Technology Adoption and the Latin American TFP Gap*

Ufuk Akcigit† Harun Alp‡ Maya Eden§ Ha Nguyen¶

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Abstract

We develop a novel methodology to study the dynamics of technology adoption across countries. We identify changes in "technology" as changes in the productivity of the frontier country that have a lagged effect on the productivity of the adopting country. A simple calibration illustrates how the results of the analysis can be used to estimate the differentials in TFP and TFP growth that are attributable to technology. We illustrate our methodology by studying the adoption process between Latin America and the Carribean (LAC) countries and the US. Our analysis suggests an 8 year adoption lag, after which technologies are fully or nearly-fully adopted; this estimate suggests that technology can account for a productivity gap of 4-10% (provided that there is full adoption in the long-run), and a TFP growth differential between 0-0.5%. We illustrate that our estimates are consistent both with the timing of the IT revolution, and with cross-country patent citation data. Finally, we provide a simple theory about the potential determinants of the measured adoption lags which highlights a possible link between the static wedges and technology adoption decisions.

JEL Classification: O14, O25, O33, O47.

Keywords: Technology adoption, economic growth, TFP gap, income gap, knowledge spillover, patents.

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†University of Pennsylvania and NBER. Email: uakcigit@econ.upenn.edu.

‡University of Pennsylvania. Email: aharun@sas.upenn.edu.

§World Bank. Email: meden@worldbank.org.

¶World Bank. Email: hanguyen@worldbank.org.

1 Introduction

There is a large and persistent income gap between countries in Latin America and the Caribbean (LAC) and the United States (US). In the year 2000, average income in LAC was only 23% of the average income in the US. Total Factor Productivity (TFP) is among the leading factors of the observed income gap. TFP in LAC, measured as the Solow residual after carefully accounting for inputs, is about half of that of the US (Caselli [2013]). There are two major potential causes for this difference in TFP: (a) technological backwardness, and (b) misallocation of resources.[1] In this paper, we focus on the former and assess the contribution of technology to the TFP difference between LAC and the US.

Identifying the technology component of TFP differences across countries is not straightforward. Traditionally, the approach has been tracking the prevalence of specific technologies. However, this approach necessarily assumes a mapping between the prevalence of specific technologies and aggregate productivity. In practice, we do not know the extent to which specific technologies contribute to TFP. In this paper, we propose a methodology that is agnostic about which technologies are important. We directly measure technological progress through its effect on TFP. Using time series methods, we identify a component of TFP growth that is plausibly attributable to technological progress. The dynamics of technology adoption can be inferred by the timing and the magnitude in which the technology component affects the adopting country.

To motivate our approach, consider figure 1. The top two figures plot the 9 year moving average of output growth for the US and for the average of Brazil, Chile and Uruguay (the period between the beginning of World War I and ending of World War II was omitted[2]). The bottom two figures plot the same series, with lagged values of the US data. Low-frequency movements in output growth in the Latin American countries are more correlated with lagged values of the US; the correlation increases from 0.3 to 0.7 in the pre-war period, and from -0.07 to 0.5 in the post-war period. This lagged co-movements may be reflective of lagged technological progress.

Formally, we can exploit lagged co-movement on a higher frequency to identify a technological component of productivity growth. Our identifying assumption is that any shock to productivity growth in the frontier country (the US) that affects the adopting countries (LAC) with a lag is a technology shock. We can then use the technological component to study the effects of a technology shock on TFP growth in LAC, both in terms of timing and in terms of magnitude.

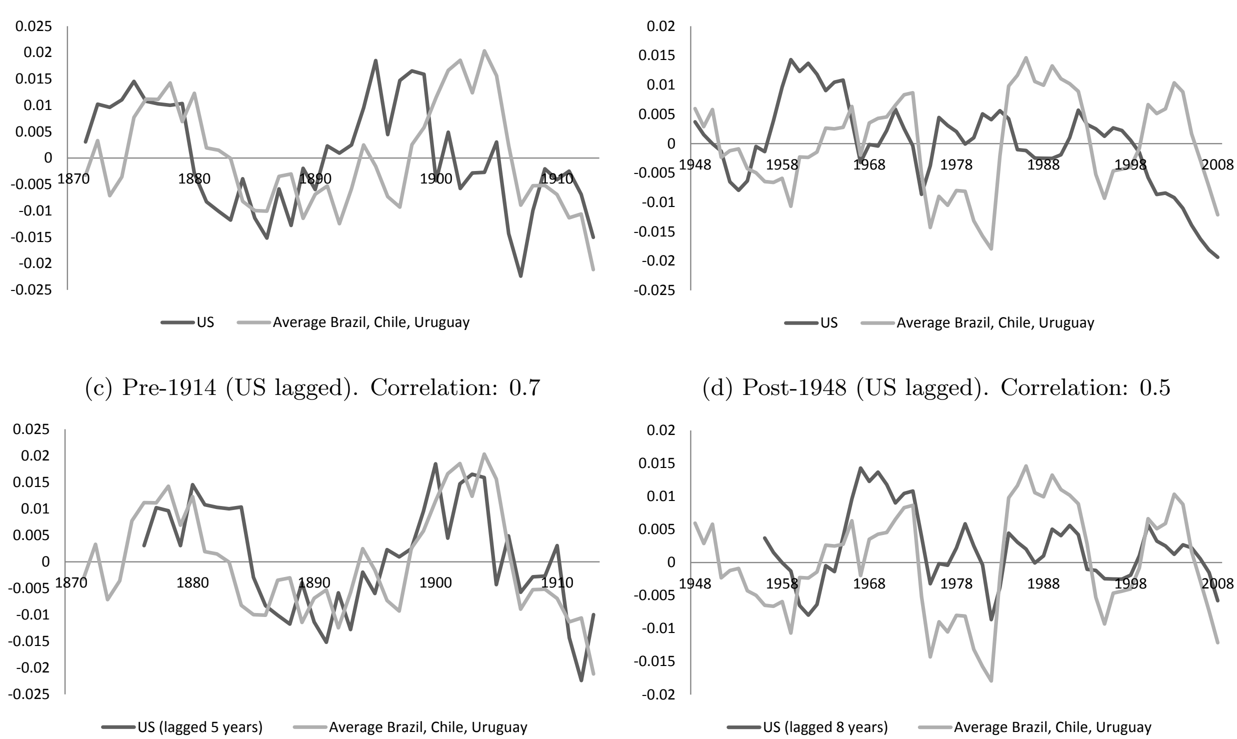
We focus on the post-war period and use several measures of productivity growth: TFP growth, measured as the Solow residual with and without human capital; GDP; and value added per worker in nine broad industries. Our estimates suggest that, compared to the US, technological improvements have a somewhat more modest long-run effect on productivity in LAC, and that the bulk of technology adoption happens within 8-10 years. At the upper bound of our confidence

[1] See Busso et al. [2012] for a study on misallocation and Cole et al. [2005] for a study on the lack of competition in LAC.

[2] In our view, the large fluctuations in output per capita growth during this period may have been primarily driven by non-technology factors.

interval, our estimates suggest that technologies are fully adopted after 8-10 years,[3] and that the long-run productivity gains from technological progress are the same as in the US. In this case, the technology gap between LAC and the US is roughly constant over time, and can account for a 4-8% gap in TFP. At the lower bound of our confidence intervals, technology levels diverge over time, as technological innovations improve long-run TFP in LAC by only half as much as in the US. In this case, the TFP gap attributable to technology increases over time, and incomplete technology adoption generates a differential in TFP growth rates of about 0.25-0.5% annually.

Figure 1: Growth of output per capita (source: Maddison)



(a) Pre-1914. correlation: 0.3

(b) Post-1948. Correlation: -0.07

(c) Pre-1914 (US lagged). Correlation: 0.7

(d) Post-1948 (US lagged). Correlation: 0.5

Notes: Each point represents the forward 9 year moving average (e.g., the point 1870 is the average growth from 1870-1879). The mean growth rates are subtracted from the series.

To gauge at the plausibility of our estimates, we look at two additional sources of data: first, we study the timing of the IT revolution in LAC and in the US. This exercise is particularly useful since the IT revolution offers a hard-to-find historical case study in which the introduction of a new major technology influences the economy drastically. A number of papers have studied the

[3]Compared to the existing estimates in the literature, our findings suggest a relatively modest adoption lags. For instance, Comin et al. [2006] and Comin and Hobijn [2010] estimate an average technology adoption lag of 45 years (averaged across many different countries and technologies). One way to reconcile the findings is to note that these papers look at a simple average of technologies, while our analysis aims to "weigh" technologies by their contribution to aggregate TFP. Consistent with our results, they find shorter adoption lags for the technologies that we believe are more essential for the aggregate TFP (Comin and Hobijn [2010] estimates 14 years adoption lags for PCs and 15 years for cell phones).

drastic impacts of the IT revolution on US productivity. For instance, Greenwood and Yorukoglu [1997] argue that the IT revolution during the 1970s has been the major factor for the productivity slowdown during the same period. They document that the IT investment rose dramatically and aggregate productivity slowed down during mid-70s. While replicating this fact, we also show that the IT investment in LAC rose and productivity slowed down during mid-80s. These findings support the 10-year lag of technology adoption between US and LAC.

Second, we study patents registered in the US Patent Office. Patent citations have been widely used to trace the knowledge flow among firms and countries (among many others, see Jaffe et al. [1993] and Jaffe and Trajtenberg [1999]). In order to assess the average lag of knowledge flow, we compute the average number of years that it takes a LAC patent to cite a US patent. Our citation analysis indicates a 9-year citation lag in IT patents and 10-year citation lag in general which is in line with the previous findings.

Finally, we provide a simple theory about the potential determinants of the measured adoption lags which highlights a possible link between the static wedges and technology adoption decisions and test its implications using our empirical methodology. We test whether our methodology can produce estimates that are consistent with a simple endogenous growth model, in which the incentives for technology adoption are decreasing with the level of static production wedges. Using our calibrated model, we infer a pre-War technology adoption lag that is consistent with pre-war differences in output per capita. We show that this calibrated adoption lag is consistent with time series estimates from the pre-war era.

The rest of the paper is organized as follows. Section 2 introduces a conceptual framework to motivate the main empirical analysis, Section 3 describes the main empirical model and provides the results, Section 4 shows the robustness of our empirical results by providing various alternative specifications and employing alternative data series, Section 5 provides supporting evidence for our main empirical findings based on various data from investment in information technologies and patent citations, Section 6 provides a simple theory about the potential determinants of the measured adoption lags, and Section 7 concludes.

2 Conceptual framework

In this section, we introduce the conceptual framework used to motivate the empirical analysis, and explain the structural interpretation of our estimated parameters.

Consider global environment with n countries indexed $i = 1, ..., n$. Time is indexed by $t = 0, 1, ...$ Measured total factor productivity (TFP) is given by $A_{i,t} = \frac{Y_{i,t}}{F(K_{i,t}, L_{i,t}, ...)}$ - in other words, $A_{i,t}$ is the rate in which the economy transforms aggregate inputs into aggregate output.

We assume that measured aggregate TFP can be decomposed as:

$$A_{i,t} = X_{i,t} Z_{i,t} \tag{1}$$

where $X_{i,t}$ is the technology component of TFP (which we will refer to simply as "technology") and $Z_{i,t}$ is the non-technology component of TFP. To be precise, it is useful to refer to the Oxford Dictionary definition of technology, which is "the application of scientific knowledge for practical purposes, especially in industry". In other words, technology captures the extent to which production units follow best practices in efficiently transforming inputs into outputs.

The non-technology component, $Z_{i,t}$, is a catch-all phrase that includes all aspects of the economy that affect measured TFP, excluding technology. For example, $Z_{i,t}$ includes misallocation, competition, as well as policies that may distort the efficient use of factors. Importantly, $Z_{i,t}$ also includes factors that may affect measured TFP, such as incomplete capacity utilization during recessions, which may be difficult to account for in the measurement of inputs (see Basu [1996]). Finally, $Z_{i,t}$ may also include a measurement error.

Measured TFP is assumed to be multiplicative in technology and non-technology components. To motivate this assumption, it is useful to think of an environment with heterogeneous firms, in which all firms share the same technology, but inputs may be misallocated across firms, or not used at full capacity. It is easy to see that such a model will imply a multiplicative structure of measured TFP (for the case of misallocation, see the model in Hsieh and Klenow [2009]).

Growth rates are denoted with lower case letters (e.g., $a_{i,t} = \ln(A_{i,t}) - \ln(A_{i,t-1})$). Given the multiplicative structure, the growth rate of measured TFP takes an additive form:

$$a_{i,t} = x_{i,t} + z_{i,t} \tag{2}$$

where $x_{i,t}$ is the growth in the technology component of TFP (which we will refer to simply as "technology growth") and $z_{i,t}$ is the growth in the non-technology component (which will be referred to as "non-technology growth"). It is important to note that, empirically, non-technology factors may have significant effects both on the level of measured TFP (e.g., Hsieh and Klenow [2009]) and on its growth rates (as in Basu [1996], Basu and Fernald [2002] or Shapiro [1987]).

Technology adoption. There is one country that is identified as the *frontier*, and the rest of the countries are identified as *adopters*. We will denote the frontier economy $i = us$ and the adopting countries with $i = lac$ (where, in principle, different adopting countries may be given different sub-indexes). Technology growth in the frontier represents the growth of the frontier technology. In adopting countries, a technological innovation may affect TFP growth with some lag, reflecting the possibility of learning and adoption frictions. Thus, current technology growth in adopting countries is a function of current and lagged values of the technological progress in the frontier (e.g., growth in LAC today may reflect technological innovation in the US several years ago, as the technology is adopted with some delay). We assume that this function takes the following linear form:

$$x_{lac,t} = \sum_{j=0}^{\infty} \lambda_j x_{us,t-j} \tag{3}$$

where $\lambda_j \geq 0$, ruling out the possibility that technological progress in the frontier has a negative effect on technology growth in adopting countries.

Note that the sum $\sum_{j=0}^{\infty} \lambda_j$ has the interpretation of the long-run adoption rate: an innovation in the technological frontier today will have a contemporaneous effect of λ_0, an effect of λ_1 in the next period, and so one. The infinite sum $\sum_{j=0}^{\infty} \lambda_j$ is the total growth in the adopter's technology implied by a 1% growth in the technological frontier.

The technology gap. In what follows, we will aim to identify the sequence $\{\lambda_j\}_{j=0}^{\infty}$ using time series methods (to be discussed shortly). It is useful to show how these parameters can be used to estimate the differences in TFP or TFP growth that are attributable to technology. Let $\bar{x} = E(x_{us,t})$ be the mean growth rate of the technological frontier. The average growth rate in the adopting country is then given by:

$$\bar{x}_{lac} = E(\sum_{j=0}^{\infty} \lambda_j x_{us,t-j}) = \bar{x} \sum_{j=0}^{\infty} \lambda_j \tag{4}$$

Thus, the technology growth rate differential is given by:

$$E(x_{us,t} - x_{lac,t}) = \bar{x}(1 - \sum_{j=0}^{\infty} \lambda_j) \tag{5}$$

Given $\bar{x}$ and $\{\lambda_j\}_{j=0}^{\infty}$, we can calculate the difference in TFP growth that is attributable to different rates of technological progress using the expression above.

In terms of technology levels, using the identity $X_{i,t} = X_{i,0} e^{\sum_{\tau=0}^{t} x_{i,\tau}}$, under the assumption that $X_{us,0} = X_{lac,0}$[4] the technology level gap evolves according to:

$$E(\ln(\frac{X_{us,t}}{X_{lac,t}})) = E(\sum_{\tau=0}^{t}(x_{us,\tau} - x_{lac,\tau})) = E(\sum_{\tau=0}^{t}(x_{us,\tau} - \sum_{j=0}^{\tau} \lambda_j x_{us,\tau-j})) \tag{6}$$

$$= \bar{x}(\sum_{\tau=0}^{t}(1 - \sum_{j=0}^{\tau} \lambda_j)) \rightarrow_{t \to \infty} \bar{x}(\sum_{\tau=0}^{\infty}(1 - \sum_{j=0}^{\tau} \lambda_j))$$

Using the expression above, we can calculate the difference in TFP levels that is attributable to technology as a function of $\bar{x}$ and $\{\lambda_j\}_{j=0}^{\infty}$.

It is useful to distinguish between three cases: if $\sum_{j=0}^{\infty} \lambda_j < 1$, technologies are never fully adopted; an innovation in technology has a smaller long-run effect on TFP in the adopting country than in the frontier country. In this case, incomplete technology adoption generates a growth-rate differential, as technology levels diverge over time. The ratio of technology levels in equation 6 converges to ∞.

If $\sum_{j=0}^{\infty} \lambda_j = 1$, technologies are fully adopted in the long run, and the average rate of technological progress in the adopting country is the same as in the frontier. Technology levels move

[4] In this context, $t = 0$ represents an arbitrary date, in which all people shared the same technology (for example, pre-historic man in Africa).

in tandem; given any lags in technology adoption ($\lambda_0 < 1$), the average technology gap in equation 6 converges to a positive and finite level. It is easy to see that, in this case, the technology gap is increasing with the time to full adoption. Formally, for any $\{\lambda_{1,j}, \lambda_{2,j}\}_{j=0}^{\infty}$ such that $\sum_{j=0}^{\infty}(\lambda_{1,j}, \lambda_{2,j}) = (1,1)$ and $\sum_{j=0}^{t}\lambda_{1,j} \geq \sum_{j=0}^{t}\lambda_{2,j}$ for all t, the average technology gap implied by $\{\lambda_{j,1}\}$ is smaller than the average technology gap implied by $\{\lambda_{j,2}\}$. In this case, we can use estimates of $\{\lambda_j\}$ to estimate the gap in TFP levels that is attributed to differences in technology, using the formula in equation 6.

Finally, if $\sum_{j=0}^{\infty}\lambda_j > 1$, average technology growth is higher in the adopting country than in the frontier country. While it may be possible to come up with specific examples in which technologies have larger long-run effects on TFP in adopting countries (for example, if a certain technological innovation is particularly complementary to the factors of production that are abundant in the adopting countries), it seems unlikely that this will be true for the "average" technology. We therefore restrict parameters to satisfy $\sum_{j=0}^{\infty}\lambda_j \leq 1$.

To summarize, given an average rate of technological progress at the frontier ($\bar{x}$), marginal adoption rates $\{\lambda_j\}_{j=0}^{\infty}$ provide sufficient statistics for estimating the average growth differential between the frontier and adopting economies that is attributable to technological progress. In the case of full adoption in the long run ($\sum_{j=0}^{\infty}\lambda_j = 1$), we can also back out the average TFP level gap that is attributable to lags in technology adoption.

3 Baseline specification

To estimate the marginal adoption rates $\{\lambda_j\}_{j=0}^{\infty}$, we would like to exploit co-movements between technology growth in the adopting countries (LAC) and technology growth in the frontier country (the US). Of course, the problem is that technology growth is not directly observable. Instead, we observe only measured TFP growth (for example, the growth of the Solow residual or some other measure of productivity). We therefore need to impose further structure on the processes of technology and non-technology growth, and make some identifying assumptions that allow us to use co-movements in measured TFP growth for this purpose.

Our model of technology adoption suggests a natural identification strategy: while non-technology shocks (e.g., demand shocks) may be contemporaneously correlated across countries, technology shocks are likely to have a *lagged* effect on TFP growth in the adopting countries. We can therefore identify shocks to technology in the frontier as shocks that have lagged effects on measured TFP in adopting countries.

Since our main concern is with the long-run impact of technology (the infinite sum $\sum_{j=0}^{\infty}\lambda_j$), and since technology may impact TFP in adopting countries with potentially long lags, we impose a parametric restriction on the sequence $\{\lambda_j\}_{j=0}^{\infty}$, that allows us to obtain estimates for the entire sequence by estimating just a finite number of parameters. Specifically, we assume that the sequence

$\{\lambda_j\}$ takes the following discrete Normal form:

$$\lambda_j = p_1 \exp(-\frac{(j-p_2)^2}{p_3}) \tag{7}$$

where $p_1, p_2, p_3 \geq 0$. We believe that this restriction allows for sufficient flexibility in the adoption process. Importantly, the value $p_1 = 0$ embeds the case of no technology adoption, as $\lambda_j = 0$ for all j. In general, p_1 plays a role in determining the level of adoption. The parameter p_2 controls the "peak" of the adoption process: if $p_2 = 0$, marginal adoption rates are decreasing over time; if $p_2 > 0$, marginal adoption rates are increasing initially and start declining after p_2 periods. Finally, p_3 controls the dispersion of the adoption process. Larger values of p_3 imply that adoption takes place during a longer period of time; a smaller p_3 would imply that adoption is more concentrated in a few "peak" years around p_2. Figure 13 in the appendix presents several examples of adoption processes that follow a discrete-Normal distribution.

We estimate the following model:

$$\begin{aligned}
a_{us,t} - \bar{a}_{us} &= (z_{us,t} - \bar{z}_{us}) + (x_t - \bar{x}) && (8)\\
a_{lac,t} - \bar{a}_{lac} &= (z_{lac,t} - \bar{z}_{lac}) + \sum_{j=0}^{\infty} \lambda_j (x_{t-j} - \bar{x}) && (9)\\
z_{i,t} - \bar{z}_i &= \rho_i (z_{i,t-1} - \bar{z}_i) + \nu_{i,t} && (10)\\
x_t - \bar{x} &= \alpha(x_{t-1} - \bar{x}) + \epsilon_t && (11)
\end{aligned}$$

$$\begin{bmatrix} \nu_t^{us} \\ \nu_{lac,t} \\ \epsilon_t \end{bmatrix} \overset{i.i.d}{\sim} N(0,\Omega) \qquad \Omega = \begin{bmatrix} \sigma^2_{us,us} & \sigma^2_{us,lac} & 0 \\ \sigma^2_{lac,us} & \sigma^2_{lac,lac} & 0 \\ 0 & 0 & \sigma^2_{x,x} \end{bmatrix}$$

$$|\ \alpha\ |, |\ \rho_{us}\ |, |\ \rho_{lac}\ | < 1$$

$$\lambda_j = p_1 \exp(-\frac{(j-p_2)^2}{p_3}) \tag{12}$$

$$p_1, p_2, p_3 \geq 0, \ \sum_{j=0}^{\infty} \lambda_j \leq 1 \tag{13}$$

Two notes are in order. First, note that both $z_{i,t}$ and x_t are specified as AR(1) processes. The distinguishing feature of x_t is its lagged effect on measured TFP growth in the adopting countries: while shocks to $z_{i,t}$ may be persistent and contemporaneously correlated across countries, shocks to $z_{us,t}$ have no lagged effect on $a_{lac,t}$.

Second, note that we assume the independence of x_t and $z_{i,t}$. Formally, our assumption is that shocks to technology have no effects on demand or capacity utilization. This assumption is obviously problematic, as there is evidence suggesting that technology shocks may affect capacity utilization (either negatively, as in Basu et al. [2006], or positively, as in Greenwood et al. [1988]). However, it is worth noting that this independence assumption can be relaxed, provided that the effect of technology shocks on non-technology components of TFP is the same across countries. See Appendix A for details.

We estimate the model's parameters using a maximum likelihood estimation procedure, which is detailed in Appendix B. We assess the uncertainty regarding our parameter estimates by constructing 90% confidence intervals using a bootstrap methodology, also detailed in the Appendix.

Data. We measure aggregate TFP as the Solow residual. Following Caselli [2005], TFP is computed as follows: $y = TFPk^{\alpha}h^{1-\alpha}$ where y and k are output and capital per worker (i.e. $y = y/L$ and $k = K/L$) and $\alpha = \frac{1}{3}$. K is calculated from the investment series at the Penn World Table, with the depreciation rate of 6% per year. h_t represents human capital. Also following Caselli [2005], h is defined as $h = e^{\phi(a)}$ where a is the average years of schooling, and $\phi(s)$ is a piecewise linear with slope 0.13 for $s < 4$, 0.10 for $4 < s8$, and 0.07 for $8 < s$. Output, investment and labor force data are from the Penn World Table. Data on average years of schooling are from Barro and Lee [2001]. As alternative specifications, we also consider the Solow residual without consideration of human capital (by setting h equal to 0), or simply real GDP. Data are available at an annual frequency from 1960 to 2009.

The frontier economy is specified as the US. We begin by specifying a single adopting "country", which is a GDP-weighted average of LAC countries.

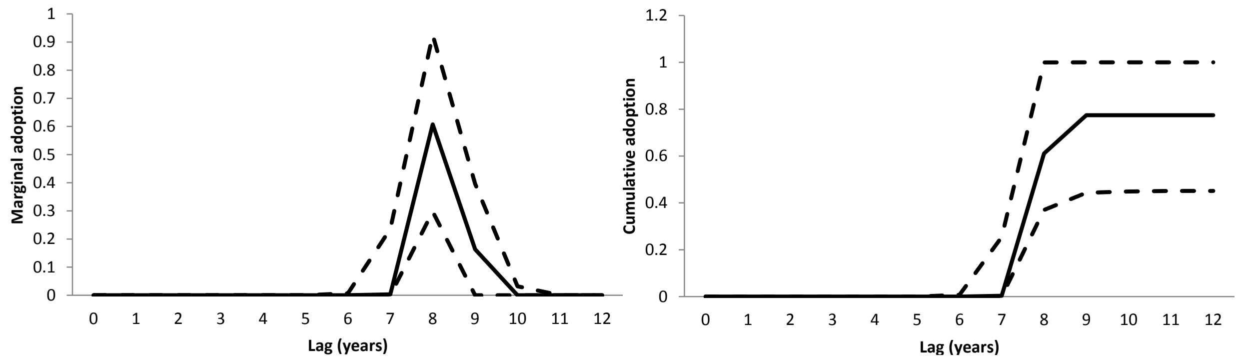
3.1 Results

Figure 2 presents the estimation results. The left panel represents the estimated marginal adoption rates (λ_j), and the right panel represents the estimated cumulative adoption rates ($\sum_{j=0}^{t} \lambda_j$). The estimation suggests that the bulk of technology adoption happens at an 8 year lag. The point estimate suggests that technological innovations in the frontier have a somewhat smaller effect on productivity in LAC: the point estimate of the infinite sum $\sum_{t=0}^{\infty} \lambda_j$ is about 0.8, suggesting that a 1% improvement in technology in the US increases long-run productivity in LAC by only 0.8%. However, it is important to note that the 90% confidence interval cannot reject full adoption in the long run (and in fact, after 8 years). In this case, technological innovations in the US have the same effect on TFP in LAC, with an 8 year lag.

Figure 14 in the appendix presents the baseline estimation results in which alternative series are used. Rather than using our preferred constructed TFP series, we consider two alternative series for measured TFP: (a) TFP without taking account of human capital, and (b) GDP. The results are broadly consistent with those presented here, with point estimates suggesting a similar 8-year lag. However, it should be noted that, when using the simple Solow residuals, the point estimates suggest full adoption in the long run (which also falls within the 90% confidence intervals here).

Figure 2: Estimated marginal and cumulative adoption rates in the baseline

(a) Marginal adoption rates



(a) Marginal adoption rates (b) Cumulative adoption

Measured TFP growth is constructed as the growth of the Solow residual (with consideration of human capital), at an annual frequency. The "frontier country" is the US, and the "adopting country" is a GDP-weighted average of LAC countries. Dotted lines represent the bounds of the 90% confidence intervals.

3.2 The contribution of technology to the TFP gap and the TFP growth gap

Using equations 5, we can derive the implications of our empirical estimates for the contribution of technology to differences in TFP growth. At the upper bound of our confidence interval, technological progress has the same long-run effect on TFP in LAC and in the US. With $\sum_{j=0}^{\infty} \lambda_j = 1$, the growth differential in equation 5 collapses to 0.

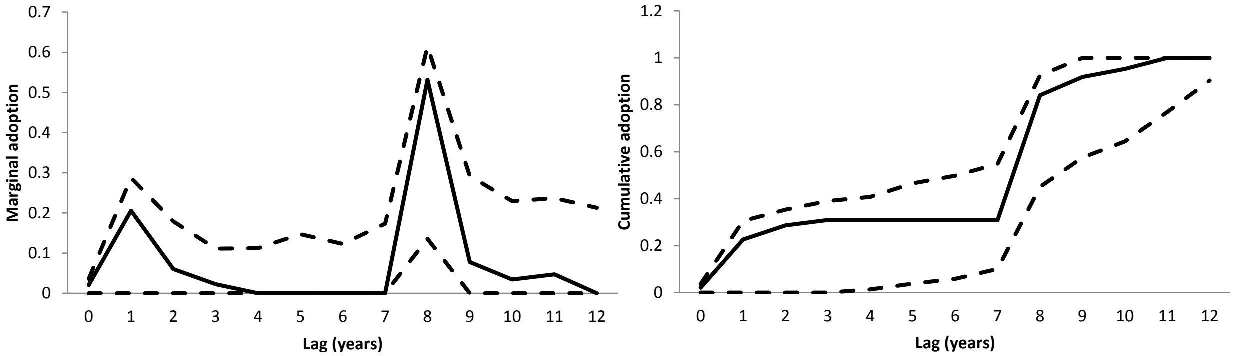
At the bottom end of our confidence interval, $\sum_{j=0}^{\infty} \lambda_j \approx 0.5$. In this case, the TFP growth gap is given by $0.5\bar{x}$. If we assume that technological progress grows at about $\bar{x} = 0.5\%$ annually (which is the average growth rate of TFP in the US in our sample),[5] the upper bound of the growth rate differential generated by incomplete technology adoption is 0.25%. For $\bar{x} = 1\%$ (which is consistent with later observations of TFP growth), the technology growth gap is about 0.5%.

For the case $\sum_{j=0}^{\infty} \lambda_j = 1$, the TFP gap converges to a constant in the long run. At the upper bound of our confidence interval, cumulative adoption is approximately 0 up to $j = 8$ and 1 for $j > 8$. Plugging in these numbers into equation 6, the technology component of the TFP gap is given by:

$$\bar{x} \sum_{\tau=0}^{\infty} (1 - \sum_{j=0}^{\tau} \lambda_j) \approx \bar{x} \sum_{\tau=0}^{8} (1 - 0) = 8\bar{x} \tag{14}$$

For $\bar{x} = 0.5\%$, the TFP gap attributed to technology is 4%; for $\bar{x} = 1\%$, the TFP gap attributed to technology is 8%.

[5] This estimate is conservative in our context, as it assumes that non-technology factors had no role in long-run TFP growth in the US throughout the period in question.



(a) Marginal adoption rates (b) Cumulative adoption

(a) Marginal adoption rates

Figure 3: Estimated marginal and cumulative adoption rates, without imposing the discrete-Normal assumption on the distribution of marginal adoption rates. Measured TFP growth is constructed as the growth of the Solow residual (with consideration of human capital), at an annual frequency. The "frontier country" is the US, and the "adopting country" is a GDP-weighted average of LAC countries. Dotted lines represent the bounds of the 90% confidence intervals.

4 Alternative specifications

This section presents several alternative empirical specifications. First, we relax the discrete Normal assumption and consider an unrestricted specification with a finite number of positive marginal adoption rates. Second, we consider alternative identification strategies, that exploit the co-movements of measured TFP growth in LAC with measured TFP growth in the US at various frequencies. Finally, we estimate the model on alternative series, that provide estimates of technology diffusion by country and by industry.

4.1 Relaxing the discrete-Normal assumption

Given that the baseline estimation suggests that the bulk of technology adoption happens within the first 10 years, we relax the discrete-Normal restriction on the sequence $\{\lambda_j\}_{j=0}^{\infty}$ and estimate an unrestricted sequence of marginal adoption rates, allowing for up to 12 positive lags. The results are presented in figure 3. The results obtained from using the alternative aggregate series (the Solow residual without consideration of human capital and GDP) are presented in figure 15 in the appendix.

Similar to our baseline specification, the unrestricted estimation suggests that the bulk of technology adoption occurs with an 8 year lag, and that full adoption in the long run cannot be rejected. In fact, the point estimates suggest full adoption after 12 years, with a tight 90% confidence interval of $[0.9, 1]$.

However, contrary to our discrete Normal assumption, the unrestricted estimation suggests two adoption peaks: the smaller of the two occurring with a 1-2 year lag, and the larger occurring with roughly an 8 year lag. While the first peak may be evidence of some contemporaneous adoption, there is a concern that this may reflect business cycle dynamics associated with the technology shock in the US. For example, a technology shock in the US may generate demand for materials supplied from LAC, which may translate into a (non-technology) increase in measured productivity in LAC. In light of this concern, we view the discrete Normal specification as the more conservative approach, as it effectively leaves out the potential contemporaneous spillovers of technology, which may be of cyclical nature.

4.2 Alternative identification strategies

As robustness checks, we consider alternative ways of identifying the sequence of marginal adoption rates, using co-movements between measured TFP in LAC and different frequencies of lagged measured TFP growth in the US. We impose the discrete-Normal parameterization of $\{\lambda_j\}_{j=0}^{\infty}$ and consider several alternative identifying assumptions:

Orthogonality of $z_{us,t}$ and $z_{lac,t}$ at an annual frequency (annual growth rates strategy). Under the assumption that non-technology shocks are uncorrelated in LAC and in the US at all leads and lags, lagged comovements in measured TFP reflect lagged comovements in technology. Note that this identification does not require that *any* movement in TFP reflects movements in technology; rather, it requires that any movement in the non-technology component of TFP in the US is independent from movements in the non-technology component of TFP in LAC.

This assumption is likely to be violated if movements in TFP at an annual frequency have a strong demand component: domestic demand shocks are likely to generate demand for foreign goods as well, and thus boost demand abroad, generating a natural contemporaneous comovement of the non-technology components of TFP (due, for example, to comovements in unobserved capacity utilization). The identifying assumption is therefore that movements in demand play a limited role in the growth of measured TFP at an annual frequency.

Orthogonality of the trend components of $z_{us,t}$ and $z_{lac,t}$ (HP filter trend strategy). Given the potential role of demand shocks in generating TFP fluctuations at an annual frequency, we consider a more conservative specification that, rather than using annual growth rates, uses the HP filtered trends of measured TFP growth. As long as demand-driven growth in measured TFP is relatively transitory, it will be smoothed out by the HP filter trend. The non-technology component of the HP-filter trend in measured TFP growth is likely to reflect deeper structural changes, such as changes in misallocation, competitiveness, etc. While it is always possible to come up with transmission mechanisms generating comovements in these non-technology components, there is no strong a-priori reason to believe that this is the case. This identification is in the spirit of Blanchard and Quah [1989], who, in a structural VAR analysis, identify technology disturbances as shocks that have a long-run effect on labor productivity.

Orthogonality of the cycle components of $z_{us,t}$ and $z_{lac,t}$ (HP filter cycle strategy). While subject to the same critiques as the first strategy (the possibility of demand shocks), this strategy is a useful robustness check as it is assesses whether our results are robust to the exclusion of trends. The inclusion of trends may, in principle, generate spurious correlation between lagged movements in measured TFP in the US and movements in measured TFP in LAC.

We estimate the parameters p_1, p_2 and p_3 using maximum likelihood estimation, and produce 90% confidence intervals for the marginal and cumulative adoption rates (λ_j and $\sum_{j=0}^{t} \lambda_j$) using a bootstrap procedure. To execute our alternative identification strategies (the annual growth rates strategy, the HP filter trend strategy and the HP filter cycle strategy), we estimate the parameters p_1, p_2 and p_3 using the following equation:

$$a_{lac,t} = \sum_{j=0}^{n} \lambda_j \hat{x}_{t-j} + z_{lac,t} = \sum_{j=0}^{n} p_1 \exp(-\frac{(j-p_2)^2}{p_3})\hat{x}_{t-j} + z_{lac,t} \tag{15}$$

Where $a_{lac,t}$ is annual measured TFP growth in LAC and $\hat{x}_t$ is a proxy for technology growth in the US which, depending on the identification strategy, is either annual growth rates of measured TFP in the US, the HP filter trend component of measured TFP growth in the US or the HP filter cycle component of measured TFP growth in the US. Note that the condition for unbiased OLS estimates is that the error in $\hat{x}_{t-j}$ is uncorrelated with $z_{lac,t}$. In this context, the error in $\hat{x}_t$ is precisely $z_{us,t}$ (with the relevant filtering), consistent with the identifying assumptions underlying the analysis.

The results are highly consistent with our baseline specification, and are presented in figure 16. This confirms that our results are not driven by a particular frequency of the data (either the trend or the cycle).

4.3 Alternative series

Instead of assuming one LAC "country" (which is a weighted average of countries in the region), we conduct the analysis by (a) including each country in LAC as a separate adopting country, and (b) estimating the marginal adoption rates by industry. These extensions allow for the sequence of marginal adoption rates to differ across countries and across industries. However, while there is some variation in the results, they broadly confirm the findings on the aggregate level.

Country-level estimation. To estimate the country-level adoption lags, we estimate a richer model that includes one frontier country (the US) and 19 adopting countries, corresponding to countries within the LAC region. Given the large increase in the number of parameters (as we must estimate 19 different sequences of marginal adoption rates), we simplify the model by imposing that the non-technology component of measured TFP growth is an i.i.d process (rather than an AR(1) process). We also confirm that the baseline results (with the LAC aggregate) do not change much when we impose this alternative assumption on the stochastic process of the non-technology component.

The results are presented in figure 17 in the appendix. The results are highly consistent with those obtained with the LAC aggregate. For most countries in LAC (12 out of 19), the point estimates suggest full adoption of technologies after 8 years at most. While there is some variation across countries, the variation is not statistically significant in the sense that full adoption after 8 years is within the 90% confidence interval for all countries in our sample.

Industry-level estimation. At the industry level, we proxy measured productivity growth with growth in value added per worker by industry, using the value added in constant prices from the Groningen Growth and Development Centre 10-sector database for LAC countries and the US. Note that for LAC countries, only 9 sectors are available. Data is available from 1950- 2005. We estimate the baseline model for each industry separately, using a LAC weighted average in which weights are given by real value added in each industry.

The results are presented in figure 18. Broadly, the results at the aggregate level are consistent with the industry-level results, in the sense that full adoption within 12 years (as well as 0.8 long-run adoption) fall within the confidence intervals of each of the industry-level results. However, there is some interesting variation across industries, both in the point estimates and in the confidence intervals. For example, manufacturing - a sector which is widely viewed as a "fast" adopter - delivers point estimates suggesting full adoption after 8 years, with a relatively tight confidence interval. Mining, a sector with significant foreign presence, seems to exhibit faster adoption, with the bulk of adoption occurring at a 1 year lag (however, it should be noted that the magnitude of long-run adoption is rather imprecisely estimated, though statistically significant).

The agriculture sector, which has been the focus of many studies relating to technological differences across countries, exhibits slower adoption, with full adoption taking place only after 12 years, if at all. In fact, the point estimate suggest that long-run adoption is about 0.5. This is consistent with the finding that productivity differences in agriculture are larger than productivity differences in other sectors (see, for example, Caselli [2005] and Restuccia et al. [2008]).

Finally, the estimation delivers very wide confidence intervals for the government and service sectors (finance, public utility and community, social and personal services which includes the government sector). For these industries, both full adoption and no adoption (or close to no adoption) are within the 90% confidence interval.

5 Supporting Micro Evidence

In this section, we support our finding using two sources of data: the first is data on information technology (IT) investment, that illustrates an 8-9 year lag in IT investment in LAC relative to the US. The second is patent citation data, that illustrates that patents issued in the US are cited in LAC with an 8-9 year lag.

5.1 Technology-level evidence: the case of IT

Information technology has been one of the most influential technological innovations in the last fifty years. In this section, we present evidence suggesting that information technology was adopted in Latin America within 10 years of its adoption in the U.S. In particular, we establish that telecommunication investment in LAC took off around the mid-1980s, about 10 years after it took off in the US. In addition, we document that internet coverage in Latin America lags 10 years behind the U.S.

It is difficult to know precisely when information technology was first introduced in Latin America, because obtaining historical data on information technology is difficult. We can only obtain historical investment data on telecommunication. The data are from the World Telecommunication/ICT Indicators Database. The analysis shows that growth in Telecommunication Investment in Latin America took off indeed in the mid-1980s.

We focus on telecommunication investment per capita. In Figure 4 we show the telecommunication investment per capita in Latin America, in real 2005 U.S. dollars [6]. The graphs suggest that telecommunication investment in Latin America took off around 1986. This is about 10 years after telecommunication investment in the U.S. took off in the mid-1970s.[7]

We also construct the levels of the telecommunication capital stock for the U.S. and Latin America by adding up investment (and assuming capital depreciates at a rate of 6% a year). Figure 5 shows the LAC-US ratios of telecommunication capital level per capita and of the aggregate capital level per capita[8]. We can see that the LAC-US ratio of telecommunication capital stock gradually rises and eventually converges to and tracks the ratio of aggregate capital stock. In our view, this suggests full adoption of telecommunication technologies, as the gap in the stock of telecommunication-related capital is fully accounted for by the capital gap.

We proceed with the analysis of internet coverage. We obtain the data on percentage of population using the internet from the World Telecommunication/ICT Indicators Database. We then construct the LAC-wide measure of percentage of population with access to the internet. As illustrated in Figure 6 internet coverage in Latin America lags that of the U.S. within 10 years: the first 1% of LAC population had access to the internet in 1998, 7 years after the first 1% in the U.S. Similarly the first 10%, 20% and 30% of LAC had access to the internet within 10 years after U.S. After that, the internet coverage levels in LAC and the U.S. seem to move along its steady state paths, and the gap between the two levels persists.

5.2 Patent-level evidence

We now turn to the patent level analysis. Earlier studies of knowledge flows have used patent citations as an indicator of knowledge flows from more advanced countries to developing countries

[6]Due to unavailable data, telecommunication investment is interpolated between 1966-1969 and 1971-1974 from the data points at 1965, 1970 and 1975.

[7]See Greenwood and Yorukoglu [1997] for a detailed discussion on the growth in IT investment in the US during the 1970s.

[8]The aggregate capital levels are calculated from investment data obtained from the Penn World Table

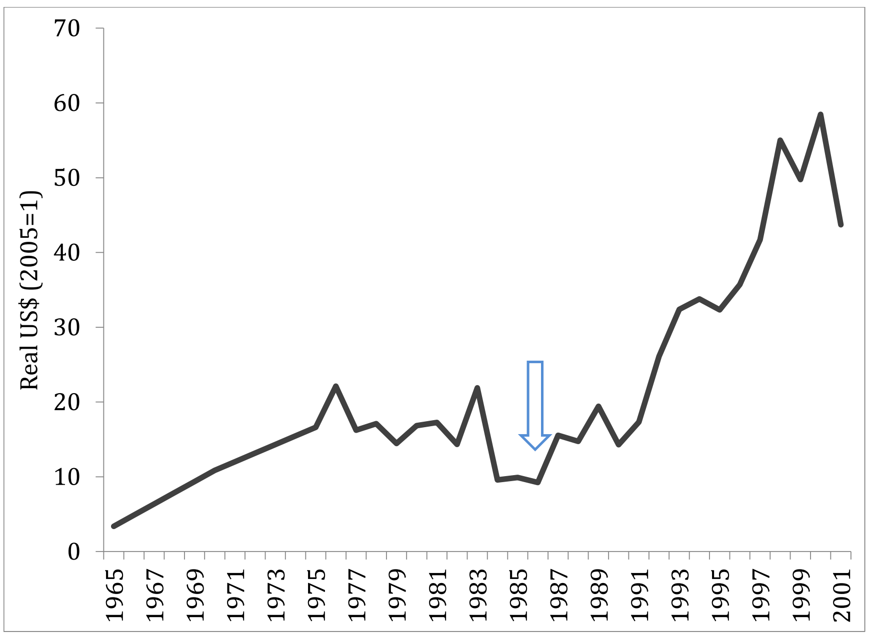


Figure 4: Real Telecom Investment per capita, Latin America average (2005 US dollars). Annual data starting from 1975 onward. Data between 1965,70,75 extrapolated.

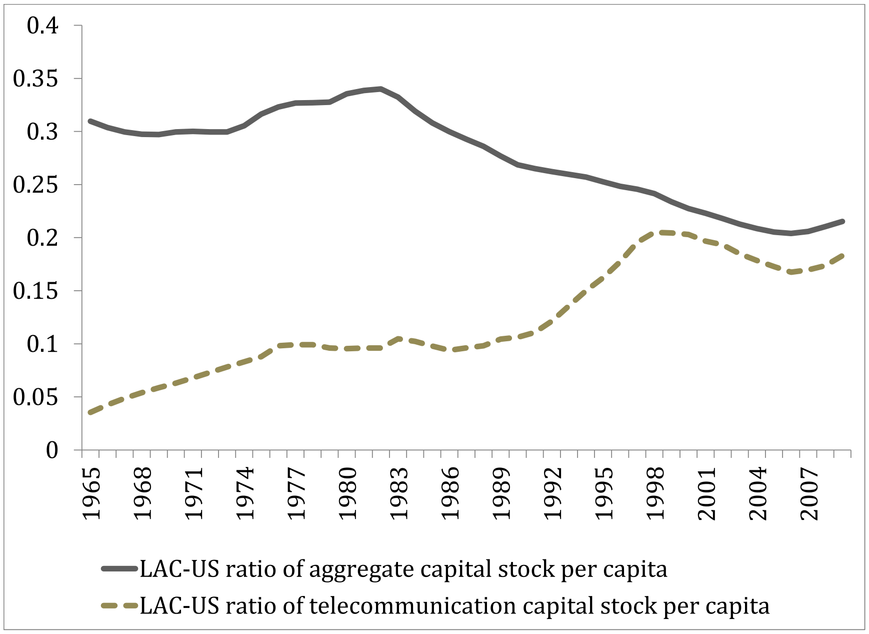


Figure 5: LAC-US ratios of telecommunication and aggregate capital levels

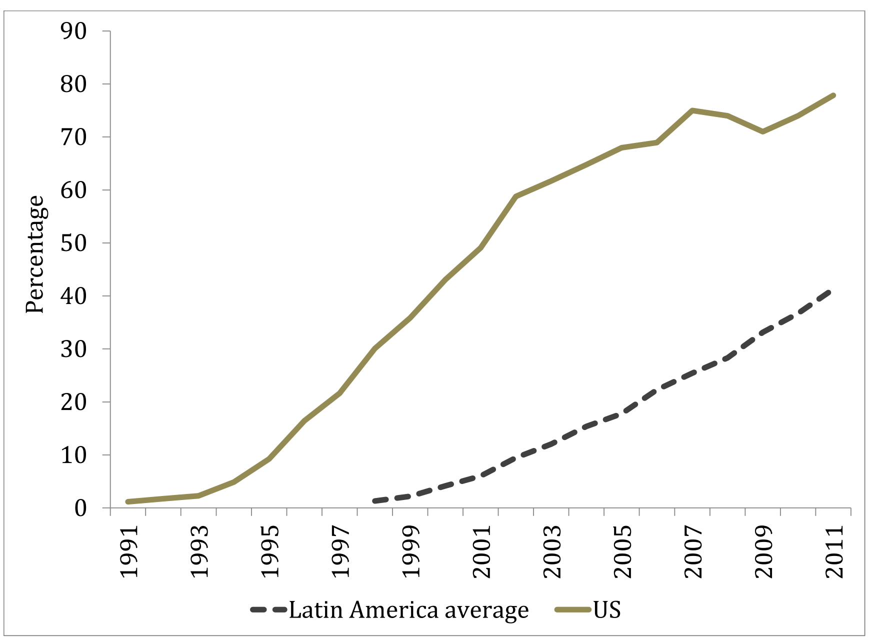


Figure 6: Percentages of population using the internet

(see for instance, Jaffe et al. [1993] and Jaffe and Trajtenberg [1999]). We follow this literature by studying the citation lags between LAC and US inventors. In particular, we compute the average time that it takes for a LAC inventor to cite a US inventor.

The data we are using for this analysis comes from the USPTO/NBER Patent Database Project (PDP). The full dataset contains more than 3 million patents registered from all over the world between 1976-2006. This dataset contains information on:

- the patent number,
- the country of the primary inventor,
- the year of application of the patent, and
- the identity of the patents that are cited by the current patent (cited-citing pairs).

For our purpose, we focus on patents that are invented in LAC and cite a patent invented in the US. Truncation is an important concern when studying the citations: A 1976 patent has 30 years to receive a forward citation as opposed to a 2005 patent which had only 1 year to receive a forward citation. Since the majority of the citations are done within the first 7 years, we restrict our attention to the US patents that have been applied between 1976-1996. This way, we leave at least a 10-year window for each patent to receive citations. We identify more than 5,000 patents that satisfy this criteria. Table 1 reports the detailed patent counts by industries.

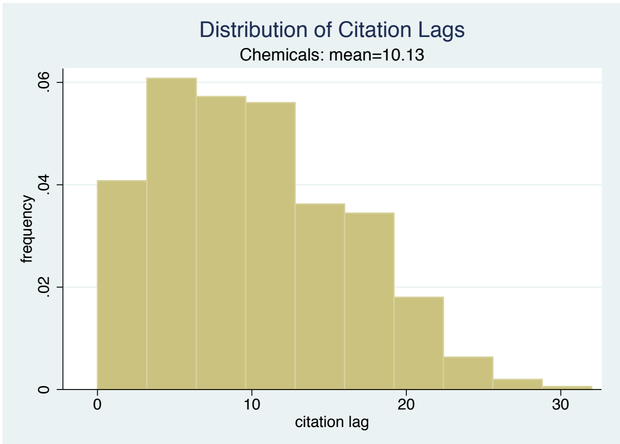
Table 1: LAC patents that cite a US patent (by industry)

Industry	**Count**	**%**
Chemicals	1,578	31.0
Comp & Comm	191	3.8
Drugs	546	10.7
Electronics	416	8.2
Mechanical	926	18.2
Others	1,440	28.3
TOTAL	5,097	100.2

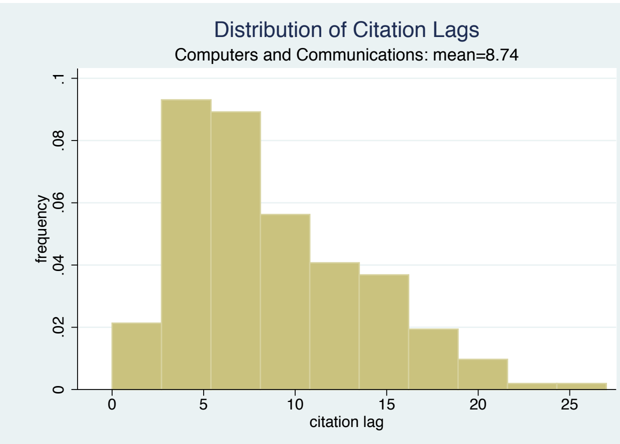
Figure 7 presents the distribution of citation lags by each industry. Interestingly, our main finding in this section is that the mean citation time between a LAC and US patent in IT (Computers and Communications) is 8.7 years. This is very much in line with our earlier findings. The average citation lags in the remaining sectors vary between 9.36 years (drugs) and 11.52 years (electrical and electronics).

5.3 Contrasting with Comin and Hobijn [2010]'s results for Latin America

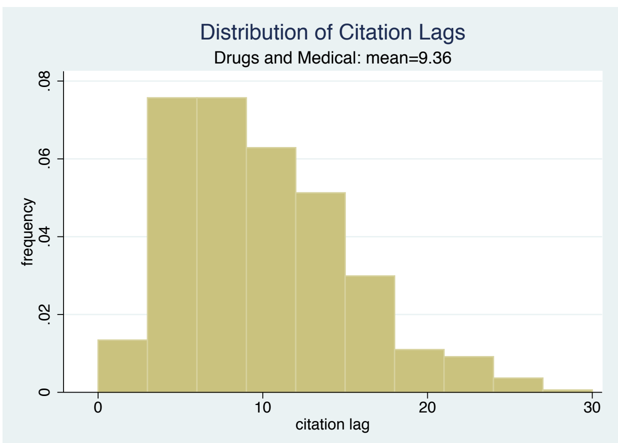
Comin and Hobijn [2010] use data on the diffusion of 15 technologies in 166 countries over the last two centuries to show that in general countries take a long time to adopt new technologies: on average, countries have adopted technologies 45 years after their invention. However there is



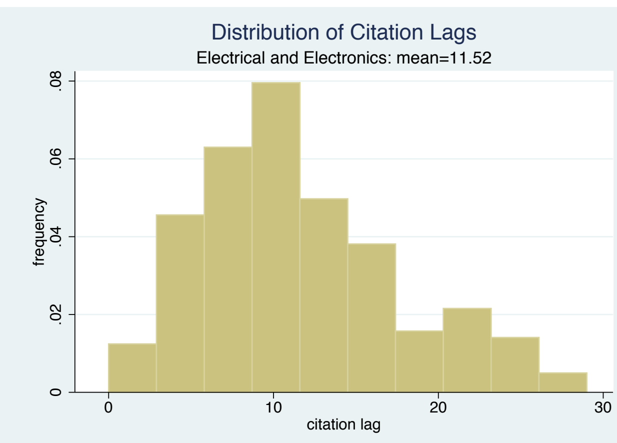
(a) Chemicals



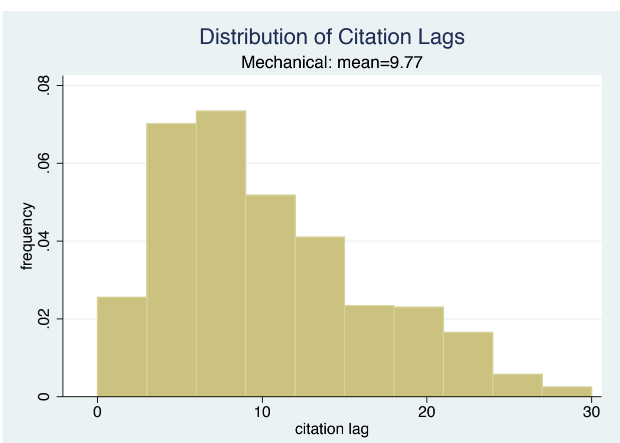
(b) Computers & Communications



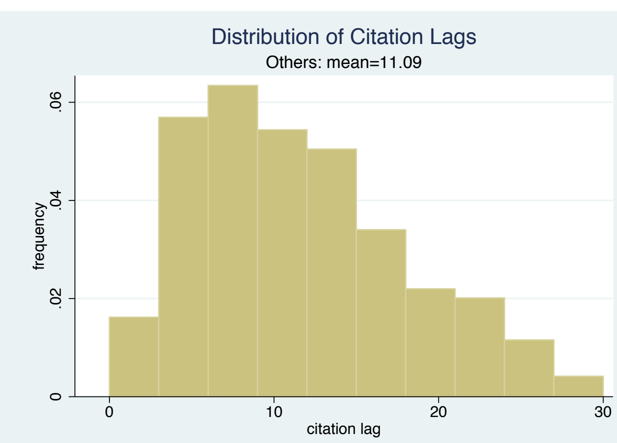
(c) Drugs and Medical



(d) Electrical and Electronics



(e) Mechanical



(f) Others

Figure 7: Age of a US patent when cited by a LAC patent (by industry)

substantial variation across countries and technologies. This section shows replicated results for the U.S. and Latin America countries. Table 3 in the Appendix shows the average adoption lags for the U.S., Latin America and all countries. Overall, there is no substantial difference in adoption lags between Latin American countries and the rest of the world. However, for recent and arguably more important technologies such as personal computers (PCs) or internet, the adoption lags are much smaller. For Latin America, the adoption lag for PCs is 15.5 years, and that for internet is 8.7 years. Considering that the U.S. takes 7.7 years to "adopt" PCs and 4.4 years to "adopt" the internet, Latin America is 7.8 and 4.3 years behind the U.S., respectively. Those numbers are in line with our results.

6 Application: Static Wedges and Technology Adoption

In this section, we provide a simple theory regarding the potential determinants of the measured adoption lags and the income gap between the US and Latin America over the 20th century. In particular, we analyze the impact of static wedges (which corresponds to Z_t in our previous notation in expression (1)) on income differences, taking into account its potential effect on the optimal technology adoption decision. One potential interpretation of these wedges, among other possibilities, is the misallocation of production factors in the economy, which has received vast attention from recent literature (Hsieh and Klenow [2009, 2014], Restuccia and Rogerson [2008]).

6.1 Income Dynamics over the 20^{th} Century

Figure 8: Log GDP Per Capita over Time

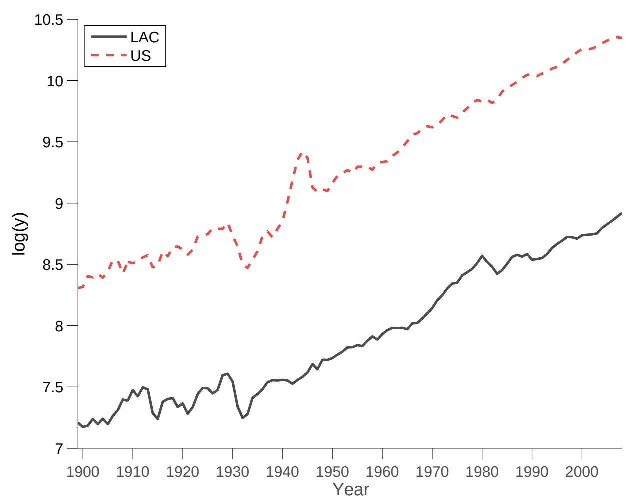
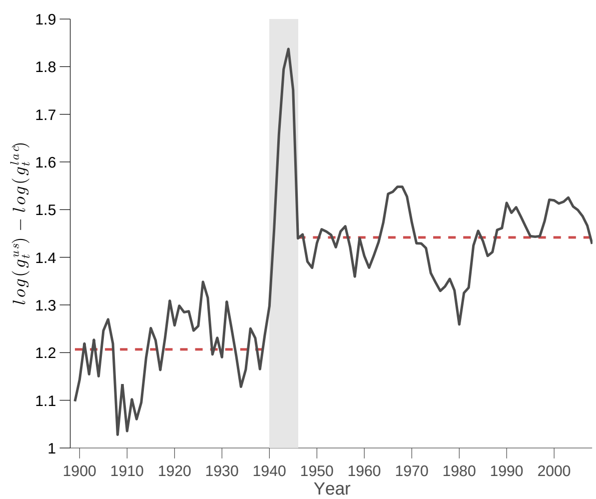


Figure 9: Income Difference over Time



Notes: Figure 10 plots the log GDP per capita over time. LAC is defined as the weighted average of Argentina, Bolivia, Brasil, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Jamaica, Mexico, Panama, Paraguay, Peru, Trinidad Tobago, Uruguay, and Venezuela. Figure 11 plots the income per capita gap between the US and LAC.

Figure 10 documents a well-known income gap between the US and LAC. Figure 11 zooms into this gap and reveals two interesting observations. First, there seems to be an obvious structural break before and after the second world war. Second, within each subperiod, there is no obvious trend in the income gap. Third, the average income gap has increased from 1.21 to 1.44 during this period.

The second observation suggests that within each period, full adoption (i.e., $\sum_{j=0}^{\infty} \lambda_j = 1$) seems to be consistent with the time-series data. The first observation then suggests that the technology adoption lags might be different between those two periods.

Our next goal is to interpret this fact through our estimates and identify the channels through which static distortions could affect the widening of this gap. We start our analysis by restating equation (1):

$$A_{i,t} = X_{i,t} Z_{i,t} \tag{16}$$

where we interpret $Z_{i,t}$ as the time-dependent static wedges. Since our attention is mainly on the technology part, for the sake of our analysis, let us assume that both countries use the same level of inputs such that

$$F_{us,t}(.) = F_{lac,t}(.)$$

where F stands for the aggregate inputs in the production function $Y_{i,t} = X_{i,t} Z_{i,t} F_{i,t}(.)$.

To understand the underlying possible mechanism behind these shifts, we first decompose the income differences as

$$\begin{aligned} \ln\left(\frac{Y_{us,t}}{Y_{lac,t}}\right) &= \ln\left(\frac{X_{us,t}}{X_{lac,t} Z_{lac,t}}\right) \\ &= \ln\left(\frac{X_{us,t}}{X_{lac,t}}\right) - \ln\left(Z_{lac,t}\right) \end{aligned} \tag{17}$$

where we abstract from capital and normalize $Z_{us,t} = 1$. Since Figure 11 shows mainly a level difference between the two periods, this can be driven by either a change in technology adoption lags or a change in the level of wedges or both. For the rest of our analysis we will rely on economic theory and utilize a tractable endogenous technical change model to shed light on these possibilities. The model will relate the speed of technology adoption to static wedges and give us a unique prediction for the composition of the observed change in income differences.

6.2 Model

Consider the following setup. In each country, a unique final good, which also serves as numéraire, is produced competitively using a continuum of intermediate inputs according to

$$Y_{it} = L_{it}^{\alpha} \int_0^1 X_{ijt}^{\alpha} y_{ijt}^{1-\alpha} dj$$

where X_{ijt} is the productivity in country i sector j at time t, y_{ijt} is the flow of intermediate good j used in general good production again at time t, and $\alpha \in [0, 1]$. Labor is fixed at some $L_i = L$. Each variety is produced by a monopolist. The marginal cost of producing each variety is $\tau_{ipt}\eta_i$ in terms of the final good, where $\eta_i > 0$ and $\tau_{ipt} \geq 1$ is the *static wedge* in the economy, which increases the marginal cost of production above its social level. The higher is τ_{ipt} the lower is the production efficiency of the economy for any given technology level X_{ijt}.

6.2.1 Static Problem

Now we are ready to solve for the static production decision. For notational tractability, we will drop the time and country indices when it causes no conflict. The demand with respect to j is

$$(1-\alpha) L^{\alpha} X_j^{\alpha} y_j^{-\alpha} = p_j \tag{18}$$

where p_j is the price of variety j. Then the monopolist's problem is

$$\pi_j = \max_{y_j} (p_j - \tau_p \eta) y_j \text{ subject to } (18).$$

This maximization problem delivers

$$\left[\frac{(1-\alpha)^2}{\tau_p \eta}\right]^{\frac{1}{\alpha}} L X_j = y_j$$

We normalize $\eta \equiv (1-\alpha)^2$ for simplicity. Hence the equilibrium quantity and price can be expressed as

$$y_j = \tau_p^{-1/\alpha} X_j L, \text{ and } p_j = (1-\alpha)\tau_p.$$

Moreover, the aggregate output and profits are simply

$$Y = XZL, \tag{19}$$

and

$$\pi_j = \Pi X_j Z,$$

where $X_t \equiv \int_0^1 X_{it} di$ is the average technology and $Z \equiv \tau_p^{\frac{\alpha-1}{\alpha}}$ is the transformed static wedge term and $\Pi \equiv (1-\alpha)\alpha L$ is a constant. Note the resemblance between expressions (19) and (1).

6.2.2 Technology Vintages and the World Knowledge Frontier

Let us denote the world technology frontier by $\bar{X}(\bar{N})$ where $\bar{X}$ is the knowledge stock at the frontier after having adopted the $\bar{N}^{th}$ vintage technology. We assume that the world technology frontier evolves through new vintages (generations) of technologies which we index by $\bar{N}$. For simplicity, every period, the frontier receives a new generation technology such that

$$\bar{N}_{t+1} = \bar{N}_t + 1. \tag{20}$$

The $\bar{N}^{th}$ generation technology produces a growth rate of $\lambda_{\bar{N}}$ at the frontier such that

$$\frac{\bar{X}_{t+1}}{\bar{X}_t} = 1 + \lambda_{\bar{N}}.$$

6.2.3 Technology Adoption

The follower country (the LAC region in our case) adopts technologies from the frontier. There is a mass of entrepreneurs that live for one period. In each period, a randomly selected entrepreneur is assigned to product line j. This entrepreneur has the option of adopting the knowledge stock from the frontier, in which case the productivity in j can increase from $X_j(N)$ to

$$\hat{X}\left(\bar{N}, N\right) \equiv X(N) \prod\nolimits_{k=N}^{\bar{N}} (1 + \lambda_k).$$

This expression implies that when the technology adoption is successful, the knowledge stock in j will improve by the respective growth rates of all the vintages between the current vintage N and the frontier vintage $\bar{N}$.

Let us denote the endogenous probability of technology adoption by μ_j in sector j. The entrepreneur pays the technology adoption cost $\gamma\frac{\mu_j^2}{2}\hat{X}\left(\bar{N}, N\right)$ in terms of the final good and in return becomes the monopolist for one period with probability μ_j or gets nothing with the remaining probability $1-\mu_j$. Note that the costs are proportional to the level of the technology to be adopted $\hat{X}\left(\bar{N}, N\right)$: If the technology to be adopted is more advanced, the cost of adopting it is also higher. This simply removes any artifical scale effect problems. Then the maximization problem can be stated as

$$\max_{\mu_j} \left\{ \mu_j \Pi Z \hat{X}\left(\bar{N}, N\right) - \gamma \frac{\mu_j^2}{2} \hat{X}\left(\bar{N}, N\right) \right\}.$$

The first order condition is simply given by

$$\mu_j = \mu = \frac{\Pi Z}{\gamma}. \tag{21}$$

Note that the incentives for technology adoption is increased by equilibrium profits. We have proved the following result:

Lemma 1 *Technology adoption incentives are decreasing in the level of static wedges τ (and increasing in Z).*

Now we can express the law of motion of the vintages in LAC as a function of their endogenous adoption rate:

$$N_{t+1} = \mu \bar{N}_t + (1-\mu) N_t \tag{22}$$

where next period's vintage is simply the frontier vintage of the last period with probability μ and remains unchanged with probability $1-\mu$. If we define the distance to the world vintage frontier by

$$n_t \equiv \bar{N}_t - N_t, \tag{23}$$

we can express (22) as

$$N_{t+1} - \bar{N}_{t+1} = \mu \left[\bar{N}_t - N_t\right] + N_t - \bar{N}_{t+1} + \bar{N}_t - \bar{N}_t$$

which then translates into

$$n_{t+1} = 1 + (1-\mu)\, n_t$$

where we used (20) and (23) and μ is given in (21). This expression implies that the next period's distance to the world frontier is a negative function of the technology adoption probability μ. If the entrepreneurs are more aggressive in their technology adoption efforts, the gap between the frontier and LAC will close. Note that this is a convergent sequence where in the long-run

$$\lim_{t\to\infty} n_t = n^* = \frac{1}{\mu} = \frac{\gamma}{\Pi Z}, \tag{24}$$

FIGURE 10: LAW OF MOTION OF n_t

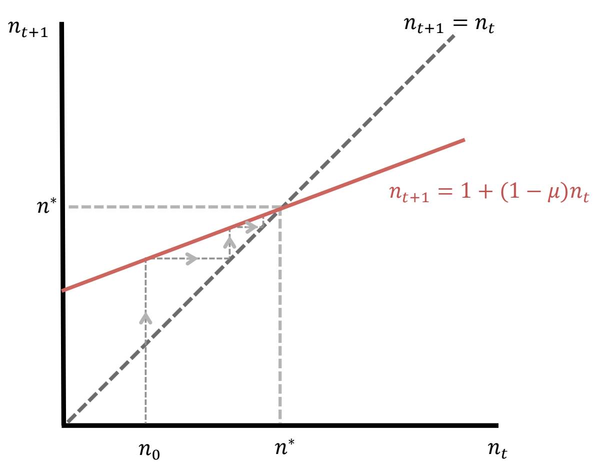
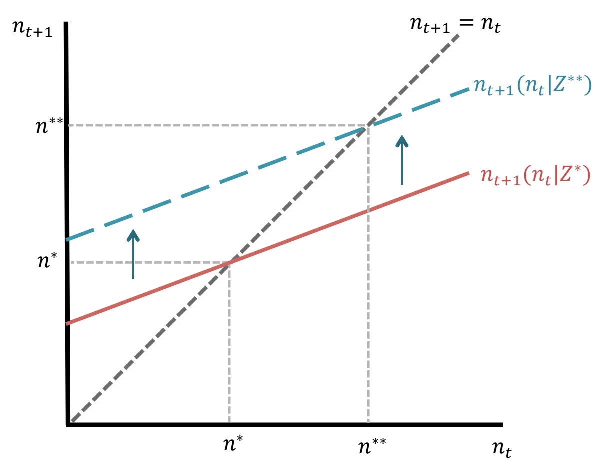


FIGURE 11: RISE IN MISALLOCATION $Z^{**} < Z^*$



Proposition 1 *In the long-run, the distance to the world knowledge frontier is positively affected by the static wedge τ_p (and negatively affected by Z).*

Our model generates an interesting prediction, a feedback from the static wedges to the dynamic technology adoption incentives. If the wedges become larger (lower Z), the dynamic incentives are worsened (lower μ), which then increases the equilibrium distance to the technology frontier n^*.

In the long-run, if the average growth rate of the frontier is λ, equation (17) can be written as

$$\begin{aligned} \ln\left(\frac{Y_{us}}{Y_{lac}}\right) &= \ln\left(\frac{(1+\lambda)^{n^*} X_{lac}}{X_{lac}}\right) - \ln\left(Z_{lac}\right) \\ &= n^* \ln\left(1+\lambda\right) - \ln\left(Z_{lac}\right) \end{aligned}$$

Combining this last expression with (24) we get

$$\ln\left(\frac{Y_{us}}{Y_{lac}}\right) = \frac{\gamma \ln(1+\lambda)}{Z_{lac}\Pi} - \ln(Z_{lac}). \tag{25}$$

Several important observations are in order. First, this expression uniquely maps the static misallocation into the observed income difference in the data. Using post-war ratios of income per-capita, together with our post-war estimates of the static misallocation, we can calibrate the ratio $\frac{\gamma}{\Pi}$; then, we can use this ratio together with pre-war differences in income to calibrate the pre-war static distortion.

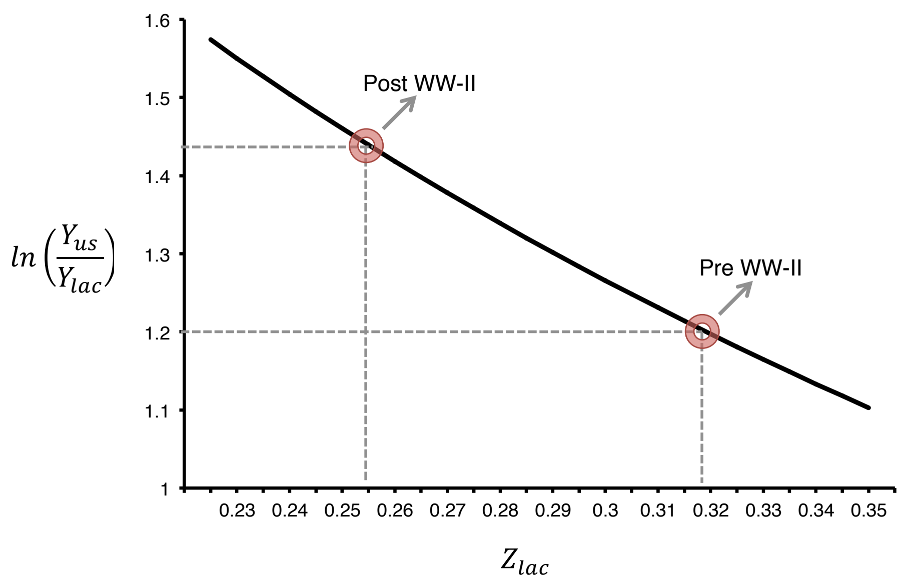
Second, this expression shows that the static misallocation not only has a well-known *direct* effect on the income difference, but also a *indirect* effect through its impact on technology adoption lags. This is mainly due to the fact that higher static misallocation lowers the return to technology adoption which, in turn, increases the equilibrium adoption lags.

Proposition 2 *Assume* $\ln(Y_{us}/Y_{lac}) > \frac{\gamma \ln(1+\lambda)}{\Pi}$ *Then there exists a unique static misallocation* $Z_{lac} < 1$ *such that (25) holds. Moreover,* Z_{lac} *and* Y_{us}/Y_{lac} *are negatively correlated.*

6.2.4 Bringing the Model to the Data

Our simple model generates the following prediction. If the change in output per-capita was caused by an increase in static misallocation, it should have been accompanied by an increase in technology adoption lags. Figure 12 depicts the negative relationship between the two.

FIGURE 12: STATIC WEDGES VS INCOME GAP



Now we can impose the observed teachnology gaps between the two periods and back out the static distortions. Table 2 summarizes our finding.

Table 2: Calibrated Levels of the Static Distortion

	$\ln(Y_{us}/Y_{lac})$
Pre-war (1900-1940)	1.21
Post-war (1948-2006)	1.44
Implied $Z_{lac}^{pre}/Z_{lac}^{post}$	1.23

Our model predicts that the misallocation in LAC has risen by 23% between the two periods. Moreover, within each period, 10% of the observed income gap is attributed to the indirect effect of the static wedges on technology adoption and the rest coming from its direct effect.

Testing the mechanism. The mechanism proposed above has a directly testable implication: if the static wedge is a major source of increased income difference, then the technology adoption lags should have increased between two periods (as illustrated by Proposition 1). To test this empirical conjecture, we reestimate our econometric model from Section 3 with pre-war data. The results show that the adoption lags between 1900-1940 was 4-5 years, which is almost half of our post-war estimates of 8-9 years. This lends support to the role of static wedges on technology adoption process.

7 Conclusion

This paper explores the quantitative importance of delayed and incomplete technology adoption for the productivity gap between the US and countries in LAC. To estimate the pattern of technology adoption, we exploit the time variation in technological progress in the US and estimate the dynamic impact of innovation on TFP growth in LAC. In our main specification, we identify a technology shock as a shock that has a delayed effect on TFP growth in LAC. We find evidence of an 8-10 adoption lag, with complete or near-complete adoption in the long run. In other words, technological progress has a similar contribution to TFP growth in LAC and in the US, with an 8-10 year delay.

A structural interpretation of these estimates suggests that incomplete technology adoption can generate a TFP growth rate differential of between 0-0.5%. In the case of full adoption, technology adoption lags generate a stable TFP gap of only 4-8%.

While our estimates suggest that technological backwardness is unlikely to generate a large difference in TFP or TFP growth, it may be symptomatic of other distortions present in the economy. In a simple endogenous growth framework, we explore the idea that static distortions may reduce the incentives for technology adoption. We use our calibration to generate out-of-sample predictions for the rate of technology adoption prior to World War 1, and find that these predictions are consistent with our empirical estimates for the period.

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Appendix

A Relaxing the assumption that shocks to technology and non-technology growth are independent

Our econometric specification assumes that shocks to the technology component of measured TFP growth (x_t) are independent from shocks to the non-technology component of measured TFP growth (z_t). However, there is some empirical evidence suggesting that changes in technology induce changes in the non-technology component of TFP (for example through cyclical changes in capacity utilization). In this Appendix, we relax the independence assumption and show that our estimation procedure is still valid, as long as the transmission of technology shocks to the non-technology component of TFP is the same across countries.

Consider a model in the spirit of Blanchard and Quah [1989], in which there are two types of disturbances: a technology shock ζ_t^{tech} and a non-technology shock $\zeta_{i,t}^{non-tech}$ (for $i = us, lac$), both i.i.d across time. It is assumed that non-technology shocks are independent from the technology shock. The technology and non-technology components of TFP follow AR(1) processes:

$$x_t - \bar{x} = \alpha(x_{t-1} - \bar{x}) + \zeta_t^{tech} \tag{26}$$

$$z_{i,t} = z_{i,t}^1 + z_{i,t}^2 \tag{27}$$

$$z_{i,t}^1 - \bar{z}_i^1 = \rho_i(z_{i,t-1}^1 - \bar{z}_i^1) + \zeta_{i,t}^{non-tech} \tag{28}$$

$$z_{i,t}^2 - \bar{z}_i^2 = \alpha(z_{i,t-1}^2 - \bar{z}_i^2) + \gamma\zeta_{i,t}^{tech} \tag{29}$$

where $\zeta_{us,t}^{tech} = \zeta_t^{tech}$ and $\zeta_{lac,t}^{tech}$ is defined by:

$$\zeta_{lac,t}^{tech} = x_{lac,t} - \bar{x} - \alpha(x_{lac,t-1} - \bar{x}) \tag{30}$$

In this formulation, the non-technology component of TFP may be affected by the the domestic non-technology shock (which may be correlated across countries), but also by the change in domestic technology, reflecting the possibility that the introduction of a new technology may change the rate of capacity utilization or the level of domestic demand. The non-technology component that changes with technology is denoted by $z_{i,t}^2$, and it is assumed to inherit the persistence of the technology shock.

Under the assumption that $\gamma_{us} = \gamma_{lac} = \gamma$, our identification is valid. Consider the following transformation of the model denoted with $\tilde{x}$, $\tilde{z}$, $\tilde{\zeta}$:

$$\tilde{x}_{i,t} = x_{i,t} + z_{i,t}^2 = \alpha(x_{i,t-1} + z_{i,t-1}^2) + (1+\gamma)\zeta_t^{tech} = \alpha\tilde{x}_{i,t-1} + \tilde{\zeta}_t^{tech} \tag{31}$$

$$\tilde{z}_{i,t} = z_{i,t}^1 = \rho_i z_{i,t-1}^1 + \zeta_{i,t}^{non-tech} = \rho_i\tilde{z}_{i,t-1} + \tilde{\zeta}_{i,t}^{non-tech} \tag{32}$$

It is easy to see that this transformed model corresponds to our original specification: ζ^{tech} and $\zeta_i^{non-tech}$ are independent; demeaned growth rates at period t are given by $\tilde{z}_{i,t} + \tilde{x}_{i,t}$; and,

$$\tilde{x}_{lac,t} - \alpha \tilde{x}_{lac,t-1} = \tilde{\zeta}_t^{tech} = (1+\gamma)(x_{lac,t} - \bar{x} - \alpha(x_{lac,t-1} - \bar{x})) = \tag{33}$$

$$(1+\gamma)\sum_{j=0}^{\infty} \lambda_{t-j}(x_{us,t} - \bar{x}) = \sum_{j=0}^{\infty} \lambda_{t-j}(\tilde{x}_{t-j} - \bar{\tilde{x}})$$

Where the last equality follows from the fact that $z^2_{us,t} - \bar{z}^2_{us} = \gamma(x_t - \bar{x})$, and $\tilde{x}_i = x_i + z_i^2$.

B Maximum likelihood estimation and the construction of confidence intervals

To estimate the model described in section 3, we follow a unified state-space modeling approach that lets us simultaneously estimate the model and extract the technology part of TFP growth.

A general state space form is given by:

$$\alpha_t = R\alpha_{t-1} + w_t \tag{34}$$

$$y_t = Z\alpha_t + \varepsilon_t \tag{35}$$

where R and Z are system matrices, as funtion of parameters to be estimated. Equation 34 is called *transition equation,* equation 35 is called *measurement equation.* For our model, we have the following mapping to general form:

$$\alpha_t = \begin{bmatrix} z_t^{us} \\ z_t^{lac} \\ x_t \\ x_{t-1} \\ \vdots \\ x_{t-N} \end{bmatrix}_{(N+1)\times 1} \qquad y_t = \begin{bmatrix} \hat{g}_t^{us} \\ \hat{g}_t^{lac} \end{bmatrix}_{2\times 1}$$

$$R = \begin{bmatrix} \Gamma & \mathbf{0}_{3\times N} & \mathbf{0}_{3\times 1} \\ \mathbf{0}_{N\times 2} & \mathbf{I}_{N\times N} & \mathbf{0}_{N\times 1} \end{bmatrix}_{N+3\times N+3} \qquad Z = \begin{bmatrix} 1 & 0 & 1 & 0 & \dots & 0 \\ 0 & 1 & 0 & \lambda_0 & \dots & \lambda_N \end{bmatrix}_{2\times(N+3)}$$

$$\Gamma = \begin{bmatrix} \rho_{us} & 0 & 0 \\ 0 & \rho_{lac} & 0 \\ 0 & 0 & \alpha \end{bmatrix} \qquad w_t = \begin{bmatrix} \nu_t^{us} \\ \nu_t^{lac} \\ \epsilon_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{(N+3)\times 1}$$

where variables with a hat on top (e.g., $\hat{x}$) refer to the demeaned version of the variables. Given our assumptions on shock processes and under some regulatory conditions, we can write the joint log-likelihood of the data as

$$\ln P\left(Y_{1:T}\right) = -T \ln 2\pi - \frac{1}{2} \ln |F_t| - \frac{1}{2} \sum_{t=1}^{T} \omega_t' F_t^{-1} \omega_t$$

where ω_t is the prediction error, given by $\omega_t = y_t - Z a_{t|t-1}$. $a_{t|t-1}$ denotes the *optimal predictor* of α_t based on the information at $t-1$ and lastly F_t is the variance of the prediction error. Note that given the parameter values of the model, $a_{t|t-1}$, F_t and ω_t can be obtained by running Kalman filter recursively. Moreover, kalman filter delivers optimal filtered and smoothed estimates of the unobserved components of the model. We initialize the filter using the unconditional mean and unconditional covariance matrix of the state vector.

MLE estimates of the model parameters are given by

$$\{\hat{\rho}, \hat{p}_1, \hat{p}_{2,}\hat{p}_3, \hat{\Omega}\} = \underset{\rho, p_1, p_2, p_3, \Omega}{\mathbf{argmax}} \left\{\ln P\left(Y_{1:T}\right)\right\}$$

subject to equation 13. Finally, the estimates for λ_j's are obtained from plugging $(\hat{p}_1, \hat{p}_{2,}\hat{p}_3)$ into equation 7.

Bootstrapping and Construction of Confidence Intervals

After getting the parameter estimates, the next step is to assess the uncertanity regarding the parameter estimates by focusing on their distributions. For this, one can use asymptotic theory which states that the MLE of the parameters of the model, $\{\hat{\rho}, \hat{p}_1, \hat{p}_{2,}\hat{p}_3, \hat{\Omega}\}$, are consistent and asymptotically normal. However, here we choose to make the inference based on finite sample distribution of the model parameters by employing a bootstrap methodology. Here is some motives to take this route;

- Our time series data have short length. Several researchers have found evidence that samples must be fairly large before asymptotic results are applicable (Dent and Min, 1978; Ansley and Newbold, 1980).

- It is also well known that problems in asymptotic inference occur if the parameters are near the boundary of the parameter space, which is a possible concern for us due to our restictrions on the parameter space.

- Moreover, it is hard to obtain asymptotic distributions of λ_j's based on the asymptotic distribution of the underlying parameters as they are nonlinear transformation of the estimated parameters. Bootstrap procedure provides a simple way of obtaining finite sample distributions λ_j and their cumulative values.

Let $\hat{\Theta} := [\hat{\rho}, \hat{p}_1, \hat{p}_{2,}\hat{p}_3, \hat{\Omega}]$ be MLE from above model. Given $\hat{\Theta}$, the steps for obtaining finite sample distribution of $\hat{\lambda}_j$, $j = 0, 1, ..., N$ as follows

1. By using $\hat{\Theta}$ and the model, construct the implied innovations (prediction errors), $\{\hat{\omega_1}, \hat{\omega_2}, ..., \hat{\omega}_T\}$. This can be done by running Kalman filter.

2. Sample, with replacement, T times from the set $\{\hat{\omega_1}, \hat{\omega_2}, ..., \hat{\omega}_T\}$ to obtain $\{\omega_1^*, \omega_2^*, ..., \omega_T^*\}$, a bootstrap sample of innovations.

3. Construct a bootstrap data set, $\{y_1^*, y_2^*, ..., y_T^*\}$ from the model equations (equation 34 and 35) by using $\hat{\Theta}$ and $\{\omega_1^*, \omega_2^*, ..., \omega_T^*\}$[9].

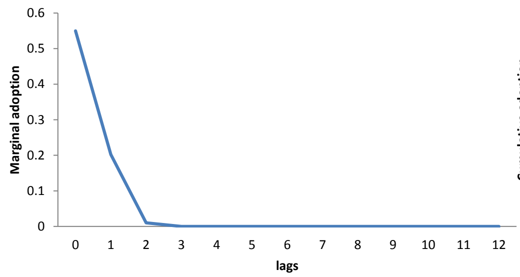
4. Using the bootstrap data set $\{y_1^*, y_2^*, ..., y_T^*\}$, construct the log-likelihood, $\ln P\left(Y_{1:T}^*\right)$, and obtain the MLE of Θ say, $\hat{\Theta}^*$. Then, by using equation **??**, obtain the corresponding $\hat{\lambda}_j^*$ for $\forall j$.

5. Repeat steps 2 through 4, a large number, B, of times, obtaining a bootstrapped set of parameter estimates $\{\hat{\lambda}_{j,b}^* \; ; b = 1, ..., B\}$. The finite sample distribution of our original MLE estimates $\hat{\lambda}_j$ may be approximated by the distribution of $\hat{\lambda}_{j,b}^*$, for $b = 1, ..., B$.

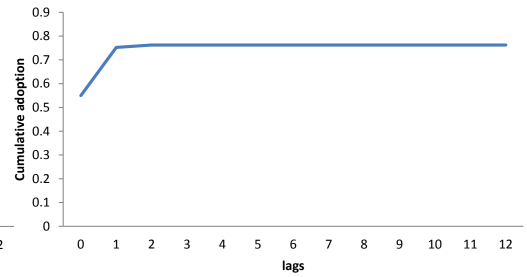
After obtaining the sequence of $\hat{\lambda}_{j,b}^*$, $b = 1, ..., B$, which constitutes the sampling distribution of $\lambda_j' s$, we construct a 90% confidence interval, based on 5% and 95% percentiles of the bootstrap sequence.

[9]The state-space representation given by (34) and (35) does not depend on prediction error, ω_t, directly. The actual practice is to construct the bootstrap data set based on what is called "one-shock representation" of the state-space model in which prediction error appears directly.

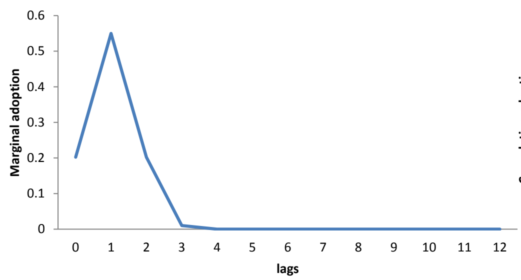
C Figures



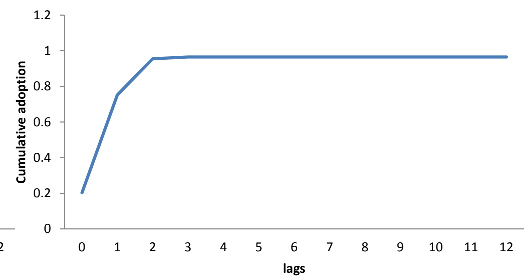
(a) $(p_1, p_2, p_3) = (0.55, 0, 1)$: λ_j



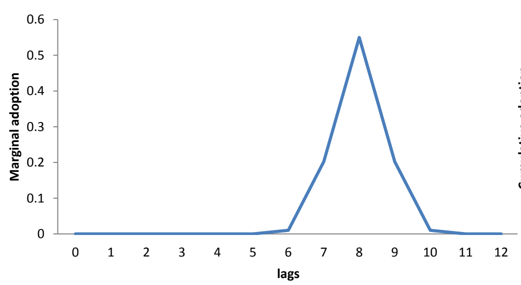
(b) Cumulative $(\sum_{\tau=0}^{j} \lambda_\tau)$



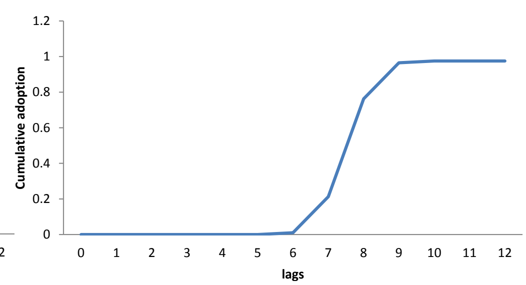
(c) $(p_1, p_2, p_3) = (0.55, 1, 1)$: λ_j



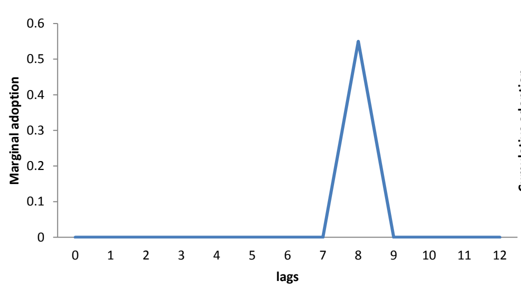
(d) Cumulative $(\sum_{\tau=0}^{j} \lambda_\tau)$



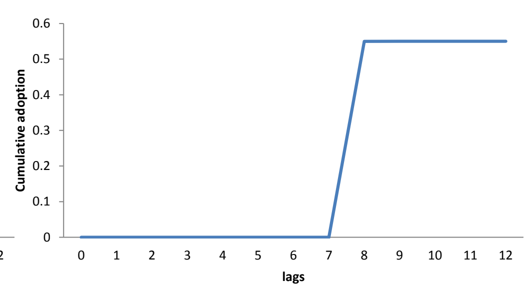
(e) $(p_1, p_2, p_3) = (0.55, 8, 1)$: λ_j



(f) Cumulative $(\sum_{\tau=0}^{j} \lambda_\tau)$

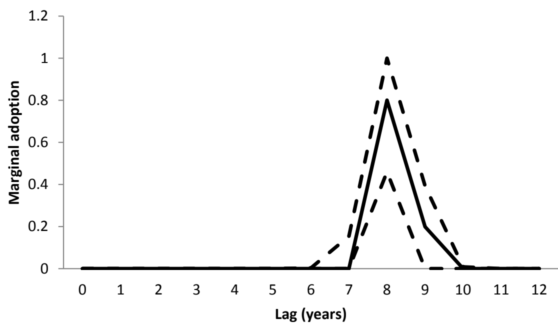


(g) $(p_1, p_2, p_3) = (0.55, 8, 0.1)$: λ_j

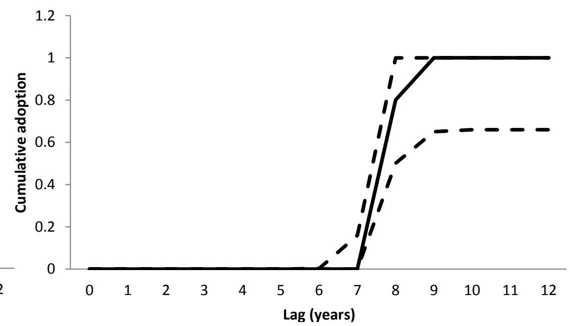


(h) Cumulative $(\sum_{\tau=0}^{j} \lambda_\tau)$

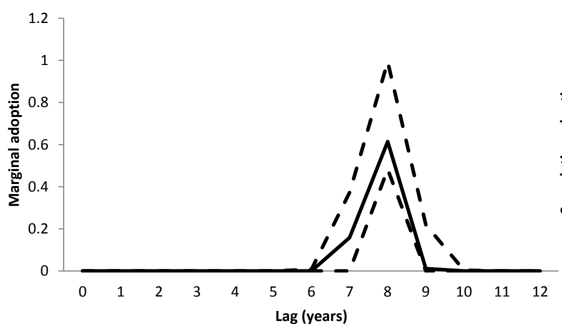
Figure 13: The distribution of adoption lags for different values of p_1, p_2, and p_3, given the discrete Normal distribution (equation 7). The left panels illustrate the implied marginal adoption rates, and right panels illustrate the corresponding implied cumulative adoption rates.



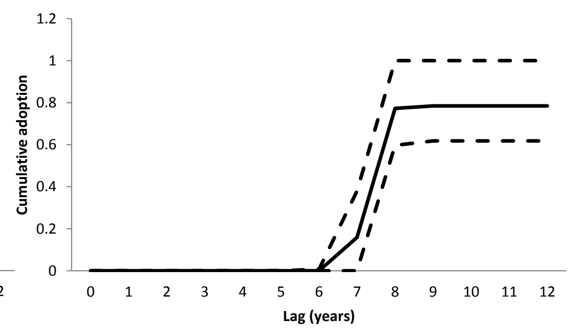
(a) Marginal adoption rates: SR



(b) Cumulative adoption: SR

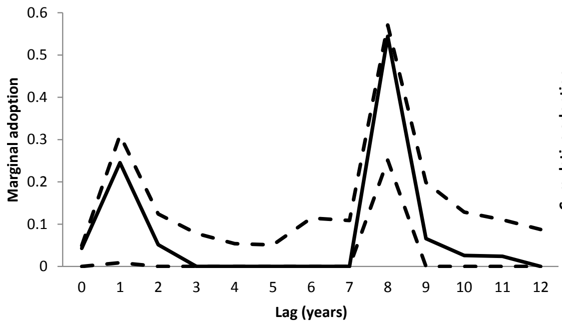


(c) Marginal adoption rates: GDP

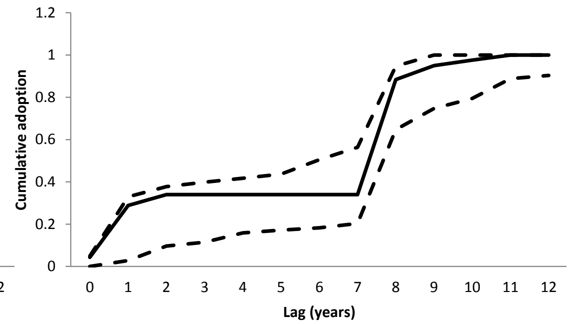


(d) Cumulative adoption: GDP

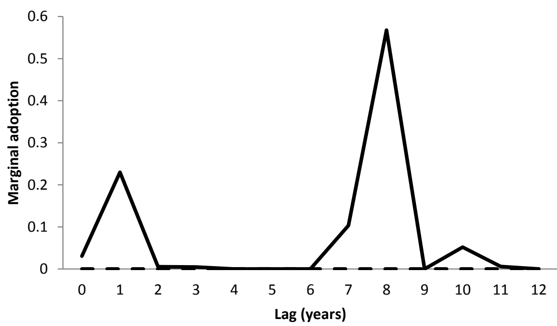
Figure 14: Estimated marginal and cumulative adoption rates in the baseline specification. In the first row, measured TFP growth is constructed as the growth of the Solow residual (without consideration of human capital). In the second row, measured TFP growth is constructed simply as GDP growth. The "frontier country" is the US, and the "adopting country" is a GDP-weighted average of LAC countries. Dotted lines represent the bounds of the 90% confidence intervals.



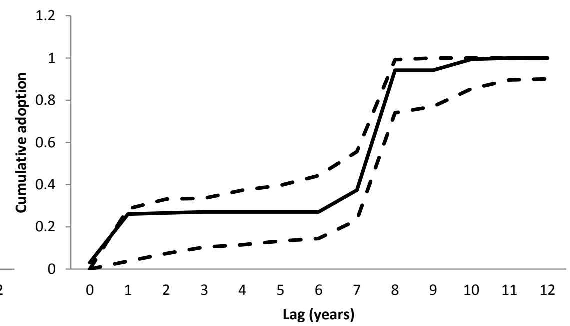
(a) Marginal adoption rates: SR



(b) Cumulative adoption: SR

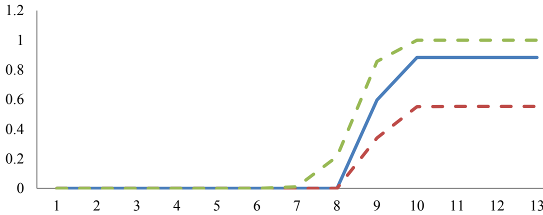


(c) Marginal adoption rates: GDP

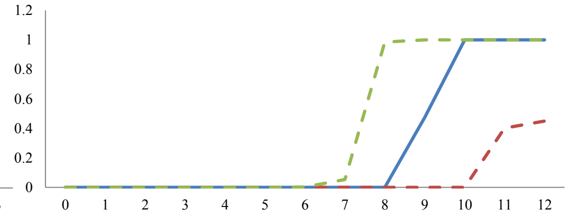


(d) Cumulative adoption: GDP

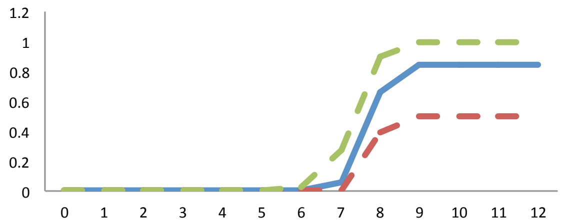
Figure 15: Estimated marginal and cumulative adoption rates, without imposing a discrete Normal distribution on the marginal adoption rates. In the first row, measured TFP growth is constructed as the growth of the Solow residual (without consideration of human capital). In the second row, measured TFP growth is constructed simply as GDP growth. The "frontier country" is the US, and the "adopting country" is a GDP-weighted average of LAC countries. Dotted lines represent the bounds of the 90% confidence intervals.



(a) Cumulative adoption: Unfiltered



(b) Cumulative adoption: HP Filter Trend

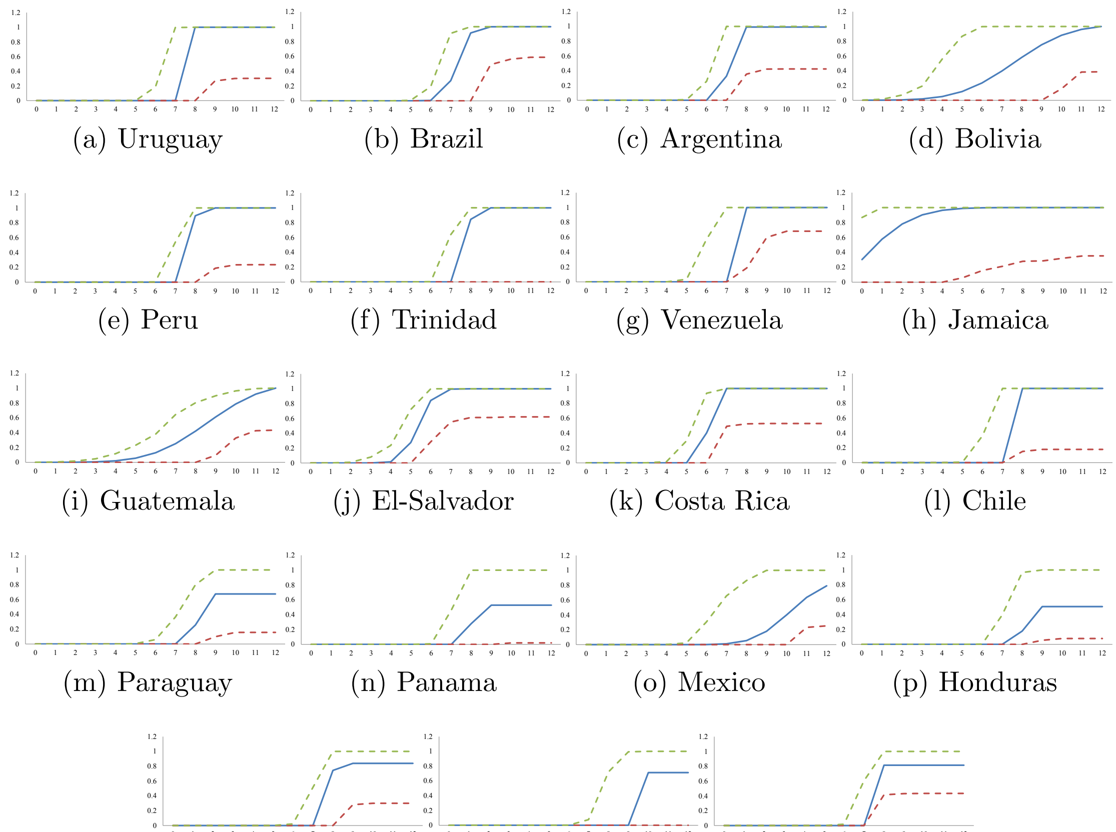


(c) Cumulative adoption: HP Filter Cycle

Figure 16: Estimated cumulative adoption rates, using three alternative identifying assumptions: the independence of $z_{us,t}$ and $z_{lac,t}$ at an annual frequency, unfiltered (panel (a)), HP filtered - trend (panel (b)) and HP-filtered - cycle (panel (c)). Measured TFP growth is constructed as the growth of the Solow residual (with consideration of human capital). The "frontier country" is the US, and the "adopting country" is a GDP-weighted average of LAC countries. Dotted lines represent the bounds of the 90% confidence intervals.

Table 3: Average adoption lags (by technology)

Technology name	**U.S.**	**Latin America**	**All countries**
Aviation freight	24.39	32.62	43.48
Aviation passengers	26.16	28.94	33.89
Cars	14.23	37.67	43.68
Cellphones	9.80	16.78	14.61
Electricity	19.40	51.67	56.36
Internet	4.40	8.68	7.79
MRI	2.92	.	5.30
PCs	7.66	15.53	13.96
Ships	29.71	111.07	120.45
Telegraph	31.85	53.27	45.61
Telephone	-0.31	40.35	51.45
Trucks	18.34	29.81	39.13
Blast oxygen steel	8.83	17.09	16.31
Railway freight	43.93	85.23	79.59
Railway passengers	55.81	98.36	97.32
TOTAL	19.81	42.08	45.48



(a) Uruguay (b) Brazil (c) Argentina (d) Bolivia

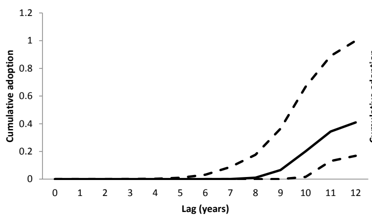
(e) Peru (f) Trinidad (g) Venezuela (h) Jamaica

(i) Guatemala (j) El-Salvador (k) Costa Rica (l) Chile

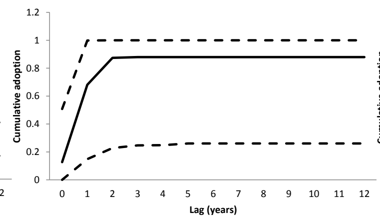
(m) Paraguay (n) Panama (o) Mexico (p) Honduras

(q) Ecuador (r) Dominican Republic (s) Colombia

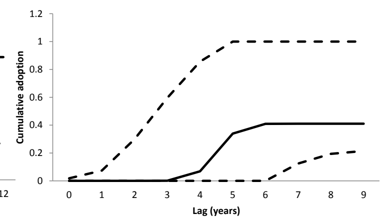
Figure 17: Estimated cumulative adoption rates, using the baseline specification in a multi-country setting. Measured TFP growth is constructed as the growth of the Solow residual (with consideration of human capital). Dotted lines represent the bounds of the 90% confidence intervals.



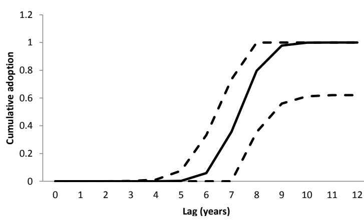
(a) Agriculture



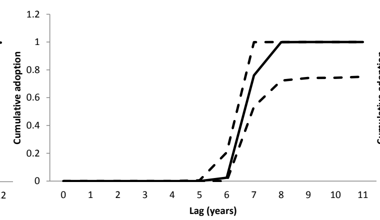
(b) Mining



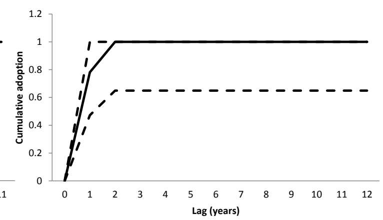
(c) Construction



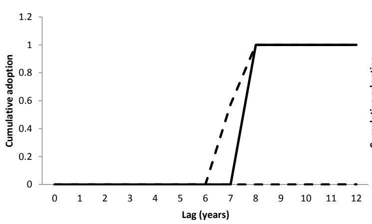
(d) Manufacturing



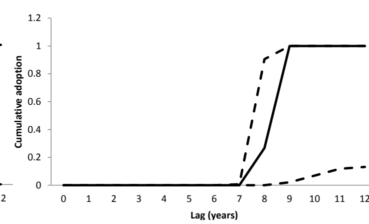
(e) Wholesale and retail, hotels and restaurants



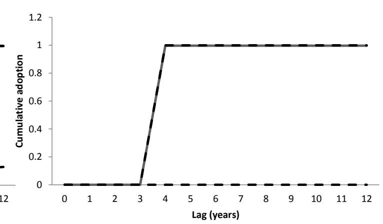
(f) Transport, storage, and communication



(g) Finance, insurance and real estate



(h) Public utilities



(i) Community, social and personal services

FIGURE 18: ESTIMATED CUMULATIVE ADOPTION RATES, USING THE BASELINE SPECIFICATION, BY INDUSTRY. MEASURED PRODUCTIVITY GROWTH IS CONSTRUCTED AS THE GROWTH OF THE REAL VALUE ADDED PER WORKER. DOTTED LINES REPRESENT THE BOUNDS OF THE 90% CONFIDENCE INTERVALS.