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Technology Diffusion

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ABSTRACT

The importance of new technologies derives from the fact that they spread across many different users and uses, as well as different geographic regions. The diffusion of technological improvements, across producers within a country and across international borders, is critical for long run growth. This paper looks at some evidence on adoption patterns in the U.S. for specific innovations, reviews some evidence on the diffusion of new technologies across international boundaries, and looks at two theoretical frameworks for studying the two types of evidence. One focuses on the dynamics of adoption costs, the other on input costs.

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1. INTRODUCTION

Sustained long-run growth requires the adoption of new technologies.[1] Thus, innovation, whether it is costly R&D or serendipitous discovery, is fundamental for growth and has—deservedly—been well studied. But the importance of most new technologies derives from the fact that they spread across many different users and uses, as well as different geographic regions. Thus, the *diffusion* of technological improvements, across producers within a country and across international borders, is arguably as critical as innovation for long run growth. Technology diffusion is the focus here.

Good data on diffusion are not readily available. Indeed, for many innovations, there are none at all. This paper looks at the evidence on adoption patterns and rates in the U.S. for several specific innovations where good micro data have permitted detailed studies. It then reviews some of the evidence on the diffusion of new technologies across international boundaries, where data is even more limited. No attempt is made to review all the work on technology adoption.

The discussion is selective and focuses on the role of cost reduction. Specifically, two aspects of cost are considered. The first involves the dynamics induced by changes in the fixed cost of adoption. Adoption takes time, and economic motives govern who adopts a new technology and how quickly they adopt it. As use of an innovation increases, its quality typically improves and its cost of adoption falls. Consequently, early adoption by some users facilitates later adoption by a broader set of users. The dynamics of adoption costs are important for explaining diffusion across users in a

[1]The Solow residual, the part of output growth that is unexplained by measurable inputs, is very large for all developed countries. The same is true for share of output differences across countries. Like any residual, Solow residual picks up the effect of anything that is omitted. But a substantial component is surely technological change.

single environment.

The second aspect of cost involves relative input prices. Many new technologies are, by design, labor-saving and capital-using, so their attractiveness depends on the relative prices of capital and labor inputs. Wage rates vary enormously across countries, while the cost of capital varies much less. Hence relative input prices are important for explaining diffusion across countries.

Direct evidence on adoption patterns across countries is rarely collected, but indirect evidence is sometimes available. Many technologies are 'embodied' in new capital goods, specific to them. This fact is useful, since good data are available on investments in tangible capital. Moreover, technologies that are embodied in capital goods have a unique method for international diffusion: the capital goods themselves are highly traded. Thus, equipment imports are a channel by which one country—either developed or developing—can acquire technology from abroad. Producer equipment is highly traded, and for developing countries a large fraction of their total investment in producer equipment consists of imported goods coming from advanced countries. Moreover, there are good data on the source of the equipment, as well as type, by fairly narrowly defined sector.[2]

Before proceeding, two limits on the scope of this study should be noted. First, only *producer* technologies are considered here. New consumer goods are also important for welfare, but their diffusion is explained by a different set of factors. For the same reason, there will be no discussion of adoption of high-yield varieties (HYV's) in India, sub-Saharan Africa and elsewhere.

Finally, note that the focus here is on diffusion of *technologies*, as opposed to *ideas*. The former are adopted by producers—industrial firms or agricultural enterprises—

[2]Cross-country evidence for developing countries suggests that openness to trade facilitates growth. It has nevertheless proven difficult to establish a causal link empirically, due to the presence of many confounding factors in the time series.

and then utilized by that producer's workforce, be it one individual or a large group. Thus, the adoption decision is at the producer level, and the technology is a non-rival input across that producer's workers. In contrast, ideas are the property of individuals: an individual can utilize only ideas that he/she has adopted. Ideas are surely a more fundamental concept: all technological innovations begin with an idea.[3] But technologies are—perhaps—easier to measure.

The rest of the paper is organized as follows. Section 2 reviews several detailed studies of the diffusion of particular technologies across producers in the U.S. Section 3 looks at the evidence on cross-country diffusion, including evidence on productivity in agriculture. Section 4 looks at two simple models of technology diffusion across producers that are compatible with much of the evidence. The first is suitable for looking at diffusion within a single country, the second for looking at cross-country diffusion. Section 5 concludes.

2. EVIDENCE ON TECHNOLOGY DIFFUSION ACROSS U.S. PRODUCERS

A. Hybrid corn: Griliches (1957)

Griliches's (1957) study of hybrid corn adoption over the period 1933-1956 is, deservedly, a classic. The goal of his paper was "to understand a body of data: the percentage of all corn acreage planted with hybrid seed, by states and by years." As he notes, there were marked differences in the patterns of adoption across geographic regions. As he also notes, these hybrids were not one-size-fits-all: they had to be bred separately for each geographic region. The variety adapted to a neighboring region was a useful starting point in the hybridization process, but a new variety need to be

[3]Lucas (2009), Lucas and Moll (2014), and Caicedo, Lucas, Rossi-Hansberg (2019), and Le (2020) develop models where the diffusion of ideas across individuals is the engine of long run growth.

developed for each locality.

Griliches's approach is first to parametrize adoption in each particular geographic region—state, county or district—in a parsimonious way, then to fit the adoption parameters by region, and finally to explain the cross-region variation in those parameters with a few economic variables.

Adoption is measured as the share of corn acreage planted with hybrid. As shown in Figure 1 (Griliches's Figure 1) for the state level, adoption is well approximated by logistic functions, with different start dates, speeds of adoption, and long-run adoption levels.

Let $P_i(t)$ denote the percentage planted in hybrid in region i at date t. For the logistic form

$$P_i(t) = \frac{K_i}{1 + e^{-\left(a_i + b_i\left(t - t_i^{\mathrm{o}}\right)\right)}}, \qquad t \geq t_i,$$

so adoption is described by the date of origin t_i^{o}, the ceiling K_i, and the parameters (a_i, b_i). Take the log of the logistic to get

$$\ln\left\{P_i(t)/\left[K_i - P_i(t)\right]\right\} = a_i + b_i\left(t - t_i^{\mathrm{o}}\right),$$

so given (K_i, t_i^{o}) the parameters (a_i, b_i), can be estimated by OLS.

Griliches's data are from 132 crop reporting districts in 31 states. The date of origin t_i^{o} is taken to be the date at which penetration is 10%, and the ceiling K_i for each region is fit by hand. The logistic curves fit well, with R^2's over 0.90 in every case, over 0.95 in most, and 0.99 in many districts.

The entry dates, the origins t_i^{o}, are quite variable, ranging from 1935 in some parts of Iowa and Illinois to 1945 in Oklahoma and 1949 in some parts of Alabama. They are lowest in the corn belt states, Iowa, Illinois and Indiana, and gradually spread out to adjacent areas. The corn belt is also where the b_i's and K_i's—the slopes and ceilings—are highest. Additionally, districts where the ceiling is $K_i = 100\%$ also have high and similar slopes, while places with lower ceilings also have slower speeds of adoption.

Griliches then explores the economic determinants of the variation in the parameters t_i^o, b_i, and K_i across regions. Farmers can't adopt if the seed companies in their region are not offering the hybrid, so t_i^o depends on suppliers: the agricultural experiment stations and private seed companies. Griliches's hypothesis is that although the origin dates depend largely on the actions of suppliers, while the slopes and ceilings depend on the actions of adopters, the incentives for both sides of the market depend on profitability.

Commercial seed companies in more profitable regions should have a greater incentive to move earlier, including a greater incentive to encourage the agricultural stations they rely on. Indeed, Griliches finds that the origins are fairly well described as functions of two variables that affect supply cost: market density—which lowers marketing costs, and a geographic variable indicating whether entry had already occurred in a contiguous market—which lowers R&D costs. The estimated slope b_i, interpreted as an expected rate of acceptance, is also useful in explaining the origins.

The speed of acceptance b_i is well explained by the degree of superiority of hybrids. Two measure are tried: the increase in yield per acre, from questionnaire data, and the pre-hybrid yield per acre. Hybrids increased yields by about 20%—at least that was the belief at the time, so a higher pre-hybrid yield was an indicator for a larger gain. The long run level of adoption K_i is fairly well explained by the same variables.

In summary, Griliches finds that hybrid adoption across geographic regions is well explained by their relative profitability across regions. They were most useful in the Corn Belt, where they were introduced earlier, were adopted more quickly, and had greater long-run success. Their use branched out gradually to adjacent regions.

B. 12 industrial innovations: Mansfield (1961)

Mansfield uses a similar methodology to look at the diffusion of twelve major innovations in four industries: bituminous coal, iron and steel, brewing, and railroads. An important new feature of these innovations compared with hybrid corn is that all except one involved purchases of new heavy equipment. Thus, in each case a major investment was required to obtain a substantial reduction in costs.

Mansfield does not have production data, so his Figure 1 shows the percentage of *firms* in the industry that have adopted. Only larger firms in each industry are represented, so the share of adopting firms is used as a proxy for the share of output produced with the new method.

Diffusion is rather slow—in many cases 20 years or more, and varies widely across innovations. The time until half of firms have adopted varies from 0.9 years to 15, with an average of 7.8.

The technologies in Mansfield's data arrived at different well-defined dates, and in each case the ultimate adoption rate was 100%, Thus, Mansfield focuses on the speed of adoption, the analog of Griliches's parameter b_i. He adopts the same overall methodology, first estimating an adoption speed for each innovation, and then regressing those adoption speeds on a small set of (economic) explanatory variables.

Mansfield's data cover different inventions in different industries requiring different levels of investment in new equipment. To accommodate these three differences, he uses a more complicate regression equation. In particular, he looks at an equation that relates the *change* in the share of adopters as a function of profitability, the cost of adoption, and interactions between those variables and the share firms that have already adopted.

Let n_{ij} denote the number of potential adopters of innovation j in industry i, and let $m_{ij}(t)$ denote the number who have adopted by date t, so $m_{ij}(t)/n_{ij}$ is the share of firms that have adopted by t. Measure profitability π_{ij} as the ratio of the average threshold payback period for the industry to the average payback period (as reported by firms) for this investment, a measure that is similar to the ratio of the two Internal Rates of Return. Measure cost S_{ij} as the ratio of the average initial investment required for adoption relative to average assets of the firms in that industry.

Let $\lambda_{ij}(t)$ denote the share of non-adopters at t that adopt by $t+1$. Mansfield's regression equation is

$$\begin{aligned}\lambda_{ij}(t) &= a_{i1} + a_{i2}\pi_{ij} + a_{i2}S_{ij} \\ &\quad +\beta_{i1}\frac{m_{ij}(t)}{n_{ij}} + \beta_{i2}\pi_{ij}\frac{m_{ij}(t)}{n_{ij}} + \beta_{i3}S_{ij}\frac{m_{ij}(t)}{n_{ij}} + ... \\ &\approx a_{ij} + \beta_{ij}t + ...\end{aligned}$$

where the second line uses

$$\begin{aligned}a_{ij} &= a_{i1} + a_{i2}\pi_{ij} + a_{i3}S_{ij}, \\ b_{ij} &= \beta_{i1} + \beta_{i2}\pi_{ij} + \beta_{i3}S_{ij},\end{aligned}$$

and an assumption that the share of adopters increases approximately linearly with time, $m_{ij}(t)/n_{ij} \approx t$.

Use this approximation to get the logistic,

$$p_{ij}(t) = \frac{1}{1 + e^{-(a_{ij}+b_{ij}t)}},$$

where $p_{ij}(t)$ is share of firms that have installed by t, and the "ceiling" is taken to be 100% adoption, $K = 1$. Take logs and use OLS, as Griliches did, to estimate a_{ij} and b_{ij} for each innovation. The fits, reported in Table IB, are very good for all the innovations.

The b_{ij}'s are then regressed on an industry constant and the profitability and cost measures, giving

$$\hat{b}_{ij} = \begin{Bmatrix} -0.29 \\ -0.57 \\ -0.52 \\ -0.59 \end{Bmatrix} + \begin{array}{ll} 0.530\pi_{ij} - 0.27S_{ij}, \\ (0.015) \qquad (0.014) \end{array} \qquad r = 0.997.$$

The coefficients are highly significant and the fit, displayed in Figure 2 (Mansfield's Figure 2), is quite good. The coefficient estimates are somewhat sensitive to the outlier (tin cans), but keep the right signs even if that point is excluded.

Mansfield also tries adding some additional regressors:

—presence of durable equipment that will be made obsolete,

—growth rate of industry sales,

—a time trend in the diffusion rate, and

—the phase of the business cycle when the innovation is introduced.

Each has the right sign but none is statistically significant.

C. Tractors: Manuelli and Seshadri (2014)

Manuelli and Seshadri (2014) look at the adoption of tractors. Adoption in this case was slow, and it was long a puzzle why it was so slow. The authors show that adoption is well explained by changes in the total costs of the services provided by tractors and by the alternative source of farm power, horses, including the required labor input.

As shown in Figure 3 (MS's Figure 1), although tractors were introduced in 1910, there was very little adoption before 1920. Adoption rose steadily between 1920 and 1960, with the number of horses and mules declining as the number of tractors increased. Over this period quality-adjusted tractor price fell very substantially, as shown Figure 4 (MS's Figure 2). The sharpest decline in price came before 1920, however, and did not induce widespread adoption. Wages, on the other hand, which were about constant until the mid-1930's, then rose sharply until the end of World War II. Manuelli and Seshadri's hypothesis is that the increase in wages made tractors—which are labor-saving—more profitable, and spurred their rapid adoption during that period.

Their model of the agricultural sector and the demand for inputs is fairly straightforward, and it fits the data well.

1. Markets for agricultural inputs.—

The production function for agricultural output has constant returns to scale, with tractors k, horses h, a vector of labor inputs $\underline{n} = (n_h, n_k, n_y)$ and land a as inputs. It is a nested CES with three layers. The innermost layers combine tractors/horses with labor inputs to produce the two individual sources of power,

$$z_x = \left[\omega_x x^{-\rho_x} + (1 - \omega_x)\, n_x^{-\rho_x}\right]^{-1/\rho_x}, \qquad x = k, h.$$

Since the weights ω_x and elasticities $1/(1 + \rho_x)$, $x = k, h$, can differ between the two power sources, changes in the wage rate can have differential effects on the costs of the two power sources. The next layer of the CES aggregates the two sources of power,

$$z = \left[\omega_z z_k^{-\rho_1} + (1 - \omega_z)\, z_h^{-\rho_1}\right]^{-1/\rho_1}, \tag{1}$$

and the outermost layer is a Cobb-Douglas aggregator of power, labor and land,

$$y = F(z, n_y, a) = A_{ct} z^{\alpha_z} n_y^{\alpha_n} a^{1-\alpha_z-\alpha_n}. \tag{2}$$

The inputs $(h, \underline{n}, a)$ of horses, labor and land are straightforward to measure. The cost of using a horse in period t is $q_{ht} + c_{ht}$, where q_{ht} is the rental rate and c_{ht} includes operating costs. Similarly, the cost of using an acre of land is $q_{at} + c_{at}$, and the wage rate is w_t. The tractor input k_t and its cost per period are more complicated.

2. Cost of tractor services.—

An important feature of tractors is that later vintages improved in terms of both durability and attributes. Thus, it is important to distinguish tractors by their vintage τ. Suppose attributes can be mapped into an aggregate of 'tractor services.' In addition, assume the market for tractor services is a perfectly competitive rental market.

For any vintage τ, there are machines of various types α, with different prices and different vectors of attributes. We will ignore that for now, and suppose that only a single type of new machine is sold at each date.

At any date t, machines of vintage $\tau = t, t-1, ...,$ are available for use. For any vintage τ, let $\delta_{k\tau}$ be the depreciation rate, and let $v(\underline{x}_\tau)$ denote the quantity of services provided per machine, where $\underline{x}_\tau$ is a vector of attributes, and the time-invariant function v maps attributes into an index of services. Let $m(\tau)$ denote the number of machines of vintage τ. Then the total supply of tractor services at t is[4]

$$k_t = \sum_{\tau=-\infty}^{t} (1-\delta_{k\tau})^{t-\tau} v(\underline{x}_\tau) m(\tau). \tag{3}$$

Let $R_{\tau t}$ denote the discount factor between τ and t,

$$\begin{aligned} R_{\tau\tau} &= 1, \\ R_{\tau t} &= R_{\tau t-1}\frac{1}{1+r_t}, \quad t = \tau+1, ..., \end{aligned}$$

where r_t is the one-period interest rate at t. Let $q_{kt}(\tau)$ and $p_{kt}(\tau)$ denote the rental rate and price at t for a tractor of vintage $\tau \le t$. These satisfy the usual no-arbitrage condition,

$$p_{kt}(\tau) = q_{kt}(\tau) + \frac{1-\delta_{k\tau}}{1+r_{t+1}} p_{k,t+1}(\tau), \qquad \text{all } \tau \le t, \ \ \text{all } t. \tag{4}$$

[4]It is easy to allow machines to have a finite lifetime T.

To close the model, assume the price of a new machine of any vintage is related to its quality by

$$p_{k\tau}(\tau) = \frac{1}{\gamma_\tau} v(\underline{x}_\tau), \qquad \text{all } \tau, \tag{5}$$

where γ_τ can represent any combination of technical change—pushing γ_τ above unity, and variable markup—pushing γ_τ below unity.

Let $c_{kt}(\tau)$ denote the variable cost (fuel, repairs) of operating a tractor of vintage τ at date $t \geq \tau$. Equilibrium in the rental market at t requires the price of tractor services, call it p^s_{kt}, be the same for all vintages in use. That is, rental and user costs satisfy

$$q_{kt}(\tau) + c_{kt}(\tau) = p^s_{kt}, \qquad \text{all } \tau \leq t, \quad \text{all } t, \tag{6}$$

where $p^s_{kt}, q_{kt}(\tau)$ and $c_{kt}(\tau)$ are measured per unit of tractor services delivered.

Data is available on prices for new and used tractors, $p_{kt}(\tau)$, for all vintages $\tau \leq t$ and dates t, and on the attribute vectors $\underline{x}_\tau$, depreciation rates $\delta_{k\tau}$, and number sold $m(\tau)$ for all vintages. The interest rates r_t and hence the interest factors $R_{\tau t}$ are also known. There is no direct information on the rental rates $q_{kt}(\tau)$ or user costs $c_{kt}(\tau)$.

To make the model empirically tractable, assume the operating cost depends only on the date t, so $c_{kt}(\tau) = \hat{c}_{kt}$, all $\tau \leq t$. Then (6) implies

$$\begin{aligned} q_{kt}(\tau) &= p^s_{kt} - \hat{c}_{kt} \\ &\equiv \hat{q}_{kt}, \qquad \text{all } \tau \leq t, \quad \text{all } t, \end{aligned} \tag{7}$$

so the rental rate $\hat{q}_{kt}$ at any date is the same for all vintages, and (4) takes the simpler form

$$\hat{q}_{kt} = p_{kt}(\tau) - \frac{1-\delta_{k\tau}}{1+r_{t+1}} p_{k,t+1}(\tau), \qquad \text{all } \tau \leq t, \quad \text{all } t. \tag{8}$$

Use (8) for the new vintage at t to find that

$$\hat{q}_{kt} = p_{kt}(t) \left[1 - \frac{1-\delta_{kt}}{1+r_{t+1}} \frac{p_{k,t+1}(t)}{p_{kt}(t)} \right], \qquad \text{all } t. \tag{9}$$

Next, assume

$$p_{k,t+1}(t) \approx \frac{1}{\gamma_{t+1}} v\left(\underline{x}_t\right), \qquad \text{all } t, \tag{10}$$

which says the price of a year-old tractor at $t+1$ is approximately equal to the services it provides, adjusted for the new markup γ_{t+1}. If (5) holds, then (10) is a good approximation if γ_t does not change too much from year to year. Use (5) and (10) in (9) to get

$$\hat{q}_{kt} = p_{kt}(t)\left[1 - \frac{1-\delta_{kt}}{1+r_{t+1}}\frac{\gamma_t}{\gamma_{t+1}}\right], \qquad \text{all } t. \tag{11}$$

The function v and the values γ_t on the right side of (11) can be estimated and used to get estimates of the evolution of average tractor quality and the rental rates $\hat{q}_{kt}$.

For the estimation, use the fact that at any date t many types α of new tractors are produced. Let $p_{kt}^{\alpha}(t)$ and $\underline{x}_t^{\alpha}$ denote the price and attribute vector for a particular new machine α, and assume the function v is log-linear, $v(\underline{x}) = \Pi_{j=1}^{n}\left(x_j\right)^{\lambda_j}$. Use the data on prices and attributes to estimate the equation

$$\ln p_{kt}^{\alpha}(t) = -d_t + \sum_{j=1}^{n} \lambda_j \ln x_{jt}^{\alpha} + \epsilon_t^{\alpha}, \qquad \text{all } \alpha, \quad \text{all } t,$$

where d_t is a time dummy. Then use market shares s_{kt}^{α} to calculate the average price at each date,

$$\overline{p}_{kt} = \sum_{\alpha} s_{kt}^{\alpha}\hat{p}_{kt}^{\alpha}, \qquad \text{all } t. \tag{12}$$

Use (12) in (11) to get an estimate of the rental rates,

$$\hat{q}_{kt} = \overline{p}_{kt}\left[1 - \frac{1-\delta_{kt}}{1+r_{t+1}}\frac{\hat{\gamma}_t}{\hat{\gamma}_{t+1}}\right], \qquad \text{all } t, \tag{13}$$

where $\hat{\gamma}_t$ is the estimated time dummy $\hat{\gamma}_t = e^{\hat{d}_t}$. The rental rate at t is proportional to the average quality-adjusted price of a new machine, with a factor of proportionality that includes the depreciation and interest rates in the usual way, and also includes the anticipated change in the markup γ_t/γ_{t+1}. An increase/decrease in the markup reduces/raises the current rental rate, as owners anticipate a capital gain/loss.

The estimate of average quality at t is

$$\hat{v}\left(\underline{\overline{x}}_t\right) = \hat{\gamma}_t \overline{p}_{kt} \approx \hat{\gamma}_t \sum_{\alpha} s_{kt}^{\alpha} \hat{v}(\underline{x}_t^{\alpha}), \qquad \text{all } t. \tag{14}$$

3. Cost minimization.—

It is then fairly straightforward to use (1) and (2) to characterize the cost-minimizing input mix in agriculture. Estimating the model parameters—the elasticities and shares in the nested CES—from the data on prices and quantities is delicate but possible.

Figure 5 (MS's Figure 3) displays the resulting estimates for tractor prices $\overline{p}_{kt}$ and quality $v(\underline{x}_t)$, as well as the parameter γ_t. Over the period of rapid adoption 1935-48, tractor quality $v(x)$ rose a little before 1940 and was approximately constant afterwards. The parameter γ_t rose over most of the period, depressing markups, and then fell sharply at the end of the war, raising the markup. The result was that the price was approximately constant over the whole period. Figure 6 (MS's Figure 4) displays the fit of the model over the entire transition period, which is quite good.

D. Other studies

There are many other papers as well looking at diffusion of particular technologies. For example, Jovanovic and MacDonald (1994a) look at adoption of diesel locomotives. Invented in 1912 and first used in the U.S. in 1925, penetration—as measured by the share of locomotives that were diesel—was slow for the first 20 years, but it was quite rapid after that, increasing from about 10% in 1945 to almost 90% by 1955 and well over 95% by 1960.

In addition, many papers have studied other aspects of technology adoption. For example, Gort and Klepper (1982) study the entry and exit of producers in markets for new products. Using data for 46 products, a mix of producer and consumer goods, they identify five stages, distinguished by entry and exit rates.

Jovanovic and MacDonald (1994b) examine industry structure for automobile tires, and consolidate Gort and Klepper's five stages into three: a period with rapid entry, followed by a "shakeout" period with lots of exit, and then a mature industry with a moderate number of firms. The authors develop a simple theoretical model that produces those three phases, and show that similar industry patterns appear for autos, airplanes, cell phones.

Grubler (1991) looks at sequences of technologies serving particular functions: the decline of the horse and rise of the automobile for land transportation; the successive use of sail, steam and motor propulsion for merchant marine transportation; five methods for steel production; and the diffusion of six new technologies for various automobile parts.

3. EVIDENCE ON CROSS-COUNTRY DIFFUSION

Detailed data on adoption patterns—arrival and penetration rates—for a broad set of countries is not available for even a small set of technologies. Thus, data availability has led researchers to ask a different set of questions. In particular studies of cross-country diffusion have asked what country characteristics explain faster adoption. Three approaches have been used.

One approach, used by Comin and Hobijn (2004, 2010), is to look at adoption lags, in the sense of date of first adoption, across a broad set of countries, for a number of particular technologies. They relate the lags to country characteristics like human capital and degree of openness. In a related paper, Comin and Mestieri (2017) look at time trends in both adoption lags and penetration rates.

A second approach, used by Eaton and Kortum (2001), Caselli and Coleman (2001), and Caselli and Wilson (2004) uses data on imports of capital goods. As noted earlier, many technologies are 'embodied' in capital goods. Thus trade in equipment is, potentially, an important mechanism by which technologies diffuse across countries.

And since good bilateral trade data are available at a rather fine product level,[5] data for capital goods in the relevant categories can be used to ask a number of questions.

A third approach, used by Chen (2018) is to look at TFP growth in agriculture. The idea here is that long-run TFP growth in that sector is due to technology adoption, and that many of the technologies relevant for agriculture—tractors, fertilizer, and so on—are sector-specific.

A. Comin and Hobijn (2004, 2010)

Comin and Hobijn (2004) look at the adoption of twenty technologies, in twenty-three developed countries, over the period 1788-2001. Specifically, they look at lags until first adoption. The data are a mix of consumer and producer goods, for some the data cover a very limited number of countries, and there's much missing data before 1938.

But four technologies are interesting for our purposes here: personal computers, measured per capita; industrial robots, measured per unit of GDP; three shipping technologies—sail, steam, and motor, measured as fraction of tonnage; and four steel technologies—open hearth, Bessemer, blast oxygen, and electric arc, measured as fraction of tonnage. In regressions, they find that human capital, per capita GDP, and openness predict earlier adoption.

In Comin and Hobijn (2010) the authors estimate adoption lags for fifteen technologies, across 166 countries, spanning two centuries. The data here are subject to the same caveats. They find long lags—an average of 45 years, but the lags are shorter for later technologies.

[5] For example, see Feenstra, et. al., (2005).

B. Comin and Mestieri (2017)

Comin and Mestieri (2017) use an extended version of the data in Comin and Hobijn (2010) to look further into adoption patterns for twenty-five technologies in 139 countries. These technologies are very heterogenous, including producer goods, consumer goods, and mixed-use goods, and as before much data is missing.[6]

They find that adoption patterns across countries and technologies can be well approximated in terms of a technology-specific shape that is the same across countries, and two country/time-specific parameters that are the same across technologies. Specifically, adoptions patterns for each technology/country pair can be described by first fitting a basic 'shape' for adoption in an advanced country where detailed, reliable data is available, and then shifting the date of origin and stretching the curve downward/rightward at later dates for other countries. The lag and penetration parameters then describe the length of time between the innovation date and the first use in a particular country and how quickly the new technology diffuses after the first adoption.

For the empirical work they aggregate the countries into two groups, Western (advanced) and non-Western. They estimate the technology-specific shapes from U.S., U.K., French or German data, and the country/time parameters with a set of decade $\times$ country-group dummies.

Thus, the approach is similar to the one in Griliches (1957) and Mansfield (1961), except that the shape is not assumed to be logistic. In addition, the definition of adoption is different. In Griliches (1957) it is the share of acreage and in Mansfield (1961) it is the share of (large) firms. Since Comin and Mestieri do not have data

[6] The technologies in the three groups are: spindles, ships, railroad freight, aviation freight, trucks, fertilizer, tractors, harvesters, steel production techniques, synthetic fibers; railroad passengers, aviation passengers, cars, medical procedures (kidney transplants and liver transplants, heart surgery); and electricity, telegraph, mail, telephones, cellphones, cars, internet.

on output at the country/industry/time level, adoption is defined as (log) output produced with the new technology relative to total GDP, or (log) input of the new technology (e.g. the stock of the new capital good) relative to total GDP. Thus, the penetration parameter also picks up cross-country differences in output composition.

Their procedure produces predicted diffusion paths for each technology $\times$ country-group pair. As a robustness check they divide the non-West group into quartiles, estimating group-time (decade) fixed effects for each group. These do not vary much across groups.

The authors find that over time, adoption lags have gotten shorter but the difference between advanced and less-advanced countries in speed of penetration has gotten larger. One candidate explanation is that less developed countries have two groups of firms operating in parallel: one adopts modern technology—although with a lag, and the other never adopts.

C. Eaton and Kortum (2001)

Eaton and Kortum (2001) pioneered the study of trade data on equipment imports and exports. They show that across countries, equipment output as a share of GDP increases strongly with GDP per capita, and net equipment exports as a share of GDP increase strongly with equipment production as a share of GDP per capita. Developing countries, on the other hand, import a large share of their total investment in new equipment and this equipment comes from a small set of exporters. Thus, new capital goods are potentially an important mechanism by which technologies diffuse to less developed countries.

For 1985, the year they use for their cross-sectional study, Eaton and Kortum identify a 'big 7' group of countries that accounted for a large share of equipment imports in most countries. The 'big 7' countries—U.S., Japan, Germany, U.K., France, Sweden, and Italy—are also R&D intensive. They show that across a broad set of countries in the rest of the world, imports from the 'big 7' accounted for 64-92% of equipment imports.

Eaton and Kortum also show that the price of equipment relative to consumption goods is strongly decreasing in GDP per capita. In a variant of a standard growth model, this fact implies that differences in the relative price of internationally traded equipment is a significant factor in explaining differences in cross-country productivity levels. Here the authors find that here it explains about a quarter of those differences.

By 2000, China, Taiwan and Korea had overtaken France, Sweden, and Italy to form a new 'big 7' group of exporters (author's calculation). Imports from the new group form a smaller—but still very substantial—share of total equipment imports in most countries in 2000. Thus, it seems likely that the mechanism identified by Eaton and Kortum continues to operate.

D. Caselli and Coleman (2001)

Caselli and Coleman (2001) look at cross-country data on computer adoption over the period 1970-1990. Most countries produced little or no computer equipment of their own during this period, especially in the earlier years, so adoption can be proxied by imports. To check robustness they try a couple of different measures, one of which involves excluding countries with computer exports.

They find that schooling levels have an important effect on computer imports. In the non-exporting sample, a one percentage point increase in the fraction of the population with schooling above the primary is associated with a five percent increase in computer imports. There is also an important shift over time, presumably because computers became better and cheaper (Figure 1 in the NBER pre-print).

E. Caselli and Wilson (2004)

Caselli and Wilson (2004) develop a simple structural model to look at adoption of embodied technologies. The model has many sectors, each of which uses sector-specific capital equipment together with homogeneous labor to produce an intermediate, where the productivity levels in each sector are country-specific. The intermediates are used in a CES function that is common across countries to produce final goods. The efficient (competitive equilibrium) allocation requires that the relative capital shares across sectors in each country equal the productivity ratios across sectors in that country.

As noted before, since most equipment is produced in a small set of countries, for the rest of the world investment is well proxied by imports. Caselli and Wilson identify nine important categories of capital equipment—electrical, non-electrical, office, communication, motor vehicles, etc.—and document large cross-country differences in import shares across categories. For the empirical work, the authors exclude big exporters and construct stocks of equipment in each sector by combining share data on capital goods imports and NIPA data on aggregate investment.

The differences in shares across categories of equipment can be interpreted as differences in adoption rates for different types of technologies. The authors relate these differences in adoption rates to country characteristics. Specifically, they conjecture that the country/sector productivity parameters depend on observable country characteristics. The relative import shares should then also depend on those characteristics. The characteristics they look at are the availability of complementary factors: educated labor, institutions, composition of GDP, level of financial development, and so on. The coefficients in the resulting regression equation are the relative importance of the country characteristics in determining the country-sector productivity parameters.

They find that human capital is complementary to computers, electrical equipment, communication equipment, motor vehicles, and professional goods; and income per capita is complementary to computers and electrical equipment. Although the results are sensitive to the set of other regressors that are included, both human capital and income per capita could be thought of as proxies for wage rates. A time trend is also significant for some technologies—computers, electrical equipment, communication equipment, and aircraft, perhaps because they had more significant price declines.

The authors also construct a measure of the R&D intensity for each category of capital equipment. They find that the median country is slower to adopt more R&D-intensive technologies, but those categories enjoy more rapid increases over time. Perhaps equipment in those categories is initially less suitable to the median country, but experiences bigger quality increases and/or price declines over time.

F. Chen (2018) Technology adoption in agriculture

The share of labor employed in agriculture declines sharply as a country develops, as seen in both cross-country data and time series for developed countries. Figures 7 and 8 (Lucas, 2009, Figures 11 and 13) show the plot for a large cross section of countries and time series for the U.S., U.K., Japan and India. Thus, improvements in labor productivity in agriculture and the movement of labor into the non-agricultural sector are critical for understanding development.

In addition, cross-country differences in labor productivity are larger in agriculture than in nonagriculture (Caselli, 2005; and Restuccia, Yang and Zhu, 2008). Figure 9 (Restuccia, Yang and Zhu's Figure 2) displays labor productivity in the two sectors (panel a) and productivity in agriculture relative to non-agriculture (panel b).

Motivated by these facts, Chen (2018) studies technology adoption in agriculture, looking at both cross-country evidence and U.S. time series. Chen starts by constructing a cross-country data set on capital intensity by sector, which shows that the patterns seen in labor productivity also hold for capital intensity. Figure 10 (Chen's Figure 1, panels a and b) displays the cross-sectional capital-output and capital-labor ratios, measured at international prices, in agriculture and nonagriculture. Chen also shows that in the U.S., the capital-output ratio in agriculture rose over the period 1920-2000 but showed no trend in nonagriculture. Figure 11 (Chen's Figure 2) shows the two time series (panel a) as well as plots of the adoption rates for various types of new capital equipment (panel b).

Chen argues that differences between the two sectors in technology adoption explain these patterns. His model starts from the fact that much technical change in agriculture is embodied in new equipment: tractors, trucks, combines, balers, and so on. Chen's two-sector general equilibrium model includes labor allocation, consumption and investment decisions, and features investment-specific technical change (ISTC). Here we will focus on the model's novel feature, which is the treatment of technology adoption in agriculture.

As in Hansen and Prescott (2002), two technology alternatives are available in agriculture. Each is Cobb-Douglas, with capital k, land ℓ, and farmer's ability s as inputs, and different share parameters. Let

$$y = A_x s^{1-\alpha_x-\gamma_x} k^{\alpha_x} \ell^{\gamma_x}, \qquad x = r, m,$$

denote the production functions for the traditional (r) and modern (m) technologies. The modern method is assumed to be more capital intensive, $\alpha_m > \alpha_r$, and (weakly) less intensive in both of the other inputs, $\gamma_m \leq \gamma_r$, and $1 - \alpha_m - \gamma_m \leq 1 - \alpha_r - \gamma_r$.

There are perfectly competitive markets for the rental of capital equipment and land. Let R_k and q denote the rental rates, normalize the output price to unity, and consider the (static) decision problem of a farmer at any date. Farmers are heterogenous in terms of ability s. It is straightforward to show that the operating profit for a farmer with ability s using either method is

$$\begin{aligned}\pi_x(s; R_k, q) &= \max_{k,\ell} \left[A_x s^{1-\alpha_x-\gamma_x} k^{\alpha_x} \ell^{\gamma_x} - R_k k - q\ell\right] \\ &= \pi_{0x} R_k^{-\alpha_x} q^{-\gamma_x} s, \qquad\qquad x = r, m,\end{aligned}$$

where the constant π_{0x} depends on A_x, α_x and γ_x. Both profit functions are linear in s, and the elasticity of profits with respect to the user cost of capital is $-\alpha_x$. Thus, both techniques become more profitable as R_k falls, but since $\alpha_m > \alpha_r$, a change in R_k has a proportionately larger impact on profits from the modern technology.

If there are no other costs, then for any fixed rental rates (R_k, q), either $\pi_r > \pi_m$ or $\pi_x \leq \pi_m$, all s, so either all farmers adopt the modern technology or none do. To make adoption gradual, Chen introduces a fixed cost of adoption, f for the modern technology. The choice for a farmer with skill s is then

$$\max\left\{\pi_r(s; R_k, q),\ \pi_m(s; R_k, q) - f\right\}.$$

For moderate levels of the fixed cost, farmers with ability s above some threshold $\hat{s}$ adopt the modern technology and the rest do not. The left panel of Figure 12 (Chen's Figure 3), which plots $\pi_r(s)$ and $\pi_m(s)$ for fixed q and two values for R_k, shows the two possibilities.

Chen models the gradual adoption of modern farming methods through the reduction in the cost of capital R_k, induced by ISTC. As R_k declines, the slopes π_m and π_r both increase, as shown in the right panel of Figure 12, but the former increases proportionately more. Thus, the threshold $\hat{s}$ declines as R_k falls, and over time an expanding set of farmers adopts the modern technology.

It is always the highest ability farmers who adopt the modern technology. Although ability is not directly observable, land use ℓ is proportional to ability s for each technology. In addition, it is straightforward to show that if $\gamma_m = \gamma_r$, and if factor prices are such that $\pi_m > \pi_r$, then farmers using the modern technology operate more land than those using the traditional technology. Hence it is larger farms that adopt modern, capital-intensive methods. Chen shows that this was the case in the U.S.

In Chen's model investment-specific technical change (ISTC) also contributes to TFP growth in the non-agricultural sector, and there are other forces at work as well, including the relative price of the agricultural output, the price of land and the wage in the nonagricultural sector. But, consistent with Figure 11, the nonagricultural sector is assumed to have only one basic technology, so the capital-output ratio in that sector is roughly constant over time.

4. TWO SIMPLE MODELS OF TECHNOLOGY ADOPTION

In this section we will develop two simple theoretical models of technology adoption. The first is directed toward explaining speeds of diffusion in a single country, the second toward explaining cross-country diffusion. Both are dynamic models based on cost reduction. Both draw on Manuelli and Seshadri's (2014) model of tractors and on Chen's (2018) model of cross-country diffusion of agricultural technologies in developing countries, as well as on the model in Jovanovic and MacDonald (1994a).

A. Hybrid corn and industrial innovations

Suppose there are two technology levels, indexed by $\chi = 0$ ($\chi = 1$) for the old (the new) technology. Assume the interest rate $r > 0$ is constant over time and that there is no entry. The state variable is $\nu \in [0, 1]$, the share of producers (or industry capacity) that has already adopted the new technology.

For hybrid corn the goal is to explain differences in adoption patterns across regions: adoption was earlier, faster, and more complete in regions where yields were higher and acreage in corn was larger. For this case let $i = 1, .., I$, denote regions. For the industrial technologies in Mansfield's study, the date of first adoption varied exogenously across innovations and long-run penetration was complete in all cases. Hence the only goal is to explain differences in the speed of adoption across innovations: controlling for industry, adoption speed was positively related to incremental net revenue per unit of capacity from adoption, and negatively to the required investment. For this case let $i = 1, ..., I$, denote the various innovations.

1. Model components.—

For both hybrid corn and the industrial examples, the key model elements are the size distribution of production units, the profitability per unit of capacity of using the old and new technologies, and the fixed (sunk) cost of adopting the new technology.

For corn, farms vary in size—acreage—within each region, and the size distribution varies across regions. Let $F_i(z)$ denote the CDF for acreage in region i, for $i = 1, ..., I$. The operating profit per unit of capacity is the profit per acre from growing the old variety and the hybrid. Let $\pi_{i1} > \pi_{i0} > 0$ denote operating profits—revenue net of variable costs—per acre in region i with the hybrid and the old variety. Corn from all regions is sold on a common domestic market, so the output price p is the same across regions. Suppose in addition that p is constant over time. Both yield per acre, call it y_i, and the seed and other input costs, call them ψ_i, vary across regions.

No capital investment is required to grow hybrid corn, but the seeds and other inputs are more expensive, and the hybrid raises yield per acre. Suppose the hybrid increases yield by a roughly constant percentage g_y across regions, and increases costs by a common constant g_ψ. Then profits per acre for the old variety and the hybrid are

$$\begin{aligned}\pi_{i0} &= py_i - \psi_i, \\ \pi_{i1} &= (1 + g_y)\, py_i - (\psi_i + g_\psi)\,, \qquad i = 1, ..., I,\end{aligned}$$

and the *incremental* profit per acre

$$\begin{aligned}\Delta_i &\equiv \pi_{i1} - \pi_{i0} \\ &= g_y p y_i - g_\psi, \qquad i = 1, ..., I,\end{aligned}$$

is higher in regions i where yield y_i is higher.

Absent other factors, all producers in region i would adopt immediately if $\Delta_i > 0$, and otherwise none would ever adopt. To explain gradual diffusion, suppose there is a one-time fixed (sunk) cost of adoption, interpreted as the cost of learning about the growing method for the new seed. Suppose further that the fixed cost falls with the share of other farms or acreage in the region that has already adopted. The interpretation is that farmers learn about the new growing requirements from their neighbors within the region. Let $\nu \in [0, 1]$ denote this share, and assume the adoption cost function $c_0(\nu)$ is the same across regions. Otherwise all difference across regions could be explained as difference in adoption costs.

For the industrial examples, measure size by capacity—output or sales (revenue) per year—or by employment, and let $F_i(z)$ denote the CDF for the size distribution of producers in industry i. In this case price p_i depends on the industry i, but "yield" is simply unity.

Suppose as before that the new technology increases output per unit of capacity by a factor g_{ip} and changes variable cost by $g_{i\psi}$, where those changes obviously vary by industry. Then profits per unit of capacity in industry i are

$$\begin{aligned}\pi_{i0} &= p_i - \psi_i, \\ \pi_{i1} &= (1 + g_{iy})\, p_i - (\psi_i + g_{i\psi}),\end{aligned}$$

and the incremental profit of adoption is

$$\begin{aligned}\Delta_i &= \pi_{i1} - \pi_{i0} \\ &= g_{iy} p_i - g_{i\psi}, \qquad \text{all } i.\end{aligned}$$

In this context $g_{i\psi}$ can be negative, if the innovation reduces material, energy, or other input costs.

The industrial innovations required substantial investments in new equipment, so the adoption cost depends on the firm's size as well as the share of earlier adopters. As before, later adopters can learn from those who adopt earlier, here by direct communication between firm managers or by poaching their workers. Assume the cost of adoption for innovation i in a firm with capacity z, as a function of the penetration rate, is $c_{i0}(\nu) + c_{i1}z$.[7] The first component represents the cost of learning the new method, and the second represents the cost of the new equipment.

In summary, in each case the model inputs are the size distributions F_i and parameters $\{\pi_{i0}, \pi_{i1}, c_{i1}\}$ and function $c_{i0}(\nu)$ describing profits and costs. For hybrid corn $c_0(\nu)$ does not vary with i and $c_{i1} = 0$, all i.

There are no interactions across regions/industries in either case. For the industrial innovations this fact is obvious. For hybrid corn it is a consequence of the assumption that the price p does not vary with production. Thus, competitive equilibrium in each region/industry i involves only the evolution of the penetration rate ν_i and the resulting evolution of the adoption cost $c_{i0}(\nu_i)$.

2. Competitive equilibrium.—

For notational simplicity we drop the subscript i in this subsection. Let r denote the interest rate. Fix F, with support $Z = [z_{\min}, z_{\max}]$, the parameters (π_0, π_1, c_1, r), and the function $c_0(\nu)$. We will maintain the following restrictions throughout.

ASSUMPTION 1: a. F has a continuous, strictly positive density on $Z = [z_{\min}, z_{\max}]$;

b. $\pi_0 > 0,\ \pi_1 > 0,\ c_1 \geq 0,\ r > 0$;

c. $c_0(\nu)$ is continuous and strictly decreasing in ν.

[7] Industry price p_i, and the price of equipment c_{i1} might also decline as adoption proceeds. In this case an additional assumption is required, restricting the relative rates of decline.

Let $G \equiv 1 - F$ denote the right tail CDF for F. Assume that the cost of adoption $c_0(\nu)$ depends on the penetration rate in the *previous* period.

Informally, in terms of sequences a competitive equilibrium is defined by a nondecreasing sequence of penetration rates $\nu_{-1} = 0$ and $\{\nu_n\}_{n=0}^{\infty}$, and associated thresholds $z_0 = G^{-1}(0) = z_{\max}$ and $\{z_n = G^{-1}(\nu_{n-1})\}_{n=0}^{\infty}$, with the following property: for each $n = 1, 2, ...$, if the penetration rate is ν_{n-1} at the end of the previous period and is expected to be $\{\nu_{n+i}\}_{i=0}^{\infty}$ in the current and subsequent periods, then it is optimal for firms with $z \geq z_n$ to adopt in the current period if they have not already done so and for all others to wait.

Since the sequence $\{\nu_n\}$ is nondecreasing, it reaches or approaches an upper bound. Let $\overline{\nu} \equiv \lim_{n\to\infty} \nu_n \leq 1$ denote this bound. If the penetration rate at the beginning of the period is $\overline{\nu}$, then either all firms have adopted already ($\overline{\nu} = 1$), or no firms with $z < G^{-1}(\overline{\nu})$ find it profitable to adopt.

Alternatively, since adoption involves an intertemporal trade-off, we can take a recursive approach. Then the individual state variable for each producer is his size z, and the aggregate state variable is the penetration rate ν at the end of the previous period. Let $V_\chi(z, \nu)$, $\chi = 0, 1$, denote the value of a producer of size z when the state is ν, and the producer has not ($\chi = 0$) or has ($\chi = 1$) adopted the innovation.

We then have the following definition.

Definition: Given $(F, \pi_0, \pi_1, c_0, c_1, r)$, a *competitive equilibrium* is pair of value functions $V_\chi(z, \nu)$, $\chi = 0, 1$, all z, ν, and a nondecreasing function $\Phi(\nu)$ with $\Phi(\nu) \geq \nu$, all ν, describing the law of motion for ν, such that:

i. for all z, ν,

$$V_1(z, \nu) = \pi_1 z + \frac{1}{1+r} V_1(z, \Phi(\nu)); \tag{15}$$

ii. for all z, ν,

$$V_0(z, \nu) = \max\left\{V_1(z, \nu) - [c_0(\nu) + c_1 x], \pi_0 z + \frac{1}{1+r} V_0(z, \Phi(\nu))\right\}; \tag{16}$$

iii. for all ν, the first option (the second option) in (16) is optimal for $z \geq \Phi(\nu)$ (for $z \leq \Phi(\nu)$).

Producers who have already adopted make no more decisions, and (i) is the Bellman equation for their value function. Producers who have not yet adopted must decide whether to adopt in the current period or wait, and (ii) is the Bellman equation for their decision problem. Condition (iii) states that Φ is the equilibrium law of motion for the state variable ν.

Notice that producers do not necessarily adopt on the first date when adopting this period dominates never adopting. The continuation value $V_0(z, \Phi(\nu))$ includes the option of adopting later, and since the fixed cost falls over time, that option is valuable. Adopting later delays the arrival of the gain, but it also reduces the adoption cost.

Next we will show that a competitive equilibrium exists and it is unique.

3. Long-run penetration.—

First consider the long-run penetration rate, call it $\overline{\nu}$. When penetration has reached this level, all firms of size $z \geq \overline{z} \equiv G^{-1}(\overline{\nu})$ have adopted, while the rest have not adopted in the past and choose not to adopt this period. To establish the existence and uniqueness of a value $\overline{\nu} > 0$ with these properties, a little more structure is required.

Let $\Gamma \equiv \Delta - \beta c_1$, denote the net one-period gain from adoption, where $\beta \equiv r/\left(1+r\right)$ annuitizes the equipment cost.

Firms gain from adoption if and only $\Gamma > 0$. Assume this holds. Assume in addition that the largest producers prefer to adopt, even if no others do so.

ASSUMPTION 2: a. $\Gamma = \Delta - \beta c_1 > 0$.

b. $\beta^{-1}\Gamma z_{\max} > c_0(0)$.

To characterize $\overline{\nu}$, first note that any penetration rate $\widetilde{\nu}$ where firms of size $z \geq$

$G^{-1}(\widetilde{\nu})$ are willing to adopt if they have not done so already and the rest are not, satisfies

$$\beta^{-1}\Gamma z \gtreqless c_0(\widetilde{\nu}), \qquad \text{as } z \gtreqless G^{-1}(\widetilde{\nu}), \qquad \text{all } z \in Z.$$

Under Assumptions 1 and 2 this condition holds if and only if

$$\Gamma G^{-1}(\widetilde{\nu}) \geq \beta c_0(\widetilde{\nu}), \qquad \text{w/ eq. if } \widetilde{\nu} < 1. \tag{17}$$

Note that (17) holds with equality if long-run penetration is less than complete. We then have the following result.

PROPOSITION 1: If Assumptions 1 and 2 hold, there exists at least one value $\widetilde{\nu} > 0$ satisfying (17).

PROOF: If $\Gamma G^{-1}(\nu) > \beta c_0(\nu)$, all $\nu \in [0, 1]$, then $\widetilde{\nu} = 1$ satisfies (17). Otherwise, by Assumption 2b the (strict) inequality holds at $\nu = 0$, and the reverse (weak) inequality holds for some $\nu \in (0, 1]$. Since both G^{-1} and c_0 are continuous in ν, it follows that $\Gamma G^{-1}(\widetilde{\nu}) = \beta c_0(\widetilde{\nu})$ for some $\widetilde{\nu} \in (0, 1]$. ■

4. Dynamics of adoption.—

Next consider the dynamics of adoption. A firm that has not yet adopted can adopt this period or next, or can wait at least two periods. Use (15) and (16) to find that under Assumption 2, adopting this period is preferred to waiting one period if and only if

$$\Gamma z \geq c_0(\nu) - \frac{1}{1+r} c_0(\Phi(\nu)). \tag{18}$$

The one-period gain from adoption must outweigh the reduction in the fixed cost from waiting one period.

Since $\Gamma > 0$, if (18) holds for $\hat{z}$, it also holds for all $z > \hat{z}$. We then have the following result.

PROPOSITION 2: Under Assumptions 1 and 2 there exists a unique competitive equilibrium adoption function Φ. The long-run penetration rate $\overline{\nu}$ is the minimum value satisfying (17), and there are two cases for Φ.

Case a: If $\overline{\nu} = 1$ and $\Gamma z_{\min} > \beta c_0(1)$, long-run penetration is complete and occurs in a finite number of periods. In this case $\Phi^{-1}(1) = [\mu, 1]$, where μ satisfies

$$\Gamma z_{\min} + \frac{1}{1+r} c_0(\mu) \geq c_0(1), \qquad \text{w/ eq. if } \mu > 0, \tag{19}$$

and Φ^{-1}, for $\nu' \in [\nu_1, \mu)$ is the single-valued function defined by

$$\Gamma G^{-1}(\nu') + \frac{1}{1+r} c_0(\nu') = c_0(\Phi^{-1}(\nu')), \tag{20}$$

where $\nu_1 > 0$ satisfies

$$\Gamma G^{-1}(\nu_1) + \frac{1}{1+r} c_0(\nu_1) = c_0(0). \tag{21}$$

Case b: If $\Gamma G^{-1}(\overline{\nu}) = \beta c_0(\overline{\nu})$, the penetration rate approaches $\overline{\nu}$ asymptotically, and if $\overline{\nu} < 1$, long-run penetration is less than complete. In this case Φ^{-1} is the single-valued function defined by (20) for $\nu' \in [\nu_1, \overline{\nu}]$, where v_1 is defined in (21).

Proof: The proof is constructive. Proposition 1 establishes that (17) has at least one solution. Since all solutions lie on the interval $[0, 1]$, the set of solutions has a minimum. We will show below that this value is $\overline{\nu}$.

Case a: To construct $\Phi^{-1}(1)$, suppose the penetration rate is expected to increase to $\overline{\nu} = 1$ in the current period. Adopters must prefer (at least weakly) to adopt when the fixed cost is currently $c_0(\nu)$, $\nu \in \Phi^{-1}(1)$ and is expected to fall to $c_0(1)$.

Assumption 1c implies immediately that $\Phi^{-1}(1)$ is a closed interval: it has the form $[\mu, 1]$, and since $G^{-1}(1) = z_{\min}$ is the critical firm, it follows from (18) that μ satisfies (19). If (19) holds at $\mu = 0$, the construction is complete.

Otherwise, $\mu > 0$ and the rest of the construction is similar, except that Φ^{-1} is single-valued. From (18), if the penetration rate is expected to increase to ν' in the current period, $\Phi^{-1}(\nu')$ satisfies (20). Since G^{-1} and c_0 are continuous and strictly decreasing, so is the left side of (20). Hence Φ^{-1}:$[\nu_1, 1) \to [0, \mu)$ defined by (20) is continuous and strictly increasing, and $\nu_1 \equiv \Phi(0)$ satisfies (21).

Moreover, since $\nu' < \overline{\nu}$, and $\overline{\nu}$ is the minimum value satisfying (17), it follows that

$$\Gamma G^{-1}(\nu') < \beta c_0(\nu') = \left(1 - \frac{1}{1+r}\right) c_0(\nu'), \qquad \text{all } \nu' < \overline{\nu}.$$

Since c_0 is a decreasing function, it then follows from (20) that $\Phi^{-1}(\nu') < \nu'$, all $\nu' < \overline{\nu}$.

Case b: If $\Gamma G^{-1}(\overline{\nu}) = \beta c_0(\overline{\nu})$, the argument is the same except that J is defined on $[\nu_1, \overline{\nu}]$, and Φ^{-1}: $[\nu_1, \overline{\nu}] \to [0, \overline{\nu}]$ is everywhere single-valued. The penetration rate approaches $\overline{\nu}$ asymptotically, and long-run penetration is less than complete if $\overline{\nu} < 1$. ■

Producers with $z < G^{-1}(\overline{\nu})$ never adopt the new technology. Nor do they exit: since there is no fixed cost of operating, they simply continue producing with the old technology. If there were a fixed cost, smaller firms might exit if $\pi_0(\nu)$ falls, or they might be bought out or consolidated into larger units. These considerations will not be explored here, although the present model could be extended to include them.

5. Empirical predictions: effects of parameter changes.—

The substantive conclusions in the studies by Griliches and Mansfield involved the economic factors leading to faster or slower penetration, and more or less complete penetration, across regions and industries. Griliches found that both the speed of adoption and the long-run level of use—the slope and ceiling of the logistic function, were increasing in the profitability of hybrids.[8] Mansfield, focusing on the slopes only, found that they were well explained by profitability and the initial investment cost.

[8] Griliches also found that the date of first adoption was earlier in regions where the hybrid was more profitable. The date of first adoption depended on the behavior of suppliers, the USDA and the seed companies. The model here does not include suppliers, and has nothing to say about dates of first adoption.

To ask if the model produces these patterns, at least qualitatively, we must look at the effects of parameter changes. Profitability net of the equipment investment cost is reflected in the parameter $\Gamma = \Delta - \overline{c}_1$. For the hybrid corn example it is also reflected in the distribution function F, since farms with higher acreage in corn have greater total benefits from adoption and a correspondingly greater incentive to incur the fixed cost. Hence we are interested in the effects of an increase in Γ or a rightward shift in F—an upward shift in G^{-1}.

The long-run penetration rate is captured by the equilibrium value for $\overline{\nu}$. The speed of adoption is reflected in the function $\Phi(\nu)$, with an upward shift implying faster and more complete adoption.

For a uniform distribution the equilibrium can easily be calculated (see the Appendix). Let $[m, m+d]$ denote the support of F. Then an increase in m or d implies an upward shift. First consider the long-run penetration rate $\overline{\nu}$. There are two possibilities, depending on the parameter values,

$$\begin{aligned} \overline{\nu} &= \frac{d\Gamma - (\beta a_0 - m\Gamma)}{d\Gamma - \beta b_0} \leq 1 \qquad \text{if} \qquad \beta a_0 - m\Gamma \geq \beta b_0, \\ \overline{\nu} &= 1 \qquad \qquad \qquad \qquad \qquad \text{if} \qquad \beta a_0 - m\Gamma < \beta b_0. \end{aligned}$$

Thus, increases in m and Γ expand the region where long-run penetration is complete, and $\overline{\nu}$ is strictly increasing in m, d and Γ in the region where $\overline{\nu} < 1$.

Next consider the dynamics. In the region of parameter space where $\overline{\nu} = 1$, all producers adopt in the first period.[9] This outcome is the consequence of the uniform distribution. In the region where $\overline{\nu} < 1$, the equilibrium adoption function is linear

$$\Phi(\nu) = \nu_1 + \frac{b_0}{d\Gamma + b_0/\,(1+r)}\nu,$$

where

$$\nu_1 = \frac{(m+d)\,\Gamma - \beta a_0}{d\Gamma + b_0/\,(1+r)} \in (0,1)\,.$$

[9]The only exception is the knife-edge case $\beta a_0 - \overline{\Gamma} m = \beta b_0$, where long-run penetration is complete, $\overline{\nu} = 1$, but adoption is gradual.

The intercept ν_1, first-period adoption, is strictly increasing in m, d, and Γ, and Φ crosses the 45^o line at $\overline{\nu}$. Thus, an increase in m, d or Γ shifts Φ upward. For this family, higher profitability implies that adoption is faster and more complete.

Figure 13a displays Φ for a baseline set of parameters and for increases, one at a time, in m, d and Γ. Figure 13b illustrates time paths for adoption for the same set of examples.

B. Cross-country diffusion

Most new technologies are developed in high-income countries, where wage rates are high. In addition, capital equipment has enjoyed a long and very significant price decline relative to consumer goods in these countries. Hence many new technologies are designed to be labor-saving and capital-using. Since in many cases all countries purchase equipment from the same advanced-country supplier(s), all enjoy the price declines. Thus, we can expect differences in wage levels and wage growth rates across countries, as well as the declining price of equipment, to be important for understanding the patterns of international technology adoption. Those are the key features of the model here.

The cross-country evidence evidence is clearest for personal (and other) computers, showing that higher levels of schooling and higher per capita GDP lead to earlier adoption. Caselli and Wilson (2004) also find that higher human capital leads to faster adoption of electrical and communications equipment, motor vehicle, and professional goods.

1. The model.—

For simplicity the model here looks at the case where the old technology uses only labor, and the new one uses both labor and capital.

Index countries by $j = 1, ..., J$, and assume the new technology is introduced at date $t = 0$. In addition, assume that the cost of equipment at any date t, call it $q(t)$, is the same across countries. Suppose the interest rate r and the cost of maintenance to offset depreciation δ are also the same across countries, and for simplicity assume they are constant over time. Then the user cost of equipment purchased at t, call it $R(t) = (r + \delta) \, q(t)$, is similar across countries and declines over time if q falls. But wages $w_j(t)$ and their growth rates vary across countries. Thus, the gains from adoption at any date are smaller, and perhaps nonexistent, in countries with lower wages levels and slower growth rates.

Suppose the production functions for the two technologies are

$$y_{0j} = A_j^{1-\beta} \ell_0^{\beta}, \qquad y_{1j} = (BA_j)^{1-\beta} \left(k_1^{\alpha} \ell_1^{1-\alpha} \right)^{\beta}.$$

For simplicity, returns to scale β are the same for the two technologies, and the shifter $B > 1$ is the same across countries. The constant A_j, which encompasses both overall productivity and a Lucas span-of-control parameter, may vary across countries.

Let p be the output price. For simplicity assume it is the same across countries and constant over time. It is straightforward to show that profits for the two technologies are

$$\begin{aligned} \pi_0(w_j; A_j) &= A_j \overline{\pi}_0 w_j^{-\zeta}, \\ \pi_1(w_j, R; A_j) &= BA_j \overline{\pi}_0 C_{\alpha} \left(w_j^{1-\alpha} R^{\alpha} \right)^{-\zeta}, \end{aligned}$$

where

$$\begin{aligned} \zeta &\equiv \beta / (1 - \beta) > 0, \\ \overline{\pi}_0 &\equiv (p\beta)^{1/(1-\beta)} > 0, \\ C_{\alpha} &\equiv \left[\alpha^{\alpha} (1 - \alpha)^{1-\alpha} \right]^{\zeta} > 0, \end{aligned}$$

are constants, w_j is the current wage, and R depends on the price q when the equipment was purchased. The gain from adoption is then

$$\Delta_\pi(w_j, R; A_j) = A_j \overline{\pi}_0 w_j^{-\zeta} \left[BC_\alpha \left(\frac{w_j}{R} \right)^{\alpha\zeta} - 1 \right].$$

The term in brackets is increasing in w_j, decreasing in R, and can have either sign. It is positive if and only if the ratio w_j/R is sufficiently high.

If the wage w_j grows over time or the equipment price q falls or both, adoption may become worthwhile, even if it is not profitable when the innovation is first introduced. The optimal adoption date τ_j^* maximizes the PDV of current and future net gains.

2. Optimal adoption.—

Suppose an infinite horizon. If w_j grows at the constant rate g_j, and q falls at the rate γ. Then τ_j^* solves

$$\max_{\tau \geq 0} \int_\tau^\infty e^{-rs} \left(w_{j0} e^{g_j s} \right)^{-\zeta} \left[BC_\alpha \left(\frac{w_{j0} e^{g_j s}}{R_0 e^{-\gamma\tau}} \right)^{\alpha\zeta} - 1 \right] ds, \tag{22}$$

and the condition for an optimum is

$$\tau_j^* \geq \frac{1}{\alpha\zeta\left(\gamma + g_j\right)} \left[\alpha\zeta \ln \frac{R_0}{w_{j0}} - \ln BC_\alpha + \ln \frac{r + (1-\alpha)\zeta g_j}{r + (1-\alpha)\zeta g_j - \alpha\zeta\gamma} \right], \tag{23}$$

$$\text{w/ eq. if } \tau_j^* > 0.$$

Thus, τ_j^* is decreasing w_{j0}, with $\tau_j^* = 0$ if and only if w_{j0} is sufficiently large. In addition, τ_j^* is decreasing in g_j.

Hence countries with higher wage levels and faster wage growth adopt sooner, as in available data.

5. CONCLUSION

Diffusion rates vary widely across technologies and countries. Although some reasons for faster or slower adoption are idiosyncratic to a particular technology or location, as social scientists we are interested in the common factors, the factors that apply broadly. Here we have focused on the dynamics of fixed adoption costs and differences in wage rates.

These cost considerations are surely important in explaining adoption patterns, but are many other factors as well. There is substantial evidence that new technologies are complementary with higher human capital, a better educated workforce.[10] If educational attainment in a country is low, that fact can act as a barrier to technology adoption. Scarcity of complementary factors can also act this way.

There may be other barriers as well, such as vested interests that will take capital losses if old equipment must be scrapped, as in Parent and Prescott, (1999). These barriers may take the form of regulations or tariffs that are imposed to protect inefficient domestic producers using older technologies. For technologies that require substantial investment in new equipment, quality improvements and price declines over time can lead to additional strategic reasons for delay.

Technology diffusion has many aspects. The cost issues studied here are surely not the only considerations, but they play an important role in many cases.

[10] See Nelson and Phelps (1966) for an early exposition of this idea, and Acemoglu (2002) for a more recent development.

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APPENDIX

A. Example in Figure 13

Assume $z \sim \mathrm{U}[m, m+d]$, so $G^{-1}(\nu) = m + (1-\nu)\, d$. In addition assume the fixed-cost function has the linear form $c_0(\nu) = a_0 - b_0\nu$.

Recall that $\overline{\nu}$ is the minimal value satisfying (17). Ass. 2b requires $(m+d)\,\Gamma > \beta a_0$. Assume in addition that $\Gamma d > \beta b_0$. Then $\overline{\nu}$ satisfies

$$\begin{aligned} \overline{\nu} &\leq \frac{\Gamma\,(m+d) - \beta a_0}{\Gamma d - \beta b_0} \\ &= \frac{\Gamma d - (\beta a_0 - \Gamma m)}{\Gamma d - \beta b_0}, \qquad \text{w/ eq. if } \overline{\nu} < 1, \end{aligned}$$

so

$$\begin{aligned} \beta a_0 - \Gamma m &\leq \beta b_0 \qquad \Longrightarrow \qquad \overline{\nu} = 1, \\ \beta a_0 - \Gamma m &> \beta b_0 \qquad \Longrightarrow \qquad \overline{\nu} \in (0,1)\,. \end{aligned}$$

Higher values for Γ and m expand the region where $\overline{\nu} = 1$, and in the region where $\overline{\nu} < 1$, clearly $\overline{\nu}$ is strictly increasing in m. In that region,

$$\begin{aligned} \frac{d\overline{\nu}}{d\Gamma} &\propto (m+d)\,(\Gamma d - \beta b_0) - d\,[\Gamma\,(m+d) - \beta a_0] \\ &= d\beta\,(a_0 - b_0) - m\beta b_0 \\ &> m\,(d\Gamma - \beta b_0) > 0, \end{aligned}$$

so $\overline{\nu}$ is also increasing in Γ, and a similar calculation shows it is increasing in d.

Next consider the dynamics of penetration. In the region where $\overline{\nu} = 1$, use (19) to find that $\mu \geq 0$ satisfies

$$m\Gamma + \frac{1}{1+r}\,(a_0 - b_0\mu) \geq a_0, \qquad \text{w/ eq. if } \mu > 0,$$

or

$$\mu \leq (1+r)\,\frac{1}{b_0}\,(m\Gamma - \beta a_0)\,, \qquad \text{w/ eq. if } \mu > 0. \tag{24}$$

If $\beta a_0 - m\Gamma = 0$, (24) holds with equality at $\mu = 0$. In the rest of the region, where $\beta a_0 - m\Gamma \in (0, \beta b_0]$, the right side of (24) is negative, so the solution is still $\mu = 0$. Evidently a linear fixed-cost function, $c_0(\nu) = a_0 - b_0\nu$, together with a uniform distribution for z, implies that if penetration is complete, it occurs in the first period.

In the region where $\overline{\nu} < 1$, (20) and (21) imply that $\nu_1 > 0$ satisfies

$$\Gamma\left[m + (1 - \nu_1)\, d\right] + \frac{1}{1+r}\left[a_0 - b_0\nu_1\right] = a_0,$$

or

$$\begin{aligned} \nu_1 &= \frac{(1+r)\,\Gamma\,(m+d) - r a_0}{(1+r)\,\Gamma d + b_0} \\ &= \frac{\Gamma\,(m+d) - \beta a_0}{\Gamma d + b_0/\,(1+r)}. \end{aligned}$$

Clearly ν_1 is increasing in m. Since

$$\begin{aligned} \frac{d\nu_1}{d\Gamma} &\propto (m+d)\left(d\Gamma + \frac{b_0}{1+r}\right) - d\left[(m+d)\,\Gamma - \beta a_0\right] \\ &= (m+d)\,\frac{b_0}{1+r} + d\beta a_0 > 0, \end{aligned}$$

it is also increasing in Γ, and a similar calculation shows it is increasing in d. Hence first-period adoption is strictly increasing in all three parameters, m, d, Γ.

For the subsequent dynamics, use (20) to find that Φ^{-1} satisfies

$$\Gamma\left[m + (1 - \nu')\, d\right] + \frac{1}{1+r}\left(a_0 - b_0\nu'\right) = a_0 - b_0\Phi^{-1}(\nu').$$

Inverting gives the equilibrium law of motion for the penetration rate,

$$\left(\Gamma d + \frac{b_0}{1+r}\right)\Phi(\nu) = \Gamma\,(m+d) - \beta a_0 + b_0\nu,$$

or

$$\Phi(\nu) = \nu_1 + \frac{b_0}{\Gamma d + b_0/\,(1+r)}\nu.$$

Hence Φ is linear in ν, it has an intercept at ν_1 and a slope less than unity, and for each fixed set of parameters it crosses the 45^{o} line at $\overline{\nu}$. The slope is decreasing in Γ and d, and does not depend on m.

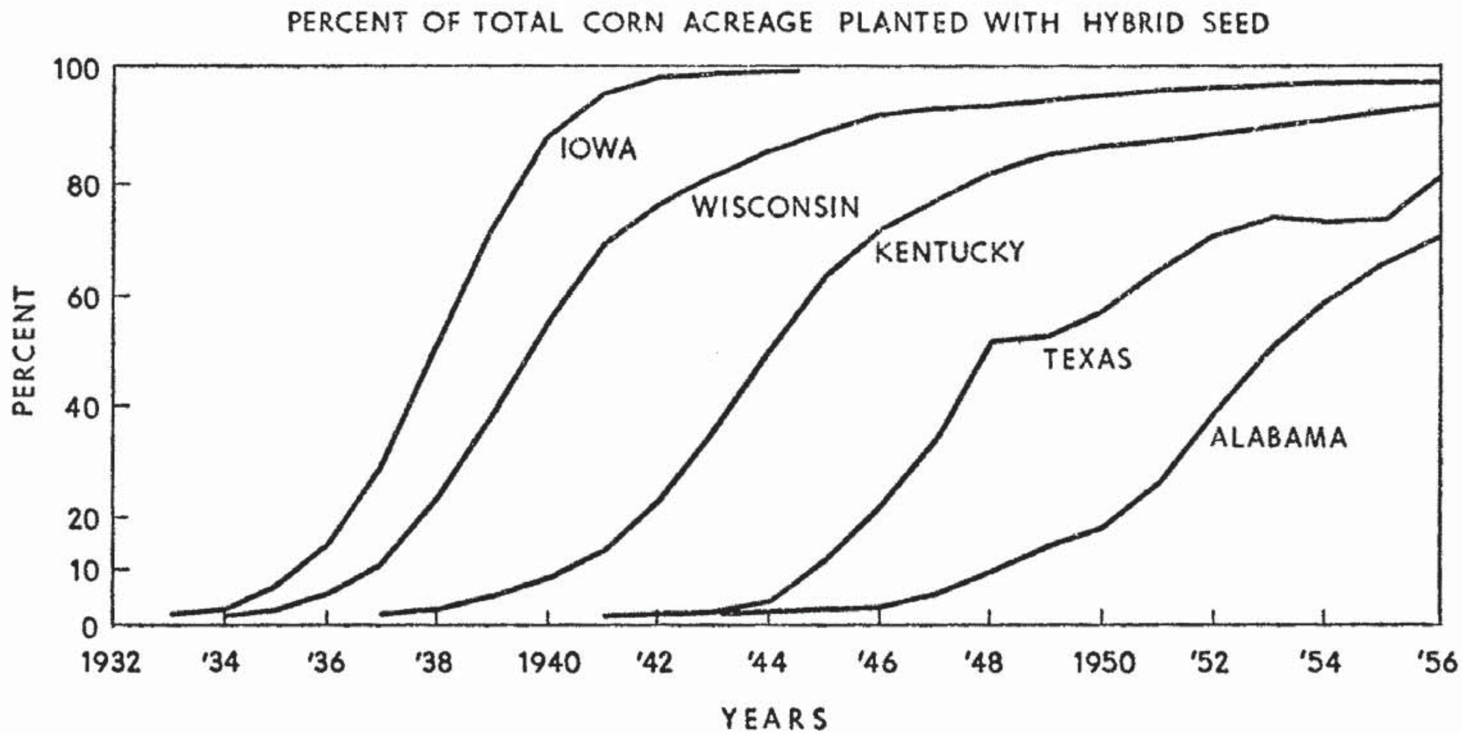


FIGURE 1.—Percentage of Total Corn Acreage Planted with Hybrid Seed. Source: U.S.D.A., *Agricultural Statistics*, various years.

Figure 1

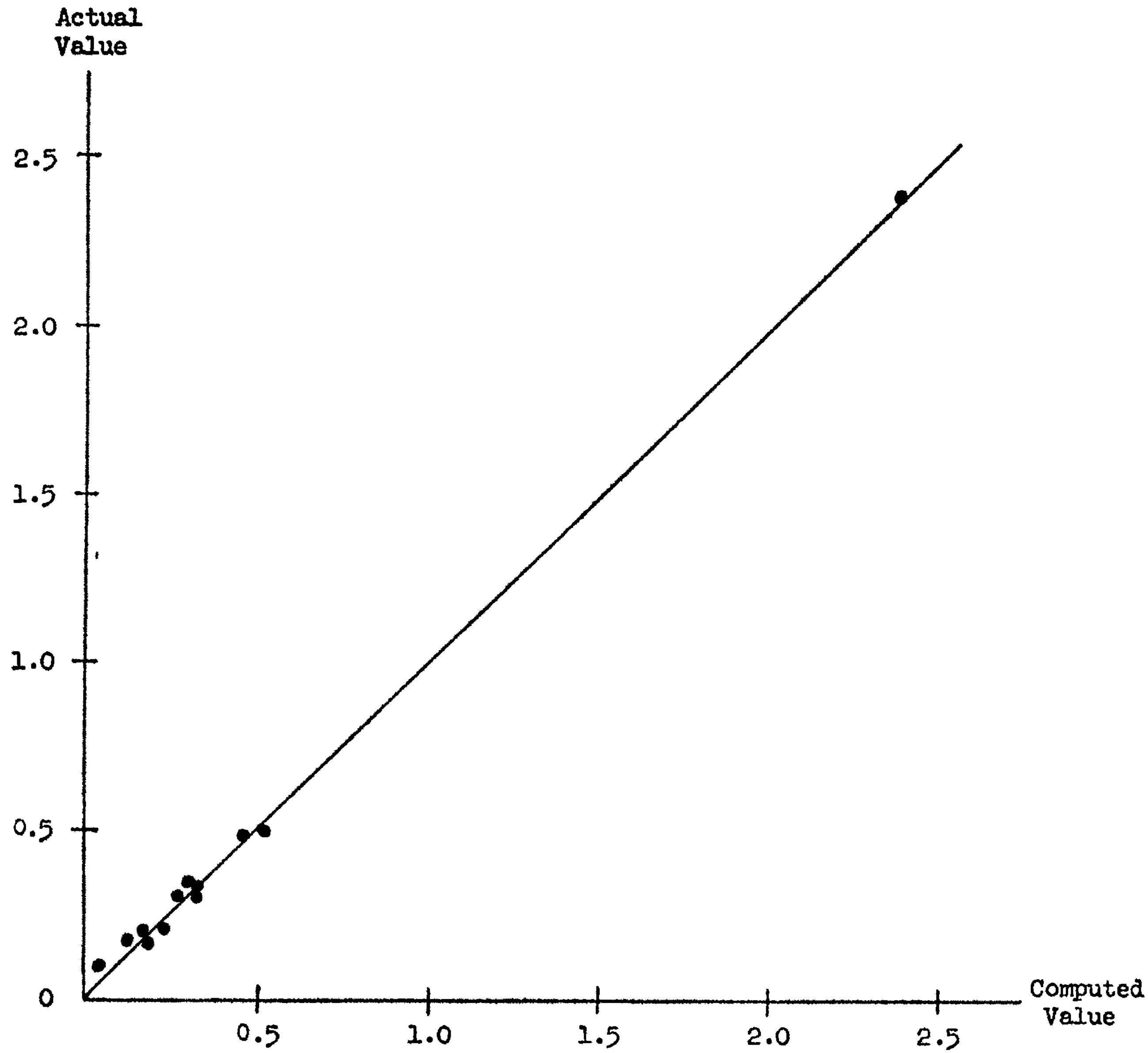


FIGURE 2.—Plot of Actual $\hat{\phi}_{ij}$ Against That Computed from Equation (14), Twelve Innovations.

Figure 2

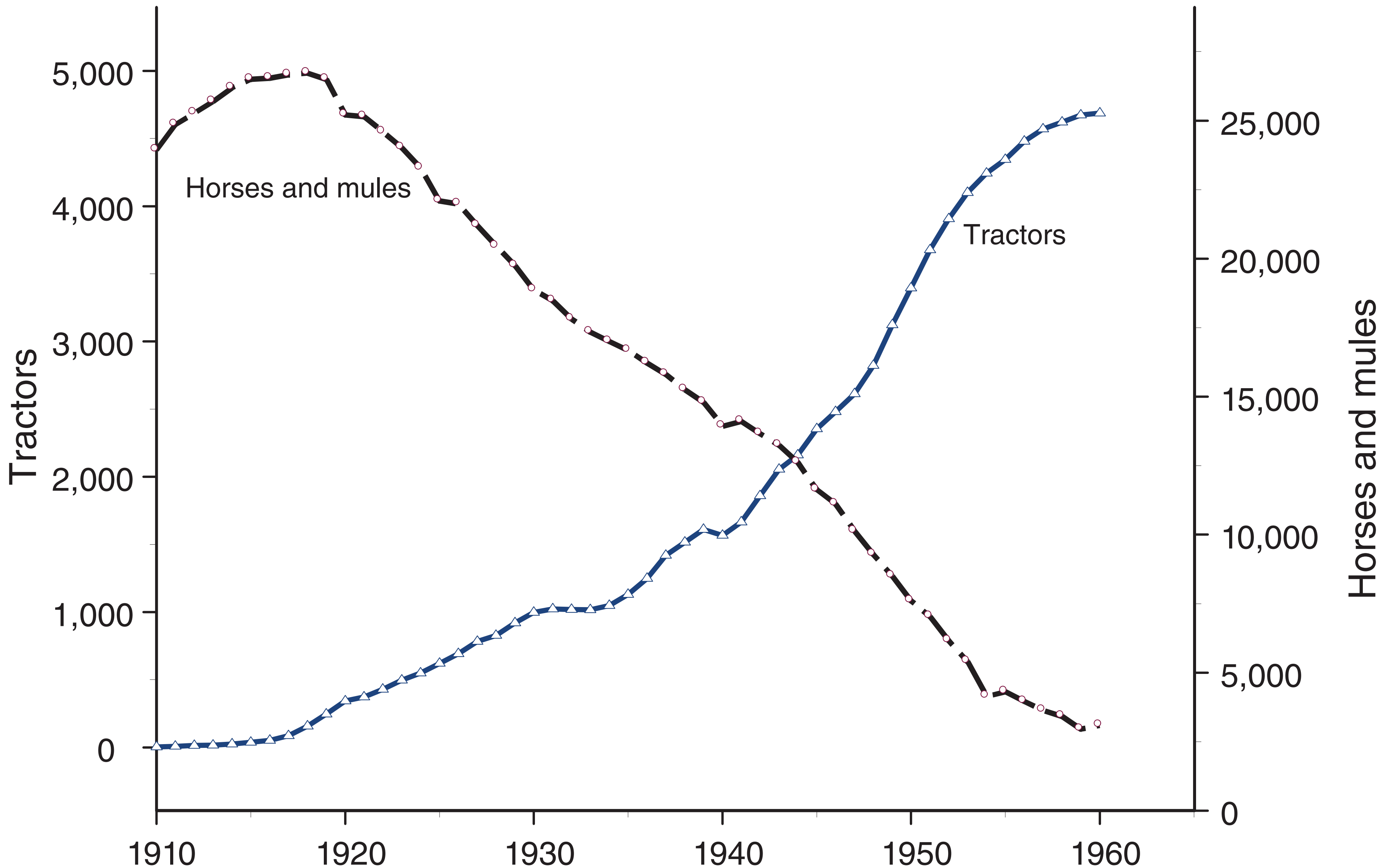


FIGURE 1. HORSES, MULES, AND TRACTORS IN FARMS: 1910–1960

Figure 3

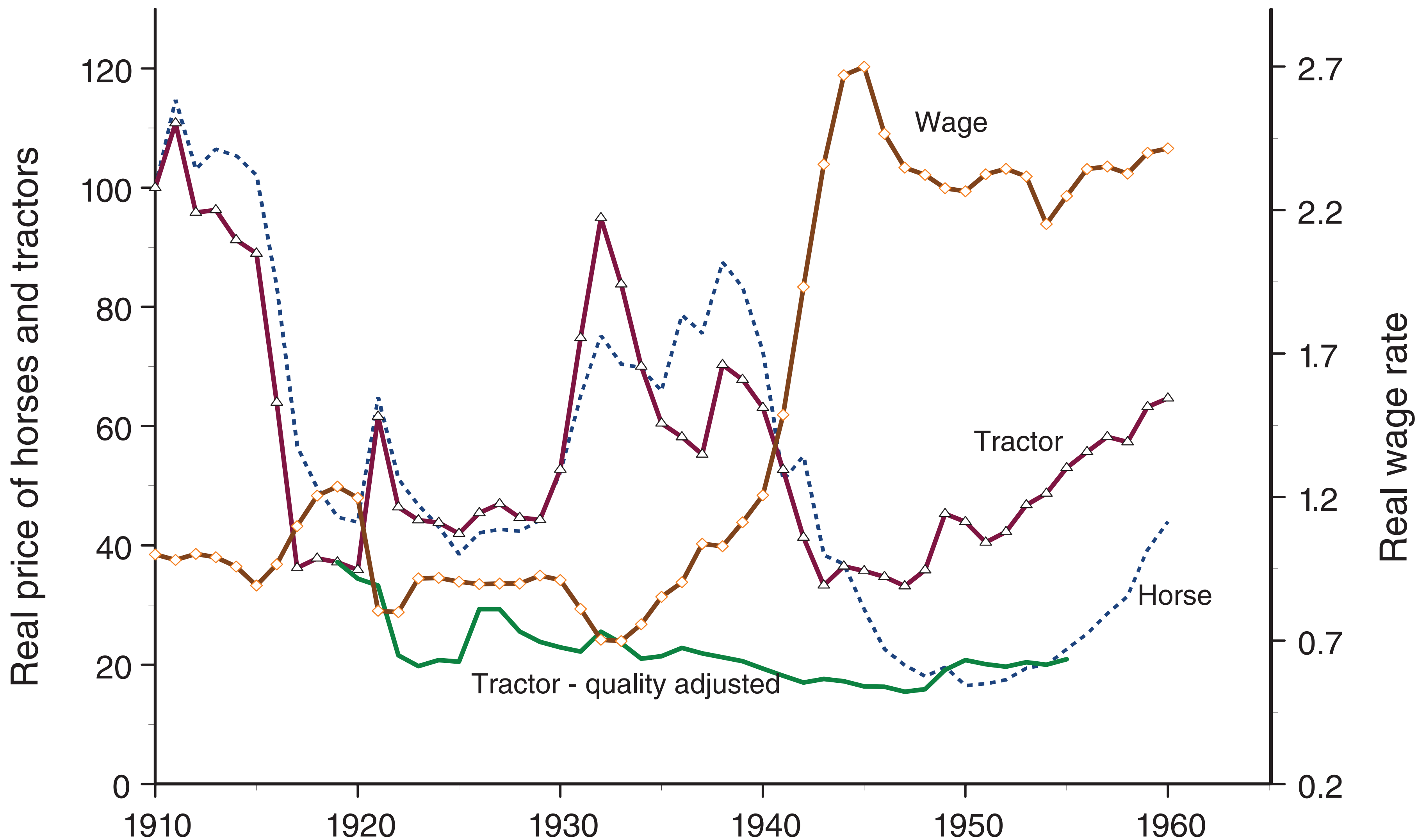


FIGURE 2. REAL PRICES FOR TRACTORS, HORSES, AND LABOR: 1910–1960

Figure 4

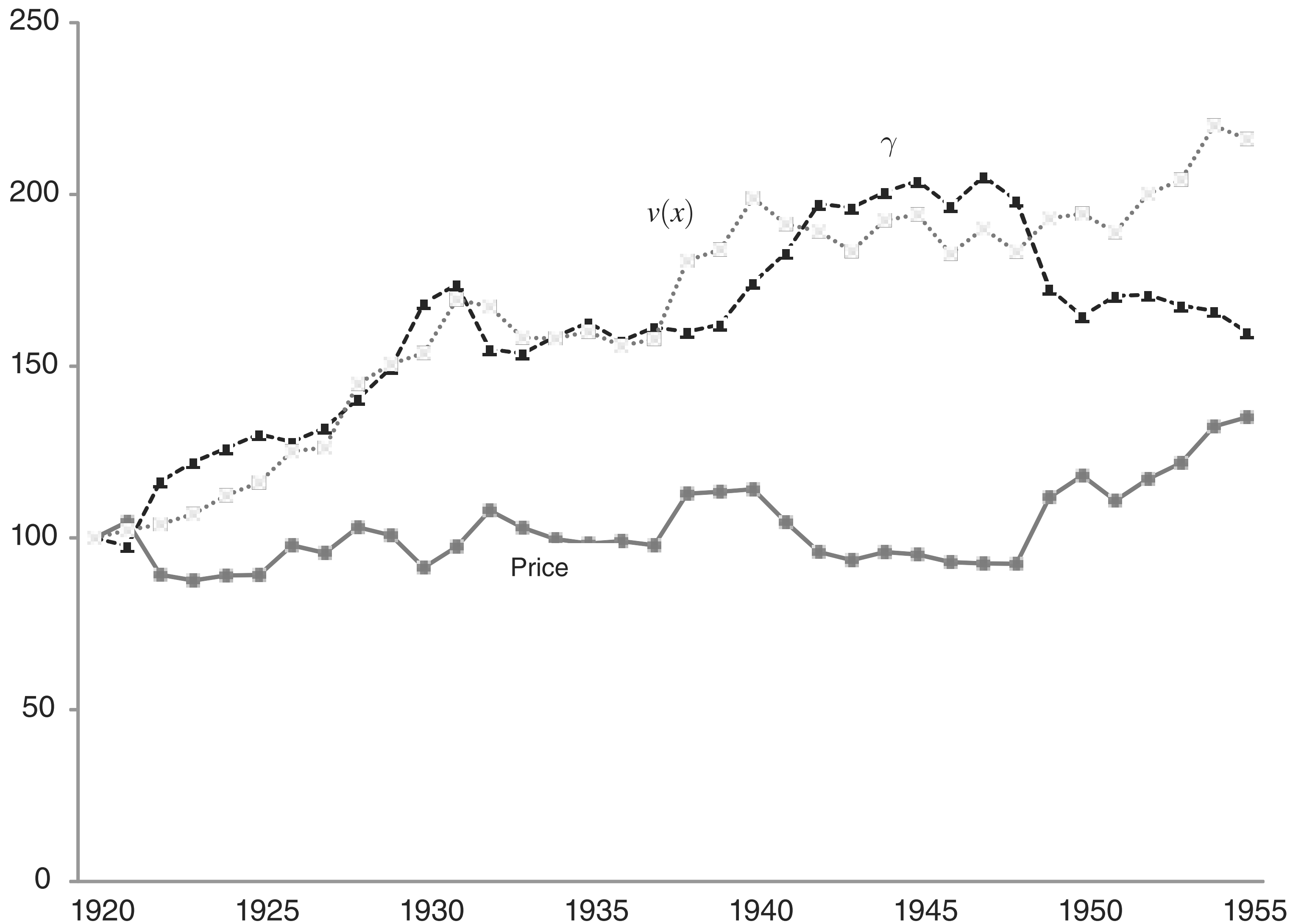


FIGURE 3. TRACTOR PRICES, QUALITY, AND PRODUCTIVITY: 1920–1955: ESTIMATION

Figure 5

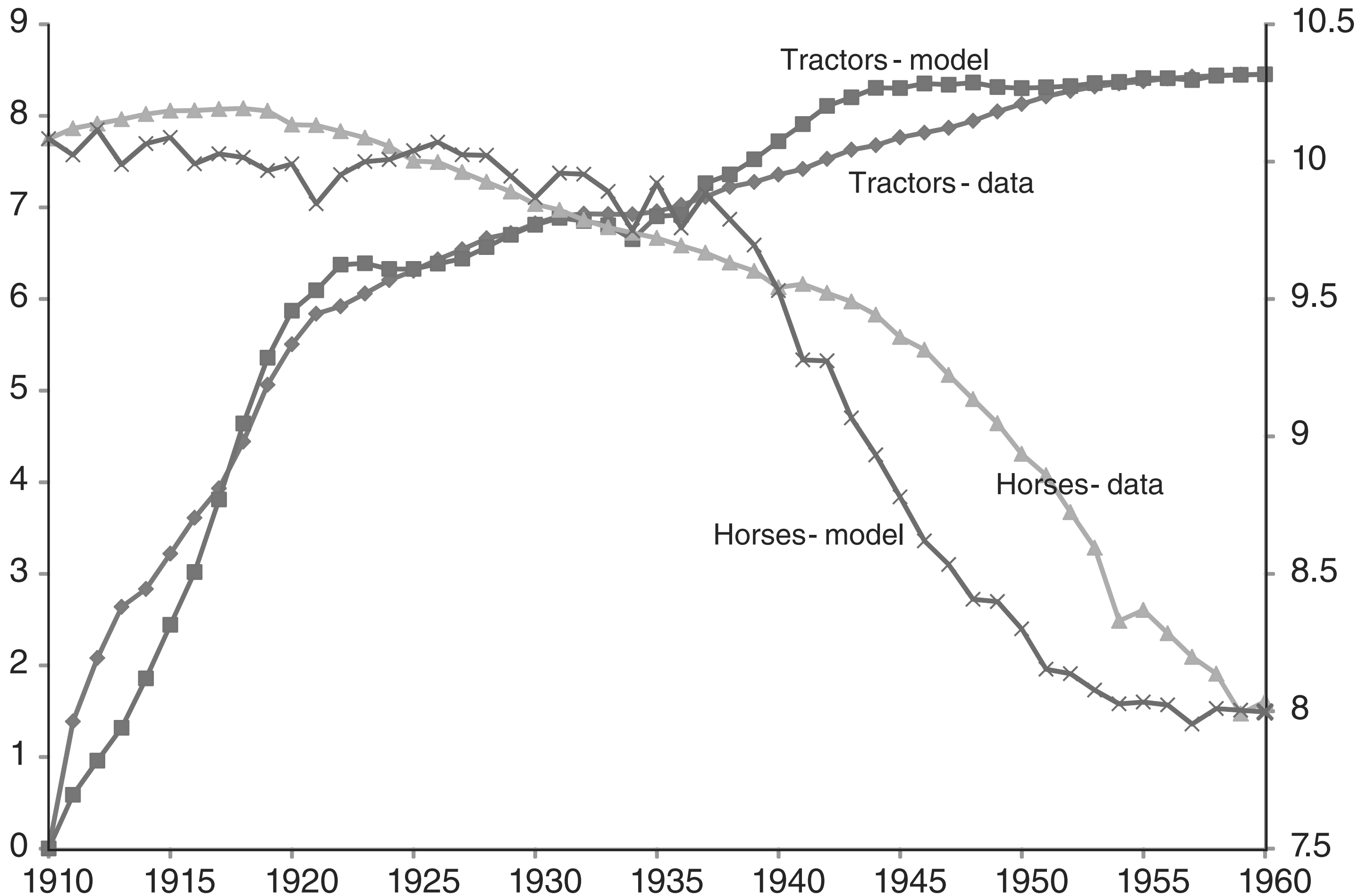


FIGURE 4. TRANSITIONAL DYNAMICS: 1910–1960: TRACTORS AND HORSES

Figure 6

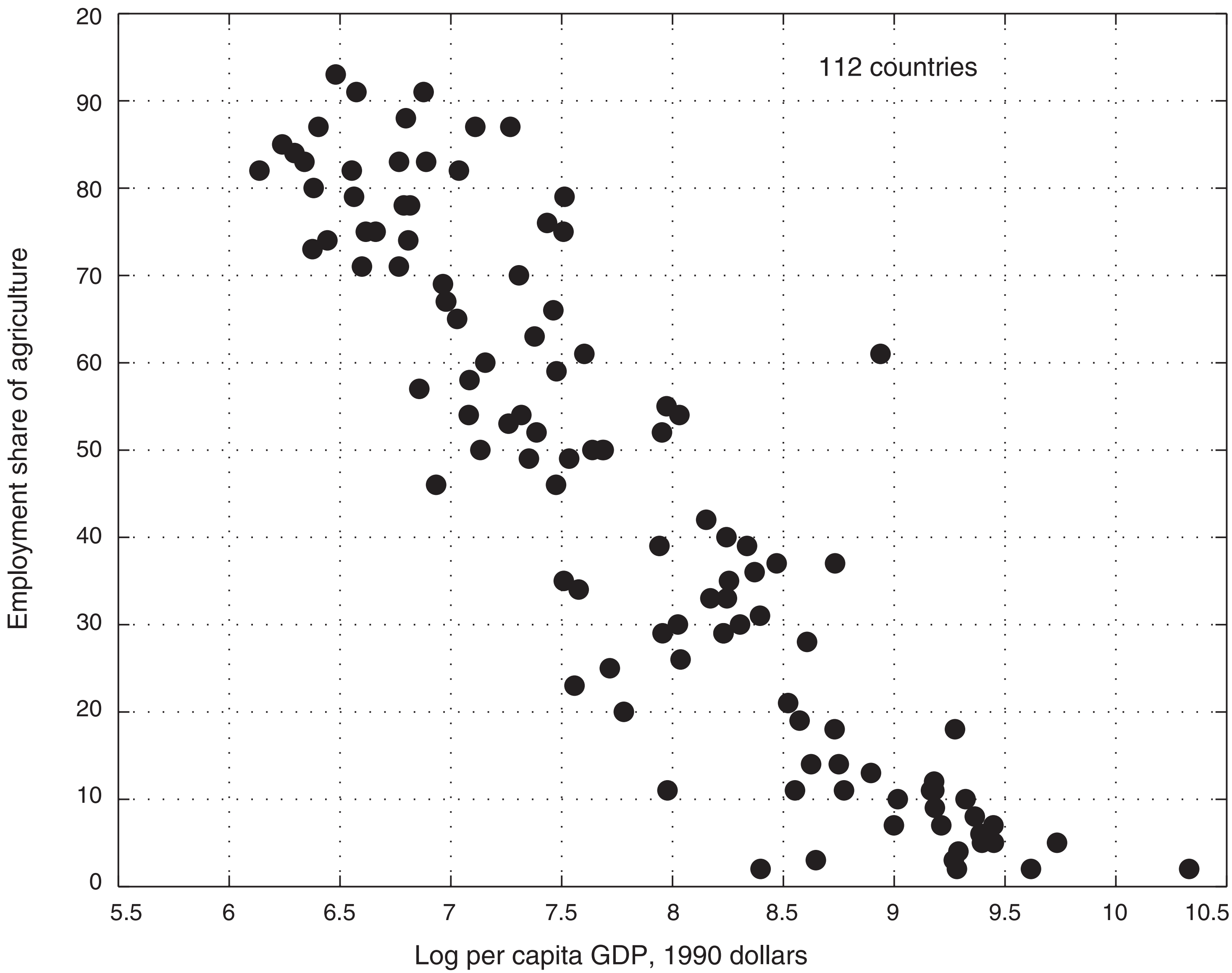


Figure 11. Agricultural Employment Shares, 1980

Figure 7

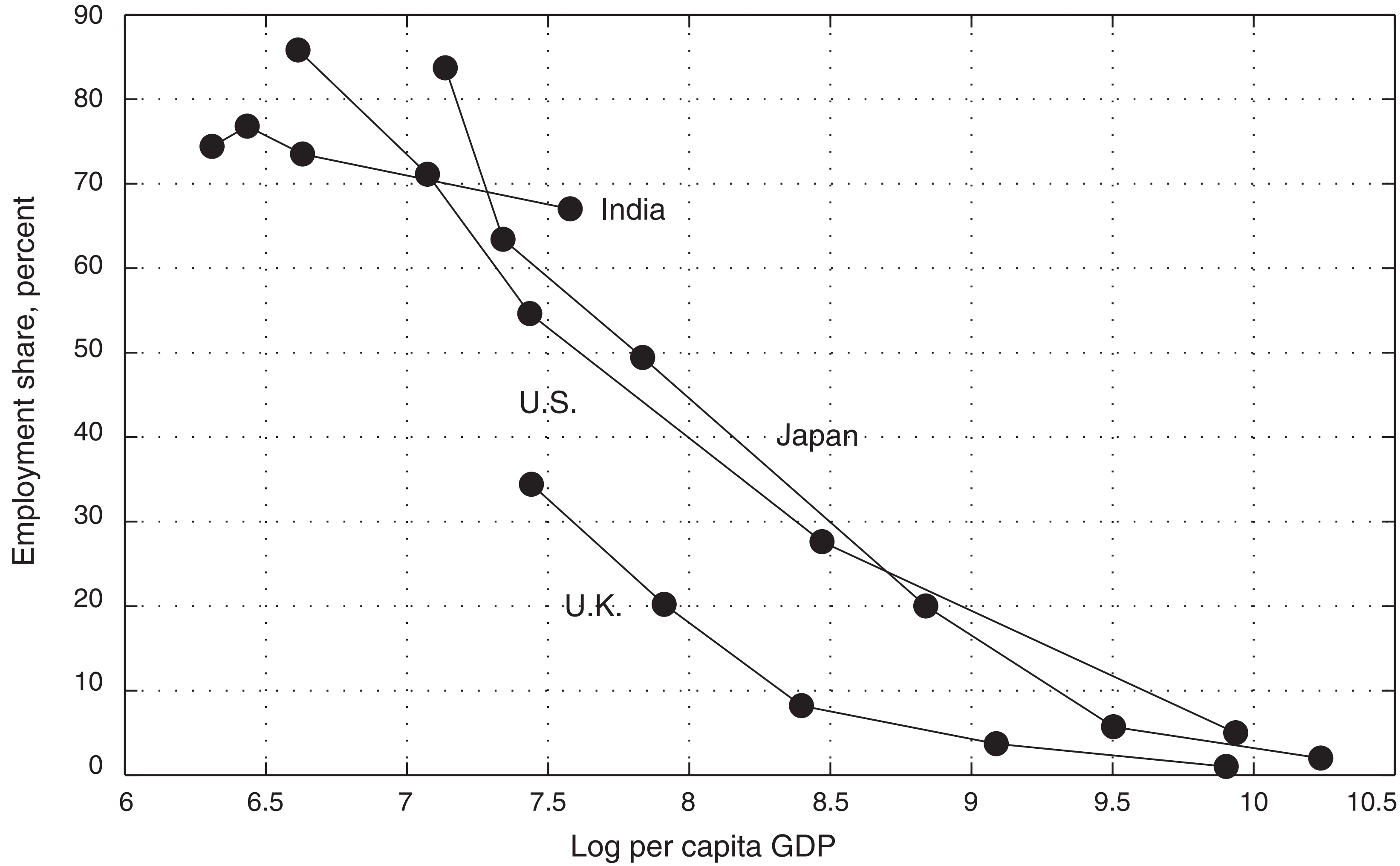


FIGURE 13. EMPLOYMENT SHARES IN AGRICULTURE

Figure 8

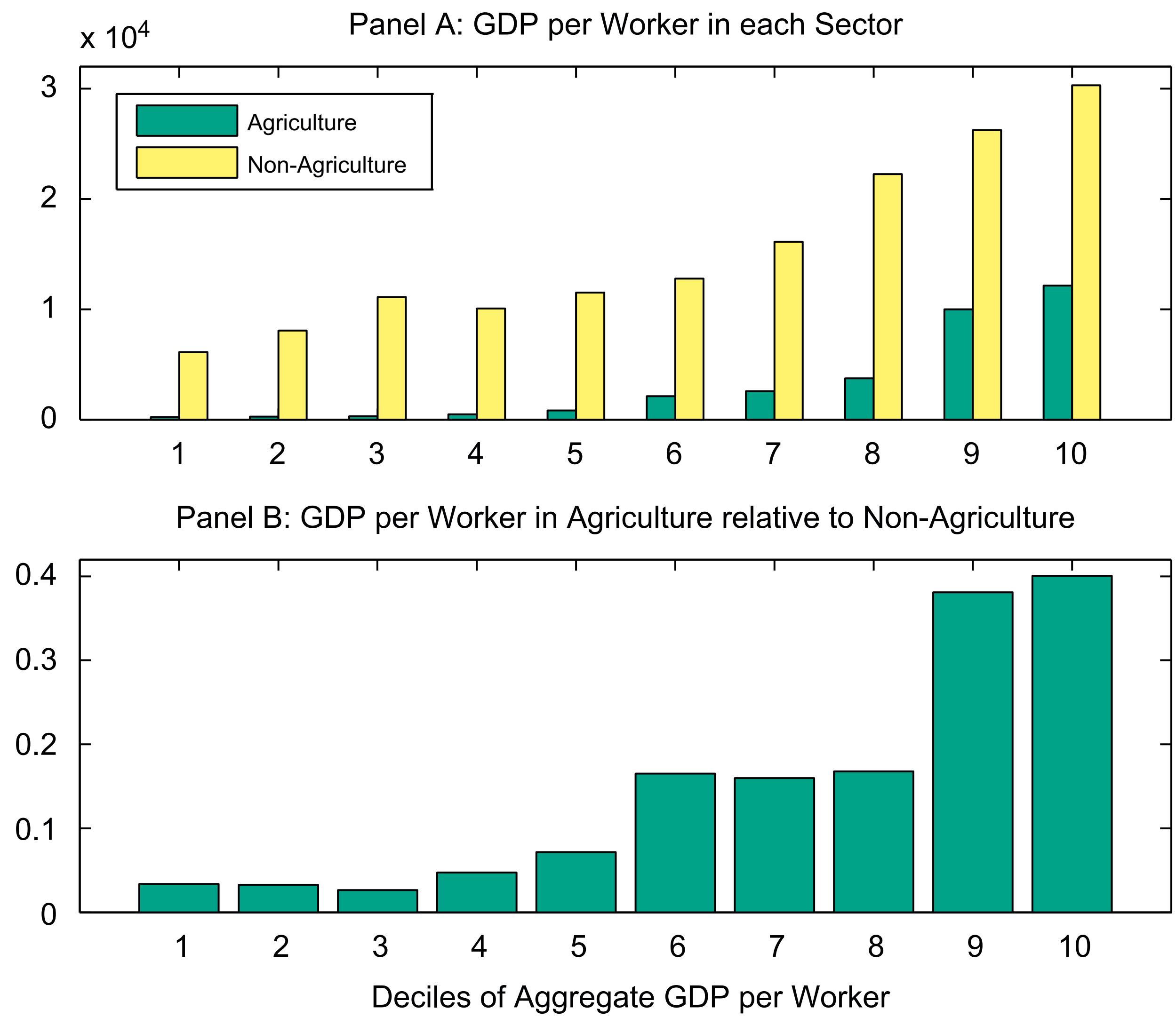
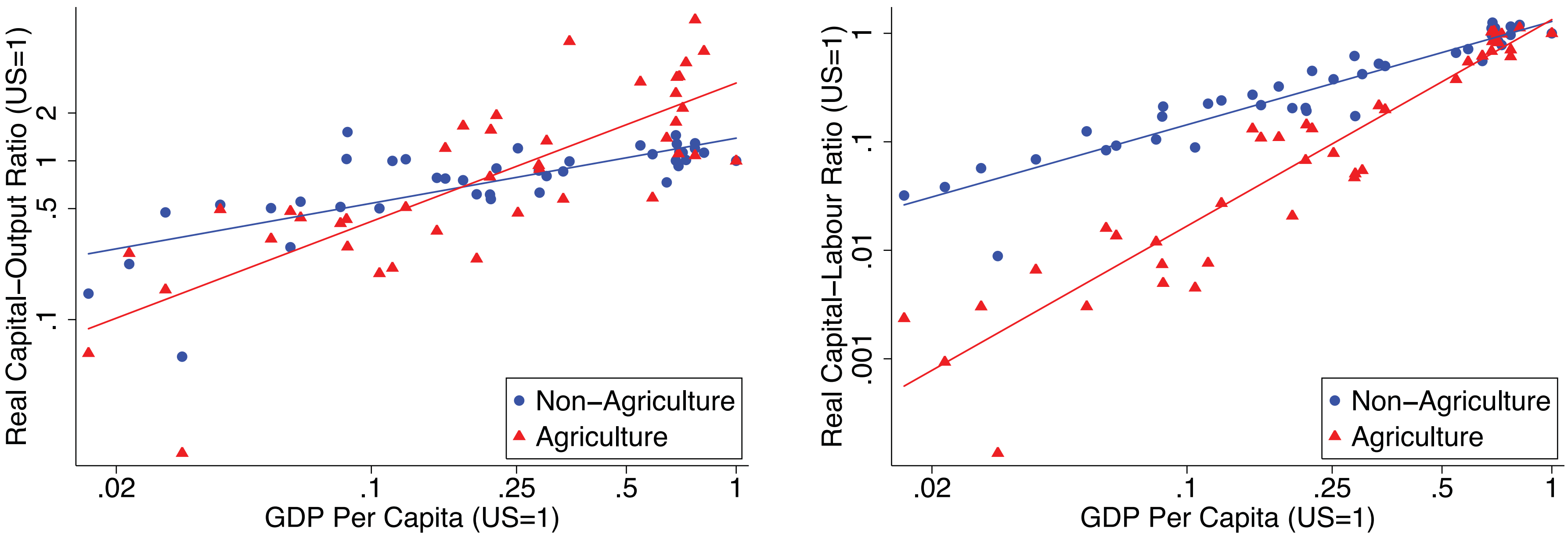


Fig. 2. Sectoral labor productivity across countries—1985. Countries are ranked according to aggregate GDP per worker from PWT5.6 where decile 10 groups the richest countries. Each decile contains eight countries (10% of countries in our sample) except decile 5, which contains 13 countries.

Figure 9

Figure 1: The Capital Intensity across Countries



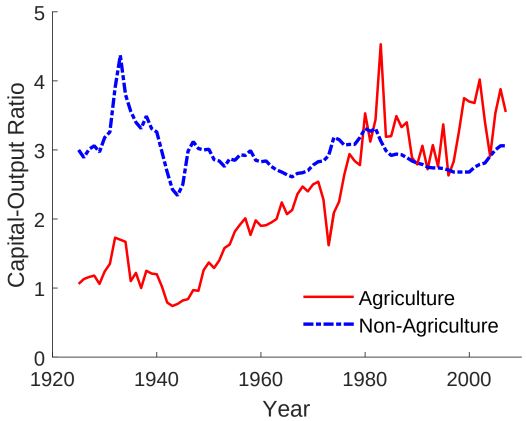
(a) Real Capital-Output Ratio

(b) Capital-Labor Ratio

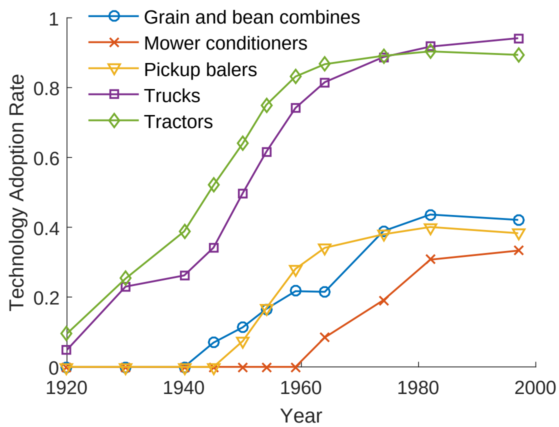
Figure 10

Figure 11

Figure 2: U.S. Historical Facts



(a) Capital-Output Ratio



(b) Technology Adoption

Note: Figure (a) shows the capital-output ratio in the U.S. measured using current prices and the data are from the U.S. Bureau of Economic Analysis (BEA). Figure (b) shows the percentage of agricultural output produced by farms with modern machinery, calculated using data from the U.S. census of agriculture.

Figure 3: Technology Choice

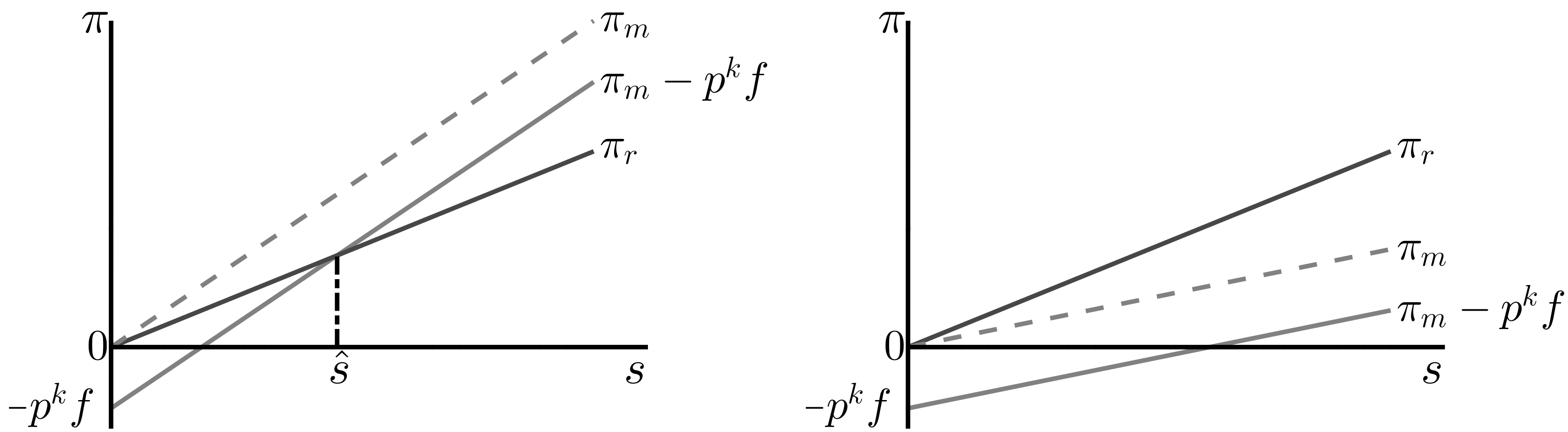


Figure 12

Figure 13a: equilibrium adoption function Φ

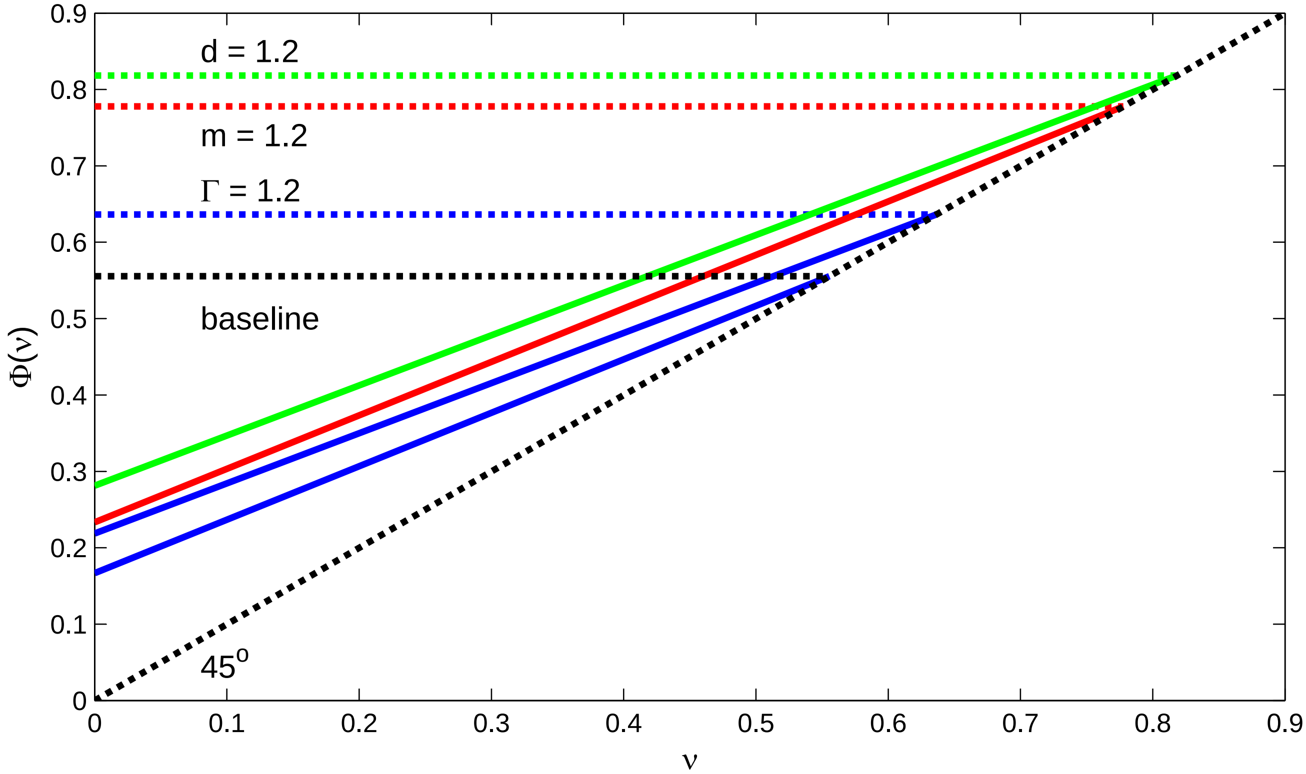


Figure 13b: Dynamics of penetration