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THE EFFECT OF FOREIGN AND DOMESCTIC PATENTS ON TOTAL FACTOR PRODUCTIVITY DURING THE SECOND HALF OF THE 20TH CENTURY

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Abstract

This paper analyses the relationship between total factor productivity (TFP) and innovation-related variables during the second half of the 20th century. We perform this analysis for several European countries (France, Germany, the United Kingdom, and Spain) and the U.S., extending Coe and Helpman's (1995) empirical specification to include human capital. We use a new dataset of patents data for the past 150 years to calculate the stock of knowledge using the perpetual inventory method. Our time series empirical analysis confirms the heterogeneous relationship between innovation variables (domestic stock of knowledge, imports of knowledge, and human capital) and productivity. Our results reveal the extent to which observed differences in technology adoption patterns and the levels of endowment of such resources can explain differences in TFP dynamics across countries. The estimated coefficients confirm the considerable gap that still exists between the European countries and the U.S. in innovation-related variables. Furthermore, we obtain a finding that may have important implications for innovation policies: the higher the level of investment in human capital, the higher the level of investment in domestic innovation, and the higher the response of TFP to a 1% increase in any of the aforementioned variables.

1. Introduction

Innovation and technological change are at the heart of long-run productivity growth for many countries. Such change is a dynamic process by definition, whose endogenous nature seems to shift the chances of both leader and follower countries being at the forefront of technological development. Growth for a leader country depends on its capability to push boundaries by generating new ideas, while in follower countries, growth depends on imports of technology from leaders and the capacity to adapt "social capabilities" (factor endowment and institutions) to the requirements of the new technologies (Abramovitz, 1986).

The Western European countries are in the selected group of OECD countries that experienced a successful catch-up process with the U.S. in the two decades after World War II. During this period, the European countries grew at over 4% per annum and the relative GDP of the region recovered to its 1913 level. In particular, the relative GDP climbed from 33% of the U.S. real GDP in the aftermath of the war, to around 70% in the mid-seventies. Most of this growth is attributed to capital deepening and, especially, to TFP growth. Scholars explain the extraordinary increase in TFP as the result of a combination of technology transfers, structural changes from agriculture, economies of scale, and a more efficient utilisation of resources, along with the exceptional conditions in post-war Europe and "social capabilities" that made the arrival of new technologies easier.[1]

[1] These conditions are characterised by a new international order, more favourable to trade liberalisation and cooperation between Europe and the U.S. Trade liberalisation helped speed up technology transfers from the U.S. to Europe, and contributed to reducing Europe's technology gap with the U.S. (Badinger, 2005 and Madsen, 2007). The U.S.'s pre-war advantages, based on its exceptional endowment of natural

At the end of the 19th century, the U.S. became the leader in most of the technologies of the Second Industrial Revolution. America was the pioneer in important organisational innovations such as the Henry Ford assembly belt, in a wide range of new products (motor vehicles, electrical durables, and machinery), and processes arising from the use of oil, electrification and new raw materials. Although some European countries started to experiment with some of these elements before the war, Europe was unable to take full advantage of them because of the economic disruption of the two World Wars and the Great Depression. After WWI and WWII, the new international context and social agreements created an environment that promoted investment, and meant that the massive adoption of these technologies was a driving force behind the rapid catch-up process with the U.S.[2]

Since the oil shock of the late seventies, however, productivity growth rates have declined in Europe, and convergence with the U.S. has ceased. The GDP level of the Western European countries has remained stagnant at 70% of the U.S. GDP level, and has even worsened since 1995. One explanation put forward by many authors is that technology imports contribute less to the growth of the European countries as Europe approaches the technological frontier, especially compared to what happened when

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resources and vast market potential, became less obvious after the war because of trade liberalisation (Nelson and Wright, 1992).

[2] Further, this process was reinforced as Europe took advantage of its "old social capabilities" such as high levels of education, and well-established political and market institutions (Abramovitz, 1986), as well as the "new social capabilities", based on the investment in human capital and R&D, and a favourable environment for investment supported by the new social set-up between firms, state and workers (Eichengreen, 2007). Additionally, Comin and Hobijn (2010) show that countries that were able to catch up most with the U.S. and accelerate the speed of adoption of new technologies were also those receiving more economic aid and technical assistance from America.

Europe was a less-developed region. Thus, as Aghion and Howitt (2006) point out, to stay at the forefront of technological advancement, some areas, such as the resources devoted to investment in high-quality education, require improvement, and the labour and product markets should seek to remove binding rigidities.

Over the last decade, the vast differences between the countries on either side of the Atlantic have been laid bare, in terms of the degree of adoption and development of ICT technologies. The U.S., with remarkably stable growth rates throughout the second half of the last century, has preserved its technological leadership, pioneering the development and dissemination of ICT technologies.[3] Meanwhile for the European countries, without overlooking the influences of other non-ICT determinants, differences in ICT adoption explains a big proportion of the gulf in productivity with respect to the U.S.[4] Mowery and Rosenberg (2000) stress that, nowadays, technology is more the result of systematic R&D in science and engineering than was the case during the Second Industrial Revolution. Thus, countries need to develop higher levels of knowledge competence and to train a skilled labour force to better accommodate new technologies.

In the European advanced economies, technology has been an important determinant in the explanation of TFP growth, and has increasingly been linked to an investment in knowledge. It is therefore interesting to analyse the role of knowledge-related activities in comparison with the U.S., to uncover significant differences in the patterns of country technology, which in turn help explain differences in the evolution of country TFP.

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[3] The increasing use of ICT equipment explains the acceleration in American productivity growth since 1995 (Oliner and Sichel, 2000; Jorgenson and Stiroh, 2001; and, Oulton, 2012).

[4] Timmer et al. (2003, 2010).

Endogenous growth models provide a suitable framework in which to analyse the relative importance of different sources of knowledge on TFP growth. Within this literature, the endogenous growth model of Romer (1990), and the quality ladder models of Grossman and Helpman (1991) and Aghion and Howitt (1992) indicate that innovations and the accumulation of knowledge are the drivers of long-run aggregate productivity and economic growth. In these models, TFP rises with the cumulative domestic R&D effort, which is a proxy for the technological knowledge within an economy. When international trade of intermediate goods is introduced into the model, productivity depends upon both the domestic stock of R&D knowledge and on any international technology spillovers through imports. International trade may have a positive impact on productivity by facilitating access to a wider range of intermediate and capital products (Rivera-Batiz and Romer, 1991).

Within the theory of new growth models, Coe and Helpman (1995) provide one of the first studies to present macro data evidence for a panel of countries, confirming that a country's TFP growth depends on both its own R&D effort and on foreign R&D that spills over into the world economy through trade. In addition to these sources of knowledge, some theoretical models consider other determinants of productivity such as infrastructures, institutions, and human capital[5]. The incorporation of human capital in endogenous growth models aims at capturing other aspects of the innovation process. These elements are related to the ability of firms to learn and absorb new information, and to facilitate the effective use of tangible and intangible inputs within firms. Engelbrecht (1997) is the first scholar to introduce a human capital variable to account

[5] Khan and Luintel (2006) and Coe, Helpman and Hoffmaister (2009), point out that the estimated coefficients of the innovation variables seem to be robust to the incorporation of new variables not strictly linked to innovation.

for innovation outside the R&D sector and other aspects of innovation outside the scope of formal R&D.[6] Extending this work, Coe et al. (2009) test the impact of institutional factors on productivity.

In this research, we follow Coe and Helpman's (1995) technology diffusion model, with the additional incorporation of a human capital variable. Using this approach, we study productivity dynamics and innovation in several European countries for the period 1950 to 2000, using advanced times series cointegration techniques. In particular, we analyse the cases of France, Germany, Spain, and the U.K., and compare them with the U.S. In order to perform country analysis and implement the appropriate cointegration time series techniques, we must first expand our study reference period. A relevant contribution of our work to the existing literature lies in considering the whole Golden Age period. This is an important issue because most of the subject-specific literature appears much later, as data on R&D are only available since 1965.

To counteract this gap in the data, we use patent data to build an indicator of innovation and technology diffusion. Most of the current OECD countries have kept annual patent data over the past one and a half centuries. Although we make no claim that patent counts are superior to R&D data as a measure of innovation activity, they are nevertheless a valuable complement to R&D-based studies, taking into account that trade with patent-based knowledge goods grew considerably during the 20th century (Madsen, 2007).

Our results are in line with those in the extant literature. Additionally, our study distinguishes between the innovation experiences of countries with different levels of

[6] Several studies have incorporated improved measures of human capital following the publication of this work. See, among others, Frantzen (2000) and Barrio-Castro et al. (2002).

development. We find a robust long-run relationship between international technology diffusion, domestic innovation, human capital, and TFP for every country analysed. There are, however, significant differences between countries. In general, TFP in the U.S. is more sensitive to changes in innovation-related variables. With regard to the European countries, the effect of the domestic stock of knowledge is significantly higher in the more advanced countries (France, Germany, and U.K.) than in Spain, whereas we find just the opposite for the foreign stock of knowledge.

The rest of the paper has the following structure. In the second section, we present the data collection method and process to calculate TFP, and some descriptive statistics of the main variables in the study, while Appendix 1 contains details of the process of data construction. In the third section, we describe the model, and, in the fourth section, we report the estimation results of the model. Finally, the fifth section brings together the study's conclusions.

2. Data and Total Factor Productivity

Coe and Helpman's (1995) empirical specification provides a suitable framework to test how international technology transfers explain the evolution of productivity in some countries in Europe. In this paper, we use Coe and Helpman's (1995) model, later extended by Engelbrecht (1997), who adds a variable that accounts for human capital. This specification allows us to explore the role of certain variables in the long-run evolution of TFP in several European countries throughout the second half of the 20th century. These variables are: domestic innovation, measured by the stock of domestic patents; international technology diffusion, measured by the stock of foreign patents diffused through trade; and human capital. Equation 1 shows a mathematical representation of this empirical model:

$$\log TFP_{it} = \alpha^0 + \alpha^d \log S^d_{it} + \alpha^{mf} m_{it} \log S^f_{it} + \alpha^H \log H_{it} + \varepsilon_{it} \qquad (1)$$

where TFP_{it} is total factor productivity for country i and year t; S^d_{it} is the stock of domestic patents; S^f_{it} is the stock of foreign knowledge (obtained as a weighted sum of the domestic stocks of patents of the trading partners of a country); m_{it} is the propensity to import (measured by imports as a fraction of GDP); H_{it} is the domestic stock of human capital; and ε_{it} is a disturbance term. The model is estimated both with and without m_{it}. As Coe and Helpman (1995) propose, the transmission of international technology spillovers through trade may be proportional to the degree of openness of the country. This may only partially be captured by the way the foreign stock of knowledge is constructed. They therefore propose the creation of an interaction between the foreign stock of knowledge and the country's average propensity to import, to account explicitly for the degree of openness of the economy. Next, we describe the procedure to calculate each of the model's variables.

We use annual data for four European countries (France, Germany, Spain, and the U.K.) and the U.S., for the period 1950 to 2000. In particular, for each country, we calculate TFP, the domestic stock of knowledge, the foreign stock of knowledge, and human capital. The variables used to calculate TFP (GDP, labour employed, physical capital stock, and labour income share in the economy) come from the *Groningen Growth Development Centre* (*GGDC*) *Total Economy Growth Accounting Database*, which covers the period 1980 to 2000. Both GDP and capital stock are in millions of U.S. dollars at year 2000 prices. For the period between 1950 and 1980, we must combine data from different sources to calculate TFP. GDP, labour employed, and labour income share come from the *Total Economy Database* of the GGDC. The stock of capital for the U.K., France, Germany, and the U.S. comes from O'Mahony's (1996) homogenous series, whereas the stock of capital for Spain comes from Prados de la Escosura and Roses (2010). TFP is calculated as the log of output minus a weighted average of labour and capital inputs, using factor shares as weights.

To build the series of domestic and foreign stock of knowledge, we use the flow of total patents applied for annually in each national office and registered in the *World Intellectual Property Organization (WIPO) Statistics Database.* Additionally, we take into account the patents directly applied for at the *European Patent Office* (EPO) since 1977. Despite this information being readily available, however, the use of patents statistics has some drawbacks. One of main shortcomings is the concern about the comparability of patent data over time and across countries. Mansfield (1986) finds no significant changes in the propensity to patent over time in the U.S. and other countries. Some authors consider that, since the Paris Convention of 1883 harmonised patenting rules, the number of claims per patent is approximately the same across all countries except for Japan (Okada, 1992). As Lerner (2000 and 2002) points out, however, patent series should be corrected, as some significant differences exist between countries, even after the Paris Convention. Appendix 1 addresses this problem.

We use the perpetual inventory method to construct knowledge stocks. The domestic stock of knowledge is calculated by cumulative patent applications in each country using a 5% depreciation rate.[7] The foreign stock of knowledge is computed as

[7] Using data of citation patents granted for in the U.S., Caballero and Jaffe (1993) find that the average annual rate of knowledge or technological obsolescence rises from about 3% at the beginning of the century to about 10–12% in 1990. As we are using patent data since 1870 to calculate the initial stock of knowledge, we follow Madsen (2007) and apply a depreciation rate of 5%. Nonetheless, the literature

the weighted sum of the domestic stocks of patents of the trading partners of each country, following the weighting scheme proposed by Coe and Helpman (1995).[8]

To construct the human capital variable, we use the proportion of individuals over 15 years old who have completed tertiary education, instead of the usual series of the average years of schooling, as we consider this variable to be a more accurate measure of a country's endowment in human capital strictly devoted to innovation. The average years of schooling may seem to be more related to a country's general education and training level or innovation capacity, as schooling may ease the adoption of innovations developed both domestically and abroad, while the proportion of individuals who have attained tertiary education is more closely linked to the endogenous potential to generate innovations within a country. The data on these proportions come from Barro and Lee's (2013) statistics. Table 1 and Figures 1 to 5 below show the summary statistics for the variables used in our empirical analysis, and plots of their evolution over time.

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fails to settle on an appropriate depreciation rate. For example, Pakes and Schankerman (1984) advocate a 20% depreciation rate. Madsen (2007), on the other hand, tests both depreciation rates and finds no significant differences.

[8] Coe and Helpman (1995) and Lichtenberghe and van Pottelsberghe de la Potterie (1998) use total imports as the channel for international technology spillovers. Other authors explore alternative channels, using different weights to build the foreign knowledge stocks. The channels that scholars habitually consider are: imports of capital goods (Xu and Wang, 1999; Luintel and Khan, 2009), inward and forward FDI stocks (Van Pottelsberghe de la Potterie and Litchenberg, 2001; Lee, 2006; Zhu and Jeon, 2007), and the pattern of international patenting (Jaffe and Tranjtenberg, 2002; Guellec and van Pottelsberghe de la Potterie, 2004; Hafner, 2008). Although most of these channels are significant for the transmission of foreign knowledge across borders, significant differences between channels are non-existent (Luintel and Khan, 2009).

Figure 1 plots the evolution of TFP for each country. To attain comparability across countries, we normalise TFP to 1 in 1985. On average, TFP increases by 2% per annum over the period 1950 to 2000. For France, Germany, and Spain, however, the total increase of TFP for the sub-period 1950–1982 was higher, 2.5, 2.4, and 6.0%, respectively. After this period, we observe a stagnation of TFP, which even turns into a decline from the mid-nineties onwards for these three countries. The evolution of TFP is different for the U.K. and the U.S. Both countries show a modest upward trend for most of the sample period, but experience a noticeable increase in the second half of the 1990s.

Figure 1. Total Factor Productivity (1985=1).

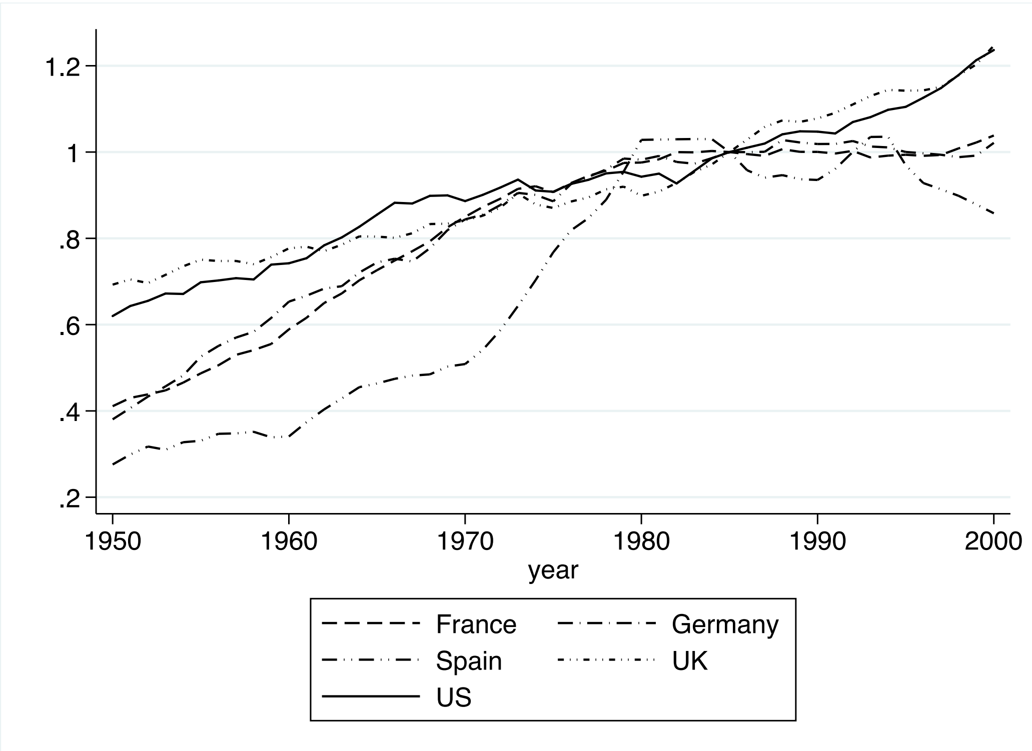


Figure 2 plots the stock of patents by domestic inventors for France, Germany, Spain, the U.K., and the U.S. in millions of patents. The increase in the domestic stock of patents is smoother than the rise in TFP. Over the whole period, the domestic stock of patents multiplies by a factor of 2.24 in France, 1.60 in Germany, 4.47 in Spain, 1.27 in the U.K., and 2.49 in the U.S. In the U.S., the stock of patents shows a slight upward trend until the beginning of the 1990s, and a sharp upswing afterwards. This impressive rise reflects a recent upsurge in the patent activity in this country.[9] The European countries display a different pattern of patenting, with a clear upward trend throughout the Golden Age, a flat trend for the period 1970–1990 and a slight increase since 1990. Among the European countries, the U.K. shows the smallest change. Figure 2 reveals significant differences in the levels of domestic innovation. On the one hand, the U.S. led the world in terms of the stock of patented domestic knowledge followed by the most developed European countries (the U.K., Germany, and France), who scarcely closed the gap with the U.S. during this period. Their relative position seems to change very little at the end of the period. On the other hand, in Spain, the very low stock of domestic patents increased sharply in the twenty years starting from 1950. Following the recession of the seventies, however, this increase stagnated, with the number of patents even beginning to decline in the eighties. Finally, from the late eighties until the second half of the nineties, Spain fell further behind the U.S., Germany, and France, in terms of domestic stock of knowledge.

Figure 2. Domestic stock of patents (in millions).

[9] Kortum and Lerner (1999) related this upsurge in patenting to both changes in firms' management of research and changes in U.S. patent policy. In particular, the rise in patenting does not reflect a widening set of technological opportunities but a higher propensity of firms to protect their investment in R&D by means of patenting in advance.

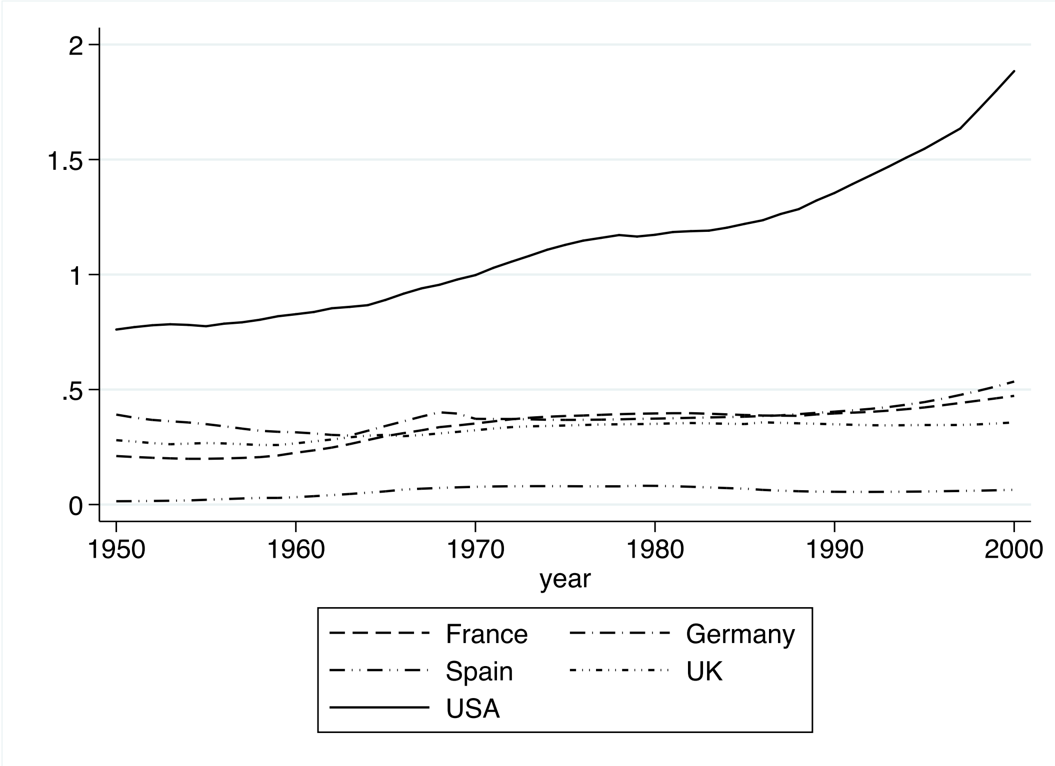
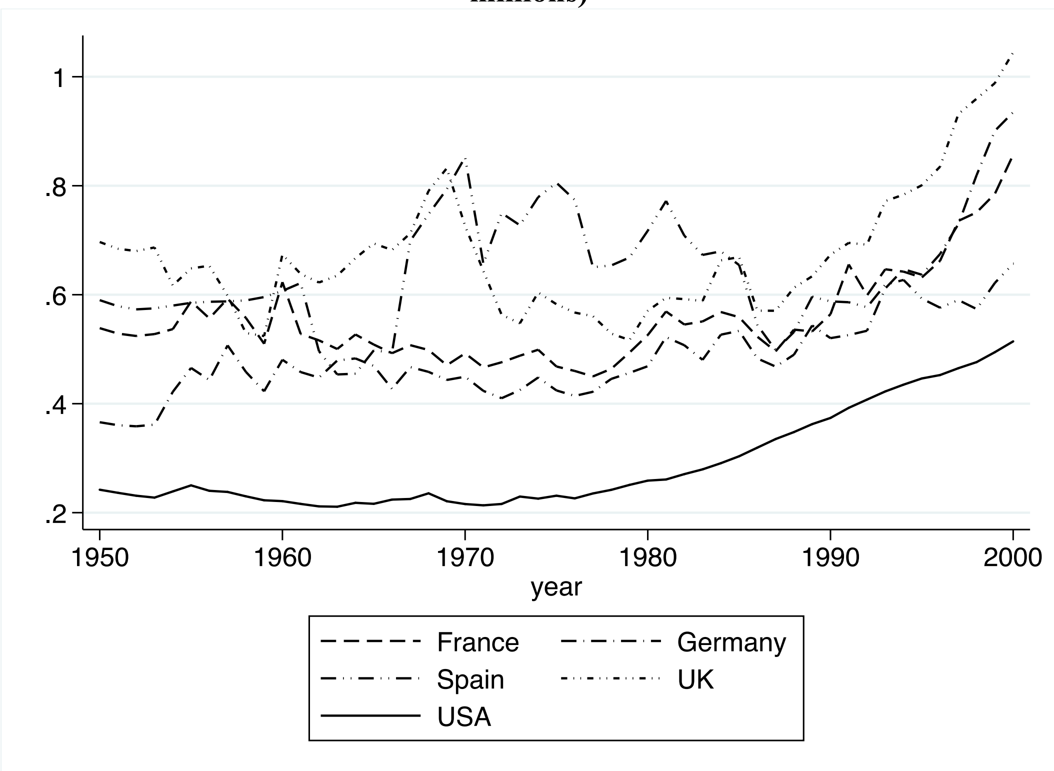


Figure 3 displays the foreign stock of knowledge series for each country. These series aim to capture knowledge imports and are a common way of building a proxy for international technology spillovers through the imports of machinery and equipment. In general, we observe a uniform flat trend for all countries, except the U.S. Two facts explain this common trend: first, the construction of this variable as a bilateral weighted average of imports bilateral import weighted average of the same 16 countries; and, second, the direction of trade of technologically advanced products switched directions during this period in favour of products coming from other European countries and against imports coming from the U.S. This had an impact on the capacity of generating international technological spillovers because the U.S., the most innovative country for the period, experienced a decrease in its share of European imports of machinery and equipment, while the share of imports from other European countries increased, even when the domestic stock of knowledge of the European countries remained stagnant between 1970–1990.

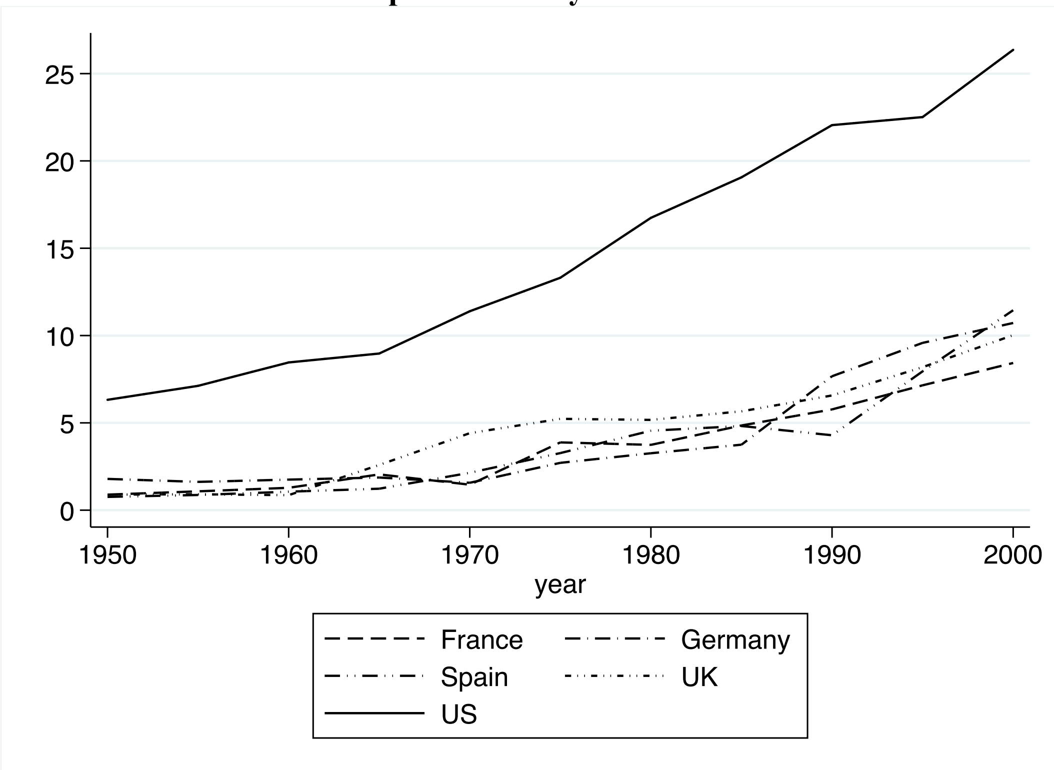
As Coe and Helpman (1995) explain, the transmission of international technology spillovers through trade may be proportional to the degree of openness of the country. It is therefore of interest to monitor the interaction between the foreign stock of knowledge and the country's average propensity to import (m_{ij}), in order to account explicitly for the effect of the degree of openness on productivity. On average, import shares rose 6.1% per annum in France, 8.0% in Germany, 3.0% in Spain, 5.0% in the U.K., and 8.6% in the U.S. between 1950 and 2000. In general, the import share has a positive slope throughout the whole period. The curves maintain considerable distance (in absolute value) between the degree of openness of the U.S. and the European countries, with Europe, especially Spain, always demonstrating greater openness than the U.S.

Figure 3. Foreign stock of patents using bilateral imports weights (in millions)



Finally, we include a human capital variable to capture the capacity of a country to generate domestic innovation and to adapt innovation generated abroad. To this end, we use the percentage of members of the population over 15 years old who have completed tertiary education. This percentage steadily increases in all European countries from 1950 to 2000. The increase is higher in the U.S., however, and the gap between the European countries and the U.S. widens over the period under study.

Figure 4. Human capital: % Population 15+ with completed tertiary education.



3. Econometric modelling and empirical results

To estimate the model of technology diffusion (Equation 1) we use cointegration time series techniques. These techniques allow us to capture the notion of long-run equilibrium relationships between non-stationary variables, which thus have a tendency to move together in the long run. This methodology is appropriate in this context as it permits us to avoid any spurious regression, while retaining the long-run information. We estimate the long-run relationship between TFP growth, the series of variables that measures technology achievement (through domestic innovation and the imports of knowledge), and a human capital variable.

To apply this methodology, we first need to test for unit roots to determine the order of integration of the series.[10] From our results, we cannot reject the null hypothesis of non-stationarity for all series in levels, independently of the test, and the hypothesis of the existence of two unit roots cannot be rejected for the domestic stock of patent series (S_t^d) for France. Therefore, according to the results of these tests, the domestic stock of patents could be I(2) or I(1).[11] Second, we study the possible presence of structural changes in the series.[12] The results for these tests indicate that the null hypothesis of non-stationarity for France is not always rejected. Consequently, we are unable to

[10] To test for the order of integration of the series, we use a modified version of the Dickey-Fuller and Phillips-Perron tests, proposed by Ng and Perron (2001), who solve the three main problems facing the conventional tests for unit roots. These modified tests are $\bar{M}Z_\alpha^{GLS}$, $\bar{M}SB^{GLS}$, and $\bar{M}Z_t^{GLS}$. A Modified Akaike Information Criteria (*MAIC*) is used to select the autoregressive truncation lag, *k*, as proposed in Perron and Ng (1996). See Ng and Perron (2001) and Perron and Ng (1996) for a detailed description of these tests and the *MAIC* information criteria.

[11] The results of these tests are available from the authors upon request.

[12] In order to provide further evidence on the degree of integration of the domestic stock of patents, we also apply the Perron-Rodriguez test (Perron and Rodriguez, 2003) for a unit root in the presence of a one-time change in the trend function, where a change in the trend function is allowed to occur at an unknown time, T_B. To apply these tests, we select the break maximising the absolute value of the *t*-statistic on the coefficient of the slope change.

conclude that the domestic stock of patents series in France is I(1) with one break.[13] Finally, after analysing the order of integration of the series, we estimate the cointegration relationship between the variables, using the appropriate order of integration of the series.

We estimate the long run, or cointegration relationship, for each country separately. Given the (relatively small) time dimension of the series in our sample, we estimate and test for the coefficients of the cointegration equation by means of the Dynamic Ordinary Least Squares (DOLS) method, put forward by Stock and Watson (1993), following the methodology proposed by Shin (1994). This method provides a robust correction for the possible presence of endogeneity in the explanatory variables, as well as serial correlation in the error terms of the OLS estimation. Also, to overcome the problem of the low power of the classical cointegration tests in the presence of persistent roots in the residuals of the cointegration regression, Shin (1994) suggests a new test where the null hypothesis is that of cointegration. We estimate a long-run dynamic equation including the leads and lags of all the explanatory variables, the so-called DOLS regression. In our case this relation is the following:

$$y_t = \alpha_0 + \alpha_1 t + \beta_k x_t + \sum_{j=-q}^{q} \gamma_j \Delta x_{t-j} + \varepsilon_t \tag{2}$$

where y_t is the log of TFP; t is a linear trend; and x_t are the explanatory variables. Specifically, x_t are: the log of the domestic stock of knowledge (measured through domestic patents); the log of the imports of knowledge (measured through foreign patents using an import weighting scheme); and a measure of human capital, as

[13] The results of these tests are available from the authors upon request.

explained in the previous section. The parameter β_k is the long-run cointegrating coefficient estimated between TFP and the explanatory variable k (or long-run elasticity).[14]

The coefficients from the DOLS regression and the results of the Shin test are reported in Table 2. We present the estimates of two specifications per country: Model 1, in which we do not include interaction between the log of the foreign knowledge stock and the country's propensity to import (m_{it}); and Model 2, in which we include the interaction of the foreign stock of knowledge with the country's propensity to import. In general, the estimated coefficients in Table 2 have the expected sign, and the magnitudes of the estimated elasticities are plausible and relatively stable across the different specifications.

We begin the discussion of our results by analysing the case of France. The imports of knowledge have a positive and significant long-run relationship with TFP, as theoretically expected. The size of the estimated coefficient (i.e., the long-run elasticity) for this variable is 0.186 (0.066) without interaction (with interaction) between the foreign stock of knowledge and the import term. This means that a 1% increase in the imports of knowledge will increase TFP in France by 0.186% (0.066%). With respect to

[14] In the empirical model, we test for deterministic cointegration using Shin's (1994) test. This test is based on the calculation of an LM statistic from the DOLS residuals, namely C_μ, to test for deterministic cointegration (when α_I= 0). If cointegration is present in the demeaned specification given in (2), this occurs when α_I = 0, corresponding to deterministic cointegration, which implies that the same cointegrating vector eliminates deterministic trends as well as stochastic trends. See Ogaki and Park (1997) and Campbell and Perron (1991) for an extensive treatment of deterministic and stochastic cointegration. We check for the presence of deterministic cointegration using the demeaned specification, and obtain that the null hypothesis of deterministic cointegration is not rejected at the 1% level in all cases. These results are available from the authors upon request.

the domestic stock of knowledge we get, in both specifications, a significant, positive and strong relationship between this variable and TFP. For the domestic stock of knowledge, the coefficients are 0.372 and 0.293 for Models 1 and 2, respectively. Finally, the human capital variable is significant and with the correct positive sign in Model 1. From our estimates we get a long-run elasticity of 0.064.[15]

We now shift our discussion to our results for Germany. In relation to the imports of knowledge, results are positive and statistically significant. The long-run elasticity estimate ranges from 0.126 to 0.178, when we do not consider the import term and when we consider it, respectively. With regards to the domestic stock of knowledge, the coefficients are positive and statistically significant, and range from 0.263 to 0.352. The estimated long-run elasticity is therefore very high, as a 1% increase in the domestic stock of knowledge would increase TFP for Germany by 0.263–0.352%. Finally, the human capital variable is always significant and has a high positive impact on TFP growth, regardless of the model considered. The elasticity of human capital ranges from 1.042 to 0.831.

Considering the case of the United Kingdom, in Model 1 the foreign stock of knowledge is non-significant. However, we get significant and positive long-run elasticity in the specification with interaction between the foreign stock of knowledge and the propensity to import, although the size of the long-run elasticity is lower than in the two cases considered above (0.032). As regards the domestic stock of knowledge, both models' estimates yield positive and significant coefficients, with values 0.289 and 0.367 for Models 1 and 2, respectively. These coefficients are very similar to the estimated elasticities for France and Germany. Finally, the human capital variable is

[15] The coefficient for the human capital variable, although positive in Model 2, is only significant at the 17.5% level.

also positive and significant, although the coefficients are very small and similar to those obtained for France (ranging between 0.046 and 0.031).

The fourth European country considered in our analysis is Spain. This country started the period under analysis with the lowest income levels of GDP *per capita* in the sample, and also the lowest levels in the two knowledge variables. Spain experienced a notable process of convergence with the most developed countries during the Golden Age, however. Our results reveal that the entry of foreign technology through trade is a relevant variable in the long-run evolution of TFP for Spain. The long-run elasticity for the foreign stock of knowledge is the highest among the European countries considered. Our estimates range from 0.220 to 0.315, for Models 1 and 2, respectively. The positive effect when we introduce the import interaction term confirms that the inflow of technology throughout trade was reinforced by Spain's increasing openness to international trade. This is a particularly striking result, as the Spanish government practically closed the borders to foreign trade in the forties and part of the fifties.

As regards the domestic stock of knowledge, results are very disappointing. The domestic stock of knowledge is either very low, 0.061 in Model 1, or even negative and significant in Model 2. These results are in line with the traditional interpretation of Spanish economic growth. This view states that, in a relatively backward economy like Spain in the middle of the 20th century, the incorporation of foreign technology through imports is a straightforward way to introduce more up-to-date knowledge; far easier than devoting scarce domestic resources to in-house R&D. A similar result appears in Madsen et al. (2010) for India. As in the other countries, human capital is a significant and positive variable, with an elasticity that ranges from 0.240 to 0.426. This confirms that Spain's notable effort to improve its relatively low level of human capital to converge with the average educational attainment level of the OECD countries seems to have had a positive impact on Spanish productivity.

Finally, we report the results for the special case of the U.S. (see Table 3). For this country, the estimated coefficients are all significant and positive, as theoretically predicted. Considering the domestic stock of knowledge, the estimates of the coefficients are significant, reaching higher levels than in the other countries in our sample (0.945–1.449). The estimate of the coefficient of knowledge imports is significant only when the import interaction term is absent, and with an elasticity of 0.389. In the case of the U.S., this result has important implications, in that the positive correlation between TFP and the foreign stock of knowledge expounded in the literature is unlikely to be driven by openness, instead resulting from a genuine relationship between TFP and knowledge generated abroad. This result is consistent with the traits of a big country, in which imports represent a small fraction of total GDP, and hence a small fraction of domestic intermediate and capital goods consumption. In this case, the penetration of foreign knowledge through trade is more important qualitatively than quantitatively, and therefore less dependent on the degree of openness. The arrival of new ideas through trade encourages competition inside the country and enhances a process of development and imitation of these new ideas, rather than stimulating an increase in the imports of goods that embody the new technologies.

The coefficient for the domestic stock of knowledge (0.945) is much higher than the corresponding coefficient of the foreign stock of knowledge (0.389). Further, the human capital variable also has a big impact on TFP (with a value of 1.245%). It is also worthwhile stressing that the domestic stock of knowledge and the human capital variable seem to share a strong correlation, as the values of the estimated coefficients change in opposite directions when the import interaction term is introduced in the estimation (Model 2). In particular, the estimated coefficient for the domestic stock of knowledge increases from 0.945 in Model 1 to 1.449 in Model 2, while the human capital coefficient decreases from 1.245 to 0.201. This result is peculiar to the U.S., while, in other countries, the coefficients remain stable, regardless of whether we introduce the import interaction term. This result is consistent with the high level of complementarity between a highly educated labour force and the capacity to generate innovations.

One of the features that distinguishes the U.S. from other countries is its early implementation—in the last quarter of the 19th century—of an innovation policy that focuses not only on public R&D spending, but also on establishing arrangements and collaborations between the state, the R&D departments in big corporations, and universities (Abramovitz and David, 2001), with strong support for education. This support for education helped the U.S. deal with the increasing demand of highly educated workers throughout the 20th century, and has led to a strong national system of innovation. In the last three decades, with the development of the knowledge society, the demand for university-educated workers has exceeded supply, as reflected in the large salary premium for more well-trained workers (Goldin and Katz, 2008).

The following discussion compares the results between countries. In the case of the most advanced countries of the sample (France, Germany, the U.K., and the U.S.), the estimated elasticity for the domestic stock of knowledge is always higher than that of the foreign stock of knowledge. Conversely, we obtain just the opposite result for Spain, a much less advanced economy, where the productivity seems to be more sensitive to the imports of knowledge than to the domestic stock of knowledge.[16] This result confirms the view that the higher the levels of the domestic stock of knowledge and human capital, the higher the returns in terms of overall productivity growth for any additional unit invested in the domestic stock of knowledge.

The above conclusion is reinforced by another notable result in our analysis. There is a considerable distance between the estimated coefficients of the U.S. knowledge variables and its European counterparts. In the U.S., the value of the estimated coefficients for the three knowledge stock variables is always higher than in Europe, including those of the imports of knowledge in Model 1. The long-run elasticity of the domestic stock of knowledge in the U.S. is close to unity and is almost three times higher than that of France, Germany, and the U.K. for Model 1. Similarly, the coefficient for the foreign stock of knowledge is roughly double the values obtained for France, Germany, and Spain. As regards the human capital variable, we find that the elasticity is also close to one, Germany being the other country obtaining a similar value for this variable.

Furthermore, when we compare the results for the U.S. with those obtained for the European countries, we uncover evidence in favour of Coe and Helpman's (1995) hypothesis. We find that the estimated coefficients of the imports of knowledge are significant in all cases (except for the U.K. in Model 1). The fact that we use Coe and Helpman's (1995) weighting scheme to construct the imports of knowledge allows us to conclude that the direction of trade matters, and that it played a crucial role in the transmission of technology for Europe and for the U.S. during the second half of the

[16] Further, our results give support to the idea that productivity relationships are heterogeneous across countries, depending on their accumulated stocks of knowledge and human capital, a result that previous panel data studies reflect (see for example, Khan et al., 2010; Coe et al., 2009).

20th century. When foreign knowledge is multiplied by the propensity to import in each country, however, the estimated coefficients are significant in the four European countries but not in the U.S. This result seems to point to the positive correlation between TFP and the imports of technology being driven and reinforced by the openness of the European countries but not necessarily the U.S. This evidence seems to be consistent with the traditional interpretation of post-war European growth, in which trade liberalisation is widely regarded as being a key factor behind receiving the benefits of technology transfer.

Also of note is that, although the values of the estimated elasticities are only partially comparable with those from the literature that uses macro panel data for 22 or more OECD countries,[17] it may be of interest to compare the direction of the coefficients. Our findings show that all the estimated coefficients for the individual countries have the correct sign and seem to be robust to changes in the variables introduced into the regression,[18] a result not always observable in the panel data analysis. Furthermore, findings confirm that the European process of openness to international trade favoured the inflow of technology during the second half of the century. Our results are in line with those obtained by Coe and Helpman (1995) and Coe et al. (2009) as regards the coefficients of the domestic stock of knowledge. Both studies find higher coefficients for the seven most developed OECD countries than for the other less developed countries. In addition, Madsen's (2007) results are in line with

[17] We compare our results with those of Coe et al. (2009), who use R&D panel data for 1970–2004, and with those of Madsen (2007), who uses patent data for the period 1870–2004.

[18] For example, the results undergo no significant change when we include the interaction of knowledge imports with the propensity to import, and when we use alternative measures of human capital. Even the different measures of human capital are statistically significant and positive.

our findings, as he obtains that the value of the coefficient for the domestic stock of knowledge increased post 1950.

Finally, achievements in innovation, either domestic or foreign, are unattainable without a great effort in human capital investment. The results of this study, with regard to the role of human capital, confirm the recent developments in the theory of innovation-driven growth. We find strong evidence in favour of complementarity between innovative efforts and human capital investment as factors explaining TFP growth. The human capital effort provides a sufficiently qualified labour force, capable of operating with new and more advanced technologies that confirm human capital as a key factor in the explanation of TFP growth.

The results in Table 4 illustrate the contribution of the three variables (domestic stock of patents, imports of knowledge, and human capital) to the overall increase in TFP. These contributions are calculated taking into account the estimated elasticities of Model 2, where the imports of knowledge interact with the propensity to import. With the exception of the U.S. and the U.K., we find that the contribution of the imports of knowledge to TFP growth exceeds the contribution of domestic innovation. It is important to note that we obtain these results in spite of the model yielding higher estimated elasticities for the domestic stock of knowledge than for the imports of knowledge in some countries (Table 2). This is so because the increase in the stock of knowledge in the rest of the world is higher than the advances in one particular country. In Germany, France, and Spain, the contributions of the imports of knowledge are above 50%.[19] These results are in line with the results of other authors. For example, Madsen (2007) concludes that, on average, for 16 OECD countries in the period 1870–2004, the imports of knowledge are responsible for at least a 93% increase in TFP.

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[19] Eaton and Kortum (1999).

Adopting another approach, Eaton and Kortum (1999) find that, even in the most innovative countries (United Kingdom, United States, France, Germany, and Japan), research performed abroad is roughly two-thirds as potent as domestic research. In fact, our results grant an even more relevant role to domestic innovation in the most advanced countries. For example, we find that, in the United States and the United Kingdom, the contribution of domestic and foreign innovation accounts for around 40% of the total contribution. If we add the contribution of human capital to the contribution of the domestic stock of knowledge, we find that, for the U.K. and the U.S., the endogenous capacity to innovate has a higher impact on the evolution of domestic TFP than the innovation performed abroad.

From these results we can draw two conclusions. First, even in the case of the most advanced countries, imports of technology emerge as a key factor for the assimilation of new technology and for productivity growth. Second, the higher the GDP level of a country, the higher the contribution of the domestic stock of knowledge. At least in the case of the U.S. and the U.K., the results suggest that the evolution of TFP is very sensitive to the generation of an endogenous capacity to innovate. The most disappointing results are for the case of Germany, which we suspect are conditioned by the changes in the level and the trend of the macroeconomic time series for the years following the unification of the East and West Germany.

4. Conclusions

This study compares the relationship between TFP and innovation-related variables (domestic stock of knowledge, imports of knowledge, and human capital) for certain European countries (France, Germany, the United Kingdom, and Spain) and the U.S. between 1950 and 2000. To conduct our analysis, we use advanced time series cointegration techniques, expanding our period of analysis to incorporate the Golden Age. The time span, the country-by-country analysis, and the use of patent data in our analysis differentiates this research from the related panel data literature, which emerges a decade and a half after data on R&D were first made available (1965).

The results of our study, despite being highly aggregated and confirming some already established notions, are nevertheless striking, as they highlight some noticeable differences in the way knowledge-related variables influenced overall productivity growth in advanced countries in the second half of the 20th century. The estimation results show that imports of knowledge, domestic knowledge stocks, and the endowments of highly qualified human capital are relevant in TFP growth. Furthermore, our results confirm the heterogeneous nature of these relationships, depending on the country level of accumulated stocks of human capital and domestic knowledge. In particular, in Section 2, we show a huge disparity in the levels of domestic stock of patents and those of human capital variables (average years of schooling or percentage of population with completed tertiary studies). Although the European countries tend to converge with the U.S over the period of 1950–2000, key differences still exist with regard to the levels reached by the U.S. Hence, the estimation of the econometric model reveals that the U.S., with greater levels of domestic knowledge stock and human capital, tends to have larger estimated coefficients for all the knowledge related variables. These differences also arise when comparing Germany with the remaining European countries, or the European countries with Spain.

Another interesting finding pertains to the role of the international spillovers through trade. Our results support Coe and Helpman's (1995) hypothesis that trade is an important channel for the diffusion of technology, as the imports of knowledge present a significant and positive sign in almost all estimates. Our results are, however, less conclusive with regard to the role of the degree of openness to international trade. In the case of the European countries, our results indicate that trade liberalisation helped in the dissemination of international technology spillovers across the European countries, a finding that is non-applicable to the U.S. Nonetheless, these findings give support to the role of the international transfer of technology in the explanation of European growth in the second half of the 20th century.

After comparing experiences between countries, perhaps the most salient findings are that the U.S., the dominant country in terms of ownership of world knowledge stocks, is also the country that yields the greatest overall productivity returns from investment in human capital and domestic knowledge, and that achieves the most leverage from the knowledge generated abroad. Its high levels of domestic how-know and competence in the use of knowledge have engendered a great willingness in this country for the exploitation of knowledge arriving from foreign shores. Our results also lead to quite similar conclusions for Germany. For the European countries as a whole, trade liberalisation and their convergence towards American levels of domestic innovation and human capital have permitted them to obtain a positive relationship between overall productivity and innovation. Nonetheless, the lower returns of innovation and education investments in comparison with the U.S. reveal the continuing existence of a considerable lag behind the U.S., which European countries should strive to rectify if they wish to improve the relationship between innovative efforts and productivity.

Current IT technologies are highly intensive in knowledge and European countries must confront the stagnation in their overall productivity levels. In this sense, our results reveal the importance of increasing the efforts in improving high-quality education and domestic innovation structures, to obtain higher returns from any investment in innovation. Our results are in line with the conclusions of Aghion and Howitt (2006) who stress that as countries get closer to the technological frontier the need for high-quality education and strong competition in product markets grows.

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Appendix I.

In what follows we describe the procedure to calculate the variables used to estimate our model.

a. Measurement of Total Factor Productivity

The construction of TFP uses a homogeneous Cobb-Douglas technology function with factor shares that vary over time and across countries:

$$TFP_{it} = \frac{Y_{it}}{K^{\beta_{it}} \cdot L^{(1-\beta_{it})}} \tag{A.1}$$

where Y_{it} is real GDP, K_{it} is capital stock, L_{it} is employment and β_{it} is the share of capital in total income. We use estimates of GDP, labour employed, physical capital stock and labour income share in the economy drawn from the *Total Economy Growth Accounting Database* (*Groningen Growth Development Centre, GGDC*), that covers the period 1980 to 2000. GDP and capital stock are in millions of 2000 U.S. dollars.

For the years previous to 1980, TFP has been calculated using value added, labour employed and labour income share in the economy drawn from the *Total Economy Database* from the same institution. Capital has been obtained using the homogenous capital stock series from O'Mahony (1996) for the United Kingdom, France and Germany. In these series, the capital stock is computed as machinery and equipment capital stock plus non-residential buildings and structures capital stock. For Spain we take the capital stock series calculated by Prados de la Escosura and Roses (2010).

In the *GGDC* database the share for labour income is calculated as the economy-wide compensation to employees divided by nominal GDP, where compensation is corrected for imputed payments to the self-employment.

All the above estimates are used to measure TFP under the assumptions that production technology exhibits constant returns to scale and perfectly competitive product markets. These assumptions are widely used in the existing literature. Under these assumptions, the output elasticity of labour services is calculated through the share of labour income in the manufacturing sector.

b. Domestic Knowledge Stock.

A novelty of this paper is that we use data of patents as an indicator of knowledge accumulation. Patents data come from the *World Intellectual Property Organization (WIPO) Statistics Database*. We use patents applied by residents instead of patents granted. For international comparisons, the number of patents applications is probably a better measure of the innovative activity of a country than the number of patents granted because the granting frequency varies across countries (Griliches, 1990). For each country we have calculated the domestic stock of patents and a weighted foreign stock of patents (or imports of knowledge). Patents are widely accepted as a reliable indicator for the innovative activity, especially when there are not appropriate data on R&D.[20]

However, when using patent statistics as an indicator of the inventive activity, a number of issues should be considered, as put forward by Dernis et al. (2001) and

[20] See among others, Schmookler (1966), Griliches (1984, 1990) Griliches et al. (1987), Schankerman and Pakes (1986), Jaffe et al. (2000) and Dernis et al. (2001).

Grilliches (1990). First, not all inventions are patented. This is so as there are other alternatives to patenting that inventors may use to protect their inventions, such as trade secrecy or technical know-how. Second, a small number of patents accounts for most of the value of all patents. This means that simple patent counts could bias the measure of technology output. Third, patent systems for protecting inventions vary across countries and industries. Fourth, applicants' different filling in strategies or preferences may make direct comparisons of patent statistics difficult across countries. A large set of innovations is not ever patented. Fifth, differences in patent systems may influence the applicant's patent filling decisions in different countries. Sixth, due to the increase in the internationalization of R&D activities, R&D may be conducted in one location but the protection for the invention is done in a different one. And, finally, cross-border patent fillings depend on various factors, such as trade flows, foreign direct investment, market size of a country, etc.

Relative to other measures of technology, patents have the advantage that data have been collected for a long period of time (more than 150 years for some countries), and for a vast number of countries, including poor countries. In this research, we find that using patents, as an indicator of the innovative activity of a country, has a clear advantage over using a measure of a country's R&D (the obvious alternative to patent data), as the series on internationally comparable country R&D are only available since 1965 and for the OECD countries. However, using patents data we can extend the time span of our research up to the beginning of the 1950s, which allows us to include the Golden Age in our analysis.

However, one of the main drawbacks in using patent statistics is that different countries have different standards of patentability. According to Lerner's work (2000 and 2002) on the differences in international patent protection there are important differences among countries analysed: concerning to patent fees, structure of patent renewals, patent office practices, etc. This means that the same invention can be patented in one country and not patented in another country. This is a common and well-known problem with patent data that affects both to the number of patents granted and the number of patent applications.

One way of correcting for differences in the propensity to patent is to calculate a scaling factor. For this we explore the correction made by Madsen (2007, p. 467) and other authors in relation to this issue. In particular, Madsen (2007) scales down Japanese patent applications by a factor of 4.9 following Eaton and Kortum (1999). This correcting factor compares the different propensity to patent (applications over granted) of any particular country with regard the propensity to patent in the U.S. Proceeding in similar way we have calculated country specific scaling factors. [21] Eaton and Kortum (1999) and Madsen (2007) scaled down only the Japanese patents, the most outstanding case. Madsen (2007) argued that not scaling the other countries should not introduce major biases in the empirical work, given the efforts for patent harmonization after the Paris convention. However, we have implemented the correcting scale factors to all countries, as we detect significant differences across countries, specially due to the length of the period analysed.

An additional issue related to patent series is related to the opening of the European Patent Office (EPO) in 1977. Since then, European inventors may decide to apply for patents at the EPO instead of using national patent offices. Therefore, patents applied in the national offices, which are also registered at the WIPO, do not represent

[21] Data have been drawn from WIPO Statistics Database. We particularly use patent grants and applications series by patent office, broken down by resident and non-resident (1883-2010).

anymore the total number of patents applied by residents in a particular country. To avoid this measurement problem and following a standard procedure, we add EPO patents to those applied at the national patent offices (or national patents at WIPO) to build the patent stocks.

Once we correct for the two issues raised above, the domestic stock of patents has been calculated from the accumulation of annual patent data based on the perpetual inventory method. The formula of the stock is:

$$S_{it}^{d} = (1-\delta)S_{it-1}^{d} + p_{it} \tag{A.3}$$

where S_{it}^{d} is the patent stock for country i in year t, p_{it} is the number of new patents in country i in year t and δ is the depreciation or obsolescence rate, assumed to be 5%.[22] The initial value for the stock of patents was calculated using the perpetual inventory method.

To measure the technology spillovers embodied in trade flows we follow Coe and Helpman (1995) to aggregate foreign stocks of patents as:

$$S_{it}^{f,CH} = \sum_{j} \frac{m_{ijt}}{m_{it}} S_{jt}^{d} \tag{A.3}$$

where m_{ijt} is the flow country i imports of goods and services from country j in period t, and m_{it} is country i total imports from its trading partners in t. This formulation assumes that a country will catch, *ceteris paribus*, more international knowledge spillovers if the country imports more from countries with a relatively high domestic capital stock.

[22] Coe and Helpman (1995) and Madsen (2007) show that the estimation results are robust to different depreciation rates.

Following Coe *et al.* (1997) and Xu and Wang (1999) the bilateral import weights are based on highly technological products, since technological spillovers through imports are more likely to take place through imports of technologically sophisticated products. To construct these measures we use 15 exporter countries: the U.S., France, Germany, the U.K., Japan, Italy, Spain, Switzerland, Sweden, the Netherlands, Norway, Denmark, Greece, Portugal, and Belgium.[23]

[23] It is important to note that imports of highly technological products come mainly (around 50% or more) from the biggest seven countries (France, Germany, Japan, Italy, Sweden, the United Kingdom and the U.S.), however, we use 15 countries to construct the stock of imports of technology for two reasons. First, because in some cases imports coming from countries not belonging to these seven countries are very high, such is the case of the U.S. where imports coming from Canada have the highest share. Second, because this is the procedure followed in other empirical researches (for example, Coe and Helpman, 1995; Keller, 1998; Xu and Wang, 1999; Lumenga-Neso *et al.,* 2005; and, Madsen, 2007).

Table 1. Descriptive statistics

	TFP	Domestic stock of patents	Foreign stock of patents	Human capital
France	0.825	339596.1	555431.8	3.613
Germany	0.831	382150.8	503086.3	4.048
Spain	0.691	56432.8	627618.9	3.677
U.K.	0.914	320959.5	673488.3	4.523
U.S.	0.914	1125813.0	524905.0	14.629

Table 2. The determinants of TFP in Europe

	Model 1: Foreign Stock of Knowledge ($S_{it}^{f,CH}$) (without import interaction term)				Model 2: Foreign Stock of Knowledge ($S_{it}^{f,CH}$) (with import interaction term)			
	France	Germany	United Kingdom	Spain	France	Germany	United Kingdom	Spain
S_{it}^{d}	0.372	0.263	0.289	0.061	0.293	0.352	0.367	-0.115
	(13.82)	(4.95)	(2.06)	(3.60)	(7.47)	(2.92)	(3.05)	(-14.95)
$S_{it}^{f,CH}$	0.186	0.126	0.018	0.220	-	-	-	-
	(3.20)	(2.95)	(0.56)	(6.00)				
$m_{it}S_{it}^{f,CH}$	-	-	-	.	0.066	0.178	0.032	0.315
					(4.24)	(2.32)	(2.03)	(6.96)
H_{it}	0.064	1.042	0.046	0.240	0.028	0.831	0.031	0.426
	(4.95)	(6.58)	(1.87)	(2.16)	(1.36)	(2.83)	(4.35)	(3.73)
C_{μ}	0.067	0.106	0.067	0.080	0.060	0.067	0.057	0.073

Notes:

[a] *t*-statistics in brackets. Standard errors are adjusted for long-run variance. The long-run variance of the cointegrating regression residual is estimated using the Barlett window, which is approximately equal to INT($T^{1/2}$), as proposed in Newey and West (1987).

[b] We choose q = INT($T^{1/3}$), as proposed in Stock and Watson (1993).

[c] C_{μ} is the LM statistic for cointegration using the DOLS residuals from the deterministic and stochastic cointegration, respectively, as proposed in Shin (1994).

[d] The critical values are taken from Shin (1994), Table 1, for m = 3: a) $C_{\mu,}$ 0.121 at the 10%, 0.159 at the 5% and 0.271 at the 1% levels.

Table 3. The determinants of the U.S. TFP

	Model 1: Foreign Stock of Knowledge ($S_{it}^{f,CH}$) (without import interaction term)	Model 2: Foreign Stock of Knowledge ($S_{it}^{f,CH}$) (with import interaction term)
	USA	USA
S_{it}^{d}	0.945	1.449
	(3.16)	(5.64)
$S_{it}^{f,CH}$	0.389	-
	(2.32)	
$m_{it}S_{it}^{f,CH}$	-	0.021
		(0.80)
H_{it}	1.245	0.201
	(2.15)	(1.89)
C_{μ}	0.071	0.069

Notes:
[a] *t*-statistics in brackets. Standard errors are adjusted for long-run variance. The long-run variance of the cointegrating regression residual is estimated using the Barlett window, which is approximately equal to INT($T^{1/2}$), as proposed in Newey and West (1987).
[b] We choose q = INT($T^{1/3}$), as proposed in Stock and Watson (1993).
[c] C_{μ} and C_{τ} are LM statistic for cointegration using the DOLS residuals from the deterministic and stochastic cointegration, respectively, as proposed in Shin (1994).
[d] The critical values are taken from Shin (1994), Table 1, for m = 3: a) C_{μ}, 0.121 at the 10%, 0.159 at the 5% and 0.271 at the 1% levels; b) C_{τ}, 0.069 at the 10%, 0.085 at the 5% and 0.126 at the 1% levels.

Table 4. Contribution to TFP growth (in %)

	Domestic stock of patents S^d	Imports of knowledge $m \cdot S^f$	Human capital, H
Germany	2.50	88.46	9.39
U.K.	48.48	40.62	10.58
France	25.97	71.28	2.73
Spain	15.06	60.45	24.48
U.S.	45.54	41.39	4.06

Note:

1. We have calculated the contributions using the estimated elasticities of Model 2, which includes the interaction of imports of knowledge with the propensity to import.
2. Madsen (2007) also comments on the contributions using the elasticities obtained with the import interaction term, and Coe et al. (2009) also discuss the results of the model with *m*.