)}\right) - \left((1-\alpha) z_{\tau',t}^{(s)} - \alpha q_{\tau',t}^{(s)} - \alpha uc_{\tau',t}^{(s)}\right)\right] \tag{41}$$

Similar equations can be derived for $\left(k_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right)$ and $\left(y_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right)$.[14]

The actual reduced form equations that we estimate are obtained by substituting the linear approximations of the logarithm of the usercost (i.e. (37)) and of the logarithm of the technology types' embodied productivity level (i.e. (39)) into (40) and (41). This yields

$$\begin{aligned} \left(y_{\tau,t}^{(s)} - y_t\right) &= \eta_{c,\tau}^{(1)} + \eta_{T,\tau}^{(1)} t + \eta_{r,\tau}^{(1)} r_t \\ &\quad -\eta_\psi^{(1)} \mu \left[\psi\left(t - \underline{v}_\tau^{(s)}; g_\tau^{(s)}\right) - (y_t - l_t)\right] - \Psi\left(t - \underline{v}_\tau^{(s)}; g_\tau^{(s)}\right) \eta_{\psi,\tau}^{(1)} \gamma_\tau^{(s)} D_{\tau,t}^{(s)} + u_{\tau,t}^{(1)} \end{aligned} \tag{42}$$

where $\eta_\psi^{(1)} = (1-\alpha)\rho_s$. Again, similar equations can be derived for $\left(y_{\tau,t}^{(s)} - y_{\tau',t}^{(s)}\right)$, $\left(k_{\tau,t}^{(s)} - y_t\right)$, $\left(k_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right)$ and $\left(y_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right)$.

[13] Recall that this is the logarithm of a CES aggregate of $Z_{\tau,t}^{(s)}$ for all technology types τ in sector s.

[14] Note that, for technologies for which we do not have data on other technologies that are close substitutes, like televisions, we estimate the elasticity of substitution with aggregate demand, ρ_s. For technologies that are close substitutes, like sail and steam- and motorships, we estimate the elasticity of substitution between them, θ_s.

We estimate equation (42) by pooling the observations for countries in our data set. Adoption lags can, in principle, vary by country, over time, and across technologies. To understand what factors determine adoption lags, we assume that $D_{\tau,t}^{(s)}$ is the same function of exogenous variables for all the countries over time. Formally, we impose that

$$\gamma_{\tau}^{(s)} D_{\tau,t}^{(s)} = \frac{\mu}{\nu} \ln\left(1 + b_{\tau,t}^{(s)}\right) = -\boldsymbol{\beta}_{\tau}' \mathbf{x}_{\tau,t} \tag{43}$$

where $\mathbf{x}_{\tau,t}$ is a vector with determinants of the adoption lags. The coefficient vector $\boldsymbol{\beta}_{\tau}$ reflects the marginal embodiment gain in percentages caused by the associated determinant in $\mathbf{x}_{\tau,t}$. A positive coefficient in $\boldsymbol{\beta}_{\tau}$ means that an increase in the associated explanatory variable in $\mathbf{x}_{\tau,t}$ reduces adoption lags and thus the embodiment loss.

2.8 Estimation and identification

The regression equation (42) includes a time trend and a country dummy. The trend captures investment specific technological change. The country-specific fixed effects, $\eta_{c,\tau}$, captures a potential country fixed effect in the productivity embodied in the technology type and differences in units of measurement across countries in some of the dependent variables[15]. The inclusion of these terms prevents us from identifying the adoption lags through the relative intensity of use of a technology in a country or by the trends in the technology measure.

The identification of $\gamma_{\tau}^{(s)}$ and the determinants of $D_{\tau,t}^{(s)}$ instead exploits the curvature of the adoption paths and the different timing of this curvature across countries. More precisely, the growth rate of embodied technological change is identified by estimating the non-linear trend component $\Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)$ and its logarithm $\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)$ in the reduced form equation (42). Intuitively, $\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)$ reflects the evolution of the gains from variety in the world technology frontier; the faster embodied productivity growth, the higher the curvature implied by the gains from variety term. From the curvature of this function, we can identify $g_{\tau}^{(s)} = \gamma_{\tau}^{(s)}/\mu$. For a given calibrated value of μ, this pins down our estimate of the growth rate of embodied technological change in the technology type τ, $\gamma_{\tau}^{(s)}$.

The effect of the variables in $\mathbf{x}_{\tau,t}$ on the adoption lags is identified by the cross-country variation in curvature and by the time series variation in curvature that is not predicted by the curvature of the world technology frontier. These marginal embodiment gain parameters are jointly identified with the elasticity parameter η_{ψ}. This is not a problem for the identification of $\boldsymbol{\beta}_{\tau}$, however, because η_{ψ} can be estimated by the effect of $\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)$ on our measures of adoption, while $\eta_{\psi}\boldsymbol{\beta}_{\tau}$ is identified through the effect of $\Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)$.

This highlights the importance of modelling the adoption decision at the worker level. It is exactly this microfoundation that yields the logistic function $\Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)$ and its logarithm that identify the

[15] We know, for example, that what is classified as an industrial robot tends to differ across the countries in our sample.

parameters of interest in our aggregate reduced form equations.

Figure 2 illustrates our approximation and identification approach graphically. It plots the immediate adoption path that we use as the time-varying approximation path for our adoption paths, as well as an adoption path that is subject to a constant adoption lag, $D_{\tau}^{(s)}$. It emphasizes two main points. First, what matters for the adoption lags is how far the adoption path is from the long run linear trend. This distance is determined by the curvature of the path. Thus, it is exactly the curvature in the adoption path that we use to identify the adoption lags. Second, the adoption lags are quantified using the log-linear approximation, which is also illustrated in the figure. Because of the highly non-linear nature of the adoption curve, this approximation works better when $t - \underline{v}_{\tau}^{(s)}$ is large.

3 Empirical results

In this section, we present the data used in the empirical analysis and the estimates we obtain for $\gamma_{\tau}^{(s)}$ and the determinants of $D_{\tau,t}^{(s)}$ for each technology type, τ. We discuss the estimates, then use them to explore the importance of the embodied mechanisms emphasized in our model for technology diffusion and growth. We do that by: (i) exploring the goodness of fit of the estimated adoption measures; (ii) computing the actual growth in the productivity embodied in technology type τ, $z_{\tau,t}^{(s)}$; and (iii) reporting the cross-country dispersion in productivity embodied in each technology type.

3.1 Data

We use technology adoption data from Comin and Hobijn (2004) which covers 19 types of technologies, τ, for 21 industrialized countries, j, over the period 1870 - 1998, t. We have classified these technologies into thirteen sectors, s. Table 1 lists the countries, sectors and technology types in our dataset. It also contains the year that we use as the invention date, $\underline{v}_{\tau}$, for our estimation, as well as whether the measure is an output measure, Y, or a capital stock measure, K. The set of technologies we cover varies from electricity, to textile spindles, to cars, to personal computers.

The historical nature of our technology adoption measures limits us to using only explanatory variables for which we have long historical time series for the countries in our sample.

The main determinants that we allow for in the vector with explanatory variables, $\mathbf{x}_{\tau,t}$, can be classified into four groups: (i) human capital, (ii) openness and trade, (iii) quality of institutions and (iv) relative level of overall advancement. The variables that we use are listed in Table 2.

The human capital variables are the average primary, secondary, and tertiary school enrollment rates of the last ten cohorts that are at least 18 years old in year t. For tertiary enrollment, we only have data from 1960 onwards and, thus, we only include tertiary enrollment as an explanatory variable for technologies mainly adopted after 1960.

The idea that skills and human capital can influence technology adoption dates back to at least Nelson and Phelps (1966). Nelson and Phelps (1966) argue that human capital might matter for how far you are off the frontier, as well as how quickly you converge to it. These two mechanisms are also present in our model if human capital reduces adoption lags. That is, highly educated countries suffer a smaller embodiment loss from the adoption lags. In addition, a smaller adoption lag speeds up the elimination of the loss from having a smaller variety of vintages available for production and, therefore, leads to faster convergence.

In addition to the theoretical motivation for including human capital measures in $\mathbf{x}_{\tau,t}$, there is ample evidence, both on the aggregate (Benhabib and Spiegel, 1994) and microeconomic levels (Doms, Dunne, and Troske, 1999 and Caselli and Coleman, 2001), that countries and organizations with more higly educated workers are better able to adopt and absorb more advanced technologies.

Our proxy for openness and trade is defined as imports plus exports as a percentage of GDP. There are two channels through which trade might affect adoption lags. First, as Holmes and Schmitz (2001) argue, the increased foreign competition reflected in trade induces faster domestic technology adoption. Second, trade causes knowledge spillovers. Coe and Helpman (1995) provide evidence that suggests that this is the case for R&D. Such spillovers would likely reduce adoption costs and thus reduce adoption lags as well.

We approximate the quality of institutions by the Polity score, taken from Marshall and Jaggers (2002). We renormalize this score such that 0 reflects a totalitarian autocracy and 1 indicates full democracy. There is widespread evidence, including Hall and Jones (1999) and Acemoglu, Johnson, Robinson (2005), that the quality of institutions matters for development. That institutions matter for development does not mean that they matter for technology adoption, however. If institutional quality across the board increases the productivity of all capital goods in place, it will likely not affect the set of technologies used in production. What matters for adoption is that institutions either affect the barriers to adoption or affect the relative productivity levels of newer technologies.

When interpreting our results for institutions, one has to bear in mind that our analysis is limited to a sample of 21 of the world's industrialized leaders. For these countries, there is a lot of variation in the quality of their institutions before WWII. After 1945, however, the Polity variable exhibits little cross-country variation. We therefore do not include our institutional quality proxy for technologies that are mainly adopted after 1945.

The last control that we include in $\mathbf{x}_{\tau,t}$ is the level of GDP per capita relative to the US. This captures the idea that relatively advanced countries are more likely to have the appropriate resources and endowments necessary for the adoption of the newest technologies. This is in the spirit of Basu and Weil's (1998) appropriate technology hypothesis.

Finally, our reduced form equation (42) includes a measure of the real interest rate to account for user cost effects on the demand for capital. We measure these by the U.S. ex-post real interest rates.[16]

[16] It is constructed using the sources listed in Table 2.

3.2 Parameter estimates and fit

The results that we present are obtained by the estimation of (42) using non-linear generalized least squares. We use generalized least squares to allow the variance of the residuals, $u_{\tau,t}$, to vary by country. The estimation method we use can be interpreted as nonlinear GMM with deterministically trending variables, as described in Andrews and McDermott (1995), and we use their results to calculate standard errors.

The parameters in our reduced form equations can be classified into three categories. The first is the set of parameters that we calibrate. The second are the reduced form parameters that we estimate, but that do not provide us with information about adoption lags. The third are the parameters that we estimate and that allow us to quantify adoption lags.

We calibrate two parameters, α and μ. We set $\alpha = 0.3$, to match the 70 percent average post-war labor share in the U.S. non-farm business sector. As shown in the Appendix A, we set $\mu = 3/14$ to match the average corporate profit rate of 10 percent observed in the US since 1945.

The second set of parameters contains those reduced form parameters that do not directly pertain to adoption lags. These are the country fixed effects, $\eta_{c,\tau}$, the trend parameter $\eta_{T,\tau}$, the user cost parameter $\eta_{r,\tau}$, and the demand elasticity parameter $\eta_{\psi,\tau}$. Because we focus on adoption lags, we do not report these estimates.

The estimated parameters of interest are the growth rate of embodied technological change, $\gamma_{\tau}^{(s)}$, and the marginal effect of our explanatory variables on the embodiment gain, $\boldsymbol{\beta}_{\tau}$. We present our results in three tables, each covering a subset of technologies. Table 3 covers transportation related technologies, Table 4 covers communication technologies, and Table 5 covers manufacturing technologies and electricity.

For example, consider the first column (I) of Table 3. The results in this column are for passenger aviation. Our sample for this technology starts in 1920, ends in 1993 and covers 21 countries. The approximation path is based on a 1919 invention date. R^2 and "R^2 detrended" are measures of the goodness of fit. The estimated growth rate of embodied technological change is 1.17 percent, which is the implied rate at which the quality embodied in new passenger planes increases per year. The marginal effect of secondary enrollment is that a 1 percent increase in secondary enrollment reduces adoption lags such that the quality of the best adopted vintage increases by 0.45%. Similarly, a 1 percent increase in relative GDP increases the quality of the best adopted vintage by 0.80 percent.

We start by considering the estimated rates of embodied technological change. The first observation is that, for 14 of our 19 technology types, we obtain estimates of the rate of embodied productivity that are significantly different from zero. The three highest rates of embodied technological change are estimated in personal computers (4.89 percent), trucks (2.86) and robots (2.13). The technologies for which we obtain an insignificant estimate of $\gamma_{\tau}^{(s)}$ are cars, radios, televisions, and ring and mule spindles. Taken literally, these estimates imply that all technological progress for these technologies is investment-specific and not embodied.

There are, however, three other likely reasons why these estimates are not significant. First, if a technology diffuses very quickly, like televisions, for example, there are too few years for which the curvature through which we identify the rate of embodied technological change drives the technology adoption path. Second, if there are very large adoption lags, the approximation we use might not be appropriate, and the estimated rate of embodied technological change is likely to be biased downward to fit the average adoption path across countries. Finally, if a technology is relatively old, like the spindle types for the textiles technologies, then the curvature and thus the rate of embodied technological change is hardly detectable by the time the sample starts.

The growth rates of embodied technological change determine the average adoption approximation path, but do not fit any cross-country variation in adoption patterns. Cross-country variation is fitted by either the country fixed effects or by the adoption lag covariates included in the vector $\mathbf{x}_{\tau,t}$. There are three positive observations we make based on our results obtained using the covariates.

First, as one would expect, we tend to find the highest embodiment gains from education, trade, institutions, and relative advancement for technologies that also have the highest rates of embodied technological change. That is, our estimates are consistent with the implication of our theory that a reduction of adoption lags yields higher productivity gains for technologies where the quality of new vintages grows faster. In our sample, this is particularly clear for aviation, personal computers, and robots.

Second, we find that the most significant effects, both economically and statistically, are for education. Educational attainment seems to significantly reduce adoption lags for technologies that were mainly adopted in the post war period, like aviation, personal computers and robots. Further, the effect of education on the adoption of these technologies seems to be mainly through secondary and tertiary education. This evidence is consistent with the view of skill-biased technological change becoming increasingly important in recent decades. We also find a large effect of secondary education on the adoption of electricity. For older technologies, like trucks and telephones, we find that primary education significantly reduces adoption lags; however, these effects are not economically significant.

Third, openness seems to matter mainly for transportation technologies. This suggests that what drives the effect of openness on adoption is not spillovers but competitiveness concerns that might reduce barriers to adoption, as argued by Holmes and Schmitz (2001). Openness also has a significant effect on electricity adoption lags. This, however, seems to be driven by the fact that larger, less open economies, like the United States, United Kingdom and Germany, were more rapid adopters of electricity.

Finally, there are several technologies for which our covariates are neither economically nor statistically significant. This is true for passenger transportation, telecommunication, and as well as steel and textiles. This insignificance may result from three very different reasons. First, if we believe in the estimate, this implies that for such technologies educational attainment, trade, institutions, and relative advancement do not matter much for adoption lags. That is, in countries with better educated workers, people might still use more phones but they simply do not seem to use a different distribution of phone vintages. Second, we use historical data to construct educational attainment and openness measures for the pre-war period. The earlier data for the explanatory variables in our sample are likely to be more imprecise, biasing the estimated coefficients to zero. Third, for textiles and steel, we only have very short samples that cover periods much more recent than the invention date. As a consequence, our sample misses the curvature in the measures of these technologies, and in these cases we would expect our empirical strategy to be less appropriate.

After exploring the determinants of the adoption lags, it is worthwhile to consider how well our theory of the evolution of technology fits the data.

Figures 3 through 7 depict the actual and fitted adoption paths for various technologies for the US, Japan, France, the UK and Germany. The technologies plotted are personal computers, electricity, telecommunications, cargo aviation and merchant shipping. In these plots, the adoption path for each country is represented by a line wih a different marker. Actual data is represented by solid lines, while fitted data is represented by dashed lines.

The first observation from these plots is that the model seems to fit the curvature of the actual adoption paths well. For all the technologies, the markers for fitted and actual data are closely aligned.

There are a few cases where the model fit seems to be less satisfactory. For computers, for example, the model does not seem to capture the cross-country variation in the curvature of the adoption path. In the US and Japan, the model does not generate sufficient curvature to match the very fast diffusion of computers. A larger growth rate of embodied productivity would have generated this extra curvature but would fail to capture the lower curvature displayed by the paths of computers in Germany and France. That could, in principle, be matched if the newest vintages adopted in France and Germany at any moment of time were closer to the world technology frontier. But the structure we have imposed on the relationship between the adoption lags and our vector of covariates restricts the cross-country variation that the model can generate in the adoption lags.

The R^2 is a more systematic way of reporting the goodness of fit of our model. The R^2 lines in Tables 3, 4 and 5 list the R^2 for these curves. These measures are all very high, and have a median of 0.989. This very high R^2, however, is driven in large part by the trends and country fixed effects that the econometric model includes. In this sense, they are artificially inflated, and it is difficult to conclude that the mechanisms emphasized by our model do a good job at explaining the diffusion paths on the basis of these R^2s.

A more informative measure of the model's ability to fit the evolution of the adoption measures involves computing the fraction of the sum of squares that remains after the fixed effect, trend and interest rate effects are filtered out that is explained by the model. This fraction is listed in Tables 3 through 5 as "R^2 detrended." The average detrended R^2 across technologies is 0.63, with a median of 0.64. For those technologies with fewer observations, like textiles, steel and robots, we obtain a slightly higher detrended R^2 and those technologies with a bad fit of the curvature, like radios and TV's, have a detrended R^2 lower than

0.5. These goodness of fit measures suggest that our structural model explains a large part of the non-linear features observed in the adoption patterns in the data, and therefore it is quite informative about both the average diffusion curve for a representative technology type and the cross-country variation in the adoption paths.

3.3 Growth in embodied productivity

Part of the interest in understanding the technology adoption processes resides in the belief that technology adoption generates an important part of productivity growth. We are now in a position to explore how much the embodiment and variety mechanisms emphasized by our model contribute to productivity growth and how they determine observed differences in diffusion across technologies.

We use our parameter estimates to compute the time series of productivity embodied in each technology type. More specifically, we compute the time-varying part of the log-level of productivity embodied in a technology type, $\hat{z}_{\tau,t}^{(s)}$, as

$$\hat{z}_{\tau,t}^{(s)} = \overbrace{\gamma_{\tau}^{(s)}\left(t - D_{\tau,t}^{(s)} - \underline{v}_{\tau}^{(s)}\right)}^{\textit{Embodiment Effect}} - \overbrace{\mu\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) - \Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)\gamma_{\tau}^{(s)} D_{\tau,t}^{(s)}}^{\textit{Variety Effect}} \tag{44}$$

Note that the first term in this expression corresponds to the embodiment effect while the last two correspond to the variety effects' influence on the approximation path as well as the linear approximation of the variety effect of the adoption lags from (39). For each technology type, we then compute the average annual increment in $\hat{z}_{\tau,t}^{(s)}$. Let ΔX denote the average annual increment of X. The average annual growth in embodied productivity equals

$$\Delta\hat{z}_{\tau,t}^{(s)} = \overbrace{\gamma_{\tau}^{(s)} - \gamma_{\tau}^{(s)}\Delta D_{\tau,t}^{(s)}}^{\textit{Growth from Embodiment}} \quad \overbrace{- \mu\Delta[\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)] - \Delta[\Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right)\gamma_{\tau}^{(s)} D_{\tau,t}^{(s)}]}^{\textit{Growth from Variety}} \tag{45}$$

The first term in this equation captures the gain in embodied productivity at the world technology frontier. The second term reflects the embodiment gain from catching up with the frontier. These two first terms together correspond to the growth in embodied productivity from the embodiment effect. The third term in (45) captures the growth in embodied productivity from the gains from an increase in variety at the world technology frontier. The last term measures the additional gains from variety when the country is below the frontier. The sum of the third and fourth terms corresponds to the growth in embodied productivity associated with the increase in the number of vintages available for production.

For each technology type, we compute the growth rate of embodied productivity over the interval described in the second column in Table 6. These intervals are selected based on the invention date of the technology, the period over which the technology is relevant for production and the number of countries for which data is available. For example, the interval for telephones and telegrams is 1913-90, while computers' interval is 1980-93. The third column of Table 6 reports the average annual growth rate in the productivity embodied in each technology type over the interval. Columns 4 and 5 decompose this growth rate between growth from the embodiment effect and growth from the variety effect.

The most interesting observation from Table 6 is that, for most technologies, the growth rate of embodied productivity is substantial. The average annual growth rate across technologies is 7.3 percent, and the median is 3.4 percent. For all the technologies in our sample except sail ships and mule spindles the average annual growth rate of productivity embodied in the technology has been over one percent.

The low growth rate of embodied productivity in sail ships and mule spindles results from low growth in both the embodiment and variety effects. The low growth of the embodiment effect is due to the low estimate of $\gamma_{\tau}^{(s)}$ for these technologies. The small gains from the increase in varieties in these technologies stem from the fact that these technologies were invented long before the beginning of the period considered here. Thus there were already many available varieties, so the gains from increasing their number were very small.

The average growth rate of embodied productivity over the relevant period is large for aviation, computers, robots, TV's, electricity, trucks and open hearth steel furnaces. Interestingly, different forces drive the growth in embodied productivity for different technologies. In aviation, for example, the growth rate of embodied productivity is driven mostly by the embodiment effect. The increment in the embodiment component of embodied productivity is driven, in turn, by two factors. First, the high estimate of $\gamma_{\tau}^{(s)}$ for both passenger and cargo aviation implies that new vintages embody substantially more productivity than older vintages. Second, the increase in human capital and in the degree of openness has reduced the average adoption lag in the aviation technologies. This catch up with the world technology frontier in aviation has led to a higher growth rate in the embodiment component of $z_{\tau,t}^{(s)}$.

The case of personal computers is similar to aviation. New vintages of computers embody much more productivity that older vintages, which explains a significant fraction of the growth in the productivity of computers. As with aviation technologies, the average adoption lag in computers has decreased over the period covered by Table 6. In this case, the variable that seems to be responsible for this catch up with the world technology frontier is the increase in tertiary enrollment. However, a very significant fraction of the growth in the productivity embodied in computers also comes from the growth in the variety component. This effect is important despite the large estimate of $\gamma_{\tau}^{(s)}$ for computers because the interval we consider is relatively small and starts shortly after the invention of the technology.

Robots are a case in which most of the growth in embodied productivity comes from the growth in the variety component. Growth in this component is more important for robots than for computers for two reasons. First, the lower estimate of $\gamma_{\tau}^{(s)}$ for robots than for computers implies that the gains from increasing the number of available varieties die out more slowly. As a result, the average growth in the embodied productivity of robots from the increase in the number of robot varieties will be larger than for computers. In addition, the growth in productivity from the increase in the number of robot varieties is larger than for computers because there is a larger average adoption lag in the adoption of robots than in the adoption of computers. That is, the average country is further from the world technology frontier in robots than in computers, and adding more vintages of robots to production significantly increases the average ideosyncratic productivity sampled by the workers. This dissection of the sources of the embodied productivity growth of robots is also an accurate description of the determinants of the growth in embodied productivity in TV's, radios and electricity.

The determinants of the growth in productivity embodied in the remaining technologies in our sample are presented in Table 6. For the sake of brevity, we do not describe them in detail here. What is worthwhile noting is that, on average, the variety effect is more important than the embodiment effect as a source of growth in embodied productivity over the periods and technologies studied here. In terms of the average contribution to embodied productivity across technologies, the split is about 1/4 vs. 3/4. In terms of the median contribution across technologies, the split between embodiment and variety is about 40 percent vs. 60 percent. This large contribution of the variety effect is surprisingly large given the length of the sample periods considered for most of the technologies in our analysis.

3.4 Cross-country disparities in adoption

The final question that we explore in this paper is: 'How important are the two endogenous embodied productivity mechanisms in generating cross-country variation in the level of embodied productivity?'

The sole source of cross-country variation in our model is the covariates that determine the adoption lags, $D_{\tau,t}^{(s)}$. Therefore, the variation in the productivity embodied in technology τ is determined by differences across countries in

$$(1 + \Psi \left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right))\boldsymbol{\beta}_{\tau}' \mathbf{x}_{\tau,t} \tag{46}$$

The above equation measures the loss in embodied productivity due to the adoption lags, both through the embodiment and variety effects.

Columns 3 and 6 of Table 7 report the standard deviation across countries of the log of embodied productivity in each technology in the initial (column 2) and final year (column 5) of the intervals considered in the section 3.3. Columns 4 and 7 report the ratio of the cross-country variation in embodied productivity for each technology relative to the cross-country variation in the log of GDP per capita for the same year and the same countries.

Two main observations emerge from Table 7. The first is that the cross-country dispersion in embodied productivity relative to the dispersion in income per capita is very large for aviation (both cargo and passengers), radios, TV's, PC's, robots and electricity and small for the rest of the technologies in our sample.

These are the technologies with higher estimates of $\gamma_\tau^{(s)}$.[17]

The second observation is that, over time, the cross-country variation in embodied productivity has decreased. Two forces produce this decline. First, the function $\Psi\left(t - \underline{v}_\tau^{(s)}; g_\tau^{(s)}\right)$ declines over time since the variety effect declines with the number of adopted vintages. Second, there has been convergence across the countries in our sample in the determinants of the adoption lags, $D_{\tau,t}^{(s)}$.

The interest of TV's and radios also resides in that they illustrate the ambiguity of the cross-country dispersion in embodied productivity with respect to $\gamma_\tau^{(s)}$. $\gamma_\tau^{(s)}$ has two effects on (46). A higher $\gamma_\tau^{(s)}$ increases the embodiment effect, but decreases the gains from variety, and thus the variety effect. This ambiguity is reflected by the fact that the technologies for which the model predicts a large cross-country variation in embodied productivity include some of the technologies with highest (computers and robots) and lowest (TV's and radios) productivity embodied in new vintages.

4 Conclusion

This paper has presented a vintage capital model that incorporates economic mechanisms that are key for the diffusion paths of technologies. The shapes of these paths are in large part determined by two important components. The first, the embodiment effect, is the rate of embodied technological change, which reflects how much better new technology vintages are than older ones. The second, the variety effect, is the gains from varieties induced by the introduction of new vintages.

The predictions of the model for the curvature of the diffusion path allows us to estimate, for each technology, the rate of productivity embodied in new vintages and the determinants of adoption lags. We have used these estimates to explore the determinants of the variation of the speed of technology diffusion both across technologies and across countries.

Several conclusions are worth noting. First, the model does a satisfactory job at fitting the diffusion curves. Second, the two adoption margins matter differently for different technologies. For some technologies, such as PC's and aviation, the growth rate of productivity embodied in new vintages is large and statistically significant. For others, such as TV's and radios, the fast growth in embodied productivity is mostly driven by the increase in the available number of varieties. Finally, for others, such as electricity and robots, the speed of diffusion has been fast both because of the rapid productivity growth embodied in new vintages and because of the increase in the number of varieties. This heterogeneity in the results emphasizes, in our view, the importance of multi-technology studies.

In terms of the adoption lags, we find that technologies such as PC's, robots and electricity are complementary to human capital in the sense that human capital reduces the adoption lags for these technologies. Openness to trade tends to reduce the adoption lags of transportation technologies. These factors generate

[17] For these technologies, the cross-country variation in the growth rates of embodied productivity is also large.

a substantial cross-country variation in the TFP embodied in technology. Other factors, such as the degree of democracy, might still affect the intensity with which technologies are used, but do not seem to be very important in explaining which technology vintages are being used.

The line of research developed in this paper leaves several doors open for future research. First, it would be interesting to compare the panel of embodied productivity estimates generated from our model with actual data on TFP at the sector level.[18] A second line of research consists of bringing the intensity of use of technologies back into the picture and try to use variation in this margin to test the relevance of various sources of barriers to technology adoption. [19] Finally, it will be interesting to extend this analysis to other technologies and countries. It may well be the case that the factors that impinge on technology adoption in advanced economies are different from those that slow down adoption in poor countries.

[18] One potential difficulty of pursuing this route at this point is the quality of sectoral TFP data.

[19] One exercise along this line is Comin and Hobijn(2005), who use cross-country variation in institutions and cross-technology variation in the presence of close substitute technologies to show that lobbies constitute an important barrier to technology diffusion.

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A Mathematical details

Derivation of equation (10)

For the vintage production function, we obtain

$$\begin{aligned} Y_{v,t}^{(\tau)} &= L_{\tau,t}^{(s)} \int_{-\infty}^{\infty} \pi\left(v, \varepsilon_{l,t}^{(v)}\right) \exp\left(\overline{y}_{v,t}^{(\tau)} + \varepsilon_{l,t}^{(v)}\right) d\varepsilon_{l,t}^{(v)} \\ &= L_{\tau,t}^{(s)} \exp\left(\overline{y}_{v,t}^{(\tau)}\right) \int_{-\infty}^{\infty} \pi\left(v, \varepsilon_{l,t}^{(v)}\right) \exp\left(\varepsilon_{l,t}^{(v)}\right) d\varepsilon_{l,t}^{(v)} \end{aligned} \tag{47}$$

where

$$\begin{aligned} & \int_{-\infty}^{\infty} \pi\left(v, \varepsilon_{l,t}^{(v)}\right) \exp\left(\varepsilon_{l,t}^{(v)}\right) d\varepsilon_{l,t}^{(v)} \\ = & \int_{-\infty}^{\infty} \exp\left(\varepsilon_{l,t}^{(v)}\right) \frac{1}{\mu} \exp\left(-\frac{\varepsilon_{l,t}^{(v)}}{\mu} - \exp\left(-\frac{\varepsilon_{l,t}^{(v)}}{\mu}\right) \frac{1}{S_{v,t}^{(\tau)}}\right) d\varepsilon_{l,t}^{(v)} \\ = & \left(S_{v,t}^{(\tau)}\right)^{1-\mu} e^{-\gamma\mu} \int_0^{\infty} x^{\mu} e^{-x} dx \\ = & \left(S_{v,t}^{(\tau)}\right)^{1-\mu} C, \text{ where } C = e^{-\gamma\mu}\Gamma(1-\mu) \end{aligned} \tag{48}$$

where $\Gamma(1-\mu)$ is the gamma function.

Derivation of equation (11)

For the technology type production function, we obtain

$$Y_{\tau,t}^{(s)} = \int_{v \in V_t^{(\tau)}} Y_{v,t}^{(\tau)} dv = CL_{\tau,t}^{(s)} \int_{v \in V_t^{(\tau)}} \exp\left(\overline{y}_{v,t}^{(\tau)}\right) \left(S_{v,t}^{(\tau)}\right)^{1-\mu} dv \tag{49}$$

Substituting in the solution for the shares, $S_{v,t}^{(\tau)}$, we obtain

$$\begin{aligned} Y_{\tau,t}^{(s)} &= \left[\frac{1}{\int_{v' \in V_t^{(\tau)}} \left(\overline{Y}_{v,t}^{(\tau)}\right)^{\frac{1}{\mu}} dv'}\right]^{1-\mu} \left(CL_{\tau,t}^{(s)}\right) \int_{v \in V_t^{(\tau)}} \left(\overline{Y}_{v,t}^{(\tau)}\right)^{\frac{1}{\mu}} dv \\ &= \left(CL_{\tau,t}^{(s)}\right) \left[\int_{v \in V_t^{(\tau)}} \left(\overline{Y}_{v,t}^{(\tau)}\right)^{\frac{1}{\mu}} dv\right]^{\mu} \end{aligned} \tag{50}$$

Derivation of equation (18):

We derive the capital demand function by combining the result that rental expenses exhaust a fraction α of revenue generated with a particular capital vintage, such that

$$R_{v,t}^{(\tau)} K_{v,t}^{(\tau)} = \alpha P_{\tau,t}^{(s)} Y_{v,t}^{(\tau)} \tag{51}$$

with (11).By substituting (5) in (11), we obtain

$$Y_{\tau,t}^{(s)} = \alpha^{\frac{\alpha}{1-\alpha}} \left(CL_{\tau,t}^{(s)}\right) \left(P_{\tau,t}^{(s)}\right)^{\frac{\alpha}{1-\alpha}} \left[\int_{v \in V_t^{(\tau)}} \left(Z_v^{(\tau)} \Big/ \left(R_{v,t}^{(\tau)}\right)^{\frac{\alpha}{1-\alpha}}\right)^{\frac{1}{\mu}} dv\right]^{\mu} \tag{52}$$

which yields that

$$K_{v,t}^{(\tau)} = \frac{1}{R_{v,t}^{(\tau)}} \frac{\left(Z_v^{(\tau)} \Big/ \left(R_{v,t}^{(\tau)}\right)^{\frac{\alpha}{1-\alpha}}\right)^{\frac{1}{\mu}}}{\left[\int_{v' \in V_t^{(\tau)}} \left(Z_{v'}^{(\tau)} \Big/ \left(R_{v',t}^{(\tau)}\right)^{\frac{\alpha}{1-\alpha}}\right)^{\frac{1}{\mu}}\right]^{1-\mu}} CL_{\tau,t}^{(s)} \alpha^{\frac{1}{1-\alpha}} \left(P_{\tau,t}^{(s)}\right)^{\frac{1}{1-\alpha}}$$

The Lagrangian associated with this problem is

$$\mathcal{L}_{v,t}^{(\tau)} = \int_t^{\infty} e^{-\int_t^s r_{s'} ds'} H_{v,s}^{(\tau)} ds \tag{53}$$

Where the current value Hamiltonian, $H_{v,t}^{(\tau)}$, is given by

$$
\begin{aligned}
H_{v,t}^{(\tau)} \quad = \quad & \left(R_{v,t}^{(\tau)} K_{v,t}^{(\tau)} - Q_{v,t}^{(\tau)} I_{v,t}^{(\tau)}\right) \\
& + \mu_{v,d,t}^{(\tau)} \left[R_{v,t}^{(\tau)} K_{v,t}^{(\tau)} - \frac{\left(Z_v^{(\tau)} \Big/ \left(R_{v,t}^{(\tau)}\right)^{\frac{\alpha}{1-\alpha}} \right)^{\frac{1}{\mu}}}{\left[\int_{v' \in V_t^{(\tau)}} \left(Z_{v'}^{(\tau)} \Big/ \left(R_{v',t}^{(\tau)}\right)^{\frac{\alpha}{1-\alpha}} \right)^{\frac{1}{\mu}} \right]^{1-\mu}} CL_{\tau,t}^{(s)} \alpha^{\frac{1}{1-\alpha}} \left(P_{\tau,t}^{(s)}\right)^{\frac{1}{1-\alpha}} \right] \\
& + \mu_{v,K,t}^{(\tau)} \left[I_{v,t}^{(\tau)} - \delta_\tau^{(s)} K_{v,t}^{(\tau)} \right]
\end{aligned}
\tag{54}
$$

The first order necessary conditions for the solution to this problem are

$$
\text{w.r.t. } R_{v,t}^{(\tau)} \quad : \quad \left(1 + \mu_{v,d,t}^{(\tau)}\right) K_{v,t}^{(\tau)} + \mu_{v,d,t}^{(\tau)} \frac{1}{\mu} \frac{\alpha}{1-\alpha} K_{v,t}^{(\tau)} = 0 \tag{55}
$$

$$
\text{w.r.t. } I_{v,t}^{(\tau)} \quad : \quad \mu_{v,K,t}^{(\tau)} - Q_{v,t}^{(\tau)} = 0 \tag{56}
$$

$$
\text{w.r.t. } K_{v,t}^{(\tau)} \quad : \quad \left(1 + \mu_{v,d,t}^{(\tau)}\right) R_{v,t}^{(\tau)} - \delta_\tau^{(s)} \mu_{v,K,t}^{(\tau)} = r_t \mu_{v,K,t}^{(\tau)} - \dot{\mu}_{v,K,t}^{(\tau)} \tag{57}
$$

This yields

$$
\mu_{v,d,t}^{(\tau)} = -\frac{1}{1 + \frac{1}{\mu} \frac{\alpha}{1-\alpha}} \tag{58}
$$

$$
Q_{v,t}^{(\tau)} = \mu_{v,K,t}^{(\tau)} \tag{59}
$$

$$
R_{v,t}^{(\tau)} = \left(\frac{1}{1 + \mu_{v,d,t}^{(\tau)}} \right) Q_{v,t}^{(\tau)} \left(r_t + \delta_\tau^{(s)} - \frac{\dot{Q}_{v,t}^{(\tau)}}{Q_{v,t}^{(\tau)}} \right) \tag{60}
$$

Because

$$
1 + \mu_{v,d,t}^{(\tau)} = \frac{\frac{1}{\mu} \frac{\alpha}{1-\alpha}}{1 + \frac{1}{\mu} \frac{\alpha}{1-\alpha}} = \frac{\eta}{1+\eta}, \text{ where } \eta = \frac{1}{\mu} \frac{\alpha}{1-\alpha} \tag{61}
$$

We obtain (18) when we substitute that $Q_{v,t}^{(\tau)} = Q_{\tau,t}^{(s)}$.

Derivation of equation (19):

When we solve for the present discounted value of the monopolist profits for the provider of technology vintage v of technology type τ, we obtain

$$
M_{v,t}^{(\tau)} = \frac{1}{\eta} \int_t^\infty e^{-\int_t^s r_{s'} ds'} K_{v,s}^{(\tau)} Q_{\tau,s}^{(s)} UC_{\tau,t}^{(s)} ds \tag{62}
$$

where $K_{v,t}^{(\tau)}$ corresponds to the capital demand of technology vintage v at time t evaluated at the profit maximizing rental price point. That is,

$$
K_{v,s}^{(\tau)} = \frac{\eta}{1+\eta} \frac{\left(Z_v^{(\tau)}\right)^{\frac{1}{\mu}}}{\left[\int_{v' \in V_t^{(\tau)}} \left(Z_{v'}^{(\tau)}\right)^{\frac{1}{\mu}} \right]^{1-\mu}} CL_{\tau,t}^{(s)} \alpha^{\frac{1}{1-\alpha}} \left(P_{\tau,t}^{(s)}\right)^{\frac{1}{1-\alpha}} \frac{1}{Q_{\tau,t}^{(s)} UC_{\tau,t}^{(s)}} \tag{63}
$$

such that we can write the market value as

$$
M_{v,t}^{(\tau)} = \left(Z_v^{(\tau)}\right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)} \tag{64}
$$

where

$$
\widetilde{M}_{\tau,t}^{(s)} = \frac{1}{1+\eta} \int_t^\infty e^{-\int_t^s r_{s'} ds'} \frac{CL_{\tau,s}^{(s)} \alpha^{\frac{1}{1-\alpha}} \left(P_{\tau,s}^{(s)}\right)^{\frac{1}{1-\alpha}}}{\left[\int_{v' \in V_s^{(\tau)}} \left(Z_{v'}^{(\tau)}\right)^{\frac{1}{\mu}} \right]^{1-\mu}} ds \tag{65}
$$

Derivation of equation (23):

Total revenue per worker for technology type τ equals

$$
\frac{P_{\tau,t}^{(s)} Y_{\tau,t}^{(s)}}{L_{\tau,t}^{(s)}} = \left(\frac{\alpha\eta}{1+\eta} \right)^{\frac{\alpha}{1-\alpha}} \left(P_{\tau,t}^{(s)}\right)^{\frac{1}{1-\alpha}} \left(\frac{\left(Z_{\tau,t}^{(s)}\right)^{1-\alpha}}{\left(Q_{\tau,t}^{(s)} UC_{\tau,t}^{(s)}\right)^{\alpha}} \right)^{\frac{1}{1-\alpha}} \tag{66}
$$

This implies that the free entry condition reads

$$W_t = (1-\alpha)\left(\frac{\alpha\eta}{1+\eta}\right)^{\frac{\alpha}{1-\alpha}} \left(P_{\tau,t}^{(s)}\right)^{\frac{1}{1-\alpha}} \left(\frac{\left(Z_{\tau,t}^{(s)}\right)^{1-\alpha}}{\left(Q_{\tau,t}^{(s)} UC_{\tau,t}^{(s)}\right)^{\alpha}}\right)^{\frac{1}{1-\alpha}} \tag{67}$$

Solving this we obtain that the price $P_{\tau,t}^{(s)}$ equals

$$P_{\tau,t}^{(s)} = \left(\frac{1}{(1-\alpha)}\right)^{1-\alpha} \left(\frac{1+\eta}{\alpha\eta}\right)^{\alpha} (W_t)^{1-\alpha} \left(Q_{\tau,t}^{(s)} UC_{\tau,t}^{(s)}\right)^{\alpha} \left[\frac{1}{\left(Z_{\tau,t}^{(s)}\right)^{1-\alpha}}\right] \tag{68}$$

which is equivalent to (23).

Derivation of equation (25):

When we substitute (23) into the CES price aggregate we can write

$$\begin{aligned} P_{s,t} &= \left[\sum_{\tau=1}^{n}\left(\frac{1}{P_{\tau,t}^{(s)}}\right)^{(\theta_s-1)}\right]^{-\frac{1}{(\theta_s-1)}} \qquad (69) \\ &= \left(\frac{1}{(1-\alpha)}\right)^{1-\alpha}\left(\frac{1+\eta}{\alpha\eta}\right)^{\alpha}\left[\sum_{\tau=1}^{n}\left(\frac{\left(Z_{\tau,t}^{(s)}\right)^{1-\alpha}}{\left(Q_{\tau,t}^{(s)} UC_{\tau,t}^{(s)}\right)^{\alpha}}\right)^{(\theta_s-1)}\right]^{-\frac{1}{(\theta_s-1)}} (W_t)^{1-\alpha} \\ &= \left(\frac{1}{(1-\alpha)}\right)^{1-\alpha}\left(\frac{1+\eta}{\alpha\eta}\right)^{\alpha}\frac{(Q_{s,t}UC_{s,t})^{\alpha}}{(Z_{s,t})^{1-\alpha}}(W_t)^{1-\alpha} \end{aligned}$$

where

$$UC_{s,t} = \left[\sum_{\tau=1}^{n}\left(\left[\frac{\left(Z_{\tau,t}^{(s)}\right)^{1-\alpha} \Big/ \left(Q_{\tau,t}^{(s)}\right)^{\alpha}}{(Z_{s,t})^{1-\alpha} \Big/ (Q_{s,t})^{\alpha}}\right]\frac{1}{\left(UC_{\tau,t}^{(s)}\right)^{\alpha}}\right)^{(\theta_s-1)}\right]^{-\frac{1}{\alpha(\theta_s-1)}} \tag{70}$$

and

$$Q_{s,t} = \left[\sum_{\tau=1}^{n}\left(\left[\frac{Z_{\tau,t}^{(s)}}{Z_{s,t}}\right]^{1-\alpha}\left(\frac{1}{Q_{\tau,t}^{(s)}}\right)^{\alpha}\right)^{(\theta_s-1)}\right]^{-\frac{1}{\alpha(\theta_s-1)}} \tag{71}$$

and $Z_{s,t}$ is as defined in the main text.

Derivation of equation (30):

This equation is derived by equating $M_{v,t}^{(\tau)}$ to $A_{v,t}^{(\tau)}$. Before doing so, it is useful to rewrite

$$M_{v,t}^{(\tau)} = \left(Z_v^{(\tau)}\right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)} = \left(\frac{Z_v^{(\tau)}}{Z_{\overline{v}_{\tau,t}^{(s)}}^{(\tau)}}\right)^{\frac{1}{\mu}} \left(Z_{\overline{v}_{\tau,t}^{(s)}}^{(\tau)}\right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)} \tag{72}$$

Equating this market value with the adoption cost yields

$$\left(\frac{Z_v^{(\tau)}}{Z_{\overline{v}_{\tau,t}^{(s)}}^{(\tau)}}\right)^{\frac{1}{\mu}} \left(Z_{\overline{v}_{\tau,t}^{(s)}}^{(\tau)}\right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)} = \left(1+b_{\tau,t}^{(s)}\right)\left(\frac{Z_v^{(\tau)}}{Z_{\overline{v}_{\tau,t}^{(s)}}}\right)^{\frac{1+\nu}{\mu}} \left(Z_{\overline{v}_{\tau,t}^{(s)}}\right)^{\frac{1}{\mu}} \widetilde{M}_{\tau,t}^{(s)} \tag{73}$$

which simplifies to

$$1 = \left(1+b_{\tau,t}^{(s)}\right)\left(\frac{Z_v^{(\tau)}}{Z_{\overline{v}_{\tau,t}^{(s)}}}\right)^{\frac{\nu}{\mu}} = \left(1+b_{\tau,t}^{(s)}\right)\exp\left(-\frac{\nu\gamma_\tau^{(s)}}{\mu}\left(\overline{v}_{\tau,t}^{(s)}-v\right)\right) \tag{74}$$

such that

$$\left(\overline{v}_{\tau,t}^{(s)}-v\right) = \frac{\mu}{\nu\gamma_\tau^{(s)}}\ln\left(1+b_{\tau,t}^{(s)}\right) \tag{75}$$

which can be rewritten in the form (30).

Derivation of equation (31):

We can write

$$\begin{aligned}\Psi_{v,t}^{(\tau)} &= \int_{v}^{\max\left\{t-D_{\tau,t}^{(s)},v\right\}} S_{v',t}^{(\tau)} dv' \\ &= \frac{\int_{v}^{\max\left\{t-D_{\tau,t}^{(s)},v\right\}} Z_{v'}^{(\tau)\frac{1}{\mu}} dv'}{\int_{v''\in V_t^{(\tau)}} Z_{v''}^{(\tau)\frac{1}{\mu}} dv''} = \frac{e^{\frac{\gamma_\tau^{(s)}}{\mu}\max\left\{t-D_{\tau,t}^{(s)},v\right\}} - e^{\frac{\gamma_\tau^{(s)}}{\mu}v}}{e^{\frac{\gamma_\tau^{(s)}}{\mu}\left(t-D_{\tau,t}^{(s)}\right)} - e^{\frac{\gamma_\tau^{(s)}}{\mu}\underline{v}_\tau^{(s)}}} \\ &= \frac{1-e^{-\frac{\gamma_\tau^{(s)}}{\mu}\max\left\{t-D_{\tau,t}^{(s)}-v,0\right\}}}{1-e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t-D_{\tau,t}^{(s)}-\underline{v}_\tau^{(s)}\right)}}\end{aligned} \tag{76}$$

which equals (31).

Derivation of equations (34) and (35):

For the output measure, we obtain from the nested two level CES that

$$Y_{\tau,t}^{(s)} = \frac{Y_{\tau,t}}{Y_{s,t}}\frac{Y_{s,t}}{Y_t}Y_t = \left(\frac{P_{\tau,t}^{(s)}}{P_{s,t}}\right)^{-\theta_s}(P_{s,t})^{-\rho_s}Y_t \tag{77}$$

while for the capital measure our model solution implies that

$$\begin{aligned}K_{\tau,t}^{(s)} &= \alpha\frac{P_{\tau,t}^{(s)}Y_{\tau,t}^{(s)}}{R_{\tau,t}^{(s)}} = \frac{\alpha\eta}{1+\eta}\frac{1}{Q_{\tau,t}^{(s)}UC_{\tau,t}^{(s)}}\frac{P_{\tau,t}^{(s)}Y_{\tau,t}^{(s)}}{P_{s,t}Y_{s,t}}\frac{P_{s,t}Y_{s,t}}{Y_t}Y_t \\ &= \frac{\alpha\eta}{1+\eta}\frac{1}{Q_{\tau,t}^{(s)}UC_{\tau,t}^{(s)}}\left(\frac{P_{\tau,t}^{(s)}}{P_{s,t}}\right)^{1-\theta_s}(P_{s,t})^{1-\rho_s}Y_t\end{aligned} \tag{78}$$

In terms of logarithms, this implies that

$$y_{\tau,t}^{(s)} = -\theta_s\left(p_{\tau,t}^{(s)}-p_{s,t}\right)-\rho_s p_{s,t}+y_t \tag{79}$$

and

$$k_{\tau,t}^{(s)} = \ln\left(\frac{\alpha\eta}{1+\eta}\right)+(1-\theta_s)\left(p_{\tau,t}^{(s)}-p_{s,t}\right)+(1-\rho_s)\,p_{s,t}-q_{\tau,t}^{(s)}-uc_{\tau,t}^{(s)}+y_t \tag{80}$$

Equations (34) and (35) are obtained by substituting in the logarithmic versions of (23) and (25), which imply

$$\left(p_{\tau,t}^{(s)}-p_{s,t}\right) = -\left[\left((1-\alpha)\,z_{\tau,t}^{(s)}-\alpha q_{\tau,t}^{(s)}-\alpha uc_{\tau,t}^{(s)}\right)-\left((1-\alpha)\,z_{s,t}-\alpha q_{s,t}-\alpha uc_{s,t}\right)\right] \tag{81}$$

and

$$p_{s,t} = \alpha\left[\ln(1+\eta)-\ln\eta-\ln\alpha\right]-\left((1-\alpha)\,z_{s,t}-\alpha q_{s,t}-\alpha uc_{s,t}\right)+(1-\alpha)\,(y_t-l_t) \tag{82}$$

such that we can write the equations for $y_{\tau,t}^{(s)}$ and $k_{\tau,t}^{(s)}$ in the form of (34) and (35), where

$$c_y^{(s)} = -\rho_s\alpha\left[\ln(1+\eta)-\ln\eta-\ln\alpha\right] \tag{83}$$

and

$$c_k^{(s)} = \ln\left(\frac{\alpha\eta}{1+\eta}\right)+(1-\rho_s)\,\alpha\left[\ln(1+\eta)-\ln\eta-\ln\alpha\right] \tag{84}$$

Derivation of equation (36):

This follows from

$$\begin{aligned}Z_{\tau,t}^{(s)} &= C\left[\int_{v\in V_t^{(\tau)}}\left(Z_v^{(\tau)}\right)^{\frac{1}{\mu}}dv\right]^{\mu} = C\left[\int_{\underline{v}_\tau^{(s)}}^{t-D_{\tau,t}^{(s)}}\left(Z_{\underline{v}_\tau^{(s)}}^{(\tau)}e^{\gamma_\tau^{(s)}\left(v-\underline{v}_\tau^{(s)}\right)}\right)^{\frac{1}{\mu}}dv\right]^{\mu} \\ &= CZ_{\underline{v}_\tau^{(s)}}^{(\tau)}\left[\int_{\underline{v}_\tau^{(s)}}^{t-D_{\tau,t}^{(s)}}e^{\frac{\gamma_\tau^{(s)}}{\mu}\left(v-D_{\tau,t}^{(s)}\right)}dv\right]^{\mu} = \left(\frac{C\mu}{\gamma_\tau^{(s)}}\right)Z_{\underline{v}_\tau^{(s)}}^{(\tau)}\left[e^{\frac{\gamma_\tau^{(s)}}{\mu}\left(t-D_{\tau,t}^{(s)}-\underline{v}_\tau^{(s)}\right)}-1\right] \\ &= \left(\frac{C\mu}{\gamma_\tau^{(s)}}\right)Z_{\underline{v}_\tau^{(s)}}^{(\tau)}e^{\frac{\gamma_\tau^{(s)}}{\mu}\left(t-D_{\tau,t}^{(s)}-\underline{v}_\tau^{(s)}\right)}\left[1-e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t-D_{\tau,t}^{(s)}-\underline{v}_\tau^{(s)}\right)}\right]\end{aligned} \tag{85}$$

Taking logarithms, we obtain (36) where

$$c_{\tau,z}^{(s)} = \ln C + \ln \mu - \ln \gamma_\tau^{(s)} \tag{86}$$

Derivation of equation (39):

Linearization of (36) around $D_{\tau,t}^{(s)} = 0$ for $t > \underline{v}_\tau^{(s)}$ yields

$$\begin{aligned} z_{\tau,t}^{(s)} &\approx c_{\tau,z}^{(s)} + z_{\underline{v}_\tau^{(s)}}^{(\tau)} + \gamma_\tau^{(s)}\left(t - D_{\tau,t}^{(s)} - \underline{v}_\tau^{(s)}\right) + \mu \ln\left[1 - e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t - \underline{v}_\tau^{(s)}\right)}\right] - \frac{e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t - \underline{v}_\tau^{(s)}\right)}}{1 - e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t - \underline{v}_\tau^{(s)}\right)}} \gamma_\tau^{(s)} D_{\tau,t}^{(s)} \\ &= \left[c_{\tau,z}^{(s)} + z_{\underline{v}_\tau^{(s)}}^{(\tau)}\right] + \gamma_\tau^{(s)}\left(t - \underline{v}_\tau^{(s)}\right) + \mu \ln\left[1 - e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t - \underline{v}_\tau^{(s)}\right)}\right] - \frac{1}{1 - e^{-\frac{\gamma_\tau^{(s)}}{\mu}\left(t - \underline{v}_\tau^{(s)}\right)}} \gamma_\tau^{(s)} D_{\tau,t}^{(s)} \\ &= \widetilde{c}_{\tau,z}^{(s)} + \gamma_\tau^{(s)}\left(t - \underline{v}_\tau^{(s)}\right) - \mu\psi\left(t - \underline{v}_\tau; g_\tau^{(s)}\right) - \Psi\left(t - \underline{v}_\tau; g_\tau^{(s)}\right) \gamma_\tau^{(s)} D_{\tau,t}^{(s)} \end{aligned} \tag{87}$$

Derivation of equation (40):

Because (34) can be written as

$$\begin{aligned} y_{\tau,t}^{(s)} &= c_y^{(s)} + \theta_s \left\{\left[(1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)}\right] - \left[(1-\alpha) z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right]\right\} \\ &\quad + \rho_s \left[(1-\alpha) z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right] - \rho_s (1-\alpha)(y_t - l_t) + y_t \end{aligned} \tag{88}$$

the first term, which reflects relative demand within the sector, cancels when $z_{\tau,t}^{(s)} = z_{s,t}$, $q_{\tau,t}^{(s)} = q_{s,t}$, and $uc_{\tau,t}^{(s)} = uc_{s,t}$, and we obtain (40).

In a similar way, we can rewrite (35) as

$$\begin{aligned} k_{\tau,t}^{(s)} &= c_k^{(s)} + (\theta_s - 1)\left\{\left[(1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)}\right] - \left[(1-\alpha) z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right]\right\} \\ &\quad + (\rho_s - 1)\left[(1-\alpha) z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right] - q_{\tau,t}^{(s)} - uc_{\tau,t}^{(s)} \\ &\quad - (\rho_s - 1)(1-\alpha)(y_t - l_t) + y_t \end{aligned} \tag{89}$$

which, when $z_{\tau,t}^{(s)} = z_{s,t}$, $q_{\tau,t}^{(s)} = q_{s,t}$, and $uc_{\tau,t}^{(s)} = uc_{s,t}$, simplifies to

$$\left(k_{\tau,t}^{(s)} - y_t\right) = c_k^{(s)} + (\rho_s - 1)\left[(1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)} - (1-\alpha)(y_t - l_t)\right] - q_{\tau,t}^{(s)} - uc_{\tau,t}^{(s)} \tag{90}$$

where the last two terms reflect the relative price of capital of technology type τ.

Derivation of equation (41):

Equation (34) can also be written as

$$\begin{aligned} y_{\tau,t}^{(s)} &= c_y^{(s)} + \theta_s \left[(1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)}\right] \\ &\quad + (\rho_s - \theta_s)\left[(1-\alpha) z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right] - \rho_s (1-\alpha)(y_t - l_t) + y_t \end{aligned} \tag{91}$$

such that because

$$(\rho_s - \theta_s)\left[(1-\alpha) z_{s,t} - \alpha q_{s,t} - \alpha u c_{s,t}\right] - \rho_s (1-\alpha)(y_t - l_t) + y_t \tag{92}$$

is the same for all technology types in the same sector. This is the case because the overall demand for output from the sector has the same effect on the demand for output of each of the technology types. This allows us to write $y_{\tau,t}^{(s)} - y_{\tau',t}^{(s)}$ as in (40).

Moreover, in a similar way, we can derive

$$\left(k_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right) = (\theta_s - 1)\left[\left((1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)}\right) - \left((1-\alpha) z_{\tau',t}^{(s)} - \alpha q_{\tau',t}^{(s)} - \alpha u c_{\tau',t}^{(s)}\right)\right] \tag{93}$$

as well as

$$\begin{aligned} \left(y_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right) &= \left(c_s^y - c_s^k\right) + \theta_s \left[\left((1-\alpha) z_{\tau,t}^{(s)} - \alpha q_{\tau,t}^{(s)} - \alpha u c_{\tau,t}^{(s)}\right) - \left((1-\alpha) z_{\tau',t}^{(s)} - \alpha q_{\tau',t}^{(s)} - \alpha u c_{\tau',t}^{(s)}\right)\right] \\ &\quad + \left((1-\alpha) z_{\tau',t}^{(s)} - \alpha q_{\tau',t}^{(s)} - \alpha u c_{\tau',t}^{(s)}\right) + q_{\tau',t}^{(s)} + uc_{\tau',t}^{(s)} - (1-\alpha)(y_t - l_t) \end{aligned} \tag{94}$$

Neither (40) nor either of the two equations above depend on $z_{s,t}$.

Derivation of equations (42):

We will derive (42) in detail and then present the equations for $\left(k_{\tau,t}^{(s)}-y_t\right)$, $\left(y_{\tau,t}^{(s)}-y_{\tau',t}^{(s)}\right)$, $\left(k_{\tau,t}^{(s)}-k_{\tau',t}^{(s)}\right)$ and $\left(y_{\tau,t}^{(s)}-k_{\tau',t}^{(s)}\right)$ that can be derived in a similar manner.

Equation (42) is obtained by substituting (37) and (39) and the condition that

$$\left((1-\alpha)\,z_{\tau,t}^{(s)}-\alpha q_{\tau,t}^{(s)}-\alpha uc_{\tau,t}^{(s)}\right)=\left((1-\alpha)\,z_{s,t}-\alpha q_{s,t}-\alpha uc_{s,t}\right) \tag{95}$$

into (40). This yields

$$\begin{aligned} y_{\tau,t}^{(s)} &= c_y^{(s)}+\rho_s\left((1-\alpha)\,z_{s,t}-\alpha q_{s,t}-\alpha uc_{s,t}\right)-(1-\alpha)\,\rho_s\left(y_t-l_t\right)+y_t \\ &\approx \left[c_y^{(s)}+\rho_s\left((1-\alpha)\,\tilde{c}_{\tau,z}^{(s)}-\alpha q_{s,\underline{v}_\tau^{(s)}}-\alpha\overline{uc}_\tau^{(s)}\right)\right]+\rho_s\left[(1-\alpha)\,\gamma_\tau^{(s)}+q_\tau^{(s)}\right]\left(t-\underline{v}_\tau^{(s)}\right) \\ &\quad -\frac{\rho_s\alpha}{\left(\overline{r}+\delta_\tau^{(s)}+q_\tau^{(s)}\right)}r_t-(1-\alpha)\,\rho_s\left(y_t-l_t\right)-\rho_s\left(1-\alpha\right)\mu\psi\left(t-\underline{v}_\tau^{(s)};g_\tau^{(s)}\right) \\ &\quad -\rho_s\left(1-\alpha\right)\Psi\left(t-\underline{v}_\tau^{(s)};g_\tau^{(s)}\right)\gamma_\tau^{(s)}D_{\tau,t}^{(s)}+y_t \end{aligned} \tag{96}$$

When we define

$$\eta_{c,\tau}^{(1)} = c_y^{(s)}+\rho_s\left((1-\alpha)\,\tilde{c}_{\tau,z}^{(s)}-\alpha q_{s,\underline{v}_\tau^{(s)}}-\alpha\overline{uc}_\tau^{(s)}\right) \tag{97}$$

$$\eta_{r,\tau}^{(1)} = \rho_s\alpha/\left(\overline{r}+\delta_\tau^{(s)}+q_\tau^{(s)}\right) \tag{98}$$

$$\eta_{T,\tau}^{(1)} = \rho_s\left[(1-\alpha)\,\gamma_\tau^{(s)}+q_\tau^{(s)}\right],\ \eta_\psi^{(1)}=(1-\alpha)\,\rho_s \tag{99}$$

we obtain (42), where $u_{\tau,t}^{(1)}$ is the approximation error.

The equation for $\left(y_{\tau,t}^{(s)}-y_{\tau',t}^{(s)}\right)$ is obtained by substituting (37) and (39) into (41). Doing so, we obtain

$$\begin{aligned} \left(y_{\tau,t}^{(s)}-y_{\tau',t}^{(s)}\right) &= \theta_s\left[\left((1-\alpha)\,z_{\tau,t}^{(s)}-\alpha q_{\tau,t}^{(s)}-\alpha uc_{\tau,t}^{(s)}\right)-\left((1-\alpha)\,z_{\tau',t}^{(s)}-\alpha q_{\tau',t}^{(s)}-\alpha uc_{\tau',t}^{(s)}\right)\right] \\ &= \theta_s\left[\left((1-\alpha)\,\tilde{c}_{\tau,z}^{(s)}-\alpha q_{s,\underline{v}_\tau^{(s)}}-\alpha\overline{uc}_\tau^{(s)}\right)-\left((1-\alpha)\,\tilde{c}_{\tau',z}^{(s)}-\alpha q_{s,\underline{v}_{\tau'}^{(s)}}-\alpha\overline{uc}_{\tau'}^{(s)}\right)\right] \\ &\quad +\theta_s\left[(1-\alpha)\,\gamma_\tau^{(s)}+q_\tau^{(s)}-(1-\alpha)\,\gamma_{\tau'}^{(s)}-q_{\tau'}^{(s)}\right]\left(t-\underline{v}_\tau^{(s)}\right) \\ &\quad +\theta_s\alpha\left[\frac{1}{\left(\overline{r}+\delta_\tau^{(s)}+q_\tau^{(s)}\right)}-\frac{1}{\left(\overline{r}+\delta_{\tau'}^{(s)}+q_{\tau'}^{(s)}\right)}\right]r_t \\ &\quad -\theta_s\left(1-\alpha\right)\mu\left[\psi\left(t-\underline{v}_\tau^{(s)};g_\tau^{(s)}\right)-\psi\left(t-\underline{v}_{\tau'}^{(s)};g_{\tau'}^{(s)}\right)\right] \\ &\quad -\theta_s\left(1-\alpha\right)\Psi\left(t-\underline{v}_\tau^{(s)};g_\tau^{(s)}\right)\gamma_\tau^{(s)}D_{\tau,t}^{(s)}+\theta_s\left(1-\alpha\right)\Psi\left(t-\underline{v}_{\tau'}^{(s)};g_{\tau'}^{(s)}\right)\gamma_{\tau'}^{(s)}D_{\tau',t}^{(s)} \end{aligned} \tag{100}$$

which yields

$$\begin{aligned} \left(y_{\tau,t}^{(s)}-y_{\tau',t}^{(s)}\right) &= \eta_{c,\tau}^{(2)}+\eta_{T,\tau}^{(2)}t+\eta_{r,\tau}^{(2)}r_t-\eta_\psi^{(2)}\mu\left[\psi\left(t-\underline{v}_\tau^{(s)};g_\tau^{(s)}\right)-\psi\left(t-\underline{v}_{\tau'}^{(s)};g_{\tau'}^{(s)}\right)\right] \\ &\quad -\Psi\left(t-\underline{v}_\tau^{(s)};g_\tau^{(s)}\right)\eta_\psi^{(2)}\gamma_\tau^{(s)}D_{\tau,t}^{(s)}+\Psi\left(t-\underline{v}_{\tau'}^{(s)};g_{\tau'}^{(s)}\right)\eta_\psi^{(2)}\gamma_{\tau'}^{(s)}D_{\tau',t}^{(s)}+u_{\tau,t}^{(2)} \end{aligned} \tag{101}$$

where

$$\eta_{c,\tau}^{(2)} = \theta_s\left[\left((1-\alpha)\,\tilde{c}_{\tau,z}^{(s)}-\alpha q_{s,\underline{v}_\tau^{(s)}}-\alpha\overline{uc}_\tau^{(s)}\right)-\left((1-\alpha)\,\tilde{c}_{\tau',z}^{(s)}-\alpha q_{s,\underline{v}_{\tau'}^{(s)}}-\alpha\overline{uc}_{\tau'}^{(s)}\right)\right] \tag{102}$$

$$\eta_{r,\tau}^{(2)} = \theta_s\alpha\left[\frac{1}{\left(\overline{r}+\delta_\tau^{(s)}+q_\tau^{(s)}\right)}-\frac{1}{\left(\overline{r}+\delta_{\tau'}^{(s)}+q_{\tau'}^{(s)}\right)}\right] \tag{103}$$

$$\eta_{T,\tau}^{(2)} = \theta_s\left[(1-\alpha)\,\gamma_\tau^{(s)}+q_\tau^{(s)}-(1-\alpha)\,\gamma_{\tau'}^{(s)}-q_{\tau'}^{(s)}\right],\ \eta_\psi^{(2)}=(1-\alpha)\,\theta_s \tag{104}$$

and $u_{\tau,t}^{(2)}$ can be interpreted as the approximation and measurement error.

In a similar manner, we can derive

$$\left(k_{\tau,t}^{(s)} - y_t\right) \approx \eta_{c,\tau}^{(3)} + \eta_{T,\tau}^{(3)}\left(t - \underline{v}_{\tau}^{(s)}\right) + \eta_{r,\tau}^{(3)} r_t - \eta_{\psi}^{(3)} \mu \left[\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) - (y_t - l_t)\right] \\ -\eta_{\psi}^{(3)} \Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) \gamma_{\tau}^{(s)} D_{\tau,t}^{(s)} + u_{\tau,t}^{(3)} \tag{105}$$

while

$$\left(k_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right) = \eta_{c,\tau}^{(4)} + \eta_{T,\tau}^{(4)}\left(t - \underline{v}_{\tau}^{(s)}\right) + \eta_{r,\tau}^{(4)} r_t - \left[\eta_{\psi}^{(4)} - (1-\alpha)\right] \mu \left[\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) - \psi\left(t - \underline{v}_{\tau'}^{(s)}; g_{\tau'}^{(s)}\right)\right] \\ -\eta_{\psi}^{(4)} \Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) \gamma_{\tau}^{(s)} D_{\tau,t}^{(s)} + \eta_{\psi}^{(4)} \Psi\left(t - \underline{v}_{\tau'}^{(s)}; g_{\tau'}^{(s)}\right) \gamma_{\tau'}^{(s)} D_{\tau',t}^{(s)} + u_{\tau,t}^{(4)} \tag{106}$$

and

$$\left(y_{\tau,t}^{(s)} - k_{\tau',t}^{(s)}\right) = \eta_{c,\tau}^{(5)} + \eta_{T,\tau}^{(5)}\left(t - \underline{v}_{\tau}\right) + \eta_{r,\tau}^{(5)} r_t + (1-\alpha)\left[-\mu\psi\left(t - \underline{v}_{\tau'}^{(s)}; g_{\tau'}^{(s)}\right) - (y_t - l_t)\right] \\ -\eta_{\psi}^{(5)} \mu \left[\psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) - \psi\left(t - \underline{v}_{\tau'}^{(s)}; g_{\tau'}^{(s)}\right)\right] \\ -\eta_{\psi}^{(5)} \Psi\left(t - \underline{v}_{\tau}^{(s)}; g_{\tau}^{(s)}\right) \gamma_{\tau}^{(s)} D_{\tau,t}^{(s)} + \eta_{\psi}^{(5)} \Psi\left(t - \underline{v}_{\tau'}^{(s)}; g_{\tau'}^{(s)}\right) \gamma_{\tau'}^{(s)} D_{\tau',t}^{(s)} + u_{\tau,t}^{(5)} \tag{107}$$

which completes the set of five reduced form equations that we estimate for the different technology types.

Calibration of μ

We calibrate μ based on profit rates. Our model implies that rental expenditures on capital goods make up a fraction α of revenue for each vintage, technology and sector. Of this fraction α, a fraction $1/(1+\eta)$ flows as profits to the capital goods producers. Thus, the fraction of total profits in total revenue in this economy is

$$s_{profits} = \frac{\alpha}{1+\eta} = \frac{\alpha}{1 + \frac{1}{\mu}\frac{\alpha}{1-\alpha}} \tag{108}$$

The average share of corporate profits in national income ($s_{profits}$) in the US since 1945 has been approximately 10 percent. This yields an estimate of μ equal to

$$\mu = \frac{\alpha s_{profits}}{(1-\alpha)\left(\alpha - s_{profits}\right)} = \frac{0.3 \times 0.1}{0.7 \times 0.2} = \frac{3}{14} \tag{109}$$

Table 1: Countries and technology measures covered in the data.

j	Country	s	τ	$\underline{v}_{\tau}^{(s)}$	Type	Technology sector/type
1.	Australia	I				PASSENGER AVIATION
2.	Austria		1	1919	Y	Aviation passengers (passenger kilometers, PKM)
3.	Belgium	II				PASSENGER TRANSPORTATION
4.	Canada		1	1825	Y	Passenger traffic on railways (passenger kilometers, PKM)
5.	Denmark		2	1885	K	Number of passenger cars
6.	Finland	III				CARGO AVIATION
7.	France		1	1919	Y	Aviation cargo (ton kilometers, TKM)
8.	Germany	IV				CARGO TRANSPORTATION
9.	Greece		1	1825	Y	Freight traffic on railways (ton kilometers, TKM)
10.	Ireland		2	1885	K	Number of commercial trucks
11.	Italy	V				MERCHANT SHIPPING
12.	Japan		1	1606	K	Tonnage of sailships in merchant fleet
13.	Netherlands		2	1788	K	Tonnage of steam- and motorships in merchant fleet
14.	New Zealand	VI				TELECOMMUNICATIONS
15.	Norway		1	1835	Y	Telegrams sent
16.	Portugal		2	1876	K	Number of mainline telephones
17.	Spain	VII				RADIO
18.	Sweden		1	1920	K	Number of radios
19.	Switzerland	VIII				TELEVISION
20.	United Kingdom		1	1924	K	Number of televisions
21.	United States	IX				PERSONAL COMPUTER
			1	1976	K	Number of personal computers
t	Sample	X				TEXTILES
	1870		1	1779	K	Number of mule spindles
	1998		2	1828	K	Number of ring spindles
		XI				STEEL
			1	1867	Y	Steel tonnage produced using Open Hearth furnaces
			2	1950	Y	Steel tonnage produced using Blast Oxygen furnaces
		XII				ROBOTS
			1	1962	K	Number of industrial robots in manufacturing
		XIII				ELECTRICITY
			1	1879	Y	KWHr produced

Table 2: Explanatory variables

Measure		
		User cost of capital
Real interest rate	Description:	Ex-post real interest rate: Average annual long bond yield minus inflation for the United States
	Source:	Bond yields from Homer and Sylla (2005). Inflation from Mitchell (1998) and from Bureau of Labor Statistics's CPI release
		(*i*) Human capital
Primary enrollment rate	Description:	Fraction of eligible aged children enrolled in primary school
	Source:	Comin and Hobijn (2004), Barro and Lee (1994)
Secondary enrollment rate	Description:	Fraction of eligible aged children enrolled in secondary school
	Source:	Comin and Hobijn (2004), Barro and Lee (1994)
Tertiary enrollment rate	Description:	Fraction of eligible aged children enrolled in tertiary education
	Source:	Comin and Hobijn (2004), Barro and Lee (1994)
		(*ii*) Trade and openness
Openness	Description:	Sum of imports and exports as a fraction of GDP
	Source:	Comin and Hobijn (2004)
		(*iii*) Relative overall advancement
Log relative real GDP per capita	Description:	Log of real GDP per capita of country minus that of the U.S.
	Source:	Comin and Hobijn (2004) and Maddison (1995)
		(*iv*) Institutions
Polity Score	Description:	Renormalized Polity IV score. 0 = full autocracy, 1 = full democracy
	Source:	Marshall and Jaggers (2002)

Table 3: Sample size and estimated coefficients (Transportation)

s	I	II		III	IV		V	
	Passenger aviation	Passenger transportation		Cargo aviation	Cargo transportation		Merchant shipping	
Sample								
start	1920	1895		1931	1906		1870	
end	1993	1993		1991	1993		1991	
no. countries	21	17		21	17		13	
no. observations	1079	923		889	962		601	
Goodness of fit								
R^2	.989	.976		.997	.989		.940	
R^2 detrended	.635	.596		.634	.641		.642	
Technology type								
τ	Planes	Trains	Cars	Planes	Trains	Trucks	Sail	Steam/Motor
$\underline{v}_\tau^{(s)}$	1919	1825	1885	1919	1825	1885	1606	1788
Growth rates of embodied technological change (annual percentage)								
$\gamma_\tau^{(s)}$	1.17** (0.16)	0.55** (0.10)	0.18 (0.28)	1.89** (0.10)	1.07** (0.08)	2.86** (0.20)	0.14* (0.06)	0.58** (0.15)
Explanatory variables (marginal percentage embodiment gain)								
Primary enr.	−0.72** (0.13)	0.00 (0.15)	0.00 (0.00)	0.08 (0.83)	0.03 (0.40)	0.03** (0.04)	0.00 (0.84)	0.00 (0.00)
Secondary enr.	0.45** (0.08)	0.00 (0.39)	0.00 (0.02)	0.11** (0.03)	−0.03 (0.08)	−0.03 (0.07)	−0.02 (0.15)	−0.02 (0.17)
Tertiary enr.	3.03** (0.09)			0.76** (0.04)				
Openness	0.42** (0.03)	0.00 (0.00)	0.00 (0.00)	0.03** (0.01)	0.01 (0.01)	0.01 (0.01)	0.03** (0.00)	0.04** (0.00)
Polity	0.51** (0.10)	0.00** (0.00)	0.00* (0.00)	−0.11 (0.10)	0.00 (0.01)	0.00 (0.01)	−0.01 (0.02)	−0.01 (0.02)
Relative GDP p.c.	0.80** (0.08)	−0.00 (0.00)	−0.00 (0.00)	0.47** (0.04)	0.01 (0.02)	0.01 (0.01)	−0.01 (0.02)	−0.01 (0.01)

** denotes significantly different from 0 at a 1% significance level, * denotes the same for 5% significance level

Table 4: Sample size and estimated coefficients (Communication and Computers)

s	VI Tele-communication		VII Radio	VIII TV	IX PC
Sample					
start	1888		1926	1947	1980
end	1993		1973	1993	1998
no. countries	21		21	21	21
no. observations	1287		566	728	233
Goodness of fit					
R^2	.989		.994	.975	.999
R^2 detrended	.363		.375	.450	.778
Technology type					
τ	Telegrams	Telephones	Radios	TVs	PCs
$\underline{v}_\tau^{(s)}$	1835	1876	1920	1924	1976
Growth rates of embodied technological change (annual percentage)					
$\gamma_\tau^{(s)}$	0.85** (0.06)	0.58** (0.11)	0.05 (0.24)	0.05 (0.18)	4.89** (1.16)
Explanatory variables (marginal percentage embodiment gain)					
Primary enr.	0.00 (0.19)	0.00** (0.00)	0.01 (0.23)	0.02 (1.59)	−0.77 (0.50)
Secondary enr.	−0.00 (0.29)	−0.00 (0.01)	0.02 (0.06)	0.04 (0.08)	1.59** (0.27)
Tertiary enr.					0.63** (0.12)
Openness	0.00** (0.00)	0.00** (0.00)	0.06 (0.07)	−0.01 (0.12)	
Polity	0.00 (0.00)	−0.00 (0.00)	0.01 (0.24)	0.03 (0.35)	
Relative GDP p.c.	−0.00 (0.00)	−0.00 (0.00)	0.05 (0.29)	0.11** (0.02)	0.43* (0.18)

** denotes significantly different from 0 at a 1% significance level, * denotes the same for 5% significance level39

Table 5: Sample size and estimated coefficients (Manufacturing and electricity)

s	X		XI		XII	XIII
	Textiles		Steel		Robots	Electricity
Sample						
start	1908		1960		1981	1879
end	1954		1993		1998	1993
no. countries	18		14		17	21
no. observations	157		185		240	1300
Goodness of fit						
R^2	.959		.930		.998	.980
R^2 detrended	.942		.730		.762	.671
Technology type						
τ	Mule	Ring	OHF	BOF	Robots	KWHr
$\underline{v}_{\tau}^{(s)}$	1770	1828	1867	1950	1962	1879
Growth rates of embodied technological change (annual percentage)						
$\gamma_{\tau}^{(s)}$	0.03 (0.04)	0.06 (0.06)	1.73** (0.38)	1.62** (0.57)	2.13** (0.69)	1.26** (0.04)
Explanatory variables (marginal percentage embodiment gain)						
Primary enr.	−0.00 (2.41)	−0.00 (0.00)	−0.00 (0.25)	−0.00* (0.00)	1.62 (8.85)	−0.31 (3.11)
Secondary enr.	0.00 (0.53)	0.00 (0.52)	−0.00 (147.36)	−0.00 (0.03)	3.56** (0.18)	2.11** (0.18)
Tertiary enr.					−0.31 (0.30)	
Openness	−0.00 (0.07)	−0.00 (0.03)	−0.00 (0.00)	0.00 (0.00)		−0.77** (0.16)
Polity	0.00 (0.00)	0.00 (0.00)				0.21 (0.12)
Relative GDP p.c.	−0.00 (0.30)	−0.00 (0.17)	−0.00 (0.00)	0.00 (0.00)	0.57 (0.37)	−1.04** (0.12)

** denotes significantly different from 0 at a 1% significance level, * denotes the same for 5% significance level

Table 6: Growth rate of the productivity embodied in each technology type and its decomposition

Technology	Period	Δz	Embodiment		Variety	
			Frontier	Catch up	Frontier	Lags
Aviation cargo	1937-90	0.041	0.019	0.012	0.019	-0.009
Aviation passengers	1937-90	0.066	0.012	0.040	0.013	0.001
Train passengers	1913-90	0.013	0.005	0.000	0.006	0.001
Train cargo	1913-90	0.021	0.011	0.000	0.011	0.000
Cars	1930-90	0.006	0.002	0.000	0.004	0.000
Trucks	1930-90	0.055	0.029	0.000	0.027	0.000
Sail ships	1913-90	0.003	0.001	0.000	0.002	0.000
Steam/motor ships	1913-90	0.011	0.006	0.000	0.006	0.000
Telegrams	1913-90	0.018	0.009	0.000	0.008	0.001
Telephones	1913-90	0.013	0.006	0.000	0.007	0.000
Radios	1930-90	0.038	0.001	0.001	0.007	0.030
TV's	1950-90	0.129	0.001	0.002	0.005	0.122
PC's	1980-93	0.237	0.049	0.015	0.053	0.120
Robots	1975-93	0.483	0.021	0.040	0.024	0.399
Electricity	1930-90	0.146	0.001	0.010	0.003	0.132
Steel open hearth	1930-88	0.048	0.017	0.000	0.017	0.014
Steel blast oxygen	1961-90	0.034	0.016	0.000	0.019	-0.002
Mule spindles	1913-70	0.006	0.003	0.000	0.003	0.000
Ring spindles	1913-70	0.013	0.007	0.000	0.007	0.000
Average		0.073	0.017			

Δz denotes the average annual growth rate in embodied productivity for the technology over the period.

Table 7: Descriptive statistics of estimated level of Z due to embodiment and variety mechanisms

Technology type	Cross section initial year			Cross section final year		
	year	$Std(z)$	$\frac{Std(z)}{Std(y-l)}$	year	$Std(z)$	$\frac{Std(z)}{Std(y-l)}$
Aviation cargo	1937	0.530	1.755	1990	0.204	0.977
Aviation passengers	1937	0.938	3.029	1990	0.511	2.443
Train passengers	1913	0.001	0.002	1990	0.000	0.002
Train cargo	1913	0.012	0.031	1990	0.005	0.026
Cars	1930	0.001	0.002	1990	0.000	0.001
Trucks	1930	0.009	0.026	1990	0.005	0.026
Sail ships	1913	0.024	0.063	1990	0.011	0.052
Steam/motor ships	1913	0.024	0.063	1990	0.011	0.053
Telegrams	1913	0.001	0.003	1990	0.001	0.003
Telephones	1913	0.001	0.004	1990	0.001	0.003
Radios	1930	0.966	2.675	1990	0.120	0.572
TV's	1950	1.153	2.396	1990	0.157	0.752
PC's	1980	0.461	2.031	1993	0.326	1.642
Robots	1975	0.740	3.085	1993	0.432	2.178
Electricity	1930	0.946	2.618	1990	0.256	1.223
Steel open hearth	1930	0.001	0.001	1988	0.000	0.001
Steel blast oxygen	1961	0.001	0.001	1993	0.000	0.001
Mule spindles	1913	0.002	0.005	1970	0.001	0.002
Ring spindles	1913	0.002	0.005	1970	0.001	0.002

Std denotes standard deviation. $(y-l)$ is log real GDP per capita.

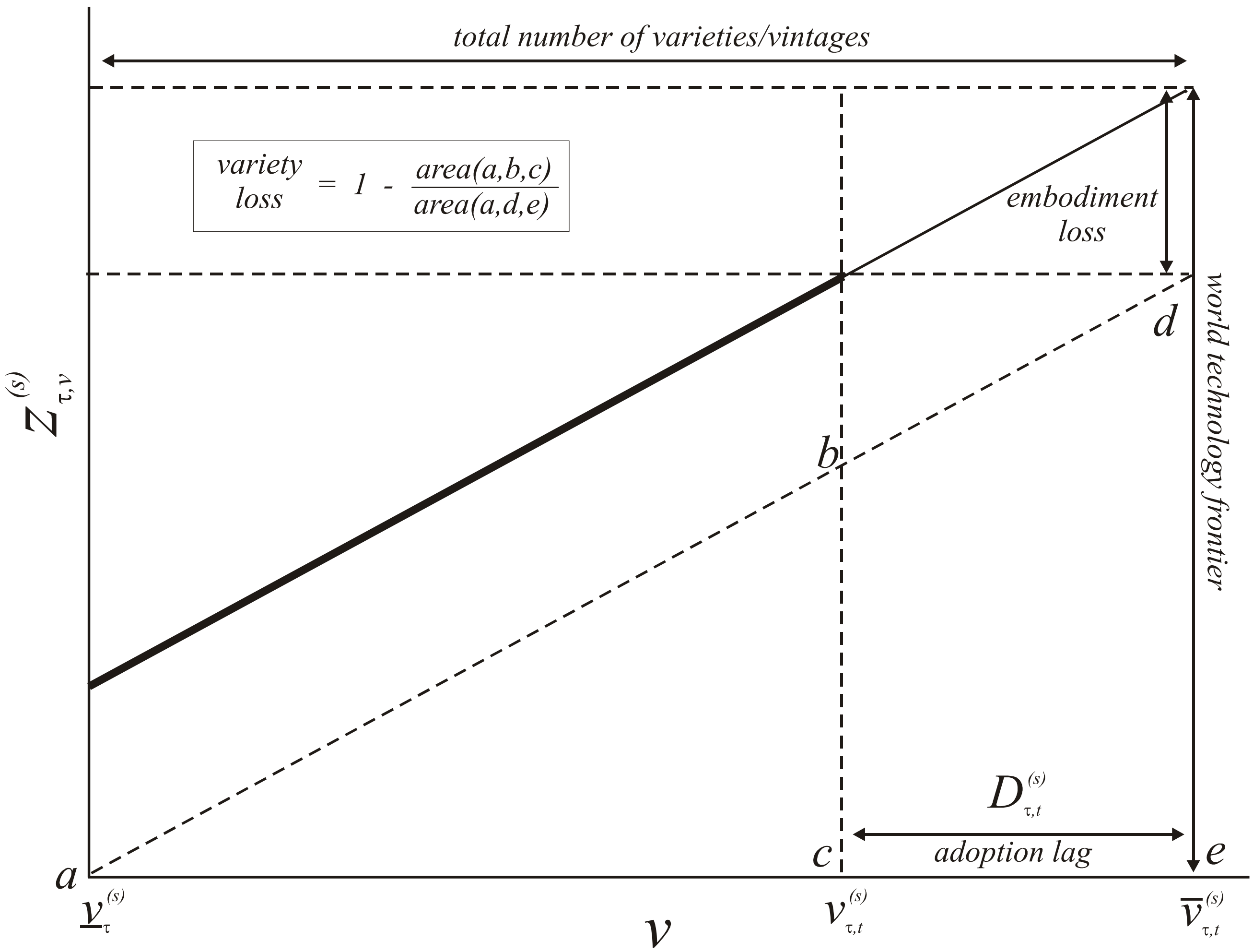

Figure 1: Decomposition of technology type total factor productivity level

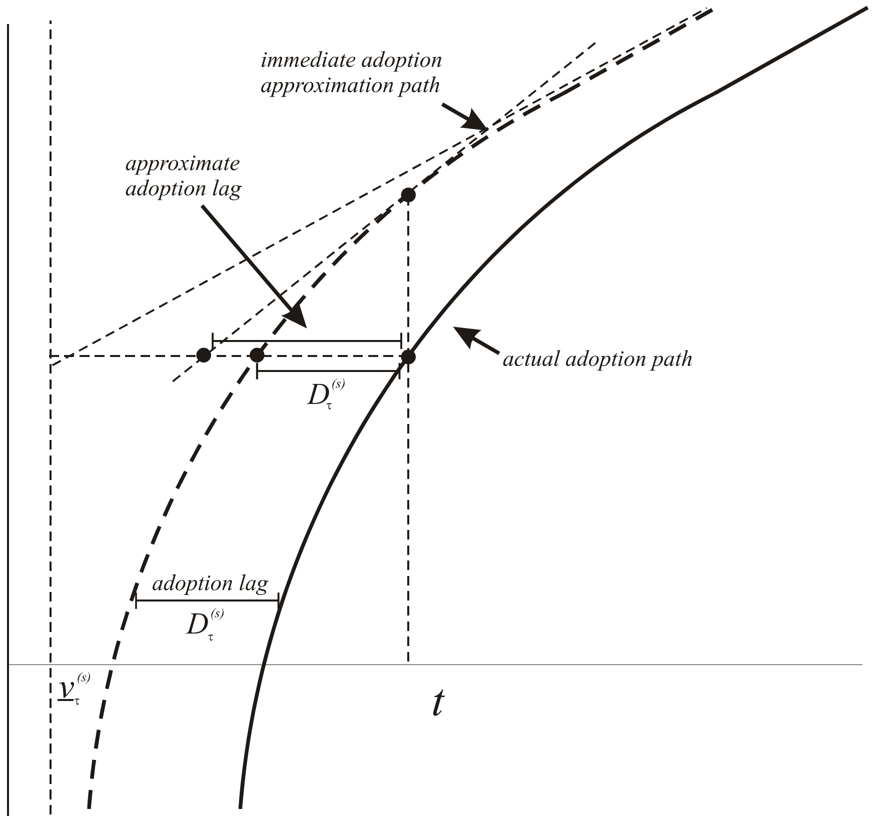

Figure 2: Approximation of adoption lags around immediation adoption path

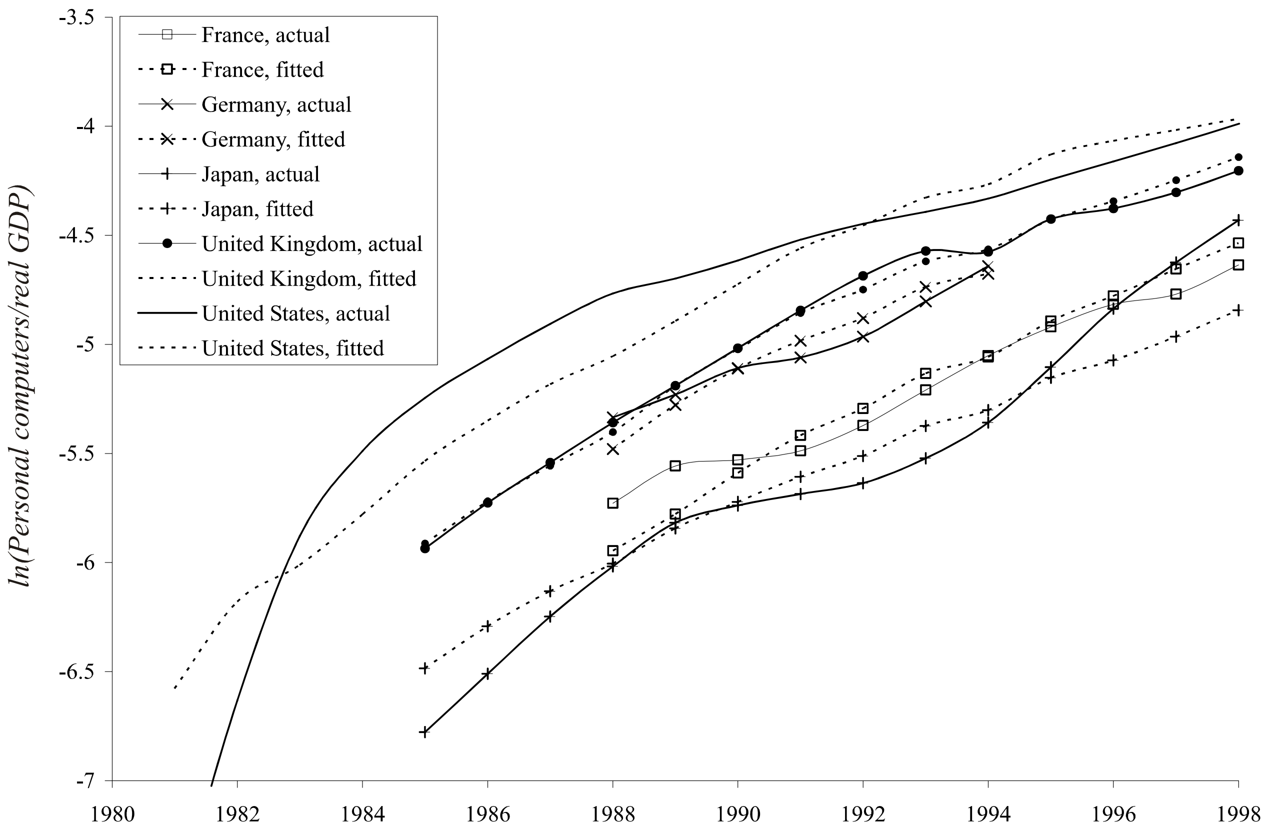

Figure 3: Actual and fitted adoption paths for personal computers

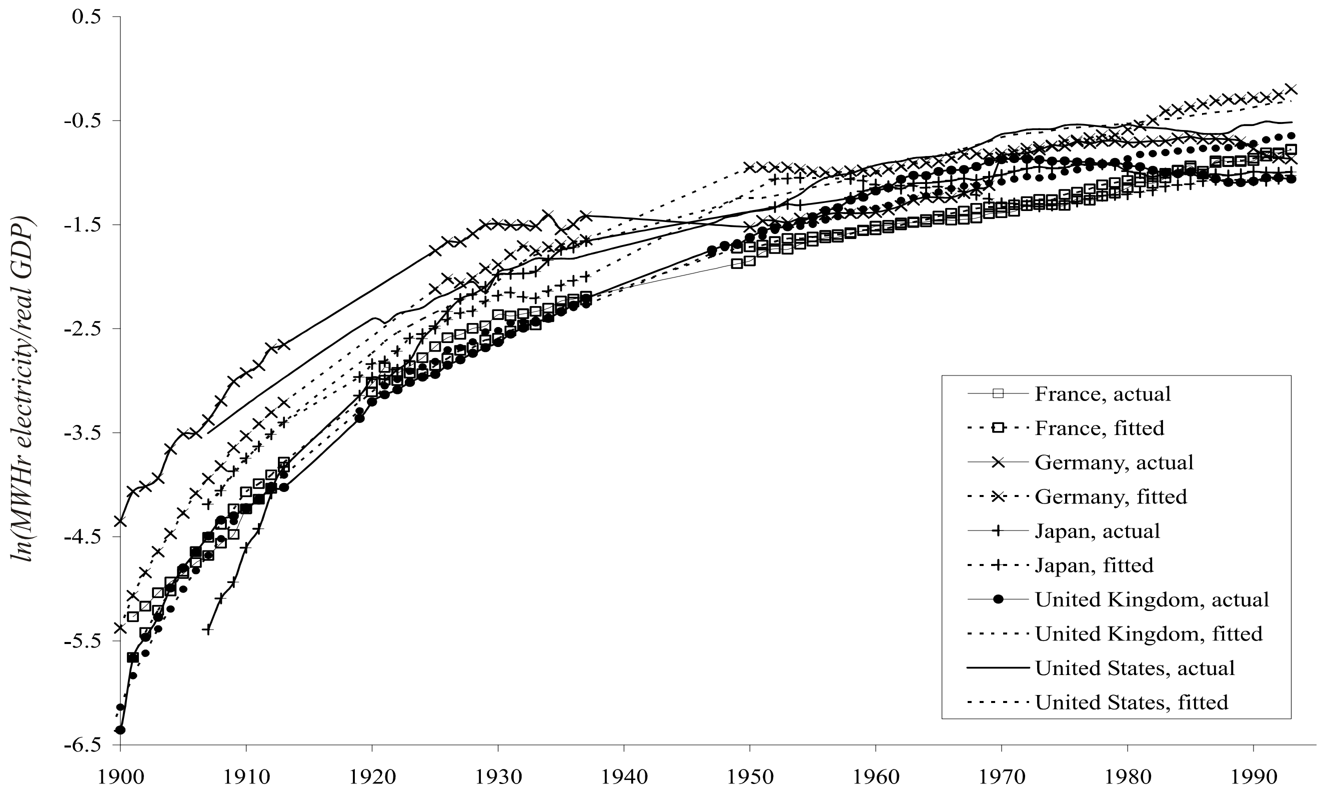

Figure 4: Actual and fitted adoption paths for electricity

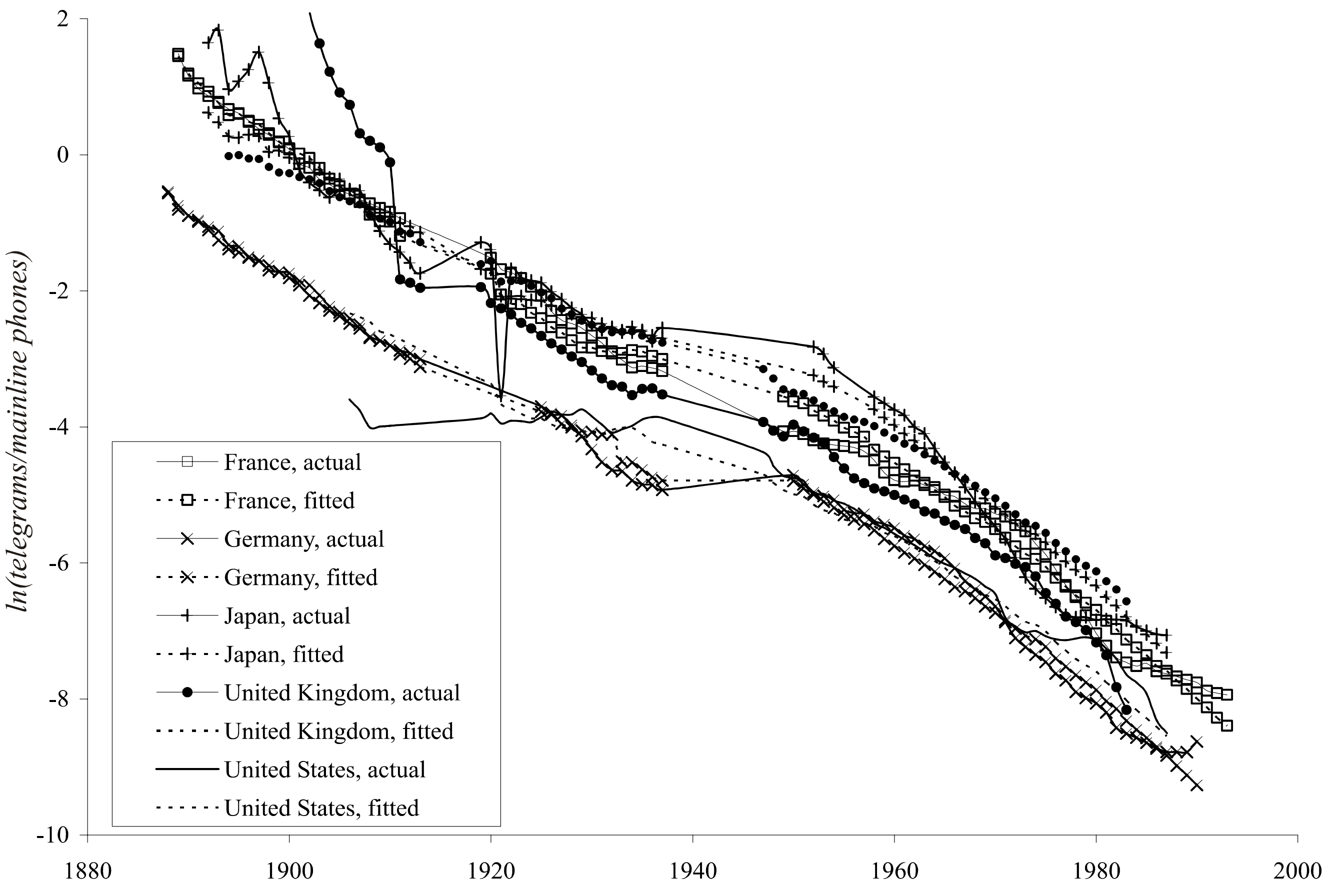

Figure 5: Actual and fitted adoption paths for telecommunications

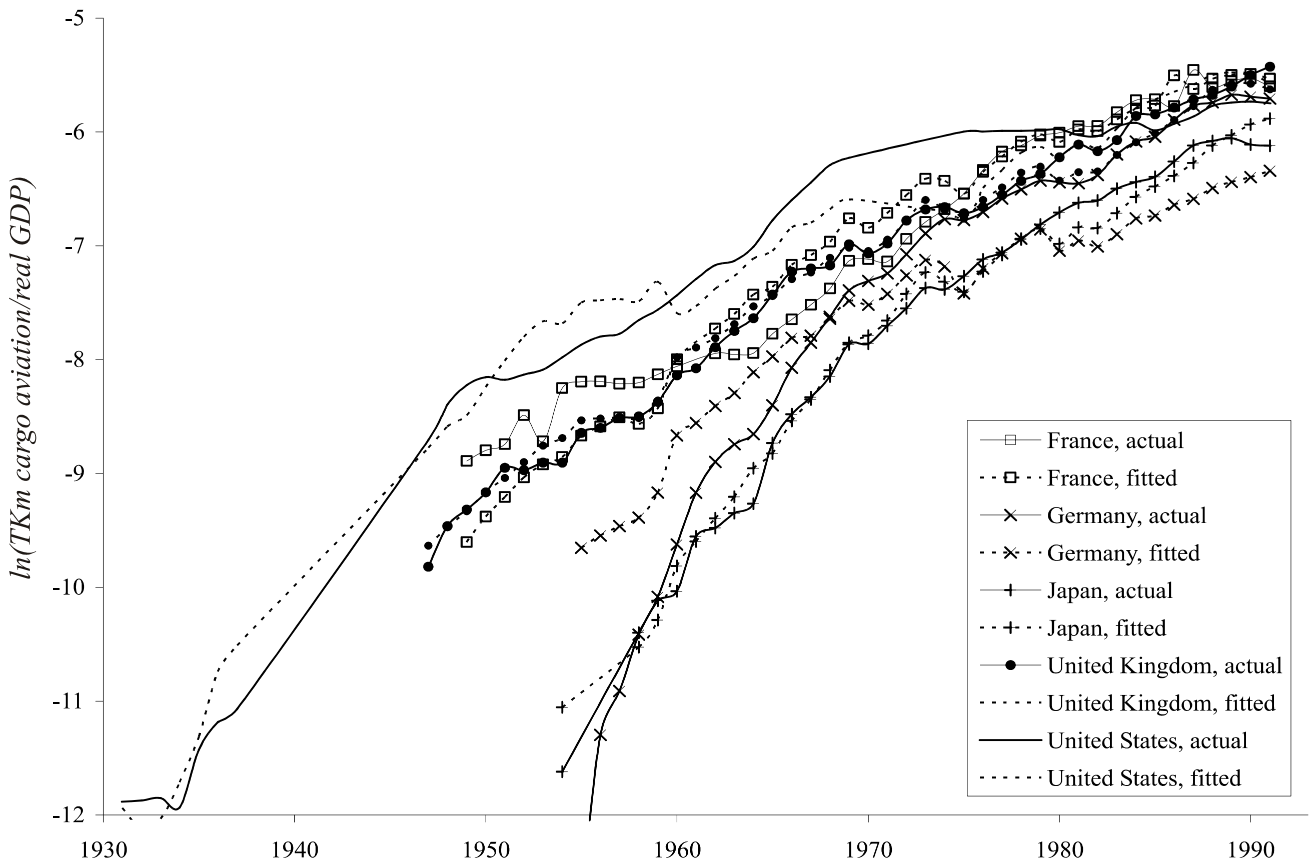

Figure 6: Actual and fitted adoption paths for cargo aviation

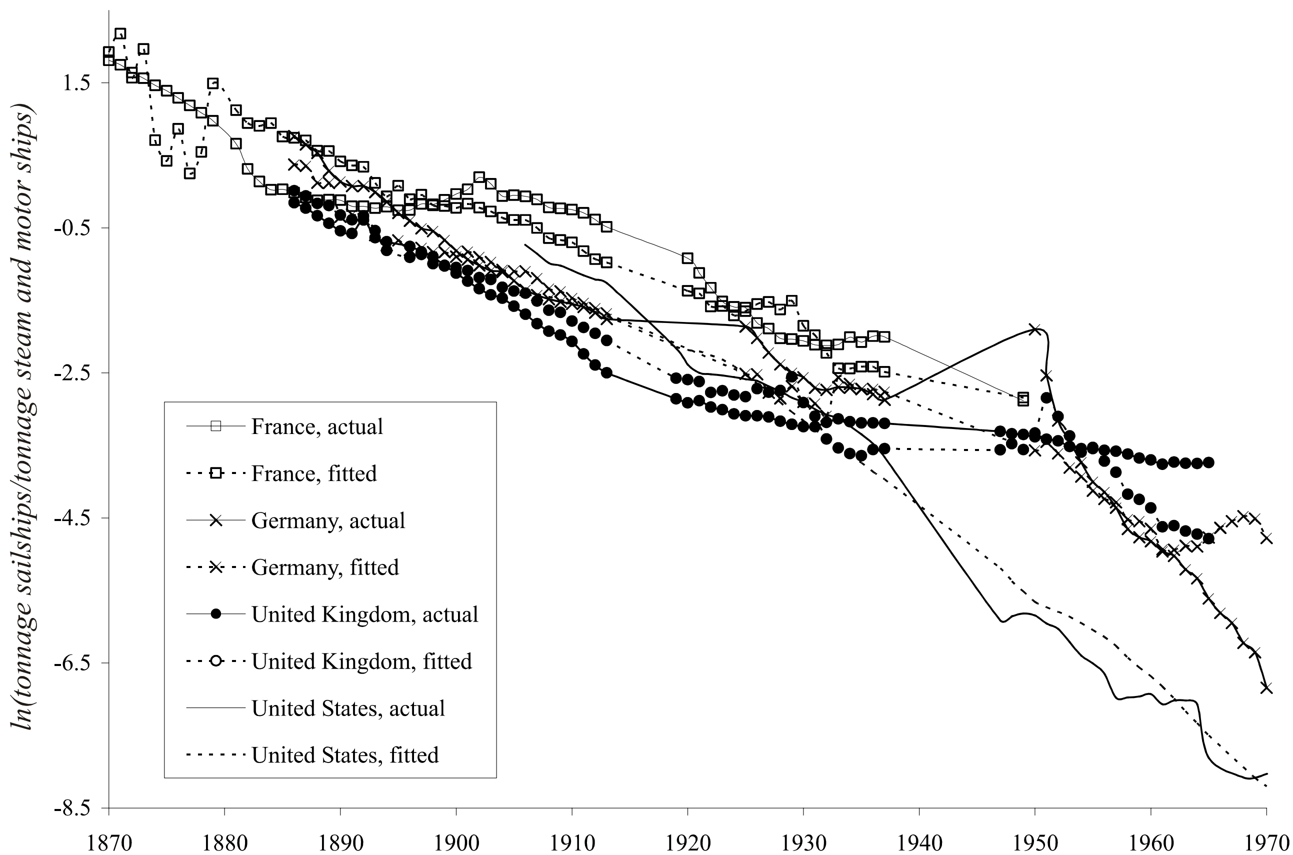

Figure 7: Actual and fitted adoption paths for merchant shipping