Technology Diffusion and Postwar Growth

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Abstract

In the aftermath of World War II, the world's economies exhibited very different rates of economic recovery. These differences are mainly due to varying paths of total factor productivity growth rather than to Neoclassical convergence. We estimate that two thirds of the residual variation in postwar economic recoveries not driven by convergence can be attributed to differences in the technology adoption patterns across countries. This estimate is obtained by combining the implications of a theoretical model on technology adoption and growth with an instrumental variables analysis to estimate the causal effect of technology adoption on economic growth. The instrument we use is the extent of postwar U.S. technical assistance received by a country.

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Wars, and especially the Second World War (WWII), are extremely disruptive episodes that lead to a major destruction of productive resources. Glick and Taylor (2010) estimate that the total number of deaths in WWII is approximately 2 percent of the 1940 world population, while the wounded made up another 3 percent. Wolff (1991) reports that the war led to a destruction or dismantling of about a quarter of the capital stock in Germany and Japan. The arguably largely exogenous nature[1] of these disruptions has made wars, and particularly the recoveries that follow them, episodes that are often studied to understand the transitional dynamics that drive economic growth.

What is especially puzzling about postwar recoveries is that countries have recovered at very different speeds after wars. For example, it took Spain 15 years to reach the pre-Civil-War level of per capita GDP. Conversely, Italy reached its pre-WWII GDP level just 6 years after the end of the war. One might be tempted to think that these different speeds of recovery are simply due to the different extent of war damage across countries. However, this turns out to be an oversimplified view of the dynamics that have driven postwar growth.

A common thread that emerged from the many studies of the postwar performance of Germany, Japan, and their industrialized counterparts,[2] is that the standard Neoclassical growth model implies a much higher postwar convergence rate than observed during postwar growth recovery of these countries, especially that of Japan.

Furthermore, many countries grew at a substantially higher rate than their steady state growth rates for several decades after WWII and did not converge to their prewar growth trajectory. Instead, they converged to a growth path substantially higher than the one they were on before the war.

In our view, these failures of the Neoclassical growth model to account for the postwar economic growth experiences suggest the importance of the path of technological progress.

[1] Some evidence, for example Hess and Orphanides (1995) and Miguel, Satyanath, and Sergenti (2004), suggests that the timing of wars might not be completely exogenous.

[2] Van Ark and Pilat (2003) provide a detailed analysis of the performance of the manufacturing sectors. Cette, Kocoglu, and Mairesse (2009) study labor productivity and TFP measures for Japan, France, the U.K., and U.S.. Hayashi (1986, 1989), Christiano (1989), and Chen, Imrohoğlu, and Imrohoğlu (2006), focus on Japan in particular.

Eaton and Kortum (1997) emphasize the importance of endogenous technology adoption for matching the postwar productivity growth experiences of the manufacturing sectors in the world's five leading industrialized economies. Gilchrist and Williams (2004) argue that endogenous productivity growth due to the putty-clay nature of capital does a better job of matching the postwar growth experience of these economies than the standard putty-putty neoclassical growth model. Chen, Imrohoğlu, and Imrohoğlu (2006), claim that in the case of Japan neoclassical transitional dynamics do just fine when one feeds the observed path of total factor productivity (TFP) growth into the standard growth model. However, they do not aim to explain how this TFP-path came about.

Hence, just like cross-country differences in TFP *levels* account for the bulk of the enormous disparities in GDP per capita *levels*,[3] cross-country differences in TFP *dynamics* drive a large part of the differences in postwar growth experiences. It is thus not only important, as Prescott (1996) advocates, to have a theory of differences in TFP levels but it is also important to understand the sources of differences in the dynamics of TFP.

In this paper we study the extent to which these differences in TFP dynamics across countries can be accounted for by observed differences in technology adoption patterns. In particular, we explore the idea that wars, in addition to destroying capital, impact the costs of adopting new technologies. This may occur for a variety of reasons. Our main focus here is on the reduction in adoption costs due to the postwar technical assistance provided by the United States to many different countries, especially Japan and those in Western Europe.

We argue that the technical assistance can be interpreted as an exogenous source of cross-country variation in the reduction of adoption costs. Therefore, we can use it to quantify the effect of technology adoption on TFP. We first explore this in the context of a standard instrumental variables (IV) framework. We find that technical assistance seems to have led to a significant reduction in the technology gap between the United States and the recipients of this assistance after WWII. This effect is robust to controlling for postwar GDP growth.

[3] See Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999).

It is natural to control for GDP growth in the first stage because increases in aggregate demand should lead to higher intensities of use of our technology measures. Of course, this is not possible in an IV setting because per capita GDP growth is the dependent variable in the second stage regression.

Non-structural approaches face, at least, another difficulty in our context. They have a hard time dealing with the non-linear dynamics of our technology measures. Consequently, failing to recognize these nonlinearities in our econometric analysis may bias our estimates.

To overcome these problems, we introduce a model, based on that used in Comin and Hobijn (2010), of endogenous TFP through technology adoption. Our model enables us to pursue a two-tiered analysis.

First, at a disaggregated level, the model provides a framework to think about the paths of observed measures of technology usage and has very specific implications for the reverse causality from GDP growth to technology adoption. We use the implications of the model for these measures to filter out the effect of GDP growth on technology adoption and to estimate the average time between the invention and adoption of a technology, what we call the adoption lag, for 10 technologies and 39 countries. We then use the exogenous changes in these adoption lags induced by the U.S.' postwar technical assistance to estimate the causal effect of technology adoption on GDP.

These structural estimates, in combination with the evidence on U.S. technical assistance, thus allow us to assess to what extent cross-country variations in the changes in the speed of technology adoption are the source of the remarkable differences in postwar growth experiences across countries. This link between estimates of technology adoption and their aggregate implications is the main distinguishing feature of our analysis compared to previous empirical studies of technology adoption and diffusion.[4]

Furthermore, our model can be used to explore the role of technology adoption dynamics

[4]Many of these studies, like Grilliches (1957), Caselli and Coleman (2001), focus only on one particular technology. Others, like Mansfield (1961), Gort and Klepper (1982), and Comin and Hobijn (2004) cover several technologies but do not aim to quantify the aggregate implications of their findings.

for productivity growth both in steady state and, especially, along the transition path.[5] We illustrate the importance of these dynamics with an example that investigates the Japanese postwar growth experience. A reduction in the capital stock in our model leads to similar aggregate dynamics to the one-sector neoclassical growth model. However, a reduction in the adoption costs leads to a pattern of technology adoption that generates a protracted transition to a new steady state with higher productivity. The expectation of higher productivity generates a wealth effect that, in the early part of the transition, leads to a reduction in the saving rate. This induces a U-shaped response in the capital to output ratio that is consistent with the evidence in Japan after WWII.

In addition to the hypothesis and the methodology, our final main contribution in this paper is that we use a new source of data for the study of postwar growth dynamics. We use data on direct measures of technology adoption from the CHAT dataset, described in Comin and Hobijn (2009b). These data cover major technologies related to transportation, communication, as well as electricity. We complement these data with data on population, real GDP and consumption per capita from Maddison (2007) and Barro and Ursúa (2008). This allows us to consider a sample of 39 countries with varying degree of involvement in WWII. This sample is significantly larger than most studies.

Our main findings are as follows. We observe that the technology assistance programs are strongly associated with the adoption of new technologies during the postwar period. In particular, the average country that benefitted from the program reduced the lags with which it adopted the new technologies in our sample by 5 years. For old technologies, instead, we find that, if anything, the assistance programs led to an increase in the adoption lags after WWII. The differential effect of the technology assistance programs on new vs. old technologies persists after including as controls GDP growth or country fixed effects. This finding reinforces our prior that the mechanism by which technology assistance reduces adoption lags is through a reduction in the costs of adopting technologies rather than through an overall

[5] In this respect, our analysis is related to, among others, Basu and Weil (1998), Gilchrist and Williams (2000), Jones, Manuelli, and Siu (2004), Comin and Gertler (2006), and Comin and Hobijn (2007).

improvement in the efficiency of institutions since the increases in efficiency associated with the latter would have a more symmetric effect across technologies. Furthermore, the effect of technology assistance on adoption lags is robust to controlling for measures of institutions, such as polity (or its postwar change), as well as policies, such as openness to trade.

Finally, we find that the reduction in the lags with which countries adopted new technologies has a significant effect on postwar growth when instrumenting the reduction in adoption lags with the total expense in the technology assistance program in the country. This effect is strong. The average country that received assistance experienced an increase in its annual growth rate in per capita income of 1.1 percentage points between 1950 and 1970. This represents approximately two thirds of the differential in postwar growth between the countries that received technological assistance and those that did not.

The structure of the paper is as follows. In Section 1 we document the main facts about the damage incurred by countries during WWII and the differences in their subsequent growth experiences. We augment the evidence on commonly studied statistics, like population and real GDP per capita, with evidence on the impact of the war on technology usage and the subsequent recovery in the technology-specific measures for different countries. We also discuss the U.S. technical assistance to Japan and Western Europe. In Section 2 we provide an exploratory reduced form analysis to illustrate how the technical assistance programs can be used to quantify the effect of technology adoption on growth. In Section 3 we introduce the model, solve for the optimal decisions of firms and households, and define equilibrium. We present the example that shows how the model's transitional dynamics closely resemble the postwar growth experience of Japan in Section 4. In the next section we explain how the implications of the model map into predictions for the path of observable measures of technology adoption and use this mapping to derive reduced form equations that can be used to estimate adoption lags. We discuss the resulting estimates of the adoption lags and their implications in Section 6. We conclude with Section 7 and leave the details of the derivations behind the data and the equations in the main text for Appendix A.

1 WWII damage and subsequent growth

A wide range of studies have documented the very strong growth experienced by many industrialized countries during the three decades that followed WWII.[6] In this section we give a brief review of economic growth in industrialized countries during these decades. Since our emphasis is on technology adoption, we augment the GDP-based analysis, which is very similar to that in other studies, with facts about the use of technologies. We first discuss the damage done during the war and then proceed by documenting postwar growth.

Figure 1 depicts the decline in real GDP per capita and technology usage per capita for three technologies. Since we focus on per capita measures we implicitly correct for war deaths. Glick and Taylor (2010) tabulate estimated casualties for many countries. Their estimates suggest that the total number of deaths in WWII is approximately 2 percent of the 1940 world population, while the wounded made up another 3 percent.

Panel (a) of Figure 1 shows pre- and postwar levels of log real GDP per capita for the countries in our sample. The horizontal axis is the 1938 log real GDP per capita level, in deviation from that in 1946 in the U.S., while the vertical axis show the minimum of the 1945 and 1946 levels of log real GDP per capita.[7] The dashed line is the 45-degree line.

Points below the 45-degree line depict countries that saw a GDP decline during the war. The vertical distance between the point and the 45-degree line approximately equals the percentage decline in real GDP per capita during the war. Germany, Japan, Austria, The Netherlands, Greece, as well as Indonesia, the Phillipines, and Taiwan all saw real GDP per capita declines in excess of 40 percent during WWII. To put this in a historical perspective, the decline in U.S. real GDP per capita during the Great Depression was approximately 30 percent. The U.S. and Canada geared up their industrial complexes to produce military supplies during the war period and actually saw substantial increases in real GDP per capita

[6] Among the many studies that touch upon this topic are Abramovitz (1986), Baumol (1986), De Long (1988), Wolff (1991), van Ark and Pilat (1993).

[7] We take the minimum of 1945 and 1946 because WWII ended at different times during 1945 in different countries. Hence, the 1945 data thus partially reflect economic activity during the war rather than right after it ended.

during WWII.

These declines in real GDP in war-ravaged countries coincided with substantial declines in the usage of many technologies. In terms of aggregate capital stock measures, Wolff (1991) reports that WWII led to a destruction or dismantling of about a quarter of the capital stock in Germany and Japan. Panels (b) through (d) of Figure 1 are the equivalent of panel (a) but then for three technology usage measures rather than for real GDP. The particular three technologies depicted are cars, electricity, and steam- and motorships, respectively.

The qualitative patterns in terms of declines in technology usage are very similar to those in real GDP. Countries that saw active combat on their soil during the war also saw very substantial declines in their technology usage. In fact, the merchant fleets of many countries were almost fully destroyed. Similarly, declines in cars per capita were much higher than those in real GDP per capita. Declines in electricity production, however, were less pronounced than those in overall economic activity.

The substantial declines in GDP and technology usage in war-ravaged countries was followed by a remarkable post-WWII rebound. This can be seen from Figure 2. It shows the path of log real GDP and technology usage per capita for three technologies for four countries in our sample. The countries that we have chosen for illustrative purposes are the United States, Germany, Japan, and Argentina. We follow De Long (1988) and De Long and Eichengreen (1990) here and include Argentina as an example of a country that, in spite of being relatively rich at the onset of the war and almost unscathed by WWII, did not see the type of catch-up with the United States in the postwar period that many other industrialized economies saw.

In terms of the paths of real GDP per capita (panel (a)), four things stand out from this figure. First, after all the turbulence of the Great Depression and WWII the U.S. ended up on approximately the same growth path it was on before 1929. Secondly, Argentina starts to steadily fall behind the U.S. after WWII. Argentinian per capita GDP was 84 percent of that of the U.S. in 1938 and declined to 24 percent in the 1970's. The final two things to

take away from panel (a) are the most important for the rest of the analysis in this paper.

The first is that it took Germany and Japan until between 1955 and 1960 to return back to their prewar growth paths. The second is that, contrary to the U.S., both Germany and Japan did not converge to this prewar path but instead busted through it and converged to a growth path that was substantially higher than that in the prewar period.

Just like for the declines during WWII, the postwar experiences in terms of technology usage exhibit very similar qualitative patterns as those of real GDP per capita. The U.S. saw a relatively smooth path of technology usage for all of these technologies. Contrary to the path of log real GDP, however, these technology usage paths are inherently non-linear. Argentina, while comparable in terms of technology usage at the beginning of the century, ends up trailing the other three countries by the end of it.

After the substantial declines in technology usage due to WWII we documented in Figure 1, Germany and Japan returned back to their prewar technology usage paths about as fast or even slightly faster than they returned to their aggregate growth path. Moreover, just like for real GDP per capita, they did not converge back to this path but instead moved up to higher levels of technology usage. Of course, because of the non-linear nature of the technology usage path a more formal quantitative analysis of this claim requires taking a stance on the shape of this path, which is the reason that we introduce a theoretical model in Section 3.

Germany and Japan are by no means the only two countries that, after the war, converged to a higher growth path than they were on before. Many Western European countries experienced this period of "supergrowth." As Dumke (1990) points out, the initial hypothesis was that most of the postwar experiences of these countries could be interpreted as driven by standard capital (re-) accumulation after the destruction during the war. This is often referred to as the "Reconstruction Hypothesis" and is inspired by the standard neoclassical growth model with exogenous technological progress.

As better historical cross-country real GDP data became available in the 1980's, empirical

studies (Abramovitz, 1986, Baumol, 1986) emphasized that the Reconstruction Hypothesis might be able to explain the return of these countries to their postwar growth paths but it fails to explain the upward shifts in these paths. In order to understand these shifts, one has to understand the determinants of the productivity growth differentials that caused them. The observation that it is productivity growth differentials and not capital accumulation that accounts for most of the variation in postwar growth experiences across industrialized countries is known as the "Productivity Hypothesis."

There are, of course, many potential drivers of the productivity growth differentials across countries. Our focus in this paper is on disparities in technology adoption patterns across countries as a potential *cause* of productivity growth. Technology adoption decisions are endogenous to many factors. Some factors, such as improvements in the capacity and quality of institutions, may lead to direct increases in the overall efficiency of the economy which may be amplified by an acceleration in the adoption of technologies.[8] Other factors, such as adoption history,[9] or the international transfer of kow-how about new technologies, may have small or negligible direct effects on productivity growth but may have an important indirect effect through the reduction of adoption costs and the associated reduction in adoption lags. In our attempt to establish a causal link between technology adoption and growth we will try to exploit variation in the former driven, exclusively, by exogenous changes in adoption costs.

A related difficulty when estimating the effect of technology adoption on growth is reverse causation. As is abundantly clear from Figure 2, there is a lot of comovement between technology usage and real GDP growth. The high correlations that this comovement implies does not, in any way, establish a causation from technology usage to GDP growth. In fact, there is a an extensive debate about the reverse causation, i.e. how the size of the market affects the incentives to innovate and adopt technologies.[10]

[8] E.g. Acemoglu, Johnson and robinson (2001).
[9] See Comin, Easterly and Gong (2010).
[10] See stylized fact 1 in Jones and Romer (2010) for a brief review of this discussion.

To quantify the importance of technology adoption for GDP growth, one needs to identify factors that do not affect GDP or the efficiency of the economy directly but only through their effect on technology adoption. Such factors are hard to come by. However, it turns out that a particular part of the Marshall Plan, as well as specific aid by the U.S. to Japan, was targetted at providing countries with assistance to spur the adoption of U.S. production and management techniques. As we argue in the subsection below, it is this Technical Assistance Program that can be interpreted as a largely exogenous factor that impacted productivity growth solely through its effect on technology adoption.

1.1 Technical assistance and the Marshall Plan

Following World War II, how did the U.S. go about providing technical assistance to Western Europe and Japan?

The Marshall Plan, otherwise known as the European Recovery Program, was unveiled to the world in the summer of 1947 by U.S. Secretary of State George Marshall. As Eichengreen and Uzan (1990) describe, initially the aim of the program was to provide direct economic relief to Western Europe in the form of capital transfers as well as financing for investment and import purposes. While this initial effort was effective at alleviating the oppressive economic conditions in both the European commodities and capital markets, Boel (2003) argues that it failed to address the mounting productivity gap that had formed between the U.S. and Europe during WWII.

According to Boel (2003), Western Europe was experiencing "worsening trade and payment deficit[s]" which stemmed from the considerable productivity gap and its inability to compete economically. Due to these conditions, the U.S. expanded and focused the Marshall Plan by instituting the Technical Assistance and Productivity Programme in 1949 (Bjarnar and Kipping, 1998). The main thrust of the Technical Assistance Program (TAP) was to increase productivity in Western Europe. The conventional wisdom surrounding the productivity gap was that Europe had technologically fallen behind the U.S. To address these

concerns, the U.S. used the TAP as a conduit through which to disseminate state-of-the-art technologies, technical knowledge, and managerial sciences.

The channels through which the technological transfer occurred inherently revolved around the lending of U.S. specialists to Europe and the allowance of their European counterparts to visit and observe processes in the U.S. Additionally, U.S. government agencies played an important role in transferring technological advances. The BLS, for example, contributed by providing statistical technical assistance which involved the exchange of specialists but also was focused on introducing a data and statistics-rich approach to productive efficiency in Western Europe (Wasser & Dolfman, 2005).

Europe was not the sole beneficiary of these productivity and technology exchanges. Tiratsoo (2000) documents how the U.S. in 1955 initiated its technical assistance program to Japan. Like the TAP in Western Europe, the Japanese assistance plan focused on increasing technological and productive know-how.

Anecdotal evidence provided in several studies reveals the very significant impact these technical assistance programs had on the productivity of individual companies and industries as a whole.

For example, Tiratsoo (2000) recounts that after the Mitsubishi Company received technical assistance from the US in building a new assembly plant it was able to increase productive capacity by roughly 40%. The *International Directory of Company Histories* (Saint James Press, 2001) describes how, in 1950, two leading executives of Toyota Motor Company,

> "... seeking new ideas for Toyota's anticipated growth, ... toured Ford Motor Company's factories and observed the latest automobile production technology. One especially useful idea they brought home from their visit to Ford resulted in Toyota's suggestion system, in which every employee was encouraged to make suggestions for improvements of any kind."

Similar stories emerged about the U.S. technical assistance in Europe. Wasser and Dolfman (2005) cite one source as saying productivity within individual industries "commonly

increased by 25 to 50 percent within a year with little or no investment" due to the TAP.

It is important to highlight that the productivity increases stemming from the TAP were generally considered to be "low cost". As Boel (2003) describes "technical assistance was indeed a "low-overhead item," in that it involved the transfer of know-how, ideas, attitudes, with low cost but a strong impact." Thus the TAP was not about stimulating productivity gains through capital spending as much as it was focused on the dissemination of technological and productive know-how. Unlike the rest of the Marshall Plan, the TAP was diminutive in scale. From 1948-1957 it is estimated that only $136 million was directly spent on TAP related projects and only about $12 million spent in Japan from 1955-1962.

Due to the comparatively small sums of funds allocated to the TAP it is easy to dismiss it as too small of a channel through which to stimulate growth in both Europe and Japan. However, Wasser and Dolfman (2005) cite one source as saying:

> "Reliable data indicate that through March 1957, nearly 19,000 European technicians, specialists, and leaders of industry, labor, and government had visited the United States. Nearly, 15,000 U.S. specialists had served abroad in the direct implementation of the national programs. Extensive technical services were provided including over 35,000 technical and scientific books, periodicals, and other literature; over 2,500 replies by mail to technical inquires, over 3,000 digests of articles from U.S. technical and trade magazines; some 48 Bureau of Labor Statistics' factory performance reports."

In Japan, the scope of the assistance program was much smaller but still considerable. According to Tiratsoo (2000), approximately 3,568 Japanese specialists visited the US while 100 Americans were sent to Japan.

In many ways, the technical assistance programs to both Western Europe and Japan were not about spending money but about transferring technical know-how. To this end, the U.S. TAPs can be interpreted as a relatively exogenous policy effort that helped to close the technology and productivity gaps in Western Europe and Japan.

1.2 Two measures of technical assistance

The mainly anecdotal evidence on U.S. technical assistance to other industrialized countries during the 1950's and onwards is suggestive of this assistance having played an important role in the postwar productivity catch-up of the countries that received this assistance. It is of little help, however, to a formal quantitative cross-country analysis of the effects of the program and the importance of technology adoption for productivity growth. Such an analysis requires more detailed statistics on the amount of money spent on and the number of people participating in the program.

We construct two such measures. They are reported in Table 2. The first consists of the money spent by the U.S. on the technical assistance program as part of the Marshall Plan and to support the Japanese Productivity Center. The second consists of a measure of the average number of industrial trainees per year from each country that visited the U.S. from 1949 through 1969. This is derived from immigration statistics reported by the U.S. Immigration and Naturalization Service (1949-1969).[11]

To get a sense of how these two variables relate to the postwar growth experiences of the countries in our sample, consider Figure 3. The top panel of the figure depicts average per capita GDP levels relative to the U.S. during 1950 versus 1970. The further a country is above the 45-degree line the faster it caught up with the U.S. during the three decades following the war. Black dots in the figure denote countries that received TAP funds and the size of the dots reflects the number of industrial trainees from Table 2. As can be seen from the picture, countries that received technical assistance as well as those that sent the most industrial trainees to the U.S. seem to have caught up faster than their counterparts. The United Kingdom is an exception. While Canada has a disproportionate number of industrial trainees, presumably because of its proximity to the U.S.

Productivity is most often measured in terms of output per hour, not output per person. The bottom panel of Figure 3 shows the equivalent of the top panel, but then for GDP per

[11] The particular way in which we derived them is described in appendix A.

hour, as reported by The Conference Board (2010). Because of slower growth of the labor supply in Europe and Japan than in the U.S., the catch up is more profound in terms of GDP per hour than GDP per capita. Moreover, the countries that received technical assistance funds as well as sent more industrial trainees to the U.S. seem to stand out more in this respect than in terms of GDP per capita.

Of course, Figure 3 is at best indicative of the potential effect of the technical assistance program on productivity growth in countries. In the next section we investigate this using more formal statistical techniques.

2 Reduced-form instrumental variable analysis

Because the main aim of the TAPs was to stimulate the adoption of technologies, the assistance received as part of these programs is a natural candidate for being used as an instrument in the analysis of the effect of technology adoption on GDP growth. There were very few, if any, conditions for receiving technical assistance. The main determinant was that a country was affected by the war. Whether or not a country was a recipient was arguably unrelated to changes in institutions. Both non-democratic and democratic countries received it.

Because of this, we interpret the technical assistance as an exogenous reduction in the cost of adopting technologies. This reduction led to an acceleration in the adoption of new technologies and an increase in the number of units of capital that embody the technology as well as the amount of output produced with them. Since these new technologies embody a higher level of productivity, productivity grew faster resulting in an acceleration in aggregate growth.

In this section, we present the results of a reduced form instrumental variables analysis. This analysis consists of three steps. In the first step, we show the statistical equivalent of Figure 3 to explore the correlation between technical assistance and postwar growth.

This provides us with the best possible fit we can get out of our instrumental variable analysis. In the second step, we provide evidence that technical assistance did lead to the accellerated adoption of new technologies but had much less of an effect on the adoption of older technologies. In principle, the final step would be a second-stage regression of GDP on the estimated effect of the TAP on the technology usage measures. This regression would allow for the identification of the causal effect of technology adoption on GDP. However, this final step is hard to interpret in the context of the reduced form equations used here. Instead, the final step in this section consists of an explanation of the gains that can be made here using a structural model, which is what we introduce next.

2.1 Catch-up and technical assistance

Just like Acemoglu, Johnson, and Robinson (2001), we start our empirical analysis by presenting a reduced form estimate, in this case of the relationship between technical assistance and postwar catch-up. The catch-up regression we run is similar to that in Baumol (1986) and many studies that followed. The results are listed in Table 3 and, in line with Figure 3, we present them for both real GDP per capita and real GDP per hour.

As can be seen from the table, technical assistance funding significantly contributes to catch up in both real GDP per capita as well as real GDP per hour. The coefficient is between 1 and 2 percent per million dollars of assistance. Of course, we do not think that technical assistance funding literally had such high returns. Instead, we interpret it as a proxy for many more different types of technical assistance efforts that originated from the U.S. during the postwar years, but for which, unfortunately, no reliable quantitative evidence is available.[12] As for the industrial trainees, though the sign of the estimated coefficient is positive, as expected, the effect is insignificant at any reasonable significance level.

Hence, our results indicate that technical assistance had a positive effect on postwar GDP growth in the industrialized countries that were its recipients. Of course, this crude cross-

[12] This is for example the case for royalties from licenses for which sparse international payments data to the U.S were first published in 1960.

country analysis suffers from the same limitations as many growth regressions. However, our hypothesis is not that technical assistance itself affects GDP growth, but instead that it affects GDP growth through its effect on technology adoption. The latter part can be studied independently from the reduced form regression here.

2.2 Technology usage and technical assistance

A regression analysis to establish the effect of the TAPs on technology usage and, implicitly, adoption can be interpreted as the first stage in a two-stage regression analysis aimed at estimating the causal effect of technology adoption on growth. Table 4 presents results in the spirit of such a reduced form first-stage analysis.

These results pertain to a set of regressions that is similar to the catch-up regressions for real GDP per capita and per hour from the previous subsection. That is, we regress the log technology usage level per capita in 1970, as listed for the technologies in our sample in Table 1, on its 1950 level as well as the TAP variables from Table 2. For some specifications we add average real GDP growth between 1950 and 1970 as an additional control. Since the technical assistance statistics our country-specific, we can not include country fixed effects. We do include technology fixed effects in all specifications as well as country random effects in some.

Part (a) of the table contains the results from a pooled regression that contains all the technologies listed in Table 1. From this part, it can be seen that the technical assistance variables seem to have a relatively robust positive and significant effect on technology usage and adoption across countries. However, as can be seen from (a).IX in the table, the p-value of the test for joint significance of the TAP effect increases to 8.1 percent when random effects are included.

It turns out that most of the significant effects of TAP on technology usage and adoption work through technologies that were relatively new after the war. The usage of these technologies was not in decline due to the availability of a dominant technology that was a close

substitute. Think of air- and car transportation, for example. Conversely, there is a number of technologies, like rail transportation, that had already matured by the end of the war. Table 1 lists our classification of the 10 technologies in our data set into 'old' and 'new'.

Part (b) of Table 4 is similar to part (a) except that the sample only contains 'new' technologies. As can be seen from comparing parts (a) and (b), the estimated level of the impact as well as the level of significance of the estimated effects of technological assistance on adoption increases when only new technologies are considered. This is consistent with the interpretation that TAP presumably was used to speed up the implementation and adoption of frontier technologies. To strengthen this point, part (c) of Table 4 is based on a sample that only includes 'old' technologies. None of the effects of TAP are significant in this part.

The results in Table 4 are thus indicative of technical assistance having led to a discernible effect on technology adoption in the recipient countries.

2.3 The need for a structural model

Though indicative, the results presented in Table 4 have many caveats, especially if the aim is to use them as first-stage regression results in an instrumental variables analysis where the second stage would involve estimating the effect of the fitted technology adoption on postwar GDP growth.

First of all, there is little or no theoretical foundation for running the type of catch-up specification that we used in Table 4 for technology usage patterns. That specification is based on deviations of real GDP growth from a balanced growth path. However, as can be seen from panels (b)-(d) in Figure 2, such a balanced growth assumption is not a good approximation to the inherently nonlinear nature of the technology usage paths.[13]

The analysis of these nonlinearities is complicated by the fact that there are two dimensions of technology usage. The first is the intensive margin, which is the equivalent of conventional capital deepening. It reflects how many units of the capital goods that embody

[13] See Comin, Hobijn, and Rovito (2008) for a more extensive discussion of these non-linearities.

the technology each worker is using. The second, and the one of most interest to us, is the intensive margin, which is determined by the actual adoption decision. It reflects which types of capital goods that embody the technology are being used. Distinguishing these two margins and their respective effects on the nonlinear path of technology usage is not possible without the guidance of a theoretical model.

Secondly, as can be seen from columns II, III, V, VI, VIII, and IX, of Table 4, real GDP growth seems to have a significant effect on technology adoption. This result is not specific to our analysis it is a recurring theme in many studies of cross-country technology usage and adoption patterns (Caselli and Coleman, 2001, and Comin and Hobijn, 2004). It is also consistent with almost any aggregate theory of technology adoption. However, if we include GDP growth in the first-stage regression, then we can not run the second stage.

It is useful to think of the identification problem here as a system of two simultaneous equations. The first equation captures how GDP growth depends on a set of covariates and technology adoption. The second how technology adoption depends on GDP growth, possibly some covariates, and technical assistance. If this is the underlying structural model then the estimated coefficient on GDP in Table 4 is inconsistent because it will reflect the effect of technology adoption on GDP in addition to the effect of aggregate demand on technology. What we would really like to do is to include all covariates from the GDP equation in the technology adoption regression. However, this is practically infeasible and almost surely will lead to omitted variable bias. It is much more sensible to use theory to guide us on the effect of GDP on technology adoption and then use it to filter it out of the observed technology usage paths.

Finally, as can be seen from Table 1, we are combining many different technology measures. Thus, the pooled regressions in Table 4 contain many different types of left-hand side variables. Each of these variables is a different mixture of the intensive and extensive margins in technology usage that we described above. Since we are most interested in the extensive, i.e. adoption, margin, we would benefit from having a consistent estimate of this

across technologies. Once the measures for these technologies are placed on equal footing, we can then aggregate them for use in further analysis.

The three main caveats of the analysis in Table 4 can all largely be resolved by the use of a structural model of technology adoption and economic growth. This is what we introduce in the next section.

3 Model with endogenous TFP and adoption lags

We present a version of the model of technology adoption and growth introduced in Comin and Hobijn (2010). The model that we present serves two main purposes. First, it allows us to illustrate how the endogenously determined path of the adoption of technologies determines the equilibrium level of aggregate total factor productivity. Thus relating the pattern of technology adoption to the path of productivity that is so crucial for understanding the postwar experiences of many industrialized economies. Second, we use the model to show how the endogenous technology adoption patterns yield curvature in the time-path of measures of technology diffusion for which we have data. It is the curvature in these diffusion measures that we use to identify adoption lags in the data.

Contrary to Comin and Hobijn (2010), the analysis in this paper focuses on the transitional dynamics of the model. This is important, because of the emphasis on the postwar recovery in our analysis, which is inherently a realization of the transitional dynamics.[14]

Though our empirical analysis involves a cross-section of different technologies, we present our theoretical model here in a one-sector framework to simplify the exposition and to allow for the study of aggregate dynamics that are comparable with available cross-country data.

[14] Christiano (1989), Chen, Imrohoğlu, and Imrohoğlu (2006), for example, emphasize the importance of transitional dynamics for understanding the behavior of the Japanese saving rate since 1945. Gilchrist and Williams (2004) do so for both Germany and Japan.

3.1 Preferences and technology

The unit measure of households in our model[15] are assumed to have log preferences such that their optimal savings decision implies that the growth rate of consumption equals the difference between the real interest rate, $\widetilde{r}$, and the discount rate ρ. What is non-standard is the technology side of our model. It is the focus of the rest of this subsection.

Capital vintages and adoption lags

Our framework is one in which, as in Parente and Prescott (1994) and Eaton and Kortum (1997), the level of total factor productivity is determined by the distance between a country's productivity level and the world technology frontier. Throughout, we take the evolution of the world technology frontier as exogenous.[16] Here we describe what, in particular, we mean by this distance. How this distance is the result of the technology adoption decisions of capital goods producers is explained later in this section.

The single good in this economy, which we use as the numeraire good such that it has a price of one, is produced using a Constant Elasticity of Substitution technology that is used to combine a continuum of intermediate goods each produced with their own specific capital vintage, v. At each instant, t, a new capital vintage is introduced, such that the set of available intermediate goods is given by $v \in \overline{V} = (-\infty, t]$.

We distinguish two groups of intermediates, indexed by τ. The first, denoted by $\tau = o$, is the set of intermediates produced using old production methods, $v < \underline{v}$. The second, denoted by $\tau = n$, consists of intermediate goods produced using production methods that involve newer, more recently invented, $v \geq \underline{v}$, capital vintages. Hence, $\tau = o$ can be interpreted as the old technology and $\tau = n$ as the new one.

[15] Throughout, we ignore population growth and just adjust for it in the calibration of our parameters.

[16] Eaton and Kortum (1997) find, in a different theoretical framework, that endogenizing the path of the frontier does not improve the ability of their model to explain the postwar manufacturing productivity paths of Germany, Japan, France, the U.K., and the U.S..

Aggregate output, Y,[17] is produced using

$$Y = \left(Y_o^{\frac{1}{\mu}} + Y_n^{\frac{1}{\mu}} \right)^{\mu}, \text{ where } \mu > 1, \tag{1}$$

and

$$Y_\tau = \left(\int_{V_\tau} Y_v^{\frac{1}{\mu}} dv \right)^{\mu} \text{ for } \tau = o, n. \tag{2}$$

The set of vintages in use is thus given by $V = V_o \cup V_n$. However, not all available intermediates are necessarily used for the production of output, such that $V \subseteq \overline{V}$.

The use of a more expansive set of intermediates affects productivity in two ways. First of all, as already can be seen from (1) and (2), the use of more intermediates leads to a gain from variety. We call this type of productivity gain the *variety effect*.

The second effect is because technological progress is embodied in new capital vintages. Similar to Solow (1960), newer capital vintages are more productive than their older counterparts. This difference in productivity levels is reflected in the technologies with which the intermediate goods are produced. Each intermediate, v, is produced by combining labor, L_v, and capital, K_v, using a Cobb-Douglas production function of the form:

$$Y_v = Z_v L_v^{1-\alpha} K_v^{\alpha}, \tag{3}$$

where Z_v is the level of productivity embodied in the units of the capital vintage v. Z_v is constant over time and is increasing in v. Let γ be the growth rate of embodied technological change, then

$$Z_v = Z_0 e^{\gamma v}, \text{ where } \gamma > 0. \tag{4}$$

Hence, the world technology frontier consists of the productivity levels of the set of all available vintages $\overline{V}$. Moreover, if the set of technologies used, V, expands to include newer vintages, then this increases the overall productivity level. We refer to this as the *embodiment*

[17] Here, and in the rest of this article, to save on notation we drop the time subscript, t, whenever its presence is self-evident.

effect of technology adoption.

If the most recent vintages are not used, then the embodied productivity level of the vintages in use falls short of that of the frontier. How much it falls short depends on the gap between the set of available and the set of used vintages.

Just like in Comin and Hobijn (2010) we consider the case in which the set of vintages in use is of the form $V = (-\infty, t - D]$. Here $D \geq 0$ is the time that elapsed since the invention of the newest capital vintage that is being used in production. It is the *adoption lag*.

Capital goods production

Each capital vintage, v, is produced by a single monopolistic competitor.[18] Capital goods production is fully reversible and the unit production cost of a physical unit of capital is assumed to be constant across vintages and normalized to one unit of the final good.[19] Capital goods depreciate at the rate δ. Because the suppliers of these capital vintages have monopoly power, they can choose the rental rate R_v at which they rent the capital stock out. The monopoly profits that these suppliers make are then used to pay off the initial adoption costs that they incurred to become the sole supplier of the particular capital vintage.

Technology adoption

In order to supply a particular capital vintage a firm has to incur a one-time adoption cost. These costs go up in the distance between the vintage adopted and the best vintage in place. In particular, let $\overline{v}_t = t - D_t$ denote the best vintage adopted at instant t, then the adoption of $v = \overline{v}_t + dt$ at instant $t + dt$ costs

$$\Gamma_{v,t+dt} = e^{b\chi}\overline{\Psi}\left(\frac{\gamma}{\mu - 1}\right)\left\{\frac{1}{\gamma}\frac{\frac{Z_{\overline{v}_t+dt} - Z_{\overline{v}_t}}{dt}}{Z_{\overline{v}_t}}\right\}\left(\frac{Z_{\overline{v}_t}}{Z_t}\right)^{\chi} Y_t, \tag{5}$$

[18] Jovanovic (2009) presents a model of invention and immitation in which monopolistic competition arises naturally.

[19] Comin and Hobijn (2010) are more specific about the distinction between investment-specific and embodied technological change. For the empirical methodology applied here, the distinction does not matter, however. Hence, we ignore it in the rest of our exposition.

where $b > 0$ and $\chi > 0$.

Hence, the adoption costs increase in the rate at which the set of adopted vintages expands. However, they are lower, the further away one is from the world technology frontier, as reflected by the productivity of the most recent vintage invented, Z_t. The parameter χ can be interpreted as the absorption rate. Discrete jumps in the set of adopted vintages, and thus in the adoption lag, are infinitely expensive and do not occur. Instead, the adoption lags evolve smoothly over time.

The other parameter that determines the adoption costs is b, which is similar in interpretation to the barriers to adoption in Parente and Prescott (1994).[20]

The last term of the adjustment costs reflect that they are increasing in the size of the market. This is, on a theoretical level, important to assure the existence of a balanced growth path on which adoption lags are constant. Moreover, it is consistent with evidence that technology adoption involves a substantial use of resources beyond the installation of equipment.[21] The costs of these resources are generally increasing in the size of the market, i.e. the marginal product of their use elsewhere in the economy.

3.2 Factor demands, aggregation, and productivity

Factor demands

The nested CES structure of the production function and the assumption that all factor inputs can adjust flexibly yields familiar expressions for the relative demands for intermediates and for prices. That is, the demand for the intermediate produced using vintage v equals

$$Y_v = Y \left(P_v\right)^{-\frac{\mu}{\mu-1}}, \tag{6}$$

[20] $\overline{\Psi}$ is the steady-state stock market capitalization to GDP ratio, which is derived in the appendix. We include it and the other constant term to normalize the adoption costs to simplify the equilibrium expressions of the model.

[21] See Brynjolfsson and Hitt (2000) for an analysis of the costs of adoption of information technologies.

where perfect competition in the production of intermediates yields that P_v equals the unit production cost

$$P_v = \frac{1}{Z_v}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\left(\frac{R_v}{\alpha}\right)^{\alpha}. \tag{7}$$

Here, W is the real wage rate paid for the labor input L_v.

As in Comin and Hobijn (2010), the monopolistic competitor that supplies capital goods of vintage v realizes that it faces a downward-sloping demand curve for its capital goods. This demand curve is downward sloping because an increase in the rental cost, R_v, raises the prices of the intermediates produced using capital vintage v. Such a price increase reduces demand for the intermediate good and thus for the capital goods used in their production. Taking this into account, the profit-maximizing rental rate, R_v, that the supplier of capital good v chooses is equal to a gross-markup times the user-cost of capital. This rental rate is the same across capital vintages and equals

$$R_v = \frac{\epsilon}{\epsilon - 1}\left(\widetilde{r} + \delta\right) = R, \text{ where } \epsilon \equiv 1 + \frac{\alpha}{\mu - 1}. \tag{8}$$

This, combined with (7), implies that relative prices across intermediate inputs fully reflect relative embodied productivity levels for the capital vintages used to produce the intermediates.

Aggregation

The result is that we obtain very tractable aggregate production function representations.[22] Because, for our empirical analysis, we use data at the technology level, i.e. $\tau \in \{o, n\}$, we build the aggregation results up from that level. That is, we can write the level of intermediate output associated with technology τ as

$$Y_\tau = A_\tau K_\tau^{\alpha} L_\tau^{1-\alpha}, \text{ where } K_\tau \equiv \int_{v \in V_\tau} K_v dv,\ L_\tau \equiv \int_{v \in V_\tau} L_v dv, \tag{9}$$

[22] These aggregation results heavily rely on Fisher (1969).

where the technology specific TFP level is given by

$$A_\tau = \left(\int_{V_\tau} Z_v^{\frac{1}{\mu-1}} dv \right)^{\mu-1}. \tag{10}$$

For results used for our empirical application, it is useful to realize that this aggregation result implies that the unit production cost, and thus the price, of Y_τ, equals

$$P_\tau = \frac{1}{A_\tau} \left(\frac{W}{1-\alpha} \right)^{1-\alpha} \left(\frac{R_\tau}{\alpha} \right)^{\alpha}, \tag{11}$$

while the demand for output of technology τ is given by the iso-elastic demand function

$$Y_\tau = Y \left(P_\tau \right)^{-\frac{\mu}{\mu-1}}, \tag{12}$$

and the rental cost share of capital is equal to α, such that

$$R_\tau K_\tau = \alpha P_\tau Y_\tau. \tag{13}$$

In a similar way, the technology-specific production functions yield an aggregate production function representation, which reads

$$Y = AK^\alpha L^{1-\alpha}, \text{ where } K \equiv K_o + K_n, \, L \equiv L_o + L_n, \tag{14}$$

and the aggregate level of total factor productivity

$$A = \left(Z_o^{\frac{1}{\mu-1}} + Z_n^{\frac{1}{\mu-1}} \right)^{\mu-1} = \left(\int_{-\infty}^{t-Dt} Z_v^{\frac{1}{\mu-1}} dv \right)^{\mu-1}. \tag{15}$$

Productivity and adoption lags

These aggregation results allow us to relate the technology-specific and aggregate productivity levels, A_τ and A, to the set of vintages adopted, i.e. to V, and thus to the adoption lags, D.

Solving for the technology-specific TFP level for the new technology yields

$$A_n = \left(\frac{\mu-1}{\gamma}\right)^{\mu-1} Z_{\underline{v}} \underbrace{e^{\gamma(t-D-\underline{v})}}_{\text{embodiment effect}} \underbrace{\left[1-e^{-\frac{\gamma}{\mu-1}(t-D-\underline{v})}\right]^{\mu-1}}_{\text{variety effect}}. \tag{16}$$

Here $(t-D-\underline{v})$ is the measure of vintages of the new technology that is in use, i.e. of $V_n = (\underline{v}, t-D]$. This measure shows up in two ways. First, through the embodiment effect, which reflects that the average embodied productivity level is increasing in the number of vintages of the new technology in use. This is what drives long-run growth in the adoption of the new technology and in the economy as a whole.

Second, the measure of vintages adopted also shows up because there are gains from variety in the CES production function. Since, in the long-run the growth rate of the number of varieties goes to zero, the variety effect is important during the early stages of adoption of the new technology and tapers off as the use of the technology becomes more widespread. It is this time-varying effect of the variety effect that drives curvature in the measured adoption of new technologies that we exploit in our empirical analysis.

The aggregate TFP level can be derived in a similar fashion. However, because aggregate TFP is driven by the whole set of vintages in use, i.e. $V = (-\infty, t-D]$, which does not have an expanding measure of vintages adopted, the aggregate TFP level is not subject to the variety effect. As a result, it can be written as

$$A_t = A_0 e^{\gamma(t-D)}, \text{ where } A_0 = Z_0 \left(\frac{\mu-1}{\gamma}\right)^{\mu-1}. \tag{17}$$

Hence, aggregate TFP in this model is endogenously determined by the adoption lags induced

by the barriers to entry. The adoption lag, D, can be interpreted as the distance from the world technology frontier measured in years.

3.3 Optimal adoption

So far, we have derived how the adoption lag affects the equilibrium level of productivity. We have not, however, solved for the optimal technology adoption decision that determines the lag. This is what we do here.

We denote the market value of a firm that supplies capital goods v at instant t, after entry into the market, as $M_{v,t}$. Any vintage gets adopted whenever, at time t, this market value exceeds the adoption cost, $\Gamma_{v,t}$, a firm needs to incur to enter the market. That is, for all vintages v that are being adopted at time t, it must be the case that

$$\Gamma_{v,t} \leq M_{v,t}. \tag{18}$$

If there is a positive adoption lag, then this holds with equality for the best vintage that is being adopted.

As we derive in Appendix A, the market value of the firm that supplies capital vintage v equals

$$M_{v,t} = \int_t^\infty e^{-\int_t^s \widetilde{r}_{s'} ds'} \pi_{vs} ds = \left(\frac{Z_v}{A_t}\right)^{\frac{1}{\mu-1}} \Psi_t Y_t. \tag{19}$$

Here Ψ_t is the total market value of all capital goods suppliers relative to GDP, which, if they are all publicly traded, can be interpreted as the stock market to GDP ratio.

Combining (5), (18), and (19), yields that the adoption lag satifies the differential equation

$$\dot{D}_t = 1 - \left[\frac{\Psi_t}{\overline{\Psi}}\right] e^{\chi(\gamma D - b)}. \tag{20}$$

The intuition behind this equation is as follows. The higher the current adoption lag, the cheaper the adoption of technologies and the more quickly the adoption lag declines. The

higher the stock market to GDP ratio, Ψ_t, the higher the ratio of future benefits from adoption relative to the current costs and the faster the adoption lag declines. Finally, the higher the barriers to entry, b, the more expensive is technology adoption and the adoption lag will decline less quickly. In fact, in steady state, where $\dot{D} = 0$, the adoption lag equals b/γ. In steady state, b is the percentage productivity loss due to the barriers to entry.

3.4 Equilibrium

Equilibrium is defined in a similar way as in Comin and Hobijn (2010). The details of this definition are relegated to the technical appendix. Two non-standard features of the equilibrium are worth pointing out here.

First, for the aggregate equilibrium, it is important to know the amount of resources devoted to the adoption costs. The aggregate adoption costs in this economy turn out to equal

$$\Gamma = \left(\frac{\gamma}{\mu - 1}\right) \Psi Y. \tag{21}$$

Second, the aggregate resource constraint includes the aggregate adoption costs, such that

$$Y = C + I + \Gamma. \tag{22}$$

For our empirical analysis in Section 5 and beyond, we assume that adoption costs are measured as final demand. In particular, we assume that adjustment costs are measured as gross investment expenditures. This allows us to interpret Y as measured GDP, C as measured consumption, and $I + \Gamma$ as measured investment.[23]

The long-run growth rate of the economy only depends on the, exogenously given, growth rate of the world technology frontier. In particular, on the balanced growth path, this economy grows at rate $\gamma/(1-\alpha)$.

[23] Alternatively, one could define a GDP measure as $\widetilde{Y} = Y - \Gamma = \left[1 - \left(\frac{\gamma}{\mu-1}\right)\Psi\right] Y = C + I$.

4 Transitional dynamics: A Japan-like example

So, how does the addition of technology adoption help us understand the postwar growth experience of countries that have closed the real GDP per capita gap with the U.S.? The answer to this question is probably best illustrated by a numerical simulation that is calibrated to the most studied example of postwar catch-up, namely that of Japan.

During the prewar decade, from 1929-1938, Japan's real GDP per capita averaged 37 percent of that of the U.S. During the decade from 1997-2006 this had increased to 73 percent. The bulk of this catch-up with the U.S. took place between 1950 and 1990.

There are four main stylized facts about the Japanese postwar growth experience that stand out. The first one is the *substantial gains in real GDP per capita relative to the U.S.* The second is the observation, made by both Hayashi (1989) for the overall Japanese economy as well as by Van Ark and Pilat (1993) for manufacturing, that the *wealth to income ratio*[24] *in Japan exhibited a U-shaped pattern* during the postwar period. The third is the unconventional path of the Japanese saving rate, studied by, among others, Hayashi (1986,1989), Christiano (1989), and Chen, Imrohoğlu, and Imrohoğlu (2006). Though the exact numbers vary substantially by the way one accounts for the Japanese saving rate, the gist of the data is that the *saving rate increased from a very low level at the beginning of the 1950's to a peak around 1970, and subsequently declined*, though it did not revert to its early 1950's level. Finally, as Chen, Imrohoğlu, and Imrohoğlu (2006) and Cette, Kocoglu, and Mairesse (2009) document, Japan saw *very rapid TFP growth from the beginning of the 1950's through about 1973*, averaging over 5 percent annually. After that TFP growth tapered off rapidly.

Assuming constant TFP growth, Christiano (1989) aimed to reconcile these facts with a standard neoclassical growth model. He claimed that a version of the model with subsistence consumption levels did a relatively good job matching the data. However, his model, by assumption, was not able to match the path of TFP growth. Nor was it successful at

[24] Van Ark and Pilat (1993) actually focus on the capital-output ratio.

generating a U-shaped wealth to income ratio. Subsequently, Gilchrist and Williams (2004) analyzed whether a putty-clay model of capital could match these stylized facts. Their most noteworthy simulation assumed an increase in embodied productivity growth at the end of the war. Still, the capital accumulation dynamics in their model implied a much faster adjustment in real GDP per capita in Japan than observed in the data. The most promising study that attempted to reconcile these facts with a theoretical growth model is Chen, Imrohoğlu, and Imrohoğlu (2006). They show that, if one feeds the measured path of Japanese TFP growth into a standard neoclassical growth model it generates a path of the saving rate that closely matches that observed in the data. What remains unsatisfying about this is that it interprets TFP growth as an exogenous forcing process rather than as the consequence of deliberate technology adoption decisions taken by private agents.

Our example in this section is meant to overcome this issue, because the main contribution of our model is that it explicitly adds a technology adoption decision to the neoclassical core used by Chen, Imrohoğlu, and Imrohoğlu (2006). In particular, we pursue the following though-experiment.

As a benchmark, we assume that the U.S. has been on its balanced growth on the world technology frontier, i.e. with $b = 0$, for the period that we consider.[25] We assume that Japan was approximately on its balanced growth path during the decade before WWII, 1929-1938, as well as during the last ten years for which we have data, 1997-2006. This implies that Japan's steady state real GDP per capita level relative to that of the U.S. increased from 37 percent to 73 percent.

We assume that at the end of WWII[26] two things happened in Japan. First of all, we assume that, in 1950, Japan started with a capital stock that was 25% lower than the prewar steady state level. This level of capital destruction is in line with estimates (Wolff, 1991).

[25] Braun and McGrattan (1993, Figure 2) report estimates of the U.S. capital stock during the war period, suggesting that it grew at a relatively constant rate if one includes government-owned-privately-operated capital. In terms of privately owned capital, the U.S. saw a slight decline during WWII.

[26] Just like Gilchrist and Williams (2004) we focus on 1950 as the 'end' of WWII, thus allowing for a 5 year period after the war for recovery that is unrelated to the mechanisms outlined in our model. Bix (2001) contains a detailed description of many of the political and economic events in Japan during that period.

Secondly, we assume that a reduction, either immediate or gradual but imminent, of the entry barriers occured at the end of the war. This reduction in b resulted in an increase in the steady-state trend-adjusted per capita GDP level due to a reduction in steady-state adoption lags.

We solve for the dynamics of our model during the transition from the prewar to the postwar steady state, taking into account the capital destruction. We use a continuous-time log-linearization of our model to approximate the transitional dynamics.[27] In order to approximate these transitional dynamics we use the calibration of the model parameters outlined in Table 5. The only difference in parameters between the U.S. and Japan is b, the calibration of which is based on the relative GDP per capita levels in the two decades described above. Because, for this example, we stick to the very literal interpretation of our model that all steady state per capita GDP differentials are due to adoption lags, this implies that the prewar lags in Japan were 50 years and the postwar lags 16 years.[28] This is substantially larger than those estimated by Comin and Hobijn (2010).[29]

Beside b, the model has two types of parameters: Those that affect the steady state and those that only affect its transitional dynamics. We calibrate the parameters that affect the steady state, α, ρ, δ, γ, and μ, to match postwar U.S. facts. The values for the first four of these parameters that we use are relatively common. Because μ is not a parameter that normally occurs in a standard growth model, it is worth noting that we chose its value to match evidence on markups from Basu and Fernald (1997). Our choice of μ implies a steady state profit share in GDP of 15 percent.

The steady state of the model is derived in Appendix A. What is important for what follows is that the steady state values of the investment-output ratio, adoption-cost-to-output

[27] The linear differential equations that we use to approximate the transitional dynamics of our model are derived in detail in Appendix A.

[28] Weil (2005, Ch. 15) discusses why adoption lags can probably not account for all of productivity differentials.

[29] Table 5 in Comin and Hobijn (2010) suggests the differential in adoption lags between the U.S. and Japan for technologies first adopted before WWII is more in the order of 10 to 20 years. For technologies adopted after 1970, there are seem to be very small differences in adoption lags between the U.S. and Japan.

ratio, saving rate, and the stock market to GDP ratio do not depend on b. Hence, the long-run levels of these ratios are assumed to be the same in Japan for both the prewar and postwar periods.[30]

The absorption parameter, χ, in the adoption cost specification can not be pinned down based on steady state properties of the model. The absorption parameter determines the speed of the transitional dynamics in the adoption lags. Fortunately, Benhabib and Spiegel (2006) provide estimates that can be interpreted in terms of χ. Consistent with their evidence, we choose $\chi = 3.6$.

It turns out that the speed at which b moves from its high prewar level to its new postwar level has an important impact on the shape of the postwar transition path. For this reason, we present simulated transitional paths of this economy for two different paths of the change in b. The first is an immediate decline in b from its prewar to its postwar level. The second is a very gradual, but known decline, where b converges, in levels, to its lower postwar steady state at a convergence rate, given by ξ, of 6 percent. This implies that, at the end of the 50 years for which we simulate the model 95 percent of the decline in b has occurred. We consider these two paths because they are relatively extreme cases.

The resulting simulated transition paths for detrended real GDP per capita, the wealth-to-income ratio (K/Y), the saving rate,[31] adoption lags, and the stock-market-to-GDP ratio are depicted in Figures 4 and 5 respectively. Even though, in response to a shock to K, the adoption lags, and thus TFP could move in our model, it turns out that this response is rather muted. The reason is that what would move the adoption lags in that case would be the stock market to GDP ratio. However, this ratio barely responds to the capital destruction shock. The reason for this is that the destruction of capital does lead to a decline in current

[30] The steady-state stock market to GDP ratio implied by these parameter values is 1.55. Substantially higher than the average in Hobijn and Jovanovic (2001), of about 0.8. If this difference is due to the assumption that all businesses are publicly traded, but they are not, then this suggests that over the 1945-2000 period, on average the market value of privately owned businesses was about equal to that of publicly traded ones.

[31] Given our definition of measured GDP, the saving rate here equals $1 - C/Y$. A netting out of the adjustment costs from GDP would lead to a different saving rate definition.

GDP relative to future GDP. This should, in principle increase the stock market to GDP ratio. However, the destruction of capital also raises the real interest rate leading to a higher discounting of future profits. It turns out that these two effects, in first order, almost cancel each other out. As a result, the transitional dynamics of the model with respect to a shock in K is almost as if detrended TFP is constant, which means that it closely mimics the monotone transitional dynamics of the standard neoclassical growth model.

Christiano (1989), Gilchrist and Williams (2004), and Chen, Imrohoğlu, and Imrohoğlu (2006) already noticed that such a transitional path does not resemble the Japanese postwar experience, because it does not match either of the four stylized facts we discussed above.

The addition of the TFP dynamics through technology adoption in response to a decline in entry barriers adds a lot to the dynamics of the model. First of all, notice that the TFP dynamics take much longer to unfold than the capital accumulation dynamics. In panel (a) of Figure 4 it can be seen that, after the sudden lowering of b in 1950, it takes about four decades for the economy to get back close to steady state. In case of the slow adjustment of b it takes more than half a century. This is an important observation, since it suggests that even if succesful policies manage to lower barriers to entry immediately, it takes a long time for the economy to fully reap the benefits of such policy measures.

Moreover, if these measures are implemented slowly, they can actually initially lead to a slowdown in GDP growth, rather than an acceleration. This can be seen from the path for detrended GDP under the gradual adjustment of b in panel (a) of Figure 4. This is driven by the wealth effect; the anticipation of future TFP growth induced by the slow decline in entry barriers increases current consumption and, as a result, capital accumulation is depressed to such a degree that net investment (per capita) is negative and the decline in the capital stock is not fully offset by the increase in TFP.

The transitional dynamics due to the lowering of the barriers completely overwhelmes the capital accumulation mechanism. This can be seen in Figures 4 and 5 where the difference in the transitional path with our without a shock to K are much smaller than the differences

in the transitional path for an immediate and slow lowering of the barriers.[32]

Qualitatively, the model with TFP dynamics, especially that with the shock to K and immediate adjustment of b, matches all four stylized facts we documented above. We will focus on this particular path in the rest of our discussion.

Of course, we match the GDP gain relative to the U.S. by construction. This is mainly driven by the decline in adoption lags, depicted in panel (b) of Figure 5, which shows that the bulk of this decline after an immediate reduction in b would have occurred between 1950 and the beginning of the 1970's. Similar to the actual data, the simulated transitional path predicts rapid TFP gains during that period.[33]

The model does generate a U-shaped K/Y ratio (panel (a), Figure 5). The production function (14) implies that this ratio is determined by the TFP to capital ratio. If TFP growth exceeds α times capital growth, then the ratio is declining, which is exactly what, after the initial shock to K/Y due to the capital destruction, drives the subsequent decline in this ratio. This happens for two reasons. First, the catch-up in technology adoption leads to high TFP growth. Second, the wealth effect generated by this anticipated path of TFP initially reduces the saving rate and thus capital accumulation. This can be seen in panel (d) of Figure 5 which shows, consistent with the stylized fact, an initially low saving rate, a subsequent steep rise, and then a tapering off.

One more aspect that is worth pointing out is that the immediate drop in the barriers results in a more than 20 percent decline in the stock market value. This is reminiscent of the mechanism emphasized by Greenwood and Jovanovic (1999) and Hobijn and Jovanovic (2001) in that it reflects a sudden deterioration in the future competitiveness of incumbents that are currently valued in the stock market. In this sense, it can be interpreted as the size of the vested interests of these incumbents. If our model is any guide, these interests were

[32] For the paths of the adoption lags and stock market to GDP ratio, the differences were so small that they were hardly visible. For illustrative purposes we just plotted one of the two cases for both the immediate and gradual adjustment to b.

[33] The monotone dynamics of our model cannot match a second surge in Japanese TFP growth that happened during the 1980's.

large.

It is remarkable how such a stylized example using our, very parimoniously parameterized, framework manages to replicate qualitative properties of the stylized facts about Japan's postwar growth experience. The emphasis here, however, is on 'qualitative.' The generated transition paths are off both in terms of the magnitudes and timing. Because our aim here is not to perfectly match Japan's postwar economic recovery but to simply show that it is TFP dynamics that is important in such cases not capital accumulation, fixing the quantitative shortcomings of our model is beyond the scope of our analysis here. Some likely causes of the shortcomings are worth pointing out.

Timing-wise, the model would match the data better if we had assumed that b came down in 1955, after the Korean War, rather than after WWII. As can be seen from panel (b) of Figure 4, such a change in the timing assumption would more closely align the path of TFP growth implied by the model to that reported by Chen, Imrohoğlu, and Imrohoğlu (2006) with the important caveat that it would only explain about half of the observed TFP growth. Moreover, the monotonic transitional dynamics can not match the Japanese productivity boom of the 1980's. Actual fluctuations in the saving rate were much larger than those generated by our model. Some of this can be resolved by netting out the adoption costs from GDP in (22), however this does not fully resolve the issue. Part of the actual path of the saving saving rate can be understood as an endogenous response to the boom in TFP growth during the 1980's that our model does not capture.

In spite of these shortcomings, our analysis does emphasize the importance of understanding the dynamics of TFP, and to the extent it is driven by technology adoption, the dynamics of adoption, for understanding not only cross-country per capita GDP differentials but also the very different growth experiences of countries after WWII.

In the next section, we show how our model can be interpreted as generating predictions for the path of directly observed measures of technology usage over time as a function of the adoption lags that drive TFP dynamics in our model.

5 Identification and estimation of adoption lags

So far, our focus has been on the aggregate dynamics of our model. When we described the model, we specifically defined an old and a new technology. Moreover, we derived the equilibrium path of output and capital for the new technology as a function of the adoption lags. We did so to be able to map the equilibrium variables in our model into observed measures of technology usage, taken from Comin and Hobijn (2009b). In this section we describe this mapping and how it allows us to obtain estimates of technology adoption lags.

5.1 Identification

The data we use from Comin and Hobijn (2009b) contain two types of measures of technology usage for a broad range of countries and a very long timespan. First, the equivalent of Y_n, is output produced with different technologies. Examples are mWHr of electricity generated, the number of telegrams sent, and the number of ton-kilometers of freight transported by rail. The second type of measure, equivalent to K_n, consists of the number of the units of capital goods used to produce a particular intermediate Like trucks that are used to provide road-freight transportation services, telephone. Examples of such measures were depicted in Figure 2. Table 1 contains a list of the 10 technologies we use for our analysis. The choice of these technologies is mainly determined by the data requirements of the method applied. That is, we choose technologies for which we have a substantial number of observations for many years and countries both before and after WWII.

Our model has direct implications for the paths of these variables. This can be seen by combining (11), (12), and (13) and taking logarithms. Denoting logs of variables by small letters, e.g. $y_\tau = \ln Y_\tau$, this yields that

$$y_\tau = y + \frac{\mu}{\mu - 1}\left[a_\tau - (1-\alpha)(y-l) - \alpha r_\tau - \alpha \ln \alpha\right], \tag{23}$$

and

$$k_\tau = y + \ln \alpha + \frac{1}{\mu - 1} \left[a_\tau - (1 - \alpha)(y - l) - \alpha r_\tau - \alpha \ln \alpha \right] - r_\tau. \tag{24}$$

The main driving force behind the curvature in the technology usage measures is the productivity term, a_τ. To understand how the adoption lags affect this curvature, consider Figure 6. It plots the path of a_τ for four different cases. The first is the case vintages get adopted the instant the are invented, i.e. the world technology frontier. The curvature in the world technology frontier is driven by the variety effect. That is, in the early stages of the adoption of a technology the increase in the number of vintages causes growth to exceed the long run level of embodied technological change that sets in as the variety effect dissipates. The next two curves are those for constant adoption lags $D^* > D > 0$. These curves are basically horizontal shifts in the world technology frontier, where the size of the shift determines the technology adoption lag. The final path is based on the Japan-like example from the previous section; at first adoption lags are constant at D^*. However, at a certain point the adoption barriers are lowered and there is a transition toward shorter adoption lags of length D.

As can be seen from this figure, if the adoption lags are constant then they are identified by the relative curvature of the path of a_τ at a particular point in time. This is the identification strategy used in Comin and Hobijn (2010). However, our interest here is also in seeing whether we can identify changes in adoption lags over time for the same technology. The identification is a lot more complicated in that case. The initial adoption lag is determined by the curvature in the early part of the sample and the change in the adoption lag is implied by the change in the intercept between the extrapolated initial path and the actual observed path for a_τ. The change in curvature in the middle part of the sample is due to the adjustment process.

5.2 Reduced form equation

To get from equations (23) and (24) to the reduced form equations we actually estimate, we take the steps described in this subsection. We limit ourselves to a short description and present the details behind these steps in Appendix A.

It turns out that, to first order, the productivity growth rate γ does not matter for the variety effect and thus for the curvature in a_τ. Therefore, as in Comin and Hobijn (2010), we log-linearize a_τ around $\gamma = 0$. Both y_τ and k_τ depend on the rental rate r_τ. We use the optimal saving decision in the model to log-linearize the rental rate, which yields that r_τ is approximately proportional to the growth rate of consumption, Δc.[34]

The final steps have to do with that, using data for several technologies, we need to drop the one-sector assumption we used to derive the model and need to generalize our functional forms to accommodate the multi-technology nature of our data.

Just like in Comin and Hobijn (2010), to allow for multiple sectors, we use a nested CES aggregator, where $\frac{\theta}{\theta-1}$ reflects the between-sector elasticity of demand and $\frac{\mu}{\mu-1}$ is the within-sector elasticity of demand. In addition, the embodied technological change, γ_τ, and the invention date, $\underline{v}_\tau$, vary across technologies.

Finally, in Section 1 we documented very different rates of capital destruction during WWII across the different technologies in our dataset. Since the model we considered has flexible capital mobility, it would imply an immediate replenishment of these capital losses and equate them across technologies. Hence, our model is not consistent with this varying impact. To match this feature of the data, we add a capital adjustment cost term to the equation.[35] The adjustment cost variable is denoted by X_τ below. It equals the investment to capital ratio for k_τ and output growth rate for y_τ.[36]

[34] Throughout, we have derived our results for log preferences, i.e. an intertemporal elasticity of substitution equal to 1. This log-linear approximation actually holds for CRRA preferences with any intertemporal elasticity of substitution.

[35] The profit maximization problem subject to these adjustment costs that results in the inclusion of this term in our equations is described in the appendix.

[36] We assume that these costs are only present during the postwar recovery.

We make the following assumption about the adoption lag: before the war it is equal to D^* and starting in 1945 it potentially converges to $D \neq D^*$. We study both the restricted case where $D = D^*$ as well as the unrestricted case. We exclude the war years 1939 through 1945 from our sample.

When we define the technology measures as $m_\tau \in \{y_\tau, k_\tau\}$ then the unrestricted reduced form equation that we estimate can be written as

$$\begin{aligned} m_\tau &= \beta_0 + y + \beta_1 \left[(\mu - 1) \ln \left(t - D - \mathbf{1}\left(t < 1939\right) \Delta D - \underline{v}_\tau\right) - (1 - \alpha)\left(y - l\right)\right] \quad (25) \\ &\quad + \beta_2 \left(t - D - \mathbf{1}\left(t < 1939\right) \Delta D - \underline{v}_\tau\right) + \beta_3 \Delta c + \beta_4 X_\tau. \end{aligned}$$

This equation is derived in detail in Appendix A. Here $\mathbf{1}(.)$ is an indicator function that is one if the condition holds and zero otherwise. The prewar adoption lag equals $D^* = D + \Delta D$. Finally, as we discussed above, we capture the transitional dynamics by the usercost term, β_3, and the adjustment cost term β_4.

5.3 Estimation

In principle, having data for many technologies and many countries, we can combine the country-technology equations and obtain a very large system of non-linear equations based on (25) to estimate. In practice, this turns out to be infeasible. Hence, instead of taking a system estimation approach, we estimate (25) for each country and technology separately. However, because (25) implies cross-country restrictions on the parameters, we do not do so in an unrestricted manner. We impose these cross-country restrictions by applying the U.S. estimates for all countries for the parameters that are assumed to be constant across countries. There are two parameters, μ and α,[37] which we do not estimate but for which we simply impose the calibrated parameter values we used Section 4, which are based on postwar U.S. evidence.

[37] Gollin (2002) provides evidence of the relative constancy of the output share of capital, or rather one minus the labor share, across countries.

There is another advantage of this approach over a system estimation of the parameters. Because we apply this model to a very broad sample of countries and system estimation would be affected by serious misspecification of the model or measurement error in the data for each of these countries. Using this approach, we basically assume the model is properly specified and the data are relatively reliably measured for the United States to identify the common parameters across countries.

The cross-country parameter restrictions we impose across countries are based on the assumption that the technology parameters are the same across countries and that what potentially differs are adoption lags, preferences, and adjustment costs. This assumption means that β_1 and β_2 are the same across countries and that the other parameters can potentially vary. We estimate each equation using non-linear least squares.

6 Results

We present our results in three parts. In the first part, we summarize the estimated changes in adoption lags that we obtained using the method described above. In the second part, we do the first-stage of our instrumental variables analysis and estimate the change in the speed of adoption that can be attributed to the TAPs. In the final part, we perform the second stage of our analysis to estimate the causal effect of technology adoption on real GDP per capita.

6.1 Estimated changes in the adoption lags

The parameter estimates for the U.S. specification as well as for the level of the adoption lags, D, are very similar to those reported in Comin and Hobijn (2010). Therefore, we focus on the estimated changes in the adoption lags, which we use in the rest of our analysis, here.

Just like in (25) we use the convention that a positive change in the adoption lag reflects a increase in the speed of adoption. In this sense, we estimate the *reduction* in the adoption

lag. In terms of the notation in (25), we estimate $\Delta D_{c\tau}$, where c denotes the country and τ the technology.

In practice, we obtain several estimates of $\Delta D_{c\tau}$ because we estimate various specifications nested in (25). The estimated reductions in the adoption lags turn out to be a bit sensitive to the inclusion or exclusion of the adoption costs and the usercost in (25) or to whether the adjustment cost parameter was restricted to equal to for the U.S. In light of this, we do not to take a stance on the right model specification. Instead we include all model-specifications and all estimated changes in adoption lags in the analysis here.[38]

Table 6 provides summary statistics for our estimates of the reduction in the adoption lags after WWII. On average adoption lags increased slightly after WWII in the sample of technologies and countries we analyze. There are significant differences across technologies, especially when categorized in term of those that are 'old' and those that are 'new'. Consistent with our analysis in Section 2, we find that adoption of new technologies sped up after WWII, by on average about 2 year in our sample, while the delay with which old technologies were used increased by almost 7 years.

6.2 First stage: Effect of technical assistance on adoption

The first stage of our analysis involves analyzing whether the technical assistance variables caused a change in the adoption lags after WWII. Guided by the results in Section 2 we again differentiate between the effects on old and new technologies. Contrary to the analysis in Table 4, we pool all our data here and just allow for a difference in the effect of the TAPs on the two types of technologies.

Table 7 reports the estimates when pooling the estimated changes in the adoption lags for all the technologies and specifications. In order to correct for the fact that we have more than one estimate of each $\Delta D_{c\tau}$ we cluster the standard errors at the country level. Note

[38] Unreported results based on different model selection criteria and cut off points based on fit, as used in Comin and Hobijn (2010), gave qualitatively largely the same results in terms of the instrumental variables analysis.

that, by clustering at the country level, we also correct for the possibility of correlation in the errors across technologies within a country.[39]

The main finding from our estimates, reported in columns I and II of Table 7, is that both assistance variables are associated with a reduction in adoption lags for the new technologies. This effect is considerable. The average country that participated in the TAP experienced a reduction in the lags with which new technologies were adopted of about 4.7 years. For old technologies, instead, we find that the expenditures in the technology assistance program and the number of industrial trainees are associated with an increase in the adoption lags, though only the latter is statistically significant.

One may wonder whether the effects of assistance on the adoption lags persist after controlling for any country-specific characteristic. To explore this, we re-run the regressions with country fixed effects. The results, reported in columns III and IV, show that the effect of technical assistance on adoption is very robust. Even after controlling for any possible country-specific factor, the assistance programs reduced the adoption lags of the new technologies and tended to increase the lags of the old ones. The average country that participated in the technology assistance program, for example, experienced a differential reduction in the adoption lags of 9 years for the new vs. old technologies.

This finding is relevant since most of the omitted variables that could be driving the association between the assistance programs and the reduction in adoption lags should, a priori, affect all technologies more or less symmetrically. Take property rights, for example. If the foreign intervention leads to a change in regime that preserved property rights better, this should enhance investment in all forms of capital, those that embody new technologies and those that embody old technologies. So, to a first order, we should observe that the effects of such policies be captured by the country fixed effect. The same is true for other policies that affect the efficiency of the economy such as those that lead to a more efficient bureaucracy, lower taxes, or less distorted markets. The fact that we are observing such a

[39] The results we report are virtually the same as when running the regressions separately for the estimated change in the lags obtained in each specification. Furthermore, they are very robust across specifications.

large and significant differential effect on the adoption lag of the new technologies leads us to believe that the driver of the effect of the assistance variables on the decline in adoption lags was not a general increase in efficiency but a reduction in adoption costs. In particular, with these and related programs, the new technologies were made more easily available, there was a transfer of knowledge from the U.S. to other nations and, in some instances, the U.S. technicians helped adopt the new technologies.

We conclude our exploration of the effect of the assistance variables on the post-war reduction in adoption lags by estimating the first stage regression in our IV strategy. Since we have few potential instruments, we aggregate the change in the adoption lags at the country level. We proceed as follows. First, we sustract the technology average from the change in the adoption lag. This takes care of the unbalance in the sample of estimated lags. Second, we compute the average of the change in the adoption lags across specifications and technologies for the dominated and non-dominated technologies so that we have two average changes in adoption lags per country, one for each group of technologies. Third, we run the following first stage regressions:

$$\text{Reduction lag new}_c = \alpha + \rho * y_{1950c} + \beta * \text{Assistance variable}_c + \epsilon_c \quad (26)$$

$$\text{Reduction lag old}_c = \alpha + \rho * y_{1950c} + \beta * \text{Assistance variable}_c + \epsilon_c \quad (27)$$

where the dependent variable in (26) is the average post-war reduction in the adoption lag for the new technologies while in (27) it is the reduction in the lag for the old technologies. y_{1950c} denotes the log of real per capita GDP in 1950 in country c, and the assistance variable can be any of the three variables used so far. The results from these regression are reported in Table 8.

Both technology assistance expenditures and number of industrial trainees lead to a reduction in adoption lags for new technologies and to an increase for the old technologies. However, these effects are not always significant. To avoid running into weak instruments,

we restrict our analysis to the cases where the estimates of β are significant at the 1% level. This occurs for the effect of the expenditure in the technology assistance on the reduction in adoption lags for new technologies (column 1) and for the effect of the number of industrial trainees on the reduction in the lag for old technologies (column 6). Combining several instruments together does not yield much additional explanatory power. The significance of the technical assistance for the reduction in adoption lags is robust to controlling for measures of institutions and openness to trade.[40]

6.3 Second stage: Effect of adoption on per capita GDP

Table 9 lists the results from the following second stage regression:

$$y_{1970c} = \alpha + \rho * y_{1950c} + \beta * \text{Reduction in lag}_c + \epsilon_c \tag{28}$$

In the first column of Table 9, we estimate the effect of the reduction in the new technologies adoption lags on (log) per capita income in 1970 after instrumenting the former by the total expenditures in technical assistance. We find that the reduction in the lag with which new technologies were adopted after WWII led to large and significant growth. In particular, the reduction of an additional year in the lag with which new technologies were adopted led to a 9.6 percent increase in per capita income in 1970. Given the average size of the technology assistance program and the estimated effect that the program had on the reduction in adoption lags for new technologies, this estimate implies that the TAP led to an increase in the annual growth rate of GDP per capita of 1.1 percentage points between 1950 and 1970.

In column II we estimate the growth effects of the assistance programs through the increase in the adoption lags of the old technologies. In this case, we instrument the change

[40] In particular, the results presented are robust to controlling for the polity index in 1950, changes in polity between 1950 and 1970 or between 1938 and 1970 and for the share of imports plus exports in GDP in 1950.

in the lag with the number of industrial trainees. We find that there is no significant effect on growth from increasing the lags with which the old technologies were adopted. In column III, we use both instruments to estimate simultaneously the growth effects of the postwar reduction in the adoption lags of the new technologies and the increase in the lags of the old technologies. We find again that the later had no growth effects but that the former were indeed conducive to growth. Interestingly, the magnitude of this effect is very similar to that reported in column I. Just like the first stage estimates, these second stage regresssion estimates are also robust to controlling for polity, changes in polity, as well as openness.

It turns out that the fitted changes in the adoption lags explain about two-thirds of the residual variance left after controlling for the initial GDP levels. This means that our results suggest that the active pursuit of technology transfers by the United States in the wake of WWII had a very substantial impact on the growth performance of many countries during the postwar decades.

7 Conclusion

In this paper we revisited the remarkable postwar growth experiences of Western European countries and Japan. In addition to considering the oft-studied gains in real GDP per capita, we also considered technology usage measures for ten technologies taken from Comin and Hobijn (2009b).

The evidence we presented showed that, in terms of real GDP per capita, these countries did not return to their prewar growth path. They, instead, moved up to a higher path than they were on before the war. This boost in growth was mainly driven by growth in Total Factor Productivity. It was also accompanied by commensurate increases in technology usage.

Because most theories of growth and adoption predict that both GDP growth is caused by technology adoption as well as that technology adoption is caused by growth, it is hard

to identify to what extent technology adoption caused the increase in productivity growth that drove postwar growth in these countries.

Identification of the causal effect of technology adoption on GDP would require an exogenous source that reduces the adoption cost and thus induces more rapid technology adoption and higher technology usage. We argued that the U.S.'s technological assistance to Western Europe and Japan after the war can be interpreted as such a source of exogenous variation. We used it for an instrumental variables analysis to quantify the causal effect of adoption on growth.

We started our empirical analysis by showing that technical assistance has a significant effect on postwar catch-up in per capita GDP. However, simple reduced form results that indicate that technical assistance increased technology usage are hard to use as a first-stage in the instrumental variable analysis we perform. This is because it is unclear what the specification of the reduced form equations is supposed to be, how to condition on all the variables that affect real GDP beyond technology adoption in this regression, and how to aggregate these results across technologies.

These problems can be overcome by replacing this first-stage part of the analysis with a structural estimation based on a model of growth with endogenous TFP levels due to adoption lags. We introduced such a model, based on Comin and Hobijn (2010), and showed how it is able to replicate the main stylized facts about Japan's postwar growth experience.

We used the model to estimate the reduction in the adoption lags for 10 technologies in 39 countries after WWII. U.S. technical existence significantly reduced the adoption lags of the frontier technologies in our sample and has less effect on the adoption of more matured technologies. The fitted reductions in adoption lags of frontier technologies due to technical assistance have a significant effect on real GDP levels. In particular, it suggests that technical assistance led to an increase in the annual growth rate of GDP per capita of 1.1 percentage points between 1950 and 1970.

Hence, our results imply a relatively large effect of technology transfers on standards

of living. Since such technology transfers tend to be relatively cheap, this implies very high returns on such efforts. Though our analysis includes a wider range of countries than most previous studies that focused on the same postwar growth experience, our results do not address how the lessons from the postwar technical assistance program translate into current technical assistance to developing countries. Of course, it would be great if the returns that our analysis implies can also be achieved from similar technology transfers to currently developing countries. However, in terms of institutions, human capital, and property rights protection, many of these countries have not yet reached the level that Western Europe and Japan had at the end of WWII.

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A Mathematical derivations

This appendix contains the details about the data we use and the mathematical details behind the equations presented in the main text. Because the model we use is based on the one introduced in Comin and Hobijn (2010), the derivations here are, in many respects, similar to the ones in that study. The main difference is the explicit introduction of adoption lags, D_t, as a state variable and the derivation of the resulting dynamics. Equations and results are derived in the order they appear in the main text.

Calculation of number of industrial trainees in Table 2:

These data are calculated based on the U.S. Immigration and Naturalization Service's Annual Reports from 1949-1969. Industrial trainees are persons who temporarily enter the United States with an H-3 visa. This visa type was first introduced in the Immigration and Nationality Act of 1952. Before that, industrial trainees were most likely classified as temporary visitors for business purposes. Prior to 1965 the INS did not separately report the number of H-3 visa entrants. Instead, it reported the total number of H-visa entrants, which also includes workers of distinguished merit or ability (H-1) and temporary workers (H-2). We impute the number of industrial trainees as follows. We first calculate the average number of industrial trainees per temporary visitor for business purposes for 1965-1969 for each country. We then apply these shares for the years prior to 1965 to the number of temporary visitors for business purposes.

In earlier years, the INS statistics report the number of temporary visitors for business purposes at a very coarse geographical level. We disaggregate these data based on a country's later share in the total for the geographic area that it is part of in the earlier reports.

Derivation of equation (8):

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

$$R_v K_v = \alpha P_v Y_v. \tag{29}$$

Since revenue generated from the output produced with the vintage is determined by the demand function (6), we can write

$$R_v K_v = \alpha Y P^{\frac{\mu}{\mu-1}} P_v^{-\frac{1}{\mu-1}}. \tag{30}$$

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

$$R_v K_v = \alpha Y Z_v^{\frac{1}{\mu-1}} \left(\frac{(1-\alpha)}{W}\right)^{\frac{1-\alpha}{\mu-1}} \left(\frac{\alpha}{R_v}\right)^{\frac{\alpha}{\mu-1}}, \tag{31}$$

such that

$$K_v = Y_\tau Z_v^{\frac{1}{\mu-1}} \left(\frac{(1-\alpha)}{W}\right)^{\frac{1-\alpha}{\mu-1}} \left(\frac{\alpha}{R_v}\right)^{\epsilon}, \tag{32}$$

where

$$\epsilon = \frac{\mu}{\mu-1} - \frac{1-\alpha}{\mu-1} = 1 + \frac{\alpha}{\mu-1}, \tag{33}$$

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

$$\mathcal{L}_{vt} = \int_t^\infty e^{-\int_t^s \widetilde{r}_{s'} ds'} H_{vs} ds, \tag{34}$$

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

$$\begin{aligned} H_v &= (R_v K_v - Q I_v) + \\ &\quad \lambda_v \left(R_v K_v - \alpha Y Z_v^{\frac{1}{\mu-1}} \left(\frac{(1-\alpha)}{W}\right)^{\frac{1-\alpha}{\mu-1}} \left(\frac{\alpha}{R_v}\right)^{\epsilon-1} \right) + \\ &\quad \nu_v \left(I_v - \delta K_v\right). \end{aligned} \tag{35}$$

Here λ_v is the co-state variable associated with the demand function that the capital goods supplier faces and ν_v is the co-state variable associated with the capital accumulation equation.

The resulting optimality conditions read

$$\begin{aligned} &\text{w.r.t. } R_v: \quad (1+\lambda_v) K_v + (\epsilon - 1) \lambda_v K_v = 0. \\ &\text{w.r.t. } I_v: \quad \nu_v = 1. \\ &\text{w.r.t. } K_v: \quad (1+\lambda_v) R_v - \delta \nu_v = \widetilde{r} \nu_v - \dot{\nu}_v. \end{aligned} \tag{36}$$

The first optimality condition yields that

$$\lambda_v = -\frac{1}{\epsilon}, \tag{37}$$

while the second and third yield that

$$\begin{aligned} R_v &= \frac{1}{(1+\lambda_v)} (\widetilde{r} + \delta) \\ &= \frac{\epsilon}{\epsilon - 1} (\widetilde{r} + \delta) = R, \end{aligned} \tag{38}$$

which is (8). Note that the resulting flow profits satisfy

$$\pi_v = \frac{1}{\epsilon - 1} (\widetilde{r} + \delta) K_v = \frac{1}{\epsilon} R K_v = \frac{\alpha}{\epsilon} P_v Y_v. \tag{39}$$

Derivation of intermediate technology aggregation results:

The price of intermediates produced with capital goods of vintage v and the aggregate price level equal the unit production cost

$$P_v = \frac{1}{Z_v}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\left(\frac{R}{\alpha}\right)^{\alpha} \text{ and } P = \frac{1}{A}\left(\frac{W}{1-\alpha}\right)^{1-\alpha}\left(\frac{R}{\alpha}\right)^{\alpha}. \tag{40}$$

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

$$\frac{P_v}{P} = P_v = \frac{A}{Z_v}, \tag{41}$$

where $P = 1$ is the price of the numeraire good. The factor demands for each of the vintage specific output types satisfy

$$WL_\tau = W\int_{v\in V_\tau} L_v dv = (1-\alpha)\int_{v\in V_\tau} P_v Y_v dv = (1-\alpha)\, P_\tau Y_\tau, \tag{42}$$

and

$$RK_\tau = R\int_{v\in V_\tau} K_{v\tau} dv = \alpha\int_{v\in V_\tau} P_v Y_v dv = \alpha P_\tau Y_\tau. \tag{43}$$

Hence relative factor demands are the same as relative revenue levels

$$\frac{P_v Y_v}{P_\tau Y_\tau} = \left(\frac{Y_v}{Y_\tau}\right)^{\frac{1}{\mu}} = \frac{L_v}{L_\tau} = \frac{K_v}{K_\tau}, \tag{44}$$

which allows us to write

$$\begin{aligned} Y_v &= Z_v K_v^\alpha L_v^{1-\alpha} = Z_v\left(\frac{Y_v}{Y_\tau}\right)^{\frac{1}{\mu}} K_\tau^\alpha L_\tau^{1-\alpha} \\ &= (Z_v)^{\frac{\mu}{\mu-1}}\left(\frac{1}{Y_\tau}\right)^{\frac{1}{\mu}}\left(K_\tau^\alpha L_\tau^{1-\alpha}\right)^{\frac{\mu}{\mu-1}}. \end{aligned} \tag{45}$$

We obtain that

$$\begin{aligned} Y_\tau &= \left(\int_{v\in V_\tau} Y_v^{\frac{1}{\mu}} dv\right)^{\mu} = \left(\int_{v\in V_\tau} Z_v^{\frac{1}{\mu-1}} dv\right)^{\mu}\left(\frac{1}{Y_\tau}\right)^{\frac{1}{\mu}}\left(K_\tau^\alpha L_\tau^{1-\alpha}\right)^{\frac{\mu}{\mu-1}} \\ &= \left(\int_{v\in V_\tau} Z_v^{\frac{1}{\mu-1}} dv\right)^{\mu-1}\left(K_\tau^\alpha L_\tau^{1-\alpha}\right) = A_\tau K_\tau^\alpha L_\tau^{1-\alpha}. \end{aligned} \tag{46}$$

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

Derivation of equation (16):

This follows from

$$\begin{aligned} A_n &= \left(\int_{v\in V_n} Z_{v\tau}^{\frac{1}{\mu-1}}dv\right)^{\mu-1} = \left(\int_{\underline{v}}^{t-D_t}\left(Z_{\underline{v}}e^{\gamma(v-\underline{v})}\right)^{\frac{1}{\mu-1}}dv\right)^{\mu-1} \qquad (47)\\ &= Z_{\underline{v}}\left(\int_{\underline{v}}^{t-D_t} e^{\frac{\gamma}{\mu-1}(v-\underline{v})}dv\right)^{\mu-1} = \left(\frac{\mu-1}{\gamma}\right)^{\mu-1} Z_{\underline{v}}e^{\gamma(t-D_t-\underline{v})}\left[1-e^{-\frac{\gamma}{\mu-1}(t-D_t-\underline{v})}\right]^{\mu-1}. \end{aligned}$$

Derivation of aggregate TFP, (17):

This allows us to write aggregate total factor productivity as

$$\begin{aligned} A_t &= \left(\int_{-\infty}^{t-D_t} Z_v^{\frac{1}{\mu-1}}dv\right)^{\mu-1} = Z_0\left(\int_{-\infty}^{t-D_t} e^{\frac{\gamma}{\mu-1}v}dv\right)^{\mu-1} \qquad (48)\\ &= Z_0\left(\frac{\mu-1}{\gamma}\right)^{\mu-1} e^{\gamma(t-D_t)} = A_0e^{\gamma(t-D_t)}. \end{aligned}$$

Derivation of equation (19):

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

$$P_vY_v = \left(\frac{P}{P_v}\right)^{\frac{1}{\mu-1}}Y = \left(\frac{Z_v}{A}\right)^{\frac{1}{\mu-1}}Y. \qquad (49)$$

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

$$\pi_v = \frac{\alpha}{\epsilon}P_vY_v = \frac{\alpha}{\epsilon}\left(\frac{Z_v}{A}\right)^{\frac{1}{\mu-1}}Y. \qquad (50)$$

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

$$\begin{aligned} M_{v,t} &= \int_t^\infty e^{-\int_t^s \widetilde{r}_{s'}ds'}\pi_{vs}ds \qquad (51)\\ &= \left(\frac{Z_v}{A_t}\right)^{\frac{1}{\mu-1}}\frac{\alpha}{\epsilon}\int_t^\infty e^{-\int_t^s \widetilde{r}_{s'}ds'}\left(\frac{A_t}{A_s}\right)^{\frac{1}{\mu-1}}Y_sds \qquad (52)\\ &= \left(\frac{Z_v}{A_t}\right)^{\frac{1}{\mu-1}}\left[\frac{\alpha}{\epsilon}\int_t^\infty e^{-\int_t^s \widetilde{r}_{s'}ds'}\left(\frac{A_t}{A_s}\right)^{\frac{1}{\mu-1}}\frac{Y_s}{Y_t}ds\right]Y_t \qquad (53)\\ &= \left(\frac{Z_v}{A_t}\right)^{\frac{1}{\mu-1}}\Psi_tY_t. \qquad (54) \end{aligned}$$

Here,

$$\Psi_t = \left[\int_{-\infty}^{\overline{v}_t} M_{v,t} dv\right] / Y_t \tag{55}$$

is the total market value of all monopolistic competitors.

Derivation of equilibrium adoption lag, (20):

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

$$\Gamma_v = M_v. \tag{56}$$

The adoption costs satisfy

$$\Gamma_{v,t+dt} = e^{\chi b}\overline{\Psi}\left(\frac{\gamma}{\mu-1}\right)\left\{\frac{1}{\gamma}\frac{\frac{Z_{\overline{v}_t+dt}-Z_{\overline{v}_t}}{dt}}{Z_{\overline{v}_t}}\right\}\left(\frac{Z_{\overline{v}_t}}{Z_t}\right)^{\chi} Y_t. \tag{57}$$

Taking the limit for $dt \downarrow 0$, we find that

$$\begin{aligned}\Gamma_{\overline{v}_t,t} &= e^{\chi b}\overline{\Psi}\left(\frac{\gamma}{\mu-1}\right)\left(\frac{Z_{\overline{v}_t}}{Z_t}\right)^{\chi}\left\{\dot{\overline{v}}_t\right\}^{\frac{1}{\mu-1}} Y_t \\ &= e^{\chi b}\overline{\Psi}\left(\frac{\gamma}{\mu-1}\right) e^{-\chi\gamma D_t}\left\{1-\dot{D}_t\right\}^{\frac{1}{\mu-1}} Y_t.\end{aligned} \tag{58}$$

Moreover, note that

$$M_{\overline{v}_t,t} = \left(\frac{Z_{\overline{v}_t}}{A_t}\right)^{\frac{1}{\mu-1}} \Psi_t Y_t = \left(\frac{\gamma}{\mu-1}\right)\Psi_t Y_t. \tag{59}$$

Combining this with the market value of the capital goods supplier of capital good v, we obtain that entry in the market determines that the path of the adoption lag satisfies.

$$\overline{\Psi}\left(\frac{\gamma}{\mu-1}\right) e^{\chi b} e^{-\chi\gamma D_t}\left\{1-\dot{D}_t\right\} Y_t = \left(\frac{\gamma}{\mu-1}\right)\Psi_t Y_t. \tag{60}$$

Rearranging this yields that

$$\dot{D}_t = 1 - \left[\frac{\Psi_t}{\overline{\Psi}}\right] e^{\chi(\gamma D_t - b)}, \tag{61}$$

which is (20).

Derivation of aggregate adoption costs, (21):

From (58), it can be seen that, in equilibrium, the adoption costs equal

$$\Gamma_t = \overline{\Psi}\left(\frac{\gamma}{\mu-1}\right) e^{-\chi(\gamma D_t - b)}\left\{1-\dot{D}_t\right\} Y_t. \tag{62}$$

Since

$$1 - \dot{D}_t = \left[\frac{\Psi_t}{\overline{\Psi}}\right] e^{\chi(\gamma D_t - b)}, \tag{63}$$

this simplifies to equation (21) in the main text.

Equilibrium:

Equilibrium is a path of the variables $\{C, K, I, \Gamma, Y, A, D, \Psi\}$ that satisfies the following equations: The consumption Euler equation

$$\frac{\dot{C}_t}{C_t} = \left(\alpha \frac{\epsilon - 1}{\epsilon} \frac{Y_t}{K_t} - \delta - \rho\right) \tag{64}$$

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

$$\widetilde{r}_t = \alpha \frac{\epsilon - 1}{\epsilon} \frac{Y_t}{K_t}; \tag{65}$$

The resource constraint

$$Y_t = C_t + I_t + \Gamma_t; \tag{66}$$

The capital accumulation equation

$$\dot{K}_t = -\delta K_t + I_t; \tag{67}$$

The production function

$$Y_t = A_t K_t^{\alpha}; \tag{68}$$

The aggregate TFP equation

$$A_t = A_0 e^{\gamma \overline{v}_t}; \tag{69}$$

The adoption cost equation

$$\Gamma_t = \left(\frac{\gamma}{\mu - 1}\right) \Psi_t Y_t; \tag{70}$$

The adoption lag equation

$$\dot{D}_t = 1 - \left[\frac{\Psi_t}{\overline{\Psi}}\right]^{\mu - 1} e^{\chi(\gamma D_t - b)}; \tag{71}$$

And the market value equation

$$\Psi_t = \frac{\alpha}{\epsilon} \int_t^{\infty} e^{-\int_t^s \widetilde{r}_{s'} ds'} \left(\frac{A_t}{A_s}\right)^{\frac{1}{\mu - 1}} \frac{Y_s}{Y_t} ds, \tag{72}$$

which is best written in changes over time

$$\frac{\dot{\Psi}_t}{\Psi_t} = \left\{ \alpha \frac{\epsilon - 1}{\epsilon} \frac{Y_t}{K_t} - \delta + \frac{1}{\mu - 1} \frac{\dot{A}_t}{A_t} - \frac{\dot{Y}_t}{Y_t} \right\} - \frac{\alpha}{\epsilon} \frac{1}{\Psi_t}. \tag{73}$$

Balanced growth path:

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

$$\overline{A}_t = A_0 e^{\gamma t}. \tag{74}$$

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

$$C_t^* = \frac{C_t}{\overline{A}_t^{\frac{1}{1-\alpha}}}, \; Y_t^* = \frac{Y_t}{\overline{A}_t^{\frac{1}{1-\alpha}}}, \; I_t^* = \frac{I_t}{\overline{A}_t^{\frac{1}{1-\alpha}}}, \; K_t^* = \frac{K_t}{\overline{A}_t^{\frac{1}{1-\alpha}}}, \; \Gamma_t^* = \frac{\Gamma_t}{\overline{A}_t^{\frac{1}{1-\alpha}}}, \text{ and } A_t^* = \frac{A_t}{\overline{A}_t}, \tag{75}$$

as well as D_t and Ψ_t.

Derivation of transformed dynamic system:

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

$$\frac{\dot{C}_t^*}{C_t^*} = \left(\alpha \frac{\epsilon - 1}{\epsilon} \frac{Y_t^*}{K_t^*} - \delta - \rho \right) - \frac{\gamma}{1 - \alpha}; \tag{76}$$

The resource constraint

$$Y_t^* = C_t^* + I_t^* + \Gamma_t^*; \tag{77}$$

The capital accumulation equation

$$\frac{\dot{K}_t^*}{K_t^*} = -\frac{\gamma}{1 - \alpha} - \delta + \frac{I_t^*}{K_t^*}; \tag{78}$$

The production function

$$Y_t^* = A_t^* \left(K_t^* \right)^{\alpha}; \tag{79}$$

The trend adjusted productivity level

$$A_t^* = e^{-\gamma D_t}; \tag{80}$$

The aggregate adoption cost

$$\Gamma_t^* = \left(\frac{\gamma}{\mu - 1} \right) \Psi_t Y_t; \tag{81}$$

The adoption lag

$$\dot{D}_t = 1 - \left[\frac{\Psi_t}{\overline{\Psi}}\right] e^{\chi(\gamma D_t - b)}; \tag{82}$$

and the market value transitional equation

$$\frac{\dot{\Psi}_t}{\Psi_t} = \left\{\alpha \frac{\epsilon - 1}{\epsilon} \frac{Y_t^*}{K_t^*} - \delta + \frac{1}{\mu - 1}\left\{\frac{\dot{A}_t^*}{A_t^*} + \gamma\right\} - \left\{\frac{\dot{Y}_t^*}{Y_t^*} + \frac{\gamma}{1-\alpha}\right\}\right\} - \frac{\alpha}{\epsilon}\frac{1}{\Psi_t}. \tag{83}$$

Steady state equations:

The steady state is defined by the following equations

$$0 = \left(\alpha \frac{\epsilon - 1}{\epsilon} \frac{\overline{Y}^*}{\overline{K}^*} - \delta - \rho\right) - \frac{\gamma}{1-\alpha}; \tag{84}$$

The resource constraint

$$\overline{Y}^* = \overline{C}^* + \overline{I}^* + \overline{\Gamma}^*; \tag{85}$$

The capital accumulation equation

$$0 = -\frac{\gamma}{1-\alpha} - \delta + \frac{\overline{I}^*}{\overline{K}^*}; \tag{86}$$

The production function

$$\overline{Y}^* = \overline{A}^* \left(\overline{K}^*\right)^{\alpha}; \tag{87}$$

The trend adjusted productivity level

$$\overline{A}^* = e^{-\gamma \overline{D}}; \tag{88}$$

The aggregate adoption cost

$$\overline{\Gamma}^* = \overline{\Psi}\left(\frac{\gamma}{\mu - 1}\right)\overline{Y}^*; \tag{89}$$

The steady state adoption lag, assuming that $b \geq 0$, equals

$$\overline{D} = \frac{b}{\gamma}; \tag{90}$$

and the market value transitional equation

$$0 = \left\{\alpha \frac{\epsilon - 1}{\epsilon} \frac{\overline{Y}^*}{\overline{K}^*} - \delta + \frac{\gamma}{\mu - 1} - \frac{\gamma}{1-\alpha}\right\} - \frac{\alpha}{\epsilon}\frac{1}{\overline{\Psi}}; \tag{91}$$

Steady state solution:

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

$$0 = \left\{ \rho + \frac{\gamma}{\mu - 1} \right\} - \frac{\alpha}{\epsilon} \frac{1}{\overline{\Psi}}, \tag{92}$$

such that the steady state market cap to GDP ratio equals

$$\overline{\Psi} = \frac{\alpha}{\epsilon} \frac{1}{\left\{ \rho + \frac{\gamma}{\mu - 1} \right\}}. \tag{93}$$

The steady state trend adjusted level of productivity equals

$$\overline{A}^* = e^{-b}. \tag{94}$$

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

$$0 = \left(\alpha \frac{\epsilon - 1}{\epsilon} \overline{A}^* \left(\frac{1}{\overline{K}^*} \right)^{1-\alpha} - \delta - \rho \right) - \frac{\gamma}{1 - \alpha}, \tag{95}$$

which allows us to solve for the steady state capital stock

$$\overline{K}^* = \left[\frac{\alpha \frac{\epsilon - 1}{\epsilon} \overline{A}^*}{\rho + \delta + \frac{\gamma}{1-\alpha}} \right]^{\frac{1}{1-\alpha}}, \tag{96}$$

such that

$$\overline{I}^* = \left[\frac{\gamma}{1 - \alpha} + \delta \right] \overline{K}^*, \tag{97}$$

and output equals

$$\overline{Y}^* = \overline{A}^* \left(\overline{K}^* \right)^{\alpha} = e^{-\frac{b}{(1-\alpha)}} \left[\frac{\alpha \frac{\epsilon - 1}{\epsilon}}{\rho + \delta + \frac{\gamma}{1-\alpha}} \right]^{\frac{1}{1-\alpha}}, \tag{98}$$

while the aggregate adoption cost is

$$\overline{\Gamma}^* = \overline{\Psi} \left(\frac{\gamma}{\mu - 1} \right) \overline{Y}^*, \tag{99}$$

and steady state consumption equals

$$\overline{C}^* = \overline{Y}^* - \overline{I}^* - \overline{\Gamma}^*. \tag{100}$$

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

Transitional dynamics:

The next thing is to linearize the transitional dynamics around the steady state. Note that this model has only one state variable, namely the capital stock K_t. The stock market capitalization to GDP ratio, V_t, is a jump variable and so are the adoption lag, D_t, the best vintage adopted, $\overline{v}_t$, and the trend adjusted productivity level, A_t^*. Because the experiment we perform in Section 4 includes time-variation in the barrier parameter, b, we also include deviations of b from its steady state value $\overline{b}$ in our log-linearization. The same is true for the spillover parameter χ.

The log-linearized equations are the Euler equation

$$\dot{\widehat{C}}_t^* = \alpha \frac{\epsilon - 1}{\epsilon} \frac{\overline{Y}^*}{\overline{K}^*} \widehat{Y}_t^* - \alpha \frac{\epsilon - 1}{\epsilon} \frac{\overline{Y}^*}{\overline{K}^*} \widehat{K}_t^*; \tag{101}$$

The resource constraint

$$0 = \widehat{Y}_t^* - \frac{\overline{C}^*}{\overline{Y}^*} \widehat{C}_t^* - \frac{\overline{I}^*}{\overline{Y}^*} \widehat{I}_t^* - \frac{\overline{\Gamma}^*}{\overline{Y}^*} \widehat{\Gamma}_t^*; \tag{102}$$

The capital accumulation equation

$$\dot{\widehat{K}}_t^* = \frac{\overline{I}^*}{\overline{K}^*} \widehat{I}_t^* - \frac{\overline{I}^*}{\overline{K}^*} \widehat{K}_t^*; \tag{103}$$

The production function

$$0 = \widehat{Y}_t^* - \widehat{A}_t^* - \alpha \widehat{K}_t^*; \tag{104}$$

The trend adjusted productivity level

$$0 = \widehat{A}_t^* + \gamma \left(D_t - \overline{D} \right); \tag{105}$$

The adoption lag equation

$$\dot{D}_t = \overline{\chi} \left(b - \overline{b} \right) - \widehat{\Psi}_t - \overline{\chi} \gamma \left(D_t - \overline{D} \right) - \gamma \overline{D} \left(\chi - \overline{\chi} \right); \tag{106}$$

The aggregate adoption cost

$$0 = \widehat{\Gamma}_t^* - \widehat{\Psi}_t - \widehat{Y}_t^*, \tag{107}$$

and the market capitalization equation

$$\dot{\widehat{\Psi}}_t - \gamma \left(\frac{\mu - 2}{\mu - 1} \right) \dot{D}_t + \alpha \dot{\widehat{K}}_t^* = \alpha \frac{\epsilon - 1}{\epsilon} \frac{\overline{Y}^*}{\overline{K}^*} \widehat{Y}_t^* - \alpha \frac{\epsilon - 1}{\epsilon} \frac{\overline{Y}^*}{\overline{K}^*} \widehat{K}_t^* + \frac{\alpha}{\epsilon} \frac{1}{\overline{\Psi}} \widehat{\Psi}_t, \tag{108}$$

Finally, we assume that

$$\dot{b} = -\xi \left(b - \overline{b} \right), \tag{109}$$

where $\xi > 0$ is the rate of convergence of the barriers parameter to its steady state.

Calibration of χ:

Our model implies that

$$a_t = a_0 + \gamma (t - D_t). \tag{110}$$

Taking time-derivatives of this equation yields that

$$\dot{a}_t = \gamma - \gamma D_t. \tag{111}$$

Given (17) and (20) this can be written as

$$\dot{a}_t = \gamma \left[\frac{\Psi_t}{\overline{\Psi}} \right] e^{-\chi b} \left(\frac{A_t}{A_t^*} \right)^{\chi}, \tag{112}$$

where $A_t^* = A_t \exp(\gamma t)$ is the world technology frontier. In this case χ corresponds to the parameter s in Benhabib and Spiegel's (2006) general specification.

Log-linearization of a_n:

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

$$A_n = Z_{\underline{v}} \left[\left(\frac{\mu - 1}{\gamma} \right) \left(e^{\frac{\gamma}{\mu - 1}(t - D - \underline{v})} - 1 \right) \right]^{\mu - 1}. \tag{113}$$

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

For this reason, we consider

$$\lim_{\gamma \downarrow 0} Z_{\underline{v}} \left[\left(\frac{\mu - 1}{\gamma} \right) \left(e^{\frac{\gamma}{\mu - 1}(t - D - \underline{v})} - 1 \right) \right]^{\mu - 1}, \tag{114}$$

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

$$Z_{\underline{v}} \left[\lim_{\gamma \downarrow 0} \left(\frac{\mu - 1}{\gamma} \right) \left(e^{\frac{\gamma}{\mu - 1}(t - D - \underline{v})} - 1 \right) \right]^{\mu - 1} = Z_{\underline{v}} (t - D - \underline{v})^{(\mu - 1)}. \tag{115}$$

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

$$\begin{aligned}
A_n &\approx Z_{\underline{v}} \left(t - D - \underline{v}\right)^{(\mu-1)} + \\
&\quad + Z_{\underline{v}} \left(t - D - \underline{v}\right)^{(\mu-2)} \gamma \times \\
&\quad \left[\lim_{\gamma_\tau \downarrow 0} \left(\left(\frac{\mu - 1}{\gamma} \right) \left(t - D - \underline{v}\right) e^{\frac{\gamma}{\mu-1}(t-D-\underline{v})} - \left(\frac{\mu - 1}{\gamma} \right)^2 \left(e^{\frac{\gamma}{\mu-1}(t-D-\underline{v})} - 1 \right) \right) \right] \\
&= Z_{\underline{v}} \left(t - D - \underline{v}\right)^{(\mu-1)} + \\
&\quad + Z_{\underline{v}} \left[\lim_{\gamma \downarrow 0} \left(\frac{\mu - 1}{\gamma} \right)^2 \left(\left(\frac{\gamma}{\mu - 1} \left(t - D - \underline{v}\right) - 1 \right) e^{\frac{\gamma}{\mu-1}(t-D-\underline{v})} + 1 \right) \right] \left(t - D - \underline{v}\right)^{(\mu-2)} \gamma \\
&= Z_{\underline{v}_\tau} \left(t - T_\tau\right)^{(\mu-1)} \\
&\quad + Z_{\underline{v}} \left[\lim_{\gamma_\tau \downarrow 0} \left(\mu - 1\right)^2 \frac{\frac{\gamma}{(\mu-1)^2} \left(t - D - \underline{v}\right)^2 e^{-\frac{\gamma}{\mu-1}(t-D-\underline{v})}}{2\gamma} \right] \left(t - D - \underline{v}\right)^{(\mu-2)} \gamma \\
&= Z_{\underline{v}} \left(t - D - \underline{v}\right)^{(\mu-1)} + \frac{1}{2} Z_{\underline{v}} \left(t - D - \underline{v}\right)^{\mu} \gamma \\
&= Z_{\underline{v}} \left(t - D - \underline{v}\right)^{(\mu-1)} \left[1 + \frac{1}{2} \left(t - D - \underline{v}\right) \gamma \right].
\end{aligned} \tag{116}$$

Hence, for γ close to zero, we can use the log-linear approximation

$$a_n \approx z_{\underline{v}} + (\mu - 1) \ln \left(t - D - \underline{v}\right) + \frac{\gamma}{2} \left(t - D - \underline{v}\right). \tag{117}$$

Change in D:

However, our aim is to estimate how D changes in response to the technical assistance provided by the U.S. after WWII. For this purpose, we allow for the following time-varying path of D.

$$D_t = \begin{cases} D^* = D - \Delta D & \text{for} \quad t < 1939 \\ D & \text{for} \quad t > 1945 \end{cases},$$

where we are agnostic about the path of D during WWII because we do not using data from the warperiod for our empirical analysis. This is the approximation that underlies (25) in the main text.

Microfoundation for capital adjustment costs:

The capital goods of technology τ are all produced by perfectly competitive producers. The individual producers of the vintages then buy the technology-specific capital goods and modify them to the vintage-specific specification.

The Lagrangian associated with the dynamic profit maximization problem of the supplier of capital goods for technology τ at time t equals

$$\mathcal{L}_\tau = \int_t^\infty e^{-\int_t^s \tilde{r}_{s'} ds'} H_\tau ds, \tag{118}$$

where H_τ is the current value Hamiltonian. We will drop the time subscript s in what follows. Here

$$\begin{aligned} H_\tau &= \left(\tilde{R}_\tau K_\tau - I_\tau\right) + \\ &\quad \lambda_\tau \left(I_\tau \left(1 - \xi\left(I_\tau/K_\tau\right)\right) - \delta K_\tau\right). \end{aligned} \tag{119}$$

Here λ_τ is the co-state variable associated with the demand function that the capital goods supplier faces and ν_v is the co-state variable associated with the capital accumulation equation.

The resulting optimality conditions read

$$\begin{aligned} \text{w.r.t. } I_\tau\text{:} \quad & \lambda_\tau \left(1 - \tfrac{I_\tau}{K_\tau}\xi'\left(I_\tau/K_\tau\right) - \xi\left(I_\tau/K_\tau\right)\right) = 1. \\ \text{w.r.t. } K_\tau\text{:} \quad & \tilde{R}_\tau = \left(\tilde{r} + \delta - \left(\tfrac{I_\tau}{K_\tau}\right)^2 \xi'\left(I_\tau/K_\tau\right)\right)\lambda_\tau - \dot{\lambda}_\tau. \end{aligned} \tag{120}$$

The first optimality condition yields that

$$\lambda_\tau = \frac{1}{1 - \frac{I_\tau}{K_\tau}\xi'\left(I_\tau/K_\tau\right) - \xi\left(I_\tau/K_\tau\right)}. \tag{121}$$

Taking time derivatives:

$$\dot{\lambda}_\tau = \left(\frac{\dot{I}_\tau}{I_\tau} - \frac{\dot{K}_\tau}{K_\tau}\right)\frac{I_\tau}{K_\tau}\frac{\xi''\left(I_\tau/K_\tau\right)\frac{I_\tau}{K_\tau} + 2\xi'\left(I_\tau/K_\tau\right)}{1 - \frac{I_\tau}{K_\tau}\xi'\left(I_\tau/K_\tau\right) - \xi\left(I_\tau/K_\tau\right)}\lambda_\tau \tag{122}$$

Substituting into the FOC w.r.t K_τ, it follows that:

$$\tilde{R}_\tau = UC_\tau \tag{123}$$

where the user cost term is given by

$$\begin{aligned} UC_\tau &= \left(\tilde{r} + \delta - \left(\frac{I_\tau}{K_\tau}\right)^2 \xi'\left(I_\tau/K_\tau\right) - \left(\frac{\dot{I}_\tau}{I_\tau} - \frac{\dot{K}_\tau}{K_\tau}\right)\frac{I_\tau}{K_\tau}\frac{\xi''\left(I_\tau/K_\tau\right)\frac{I_\tau}{K_\tau} + 2\xi'\left(I_\tau/K_\tau\right)}{1 - \frac{I_\tau}{K_\tau}\xi'\left(I_\tau/K_\tau\right) - \xi\left(I_\tau/K_\tau\right)}\right) \times \\ &\quad \left(1 - \frac{I_\tau}{K_\tau}\xi'\left(I_\tau/K_\tau\right) - \xi\left(I_\tau/K_\tau\right)\right)^{-1}. \end{aligned} \tag{124}$$

The problem of the monopolistic producers of the v capital good supplier of technology τ is then to

$$\max_{R_{\tau v}}(R_{\tau v}-\tilde{R}_{\tau})YZ_{v}^{\frac{1}{\mu-1}}\left(\frac{1-\alpha}{W}\right)^{\frac{1-\alpha}{\mu-1}}\left(\frac{\alpha}{R_{\tau v}}\right)^{\epsilon} \tag{125}$$

which yields the standard solution

$$R_{\tau v}=\frac{\epsilon}{\epsilon-1}\tilde{R}_{\tau}=R_{\tau}. \tag{126}$$

Functional form for adjustment costs: For the adjustment costs, we consider the following standard quadratic functional form

$$\xi\left(I_{\tau}/K_{\tau}\right)=\frac{\xi}{2}\left(\frac{I_{\tau}}{K_{\tau}}-\delta\right)^{2}. \tag{127}$$

This yields that the marginal adjustment cost, in terms of I/K net of depreciation, is given by

$$\xi'\left(I_{\tau}/K_{\tau}\right)=\xi\left(\frac{I_{\tau}}{K_{\tau}}-\delta\right)=2\frac{\xi\left(I_{\tau}/K_{\tau}\right)}{\frac{I_{\tau}}{K_{\tau}}-\delta}, \tag{128}$$

while the second-order derivative is given by

$$\xi''\left(I_{\tau}/K_{\tau}\right)=\xi. \tag{129}$$

Log-linearization: We log-linearize the expression for the rental cost around the steady state $\overline{I_{\tau}/K_{\tau}}=\delta$. The expression we log-linearize is

$$\begin{aligned} r_{\tau} &= \ln\left(\frac{\epsilon}{\epsilon-1}\right)-\ln\left(1-\frac{I_{\tau}}{K_{\tau}}\xi'\left(I_{\tau}/K_{\tau}\right)-\xi\left(I_{\tau}/K_{\tau}\right)\right) \\ &\quad +\ln\left(\tilde{r}+\delta-\left(\frac{I_{\tau}}{K_{\tau}}\right)^{2}\xi'\left(I_{\tau}/K_{\tau}\right)-\left(\frac{\dot{I}_{\tau}}{I_{\tau}}-\frac{\dot{K}_{\tau}}{K_{\tau}}\right)\frac{I_{\tau}}{K_{\tau}}\frac{\xi''\left(I_{\tau}/K_{\tau}\right)\frac{I_{\tau}}{K_{\tau}}+2\xi'\left(I_{\tau}/K_{\tau}\right)}{1-\frac{I_{\tau}}{K_{\tau}}\xi'\left(I_{\tau}/K_{\tau}\right)-\xi\left(I_{\tau}/K_{\tau}\right)}\right). \end{aligned} \tag{130}$$

Log-linearization yields that

$$\begin{aligned} r_{\tau} &\approx \ln\left(\frac{\epsilon}{\epsilon-1}\right)+\ln\left(\overline{r}+\delta\right)-\delta^{2}\xi \\ &\quad +\frac{1}{\overline{r}+\delta}\left(r-\overline{r}\right)+\delta\xi\frac{I_{\tau}}{K_{\tau}}. \end{aligned} \tag{131}$$

Hence, this specification adds the investment to capital ratio to the reduced form equation for the log-linearized rental rate. We will return to the term $(r-\overline{r})$ later.

Log-linearization of the interest rate:

Part of the issue is that, along the transition path, difference between the interest rate and the steady state

interest rate is not constant. Hence, we need to figure out a proxy for

$$(r - \overline{r})\,. \tag{132}$$

This can be done by using the consumption Euler equation, which, for the CRRA preferences that we use, implies that the growth rate of consumption equals the difference between the interest rate and the intertemporal elasticity of subsitution, σ. Note that in the main text, we assumed log-preferences such that $\sigma = 1$.

This means that

$$r - \overline{r} = \frac{\dot{C}}{C} + \sigma - \overline{r}. \tag{133}$$

Hence, the off-steady-state interest rate path term means that the growth rate of consumption is another righthand-side variable.

Derivation of reduced form equation, (25):

Substituting (117), (131), (133), and the between sector elasticity parameter, θ, into (23) and (24) we obtain

$$\begin{aligned} y_\tau &= y + \frac{\theta}{\theta - 1}\left[a_\tau - (1-\alpha)(y-l) - \alpha r_\tau - \alpha \ln \alpha\right] \\ &= y - \frac{\alpha\theta}{\theta - 1}\ln\alpha + \frac{\theta}{\theta - 1}\left[a_\tau - (1-\alpha)(y-l)\right] - \frac{\alpha\theta}{\theta - 1} r_\tau, \end{aligned} \tag{134}$$

and

$$\begin{aligned} k_\tau &= y + \ln\alpha + \frac{1}{\theta - 1}\left[a_\tau - (1-\alpha)(y-l) - \alpha r_\tau - \alpha \ln \alpha\right] - r_\tau \\ &= y + \left[1 - \frac{\alpha}{\theta - 1}\right]\ln\alpha - \frac{1}{\theta - 1}\left[a_\tau - (1-\alpha)(y-l)\right] - \left[1 + \frac{\alpha}{\theta - 1}\right] r_\tau. \end{aligned} \tag{135}$$

For the equation for the output-based measures, y_τ, we get

$$\begin{aligned} y_\tau &= \beta_0 + y + \beta_1\left[(\mu - 1)\ln(t - D - \underline{v}) - (1-\alpha)(y-l)\right] + \\ &\quad \beta_2\left[(t - D - \underline{v}) - \frac{(t - 1945)}{(t - D - \underline{v})}(D^* - D)\right] + \beta_3\frac{\dot{C}}{C} + \beta_4\frac{I_\tau}{K_\tau}. \end{aligned}$$

Here

$$\begin{aligned}
\beta_0 &= -\frac{\alpha\theta}{\theta-1}\ln\alpha + \frac{\theta}{\theta-1}z_{\underline{v}} \qquad (136)\\
&\quad -\frac{\alpha\theta}{\theta-1}\left[\ln\left(\frac{\epsilon}{\epsilon-1}\right) + \ln\left(\overline{r}+\delta\right) - \delta^2\xi + \frac{\sigma-\overline{r}}{\overline{r}+\delta}\right],\\
\beta_1 &= \frac{\theta}{\theta-1}, \qquad (137)\\
\beta_2 &= \frac{\theta}{\theta-1}\frac{\gamma}{2}, \qquad (138)\\
\beta_3 &= -\frac{\alpha\theta}{\theta-1}\frac{1}{\overline{r}+\delta}, \text{ and} \qquad (139)\\
\beta_4 &= -\frac{\alpha\theta}{\theta-1}\delta\xi. \qquad (140)
\end{aligned}$$

Using the discrete time approximation that $\Delta c_t \approx \frac{\dot{C}}{C}$ yields the reduced form equation, (25), presented in the main text.

Similarly, for the equation for the capital-based measures, k_τ, we get

$$\begin{aligned}
k_\tau &= \beta_0 + y + \beta_1\left[(\mu-1)\ln\left(t-D-\underline{v}\right) - (1-\alpha)\left(y-l\right)\right] + \qquad (141)\\
&\quad \beta_2\left[\left(t-D-\underline{v}\right) - \frac{(t-1945)}{\left(t-D-\underline{v}\right)}\left(D^*-D\right)\right] + \beta_3\frac{\dot{C}}{C} + \beta_4\frac{I_\tau}{K_\tau}. \qquad (142)
\end{aligned}$$

In this case

$$\begin{aligned}
\beta_0 &= \left[1-\frac{\alpha}{\theta-1}\right]\ln\alpha + \frac{1}{\theta-1}z_{\underline{v}} \qquad (143)\\
&\quad -\left[1+\frac{\alpha}{\theta-1}\right]\left[\ln\left(\frac{\epsilon}{\epsilon-1}\right) + \ln\left(\overline{r}+\delta\right) - \delta^2\xi + \frac{\sigma-\overline{r}}{\overline{r}+\delta}\right],\\
\beta_1 &= \frac{1}{\theta-1}, \qquad (144)\\
\beta_2 &= \frac{1}{\theta-1}\frac{\gamma}{2}, \qquad (145)\\
\beta_3 &= -\left[1+\frac{\alpha}{\theta-1}\right]\frac{1}{\overline{r}+\delta}, \text{ and} \qquad (146)\\
\beta_4 &= -\left[1+\frac{\alpha}{\theta-1}\right]\delta\xi. \qquad (147)
\end{aligned}$$

Table 1: Technology usage measures.

1. **Aviation - passengers:** Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned. Not a measure of travel through a country's airports (*New*).

2. **Cars:** Number of passenger cars (excluding tractors and similar vehicles) in use. Numbers typically derived from registration and licensing records, meaning that vehicles out of use may occasionally be included. (*New*).

3. **Electricity:** Gross output of electric energy (inclusive of electricity consumed in power stations) in KwHr. (*New*).

4. **Radios:** Number of radios used in country. (*New*).

5. **Railways - freight:** Metric tons of freight carried on railways (excluding livestock and passenger baggage). Freight for servicing of railroads is typically excluded but may be included for some countries. (*Old*).

6. **Railways - passengers:** Passenger journeys by railway in passenger-KM. Free passengers typically excluded but may be included for some countries. (*Old*).

7. **Steam- and motorships:** Tonnage of steam and motor ships (above a minimum weight) in use at midyear. (*Old*).

8. **Telegrams:** Number of telegrams sent in a year. (*Old*).

9. **Telephones:** Number of mainline telephone lines connecting a customer's equipment to the public switched telephone network as of year end. (*New*).

10. **Trucks:** Number of commercial vehicles, typically including buses and taxis (excluding tractors and similar vehicles), in use. Numbers typically derived from) registration and licensing records, meaning that vehicles out of use may occasionally be included. (*New*).

Note: All data taken from CHAT, described in Comin and Hobijn (2009b).

Table 2: U.S. postwar technical assistance for countries in our sample

No	Country	TAP funds	Industrial Trainees
1	Argentina	0	17
2	Australia	0	34
3	Austria	12	40
4	Belgium	4	32
5	Brazil	0	22
6	Canada	0	804*
7	Chile	0	19
8	Colombia	0	12
9	Denmark	9	20
10	Egypt	0	4
11	Finland	0	10
12	France	29	139
13	Germany	28	217
14	Greece	1	5
15	India	0	50
16	Indonesia	0	7
17	Italy	26	63
18	Japan	12	165
19	South Korea	0	11
20	Malaysia	0	0
21	Mexico	0	73
22	Netherlands	11	73
23	New Zealand	0	12
24	Norway	6	13
25	Peru	0	7
26	Philippines	0	16
27	Portugal	0	1
28	South Africa	0	13
29	Singapore	0	0
30	Spain	0	19
31	Sri Lanka	0	0
32	Sweden	0	46
33	Switzerland	0	106
34	Taiwan	0	0
35	Turkey	1	4
36	United Kingdom	9	262
37	United States		
38	Uruguay	0	2
39	Venezuela	0	10

Note: Technical assistance in millions of U.S. Dollars of U.S. funds commited (does not include matching funding from countries). Source: International Cooperation Administration (1958) and Tiratsoo (2000). Industrial trainees is average number of industrial trainees per year over the period 1949-1969 that visited the United States from each country. Source: United States Immigration and Naturalization Service (1949-1969) and authors' calculations. For our empirical analysis, we drop Canada from the industrial trainees sample, because it is an obvious outlier.

Table 3: Catch-up regression with technical assistance.

Dependent variable:	log real GDP per capita (1970)			log real GDP per hour (1970)		
Independent variable						
1950 level	0.924**	0.935**	0.923**	0.701**	0.693**	0.703**
	(0.057)	(0.066)	(0.062)	(0.058)	(0.061)	(0.063)
Technical Assistance	0.018**		0.018**	0.013**		0.015**
	(0.005)		(0.005)	(0.003)		(0.004)
Industrial Trainees		0.002	0.000		0.001	−0.000
		(0.001)	(0.001)		(0.001)	(0.001)
n	39	38	38	27	26	26
R^2	0.89	0.87	0.89	0.86	0.80	0.86

Note: * denotes significance at 5 percent level and ** at 1 percent level. All results standard errors reported are robust standard-errors.

Table 4: Technology usage and technical assistance.

Dependent variable: Log technology usage per capita in 1970	I	II	III	IV	V	VI	VII	VIII	IX
				(a) all technologies					
1950 level	0.871** (0.024)	0.921** (0.023)	0.900** (0.028)	0.880** (0.026)	0.932** (0.024)	0.902** (0.029)	0.873** (0.025)	0.925** (0.024)	0.897** (0.029)
Technical Assistance	0.021** (0.005)	0.015** (0.004)	0.015* (0.007)				0.018** (0.006)	0.011 (0.004)	0.011 (0.009)
Industrial Trainees				0.002** (0.001)	0.001** (0.001)	0.002 (0.001)	0.000 (0.000)	0.001 (0.001)	0.001 (0.001)
Real GDP growth		0.883** (0.125)	0.879** (0.191)		0.943** (0.124)	0.921** (0.187)		0.895** (0.126)	0.881** (0.192)
Country random effects			Yes			Yes			Yes
p-value F for insignificance TAP							0.000	0.005	0.081
n	303	303	303	294	294	294	294	294	294
R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
				(b) new technologies					
1950 level	0.814** (0.029)	0.871** (0.029)	0.733** (0.038)	0.819** (0.032)	0.882** (0.030)	0.734** (0.039)	0.811** (0.031)	0.873** (0.030)	0.728** (0.039)
Technical Assistance	0.026** (0.006)	0.020** (0.006)	0.025** (0.009)				0.023** (0.008)	0.014* (0.007)	0.019 (0.011)
Industrial Trainees				0.002** (0.001)	0.002** (0.001)	0.003** (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)
Real GDP growth		0.928** (0.164)	0.663** (0.242)		1.015** (0.164)	0.744** (0.245)		0.947** (0.166)	0.673** (0.246)
Country random effects			Yes			Yes			Yes
p-value F for insignificance TAP							0.000	0.002	0.007
n	172	172	172	167	167	167	167	167	167
R^2	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
				(c) old technologies					
1950 level	0.963** (0.040)	1.000** (0.039)	1.014** (0.041)	0.974** (0.042)	1.011** (0.040)	1.016** (0.042)	0.968** (0.041)	1.006** (0.040)	1.014** (0.042)
Technical Assistance	0.014* (0.007)	0.009 (0.007)	0.007 (0.008)				0.013 (0.009)	0.007 (0.008)	0.006 (0.011)
Industrial Trainees				0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Real GDP growth		0.805** (0.187)	0.847** (0.235)		0.837** (0.184)	0.864** (0.228)		0.811** (0.187)	0.845** (0.235)
Country random effects			Yes			Yes			Yes
p-value F for insignificance TAP							0.168	0.526	0.744
n	131	131	131	127	127	127	127	127	127
R^2	0.96	0.97	0.97	0.98	0.98	0.97	0.98	0.98	0.97

Note: * denotes significance at 5 percent level and ** at 1 percent level. All results standard errors reported are robust standard-errors and all estimates include technology fixed effects.

Table 5: Model parameters

parameter	interpretation	value	
α	Output elasticity of capital	0.300	
ρ	Discount rate	0.050	
δ	Capital depreciation rate	0.060	
γ	Exogenous growth rate of WTF	0.014	
μ	CES parameter	1.300	
χ	Absorption parameter in adjustment cost	3.6	
ξ	Rate of convergence of barriers parameter	0.060	
b	Barriers parameter	pre-WWII	post-WWII
	"United States" (balanced growth)	0	0
	"Japan"	0.70	0.22

Table 6: Summary statistics: postwar reduction in adoption lags.

Technology	New/Old	Mean	Standard Deviation	N obs	N countries
Cars	New	-3.02	12.96	298	33
Trucks	New	-5.43	8.95	273	33
Telephones	New	-5.28	7.5	225	31
Steam and Motor Ships	Old	13.68	22.4	260	30
Radios	New	-28	15	96	21
Electricity	New	15.61	16.05	147	32
Rail Freight	Old	-4.22	14.96	195	32
Rail Passengers	Old	-36	27.27	276	29
Telegraphs	Old	3.56	22.51	207	36
Aviation	New	28.96	9.73	130	25
All New	-	1.9	16.39	1169	36
All Old	-	-6.9	30.12	938	36
Total	-	-2.03	23.91	2107	36

Table 7: Exploratory first-stage-type regressions.

Dependent variable: Postwar Reduction in Adoption lags	I	II	III	IV
Independent variable				
Technology Assistance	0.384^{**} (0.087)			
Technical Assistance * Old technology	-0.669^{*} (0.287)		-0.746^{**} (0.291)	
Industrial Trainees		0.053^{**} (0.018)		
Industrial Trainees * Old technology		-0.121^{**} (0.000)		-0.137^{**} (0.026)
Country Fixed Effects			Yes	Yes
n	2107	2047	2107	2047
R^2	0.49	0.49	0.05	0.07

Note: * denotes significance at 5 percent level and ** at 1 percent level. All regressions include a full set of technology dummies. Standard errors reported are robust and clustered at the country level.

Table 8: First-stage regression.

Dependent variable:	Reduction adoption lag new technologies			Reduction adoption lag old technologies		
Independent variable	I	II	III	IV	V	VI
Log real GDP per capita in 1950	1.4	1.328	1.29	4.087*	4.67**	4.578**
	(0.76)	(0.83)	(0.835)	(1.55)	(1.60)	(1.58)
Technical Assistance	0.201**		0.194**	−0.204		−0.175
	(0.063)		(0.059)	(0.11)		(0.102)
Industrial Trainees		0.025	0.002		−0.04**	−0.011*
		(0.013)	(0.002)		(0.014)	(0.005)
n	36	35	36	36	35	36
R^2	0.26	0.24	0.26	0.21	0.29	0.25

Note: * denotes significance at 5 percent level and ** at 1 percent level. All standard errors are robust.

Table 9: Second-stage regression.

Dependent variable: Log real GDP per capita in 1970	I	II	III
Independent variable			
Log real GDP per capita in 1950	0.766** (0.08)	1.02** (0.11)	0.656** (0.105)
Reduction lags NEW technologies	0.096** (0.021)		0.116** (0.03)
Reduction lags OLD technologies		−0.022 (0.026)	0.02 (0.023)
Instruments	Technical Assistance	Industrial Trainees	Tech. Assistance and Industrial Trainees
n	36	36	36
R^2	0.77	0.82	0.69

Note: * denotes significance at 5 percent level and ** at 1 percent level. All standard errors are robust.

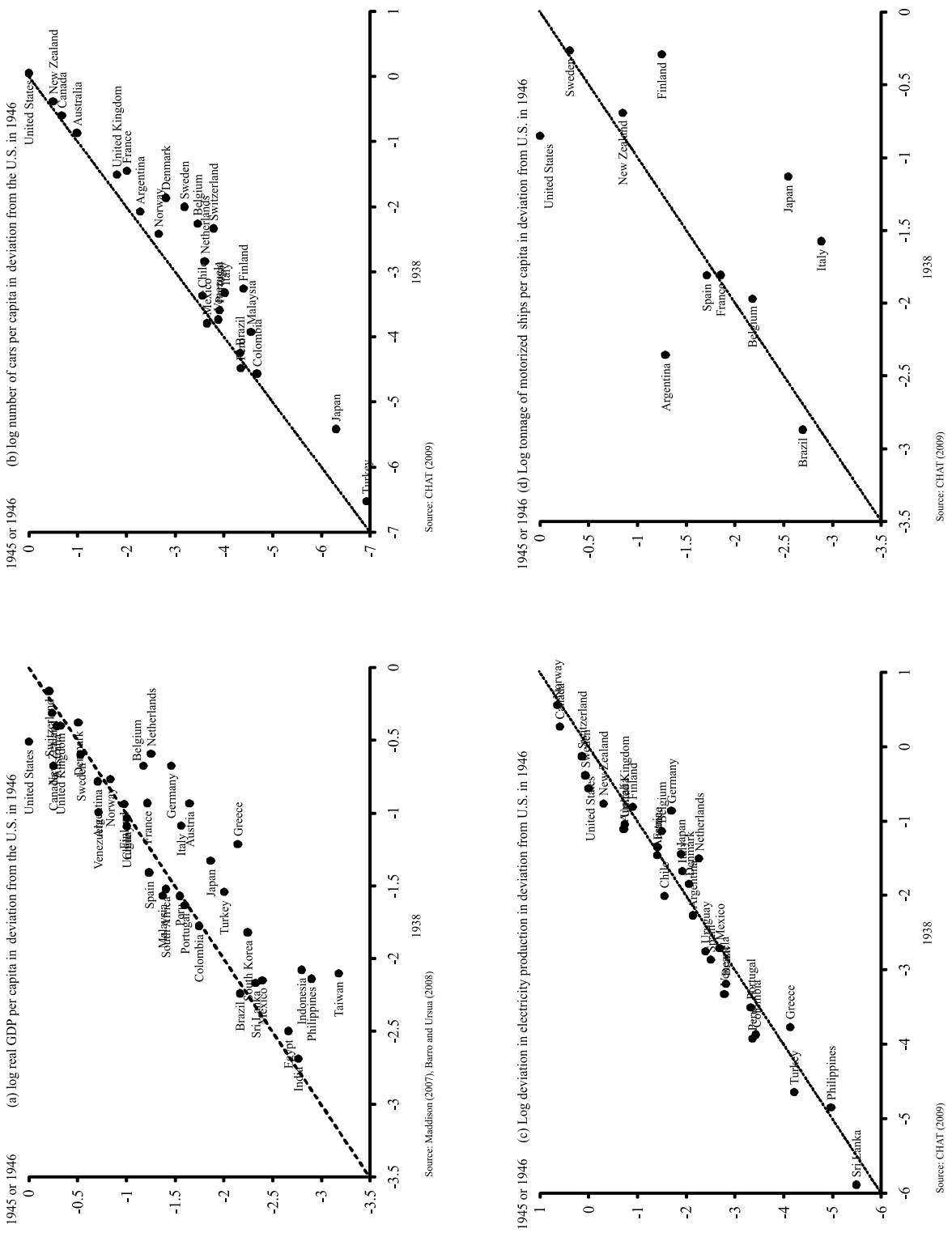


Figure 1: Changes in real GDP and technology usage per capita during WWII period.

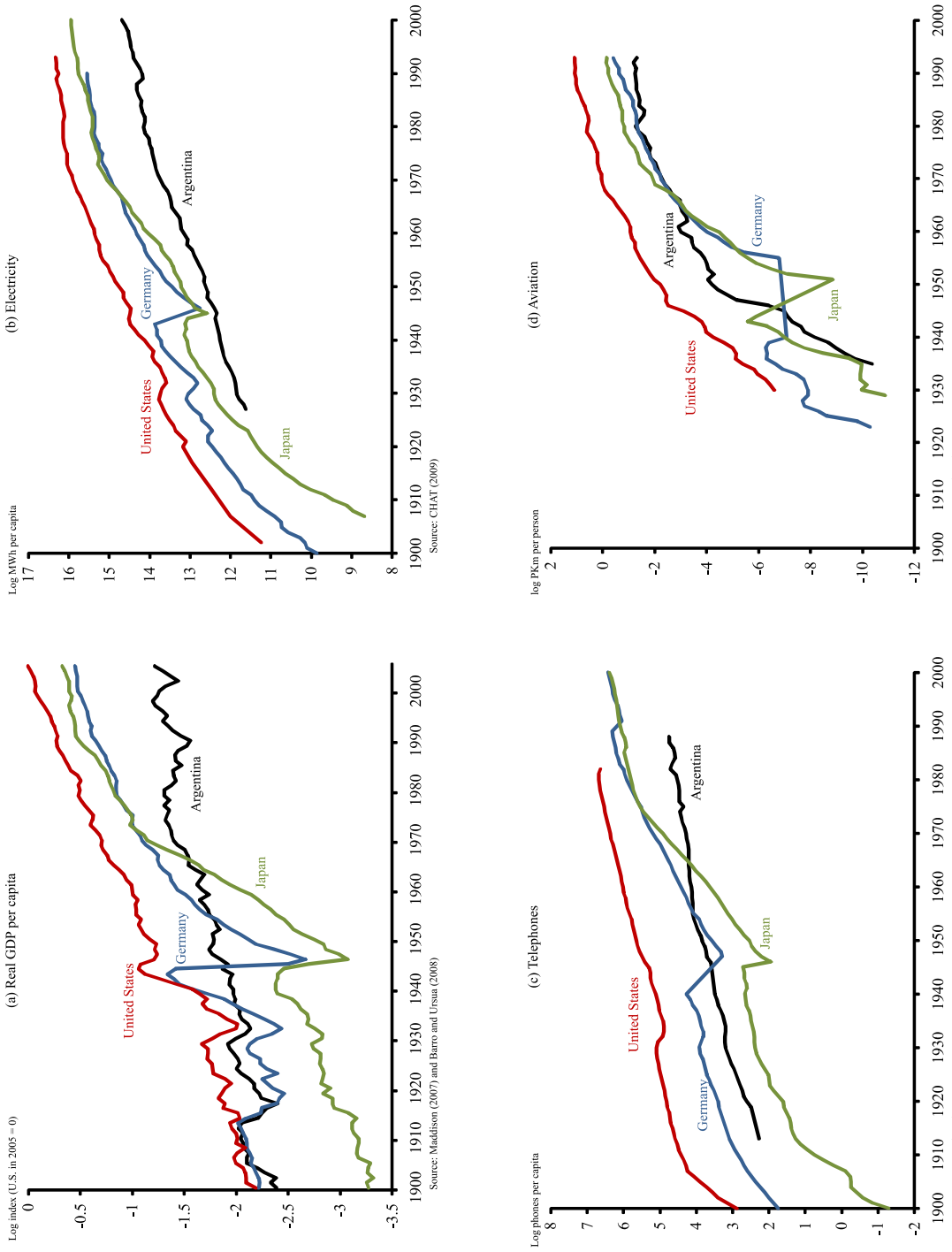
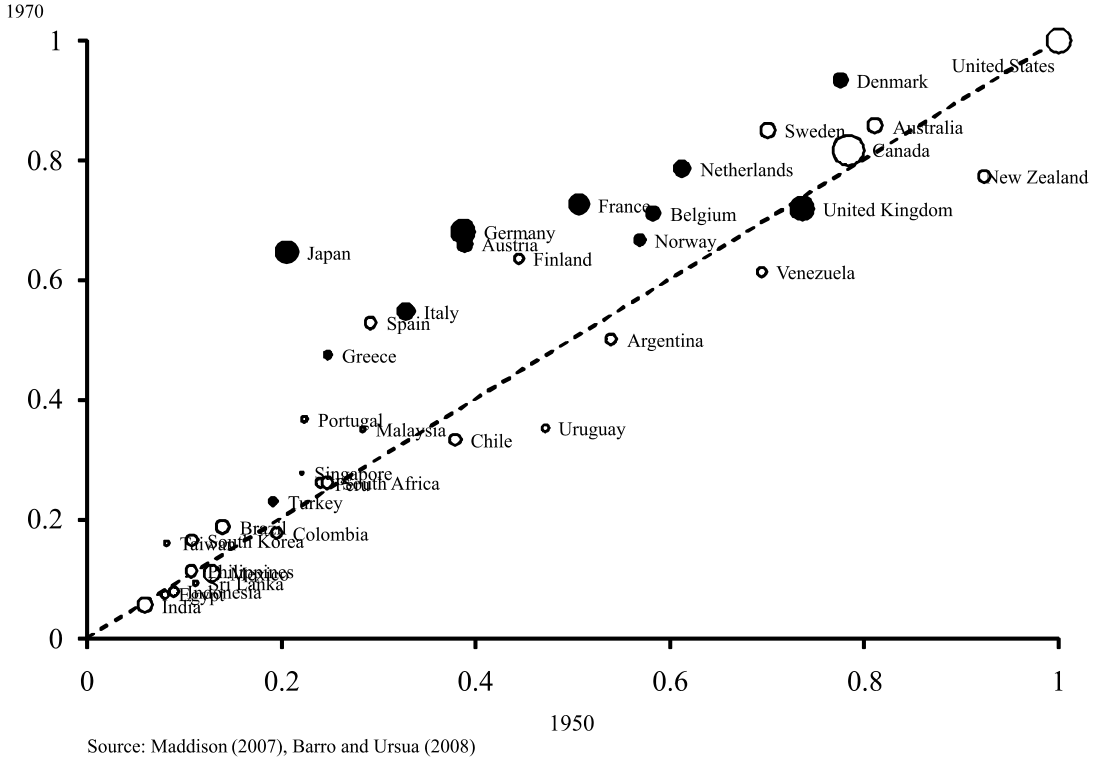


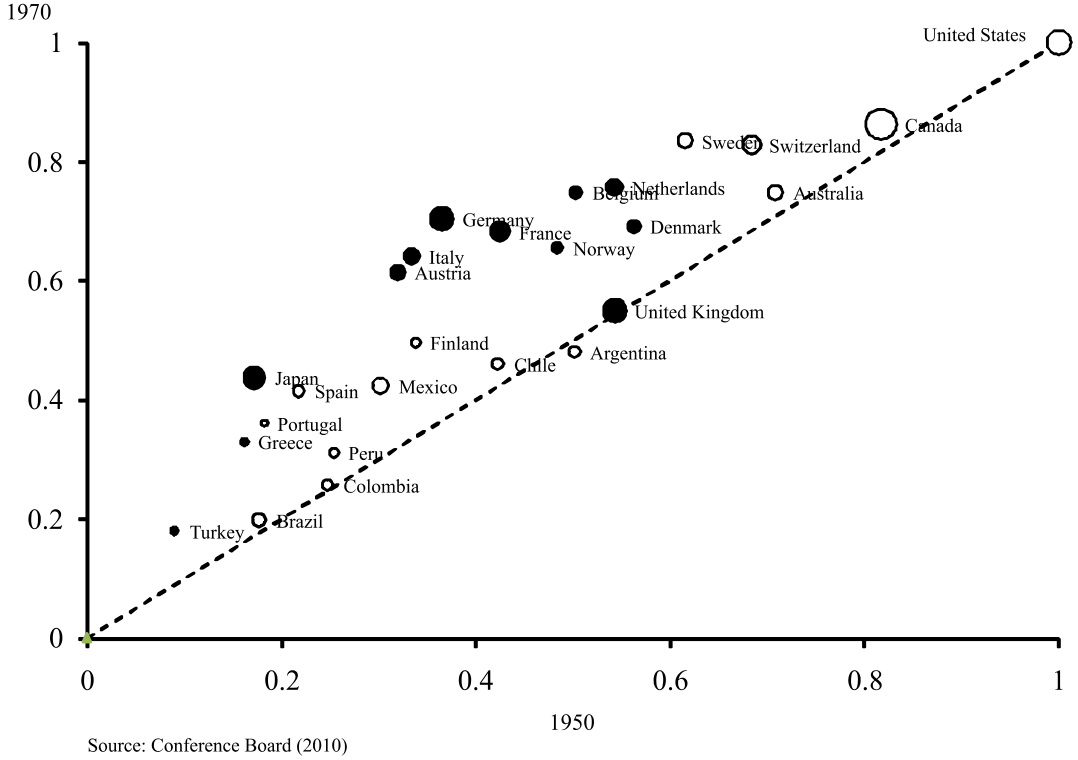
Figure 2: Real GDP and technology usage per capita for four countries

(a) Real GDP per capita, index (US=1)



Source: Maddison (2007), Barro and Ursua (2008)

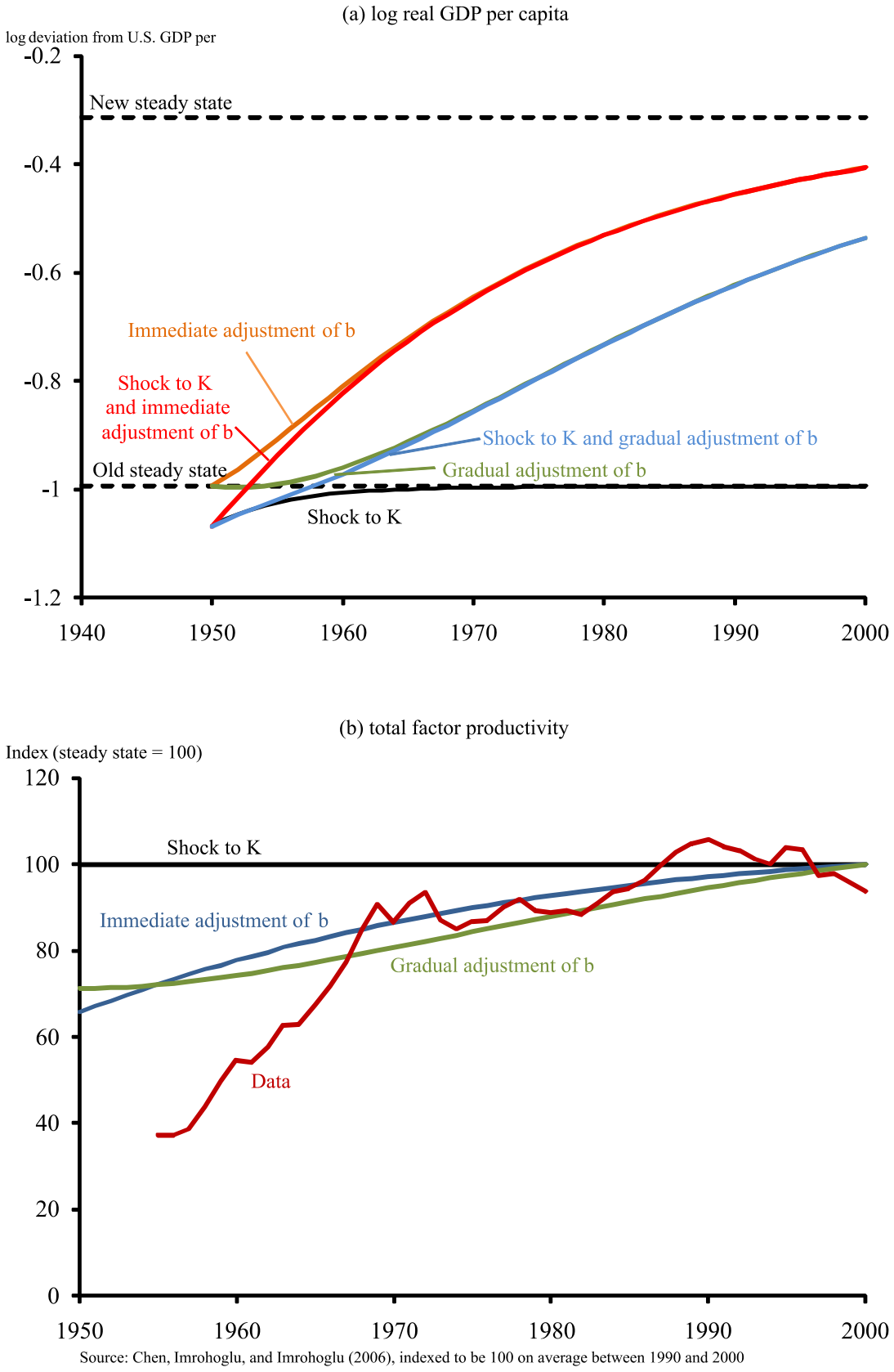
(b) Real GDP per hour, index (US=1)



Source: Conference Board (2010)

Note: Black dots are countries that received TAP funds and size of dots reflects number of industrial trainees.

Figure 3: Postwar catch-up in real GDP per capita and per hour



Source: Chen, Imrohoglu, and Imrohoglu (2006), indexed to be 100 on average between 1990 and 2000

Figure 4: Paths of GDP and TFP under different scenarios.

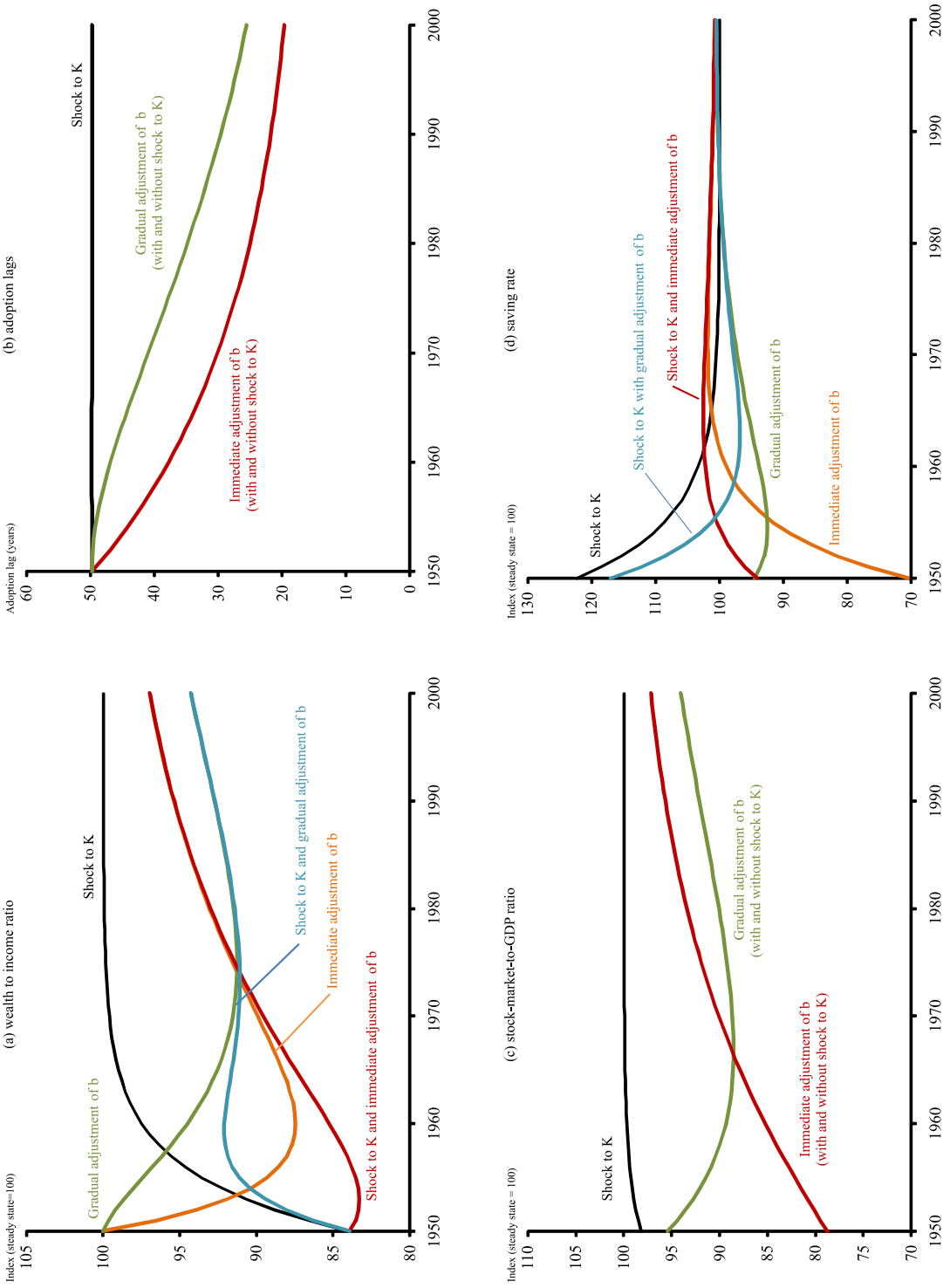


Figure 5: Impulse responses of model economy under different scenarios.

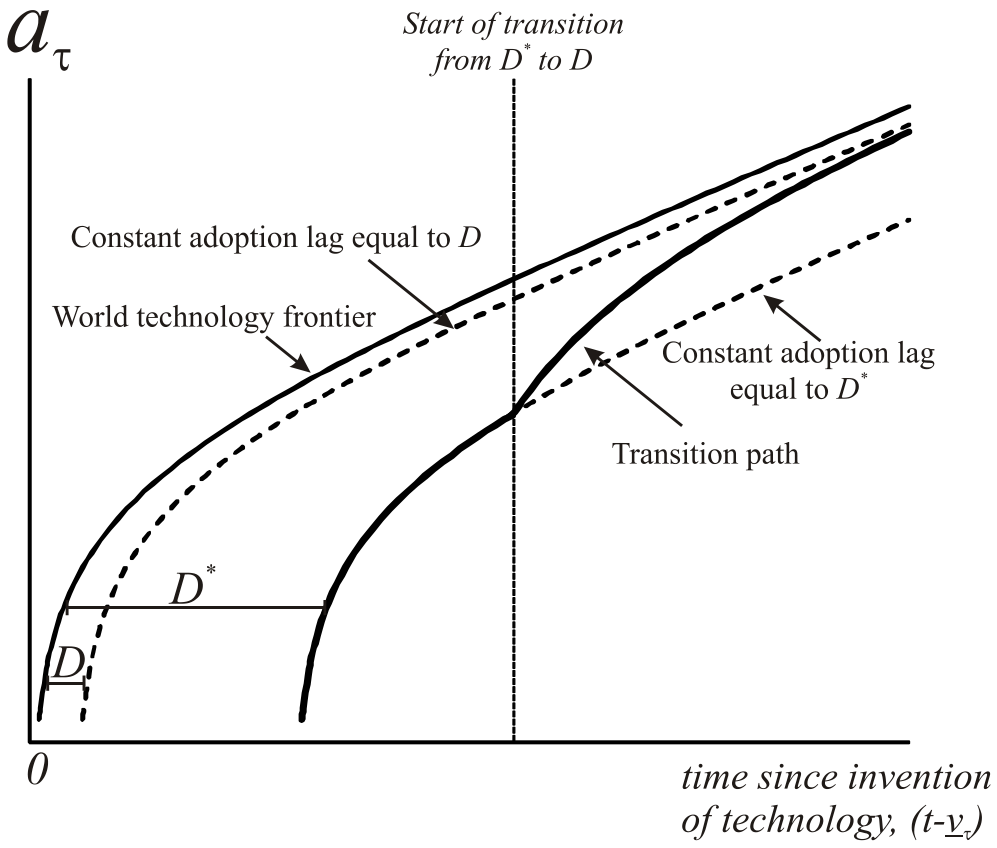


Figure 6: Path of technology-specific TFP under different scenarios.