Biased Technological Change Direction and Intensity: a Macro-funded Local Adaptive Dynamics Analysis

Rodrigo Kataishi
University of Turin

1 Introduction

This work is focused on the study of macro level technological change dynamics exploiting available long trend productivity data. The main objective is to implement the Biased technological change concept (Antonelli and Quatraro, 2014) in order to explore the adaptive dynamics that takes place when technological shocks occur.

Particularly, the interest will be focused on the exploration of the determinants of both the Biased Technological Change direction and intensity. Additionally, there are a number of linkages that are worth to explore, such as the connection between the bias intensity (as a measure of adaptive practices) and the patenting activities (as proxy of general purpose technological shifts). Furthermore, the relation of the bias with factor output elasticities as determinants of coherence in the adaptation processes will be estimated and discussed in order to address the mechanisms underlying diverse specialization patterns and the path-dependent nature of the local systems.

The analysis will be carried using a novel database comprehending the period 1973-2005 and 13 developed countries. The evidence will be treated in two sets of econometric models, a block of five fixed effects models to address the directionality of the bias and a set of five System-GMM models to explore the determinants of its intensity.

The biased technological change concept is focused on the study of the interaction between factors' relative abundance and their contribution to the production output, making use of the information provided by the factor output elasticities and the inter-temporal relative factor endowments. As so, it allows to measure the impact of localized, adaptive dynamics that take place when a technological shock occur.

The estimations of Biased Technological change allows to incorporate in the long-trend productivity analysis the effects derived from general-purpose technological shocks and local adaptive strategies. This imply a contribution to the macro-level productivity analysis and opens the possibility to elaborate more sensible and explanatory indicators from currently existent data.

The next section will discuss the conceptual milestones involved in the localized, directed and biased technological change followed by the theoretical derivation of the bias. Section 4 will describe the empirical strategy, data used to carry the analysis and will address the main stylized facts that the data shows. Section 5 is intended to address the empirical aspects and previous findings related to the bias and it's determinants. Section 6 will present the specification of the econometric models and will discuss the main results derived from the regressions to explain the bias determinants. Finally, Section 7 expose the implications of the evidence gathered and summarize the final remarks of the paper.

2 The analytical framework

Technological change dynamics have been deeply studied during the last decades, making the topic one of the most relevant at macro and micro level, particularly within the field of economics of innovation. The constitution of these studies, departing from the seminal work of Solow (1957), showed productivity as one of the central elements able to help us understand technical progress trends.

The first approaches targeting productivity estimations (Solow, 1957; Douglas, 1985; Dasgupta and Stiglitz, 1976) relayed on the idea that simplified production functions were able to capture the interactions amongst factors and, at some point, to predict future output levels. By estimating inputs and outputs according to these specific functional forms the empirical values showed differences with respect to the theoretical models. Amongst the reasons able to explain these divergences, the introduction of the concept of productivity variations due to technological change represent one of the most prolific lines of research until our days.

Technological change can be measured in different ways, one of the most regularly used involves productivity shifts through total factor productivity estimations. The most relevant estimations on total factor productivity were built upon a Cobb-Douglas production function with constant returns to scales (Solow, 1957). The assumptions behind that formulation were historically criticized by a portion of the literature for considering them too simplistic in different aspects. In spite of the criticism, this indicator is, still, one of most diffused to understand productivity differences across countries and time.

Moreover, it is important to underline that in addition to the standard assumptions regarding a Cobb-Douglas based production function, there are two additional premises that affect drastically the interpretation of productivity estimations. The first of them is the solowian proposition that address technological change as neutral. The second, the fact that the output elasticities tend to be homogeneous across countries and that are fixed over time.

The main issues this work intend to present for their discussion are based on the relaxation of these two effects. On the one hand, the neutral feature of technological change can be, indeed, a possible scenario on the real world. This, however, doesn't imply that neutrality is the generalized case that characterize every economic system. On the other hand, is not likely to think that output elasticities are fixed at certain levels for long periods of time. In other words, this paper challenges the idea that elasticities doesn't change dynamically from one period to another. Similarly, if output elasticities represent a local feature of an economy, is arguable that they present identical values for different economic systems. So, elasticities may vary from one context to another. The relaxation of these two issues, neutrality and output elasticities, are not only the very origin of the Biased Technological Change concept, but also the root for the arguments on the adaptive and local nature of the technological change.

Given a technological shock manifested through the appearance of a new general-purpose techniques, production processes of different economies may be subject to alterations. If these economies are heterogeneous in the sense that each of them present particular endowments and factoral characteristics, then technology shocks are not expected to be neutral in the production systems affected (Helpman, 1998; Antonelli, 2006). This type of heterogeneity imply that the each shock have an specific effect in every context in which is introduced and that each production system may react following different strategies.

Moreover, considering shocks to be dynamic over time, the adaptation patterns become specific of each context. In concordance with Habbakuk (1962) and David (1975), the local characteristics determined by factor's abundance and cumulative experience can lead to innovative adaptations in response to exogenous shocks. Each context adapt itself differently according to its experience and previous production practices, allowing the deployment of two parallel effects: the one that make each context different from others, and the one that limit the adaptive possibilities within a restricted range of techniques tightly related to previous experiences (Antonelli, 1995).

General-purpose technology shocks and local adaptations are two processes that are different in nature but strongly related. The first is oriented to modify the production ways, replacing the exploitation of resources based on old techniques to implement new ones and spread them in a range of related technological classes (Keller, 2002). This kind of processes are difficult to measure, but generally it is assumed that patents creation and citation represent a good approximation of how general a technology is and how much it is diffused in certain economic systems. Local adaptations, instead, are based on particular reactions that economic systems carry given a general-purpose technological shock. These adaptations are embedded in particular contexts and implemented by labor force that learn from each response they build upon every external shock. The Labor-skills biased technological change literature (Acemoglu, 1998; Acemoglu, 2002) recognize these elements in the relation that workers show with the production levels and analyze the elasticities of different types of workers in order to determine the diversity of dynamics underlying the adaptive behavior.

Hence, two broad types of technological change can be identified from the literature. On the one hand, there are innovations that affect the system level, general-purpose technologies that modify the ways in which the system interact and produce. On the other hand, the new products and processes that respond to a local need, particularly focused on the adaptation and imitation able to provide particular opportunities in an specific context. It is worth to mention that general technologies, in spite of their general diffusion, are produced from a local context too, and have their root in creative adaptation (Antonelli, 2004; Antonelli and Fassio 2014) and imitation dynamics dependent on a particular local experience.

The interaction between general technologies and local adaptation is one additional component of the relation. Local adaptation in the form of re-allocation of resources takes place not only in the third-party economies that interpret the technology as a shock, but also in the context that is source of the innovation.

A particular situation takes place if technology is not neutral[1]. Given a technological shock, two types of effect should be recognized depending on the inclusion or not of the output elasticities modifications derived from the use of novel technologies. The first effect is focused on the *pure* shift of the isoquants, as if there is no impact of the shock on the factor's output elasticities; the second is defined by the isolated consequence on the later. This measures the movements of the slope over the same isoquant due to the shock. Antonelli and Quatraro (2014) carry a comprehensive explanation of these relation and develop an empirical proposal to calculate these types of technological change with currently available data.

The technological shocks that generate shifts on the isoquants are those that posses a general impact on the economic activities. This effect is the one that Solow's productivity measurement captures if the technology is neutral. As mentioned above, in order to identify this process without assuming neutrality, a total effect have to be calculated based on fixed values of the output elasticities. The contingent adaptations take place at the local level and are reflected as a change on the factors use an their the output elasticities relation. This is the bias effect (Antonelli and Quatraro, 2010, 2014), which technically is the difference between the technological change calculated with fixed output elasticities and the Solow's traditional indicator.

A decomposition of the technological change in two effects, the movement of the isoquants and the bias effect derived from the output elasticities transformations is particularly useful for the setup presented in this work. Economies specialized on the creation of general technologies will impact on the shift of the production functions, while economies that react to new technologies, interpreting them as a shock, are expected to incur in con-

[1]Classical productivity measurements have been able to identify technological shifts calculating the empirical differences between the theoretical predictions and the actual growth rates of the economies. This type of indicator is based on Solow (1957) and reflects technological change as a particular situation: if the technology is neutral, the residual derived from the theoretical and empirical estimations is expected to identify the shifts on the isoquants towards the origin.

tingent innovations switching their allocations to a new combinations that favor the new context (Antonelli, 2004).

3 The Technological Change Decomposition

The TFP calculation implemented in this paper is one of the most direct ways to approach the productivity problem, consisting in a trans-log transformation of the Cobb-Douglas production function (Christensen, Jorgerson and Law, 1973). Departing from this standard setup, the formalization becomes $log(A^{s}_{i,s,t}) = log(Y_{i,s,t}) - \alpha_{i,s,t} log(K_{i,s,t}) - \beta_{i,s,t} log(L_{i,s,t})$ with i and t representing country and time variations, respectively. The elements considered in the function are the traditional ones, where Y stands for output (GDP), L for labor, K for capital, α and β for output elasticities and A as the inter-temporal residual between theoretical and empirical values.

The following exercises consider output elasticities as a result derived from actual data, hence this work is not concentrated on the econometric estimation of this particular item[2]. Making use of available available data, the elasticities are calculated following the standard setup $\beta_{i,s,t} = \frac{P_L L}{Y} = \frac{w_{i,s,t} . L_{i,s,t}}{Y_{i,s,t}}$, where w represents wages of the labor force (i.e. total compensations over total persons engaged) and β is the equivalence between the marginal productivity of labor and factor's prices.

As was mentioned above, if technological shocks affect the isoquants *and* the output elasticities (OE) of each production factor, the necessity to formulate the classic Solow's TFP view raises. This is so because traditional TFP isn't sensible enough to identify both, neutral shifts and OE changes, due to the holding of the neutrality assumption. The Bias Technological Change approach (Antonelli and Quatraro, 2010, 2014) addresses this issue by using a a two-step index. The first step isolate the effect of technology changes over output elasticities, and will be denominated Technological Change with Fixed Output Elasticities (A^{foe}). This index measures technological change as if OE are constant over time, accounting for productivity variations that involve both, neutral shifts and factors' output elasticities alterations[3]. The formal trans-log expression of it is $log(A^{foe}_{i,s,t_n}) = log(Y_{i,s,t_n}) - \alpha_{i,s,t_0} log(K_{i,s,t_n}) - \beta_{i,s,t_0} log(L_{i,s,t_n})$ noting that t is fixed at $t = 0$ (or t_0). The main element to take into account is that α and β are now invariant over time. This particular feature will allow to isolate the elasticity variations from the

[2]Although there are extensive debates regarding this aspect, the estimation of the elasticities concerns other kind of research questions (and specially other assumptions). The works of e.g. Miller (2008) and De Loecker (2009) illustrate the main elements of this discussion.

[3]Indeed, Antonelli and Quatraro (2010, 2014) define the same indicator as the *Total Output Elasticty* index.

main technological shifts effect.

The Bias component of the Technological Change consists in the calculation of the residual between the fixed output elasticities technological change A^{foe} and the traditional index A^s. The conceptual reason to do this is that the Biased Technological Change should account *exclusively* for the transformations in the factor's output elasticities. If A^{foe} measures the total effect (neutral and elasticities variations, together) and Solow's TFP measures only the changes due to neutral technology variations, then the difference between the first and the second turns to be the isolated effect of the OE. Hence, the Biased Technological Change (BTC) is the difference between the two indexes, which can be expressed as $(A^{foe}_{i,s,t_n}) - (A^{s}_{i,s,t_n}) = (A^{Bias}_{i,s,t_n})$.

Different states of the Bias can be outlined. If the BTC is equal to zero, then technological change is neutral, so the entire effect of technology shocks is measured by the traditional Solow's TFP. If the bias is different from zero the neutrality assumption doesn't hold.

3.1 Biased Technological Change and the Localized Adaptive Processes

Different states of the Bias can be outlined, each of them determine the interpretation of this indicator. From a static point of view, the BTC offers information about the economy: if it is equal to zero, then such structure doesn't react to output elasticities alterations. This can only happens due to particular features of the system such as similar output elasticities or factoral endowments, and represent a theoretical case that hardly encounter an empirical manifestation. This case will be characterized as a neutral structure because of the spurious effect that productivity changes may have on the system's composition. If the bias is different from zero, additional information on the structural characteristics of the economy can be collected.

The Biased Technological Change indicator contain it's strongest explanatory feature within it's sign. A positive BTC can be interpreted as a *coherent* relation between the factor's ratio and their output elasticities. Negative values of the bias represent the opposite, endowments and output elasticities going in different directions, obtaining a *non-coherent* technological structure . The static states of the BTC can be summarized as:

$$
\begin{cases}
BTC = 0, \quad Neutral\ Structure & \Rightarrow \beta = \alpha\ or\ L = K \\
\\
BTC > 0, \quad Coherent\ Structure & \Rightarrow \beta > \alpha\ and\ L > K \\
& \Rightarrow \beta < \alpha\ and\ L < K \\
\\
BTC > 0, \quad Non-Coherent\ Structure & \Rightarrow \beta < \alpha\ and\ L > K \\
& \Rightarrow \beta > \alpha\ and\ L < K
\end{cases}
$$

From a dynamic point of view, the BTC offers allows to analyze trends on the adaptive processes within an economy, complementing the information compiled through the traditional TFP indicator. It BTC is equal to zero, then the solowian neutrality assumptions hold and technological change affect factor output elasticities in the same proportions. Instead, if the bias differ from zero, new information on the adaptive mechanisms can be collected. According to this framework, given an L intensive region (so, where $L_i > K_i$) and a variation over time Δ, the dynamic instances of the bias can be summarized as:

$$
\begin{cases}
\Delta BTC = 0, \quad Neutral\ Adaptation & \Rightarrow \Delta\beta = \Delta\alpha = 0 \\
\\
\Delta BTC > 0, \quad Coherent\ Adaptation & \Rightarrow \Delta\frac{L}{K} > 0\ and\ \Delta\beta > 0 \\
& \Rightarrow \Delta\frac{L}{K} < 0\ and\ \Delta\beta < 0 \\
\\
\Delta BTC < 0, \quad Non\ Coherent\ Adaptation & \Rightarrow\ \Delta\frac{L}{K} > 0\ and\ \Delta\beta < 0 \\
& \Rightarrow\ \Delta\frac{L}{K} < 0\ and\ \Delta\beta > 0
\end{cases}
$$

A positive Bias imply a concordance between the relative factor abundance and the factor output elasticities (Antonelli, 2010). Hence, shifts of output elasticities towards a relatively abundant resource will be expressed as a BTC greater than zero[4] . When the specialization of a region is oriented to the factor that shows decreasing output elasticities, even if it is the most abundant on the region, the bias will be negative. So, if the local abundant resources are not evolving in the same direction than the output elasticities favored by the technological shock, then the specialization tends to be *non-coherent* (according to Antonelli and Quatraro, 2014).

As said, a BTC associated with a zero-value reflects the empirical manifestation of the neutrality assumption. In this case, the lack of bias connote that Solow's framework have a correlation with the empirical evidence. When the Bias differs from zero, then techno-

[4]Equivalently, the bias will be positive in cases in which the scarce resource of an economy shows diminishing elasticities.

logical change is not neutral and can be interpreted in different ways.

On the one hand, a positive Bias may imply a concordance between the relative factor abundance and the factor output elasticities (Antonelli, 2010). Hence, shifts of output elasticities towards a relatively abundant resource will be expressed as a BTC greater than zero[5] . On the other hand, when the specialization of a region is oriented to the factor showing decreasing output elasticities, the bias will be negative. So, if the local abundant resources are not evolving in the same direction than the output elasticities favored by the technological shock, then the specialization tends to be non-coherent (according to Antonelli and Quatraro, 2014).

Output elasticities are specific of each context, and their nature is attached to localized factors (e.g. labor and capital) that evolve over time augmenting the specific evolutionary trend of each particular context (region, country, etc.). If some variation exist within these indicators, then technological change is not neutral and the local effect plays a role. In this sense, locally abundant goods and technological trajectories matter. These issues are the focus of this work, and their trends and determinants will be explored in the following sections.

The segmentation of the technological change in distinctive effects, the shift due to the neutral changes and the bias, due to the local adaptation, offers an interesting insight on productivity analysis. It allows to explore the determinants and the relations between two types of innovation and how they behave over time, as well as differentiate and explain specific technological trajectories based on empirical data.

4 Methodology and Data Description

Following the presented framework, a number of key variables including the Bias Technological Change were calculated for 13 countries[6] within the period 1973-2005. The sources utilized to construct the dataset are the KLEMS database[7] for the raw indicators used to obtain the TFP and Biased Technological Change estimations; the World Development Indicators (WDI[8]) for patents and other control variables; last, the Groningen Productivity level database (GGDC[9]) for the relative pricing adjustments at sector level (Inklaar and

[5]Equivalently, the bias will be positive in cases in which the scarce resource of an economy shows diminishing elasticities.

[6]The countries are Australia, Belgium, Denmark, Spain, Finland, France, Germany, Italy, Japan, Korea, Netherlands, UK and US.

[7]http://www.euklems.net

[8]http://data.worldbank.org/data-catalog/world-development-indicators

[9]http://www.rug.nl/research/ggdc/data/ggdc-productivity-level-database

Timmer, 2006), used to adjust the Gross Output and, indirectly, the wages[10]. Combining these sources, a strongly balanced panel data with specific information on the selected countries was built.

For some of the exercises of the next section, sector level data on TFP is arranged in 4 groups according to the OECD Technological Instensity Classification (ISIC, Rev. 3[11], OECD, 2011). Each sector is classified according to this categories, although due to restrictions on data availability (mainly before 1990) the matching of each case across time was partially accomplished. In this sense, the grading from High to Low tech is merely descriptive and oriented to involve control's variability with respect to the Bias within the econometric models.

As was mentioned in **Section 3**, the TFP indicator is constructed as a normalized index that equals a unit at the beginning of a given period (1973 in this case), such that:

$$log(A^s_{t,i}) = log(Y_{t,i}) - \alpha_{t,i} log(K_{t,i}) - \beta_{t,i} log(L_{t,i}) \tag{1}$$

$$TFP_{t,i} = 1 + \Delta log(A^s_{i,t}) = 1 + \frac{log(A^s_{i,t}) - log(A^s_{i,t-1})}{log(A^s_{i,t-1})} \tag{2}$$

$$\forall i,\ \forall t > 1973,\ \ where\ TFP_{t,i} = 1\ \ if\ \ t = 1973$$

Equation (1) and (2) provide the specification of the TFP derivation[12]. The Biased Technological Change indicator, hence, is the difference between A^s and an estimation of the TFP with fixed factor output elasticities over time A^{foe}. In effect, A^{foe} is calculated considering that $\alpha_{t,i}$ and $\beta_{t,i}$ are constant for the period[13]. The bias index is expressed as the difference between the total effect of technological change and the one based on the neutrality assumption, as $A^{foe} - A^s = A^{bias}$.

In order to present some basic indicators derived from the data and to address the dynamics of the key variables in a summarized way, the time span of the sample is split in three periods: 1973-1985, 1986-1995 and 1995-2005. Table 1 shows the five indicators that will conform the core of the analysis: income per capita (Y/L), TFP average growth for each period, the Biased Technological Change (BTC) and the Labor Output Elasticity

[10] The prices are normalized at sector level using the Parity Purchase Power pricing of 2005.

[11] Further information at http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=2

[12] TFP and other indicators are also calculated at the sector level for some of the econometric estimations of the next section. So, for each country i there may be a set of sectors $s = \{1, 4\}$ with their specific TFP proportions.

[13] The values of the fist year $\alpha_{1973,i}$ and $\beta_{1973,i}$ are extended $\forall \alpha_{t,i}, \beta_{t,i}$

(LOE, or β on both, Solow's (1957) and Antonelli and Quatraro's (2014) specifications) values and growth rates.

Table 1: Key Variables by Period, 13 Countries Average.

Periods		Y/L	TFP Growth	BTC	LOE	LOE Growth
1973-1985	*mean*	3.225237	.0927851	.0114584	.5650496	.0011271
	std. dev.	3.859594	.0866665	.0199014	.0869974	.0180777
	Range (max-min)	25.55491	.7024555	.1108698	.4127587	.1381516
	Cv (mean/sd)	1.196685	.9340562	1.736836	.1539641	16.03847
1986-1995	*mean*	4.13493	.0414461	.0059806	.5585475	.000044
	std. dev.	6.144102	.0611039	.0296117	.05847	.0141417
	Range (max-min)	36.86533	.3461146	.1329368	.2678231	.1023288
	Cv (mean/sd)	1.485903	1.474297	4.951284	.1046823	321.4473
1996-2005	*mean*	3.924263	.023493	.0077456	.5592808	.0006108
	std. dev.	7.13458	.0495006	.0307563	.0575267	.0103427
	Range (max-min)	53.43374	.3399501	.1308643	.2616257	.0688759
	Cv (mean/sd)	1.818069	2.107036	3.970827	.1028583	16.93397
1973-2005	*mean*	3.727961	.0550879	.0086734	.5613312	.0006273
	std. dev.	5.768852	.0750518	.0266531	.0707656	.0147538
	Range (max-min)	53.43374	.7024555	.1421844	.4240237	.1381516
	Cv (mean/sd)	1.547455	1.362402	3.072979	.1260675	23.51988

Source: Own Elaboration based on KLEMS, WDI and GGDC databases. Y/L are in millions of PPP U\$S; also LOE is calculated using yearly compensations normalized to U\$S PPP for 2005, together with GDP and Labour Force as quantity of Engaged Personnel. See Technological Change Decomposition subsection for further detail on LOE construction.

Table 1 shows that, during the time window considered there is in an increasing dynamic of the Income per Capita (Y/L) considering the average of the 13 countries of the sample. The mean income per capita for 1973-2005 is 3.72 millions of U\$S PPP. This average is higher than the values for 1973-1985 (3.22) but lower than the two most recent time intervals. The peak of Y/L was achieved during the years 1986-1995, 0,21 units higher than in the most recent period.

The TFP Growth Rate is an index that considers the average yearly differences for each of the three intervals. The sample's TFP growth is decreasing over time suggesting a slow-down dynamic. For the entire period the TFP growth is slightly higher than .05 percentage points, with the most important growth during the period that start in the seventies (of .09).

The Bias Technological Change index show in average values near zero for the entire time window (.009) with the lowest value in the interval 1986-1995 and the highest during the years 1973-1985. Despite this aggregate trend, regional heterogeneity show figures that suggest that the bias does not behave homogeneously from country to country. From their side, labor output elasticities surrounds the .56 points and, as the bias, are notably stable over the last 30 years, with average variations of .0006 (this is the entire period LOE Growth).

Table 2: TFP and Income per capita by country and period

	Period 1973-1985		Period 1986-1995		Period 1995-2005	
	TFP Index	Y/L	TFP Index	Y/L	TFP Index	Y/L
Australia	1.578434	86.42334	1.501543	62.61677	1.21056	25.83666
Belgium	1.411428	72.13943	1.344253	50.91661	1.15923	24.49079
Denmark	1.332776	423.9943	1.288689	300.4703	1.134518	138.8483
Spain	2.218234	45.03414	2.076972	30.34919	1.462146	9.391023
Finland	1.955864	62.95258	1.791274	38.59437	1.378104	15.4768
France	1.440428	59.60337	1.395652	47.65792	1.162934	21.05193
Germany	1.280618	54.8773	1.215992	40.47454	1.080087	23.79358
Italy	2.171076	61.42938	1.9830	37.80574	1.422708	11.07388
Japan	1.046568	85.75852	1.085054	83.40566	1.054056	53.97445
Korea	1.717608	41.84095	1.5613	175.0383	1.274825	43.76594
Netherlands	1.289054	52.51111	1.216983	39.4917	1.11384	27.11373
U.K.	2.065573	37.05063	1.902748	23.41537	1.35645	8.089779
United States	1.326672	76.34059	1.250145	52.5932	1.107642	29.29434

Source: Own Elaboration based on KLEMS, WDI and GGDC databases

Table 2 show how TFP and Income per-capita evolved in the past decades. In general, a downward trend can be observed in most of the countries of the sample when the time dynamics are observed. This trends, however do not behave in an homogeneous way. Particularly, within the group of developed countries considered[14] Spain shows one of the most critical downward tendencies, together with Italy and UK passing from TFP values higher than 2 in the seventies to figures surrounding a unit for the period 1995-2005. The highest TFP levels for the last period, although, belong exactly to these three countries, manifesting a productivity slow down pattern trend (such as the ideas addressed in Acemoglu et. al., 2014).

Income per-capita is a raw indicator that determines the production level of an economy according to its dimension. Particularly it is able to address in a very approximated fashion how rich a country is (disregarding the distributive aspects that can obviously affect the overall economic performance and sustainability) and how many resources it has.

[14] In fact, the presence of Korea in this group and it's denomination of developed country might be challenged by a part of the literature. In any sense, Korea have shown substantial progress in several aspects of their economic performance and, if not developed, can be taken into account as an advanced-developing country and can be contrasted with the rest of the panel.

Per-capita income levels (GDP over Labor force) showed in Table 2 detail a decreasing trend, similar to the one observed in the TFP. With exception of Korea, that reached an average peak during the period 1986-1995 and denotes improvements over time, the rest of the countries of the panel evidence a decay in this variable. The highest levels for Y/L in the most recent years (1995-2005) are achieved by Denmark (138.8), Japan (53.9) and Korea (43.8). The ranking doesn't show radical variations over the years, maintaining Denmark and Japan on the first three positions with Australia in 1973-1985 and Korea during the average peak of middle eighties to middle nineties.

Table 3 shows the country level detail for the Biased Technological Change and the Labor Output Elasticities (LOE, or β according to the previous notation) within the three time periods. As said, the BTC indicator should be null if technological change is neutral. Although this condition seems to hold in the aggregated level (see Table 1), the empirical calculations show that this indicator diverge from zero in major or minor degree for all the considered countries. During the time span we can observe different trends per country, oscillations from positive to negative values, recurrent differences from zero-values and, of course, fluctuations over time of the BTC.

Table 3: Biased Technological Change and Labor output elasticities by country and period

	Period 1973-1985		Period 1986-1995		Period 1995-2005	
	BTC Index	LOE	BTC Index	LOE	BTC Index	LOE
Australia	.0204963	.5353162	-.0257552	.5368392	-.0289471	.5974367
Belgium	.0327998	.5558003	.0106327	.5573222	.0148456	.5787216
Denmark	.0223845	.6486163	.0253358	.6456023	.0233783	.6444869
Spain	.0130055	.5306762	.0140225	.4974126	.0267826	.515945
Finland	-.0135068	.5416538	-.0122533	.587758	-.0607389	.5796584
France	.0262961	.6116759	-.0192421	.5924944	-.0174041	.5979054
Germany	.0118071	.6072135	-.0116291	.6197691	-.0388847	.6342067
Italy	-.0168927	.4458515	-.0666175	.4862166	-.1100622	.529206
Japan	.0546669	.5198265	.0759484	.4874466	.0624327	.4409441
Korea	.0426432	.4864727	.1113603	.4732701	.1084194	.355302
Netherlands	.0002825	.5978549	-.038867	.5938779	-.0410042	.6371915
U.K.	.0167347	.6239046	-.0340608	.6082837	-.039749	.6496711
United States	-.0185839	.5657875	-.0084818	.5748247	-.0036969	.5849698

Source: Own Elaboration based on KLEMS, WDI and GGDC databases

During the first period (1973-1985) the amount of countries with a bias below zero is lower than in the other two. The three countries (Finland, Italy and US) with a negative bias in that years remain in the same situation for the other time intervals. At the same time, five countries show a positive bias for the whole time window (Belgium, Denmark, Spain, Japan and Korea). It is worth to note that the cross-country differences manifested in the BTC dispersion increases when comparing the first period to the most recent ones. In the last two periods the country-to-country comparison show more dispersion having Italy a minimum value of -.11 and Korea a maximum of .10 during 1996-2005. In the interval 1973-1985 the extremes are -.018 (U.S.) and .05 (Japan), respectively. During the middle eighties until the half of the nineties the extremes are -.025 (Australia) and .11 (Korea).

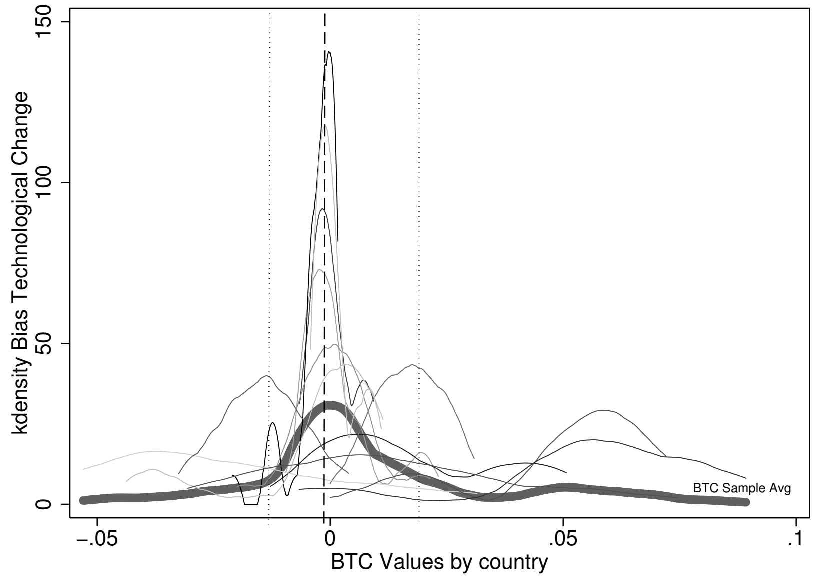
Labor Output Elasticities figures vary between 0.35 and 0.66 for all periods and countries, but the most important part of the values surrounds .55, as was shown in Table 1. Over the three time intervals Denmark, UK, Germany exhibit the highest LOE, with elasticities above 0.6; whilst on the other hand, Korea, Italy and Japan show the lowest labor elasticities with average values surrounding 0.45.

As was mentioned before, the Biased Technological Change study is based on the relaxation of the premise sustaining the neutrality of the technological change (Antonelli and Quatraro, 2010; Feder, 2014). Following Antonelli and Quatraro (2014) method, an estimation of the effects of technology on output elasticities and factor shares can be estimated. Table 3 show how heterogeneity plays a role in the different BTC estimations per country. In addition to that, Graph 1 show the density functions for the BTC indicator considering every year and country individually. The main gray line show the sample average, the thick lines address each country data.

It is expected that biased Technological Change trends differ from country to country and over time. From Graph 1, it can be seen that there is a group of economies that are located on the positive side of the BTC, others that show a negative trend and a third group in which the values are close to zero.

After Graph 1, two interesting issues can be pointed. First, there are some cases in which technology seems to be close to neutral, meaning that the density is concentrated nearby zero. For these countries the Bias Effect is marginal and the technological change affecting their production systems can be understood as a traditional shifts on the isoquants, so, can be measured *mainly* by the TFP. The second point apply for the majority of the cases, meaning those with Bias values concentrated away from zero. Data suggests that the neutrality assumption isn't entirely supported on these countries since their bias densities show dispersion in two ways: their tails are wide escaping from the zero area and the most frequent values (so, not only the tails but the entire distribution) are situated in negative or positive values. Last, note that whilst some countries are recurrently on the positive side of the Bias and others are negative, there is a group that passes from one state

Graph 1. Kernel Density of BTC, sample average for 1973-2005 and country values.

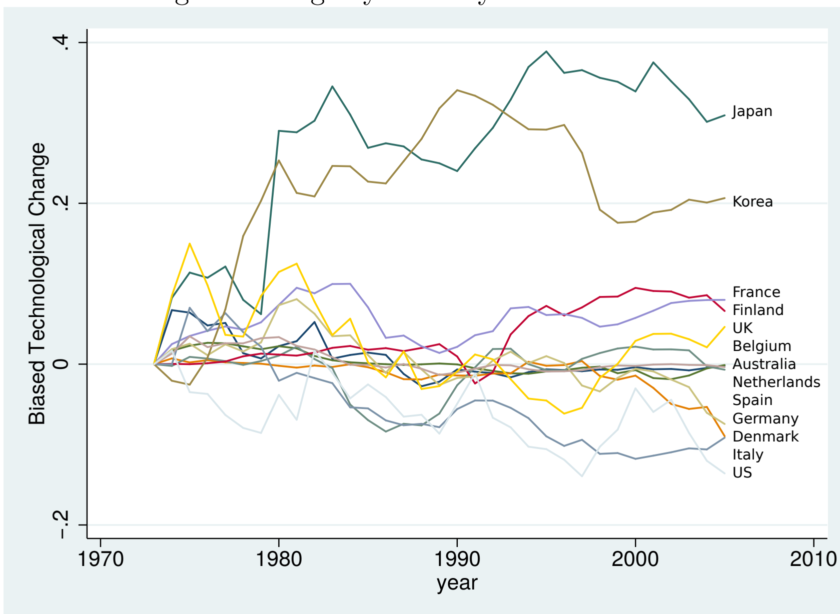


Source: Own Elaboration based on KLEMS, WDI and GGDC databases

to the other. Since the kernel density graph doesn't contemplate the time dimension, the next figures will pay attention to the BTC dynamics over time with country-level details.

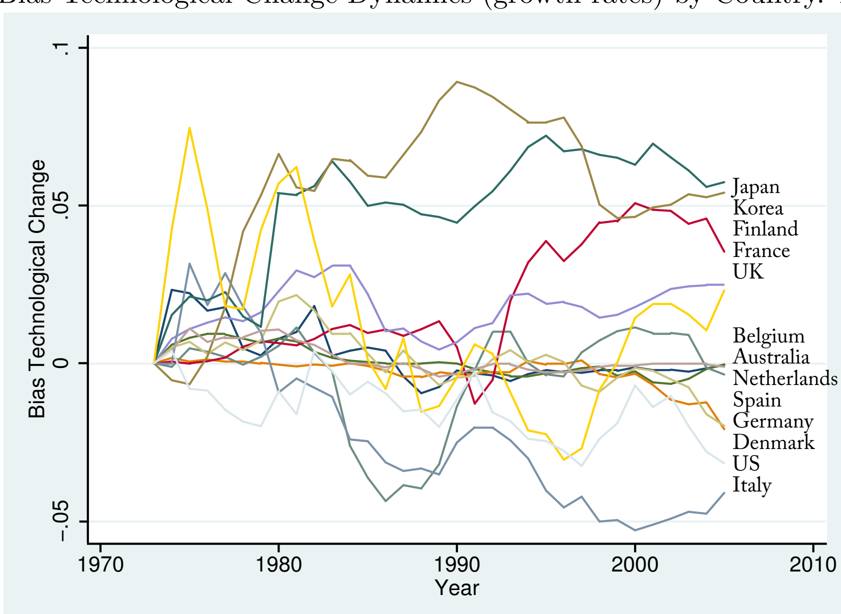
Graph 2 shows the absolute values of the BTC indicator over time. Since this indicator is constructed from an specific year-base (1973, as explained in the previous section) all values depart from zero. Japan, Korea and Finland show a positive bias trend, the rest passed from a positive state to a negative one and vice-versa. When analyzing the growth rates instead of the absolute values, the bias dynamic can be appreciated. Graph 3 show that this trends are far from being static or monotone. Each country show their own path and individual dynamic regarding the Bias.

Graph 2. Bias Technological Change by Country. 1973-2005.



Source: Own Elaboration based on KLEMS, WDI and GGDC databases

Graph 3. Bias Technological Change Dynamics (growth rates) by Country. 1973-2005.

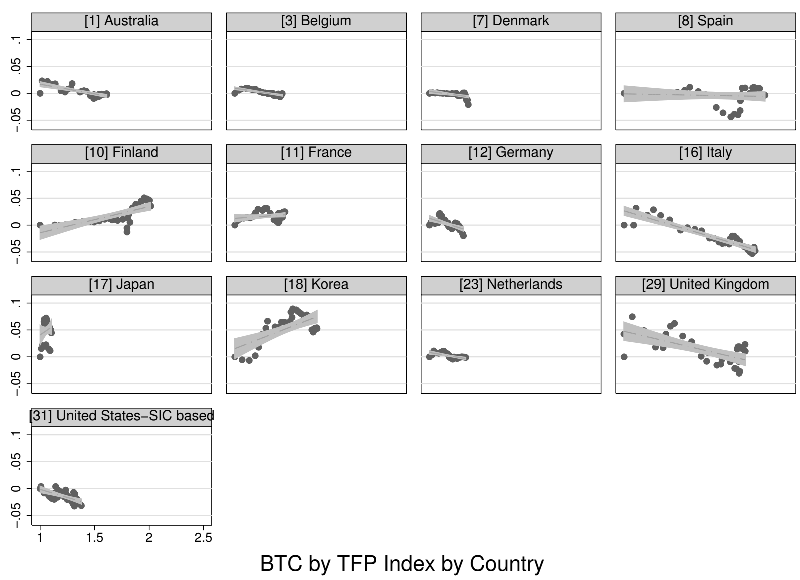


Source: Own Elaboration based on KLEMS, WDI and GGDC databases

BTC movements are heterogeneous from country to country because they refer to a local feature that is embedded on each economy and is manifested when they react to technological changes. The localized characteristics of production factors (e.g. labor specialization) and their relative abundance on a region are the core of the trends observed in graphs 2 and 3. In the next sections, the focus will be put on the determinants of these localized adaptive processes.

Last, regarding the relation and trends between traditional productivity measures and the bias, it is important to underline that TFP and BTC are two complementary indicators that are oriented to inquire on technological change dynamics, but the explanatory power of each differ in substantial aspects. TFP is oriented to measure the shifts on the isoquants, while BTC is focused on estimate the changes on their slope. The different behavior of the two estimations is showed in Graph 4, in which the interaction of the two variables is presented at the country level (TFP in the horizontal axes and BTC in the vertical ones).

Graph 4. TFP and Biased Technological Change by country. 1973-2005.



Source: Own Elaboration based on KLEMS, WDI and GGDC databases

Graph 4 shows the interaction of TFP and BTC. A number of patterns can be distinguished: positive correlations, as is the case of Korea, Finland and, with attenuated intensity, France; negative correlations, affecting Italy, UK and, with minor intensity, Germany, US and Australia; and neutral relations, meaning that the movements on TFP intensity take place without affecting the Bias trends, mainly represented by Belgium, Denmark and Netherlands. One last case is that of Japan, in which the TFP levels remain relatively fixed, but the BTC showed upwards movements.

This graph is oriented to show that there is few evidence supporting the fact that TFP and BTC trends are similar. The mechanisms that trigger each indicator respond to different determinants, because the processes they are measuring are, by nature, different. The movements of the TFP are those affecting the entire economy by modifying available techniques and production practices. On the other hand, the BTC respond to adaptive processes that take place on each specific context.

5 Exploring the determinants of the BTC

This section will present the core of the discussion of this paper, which is oriented to explore the determinants of the biased technological change. Since the intention is to measure technical adaptations that take place at the local level after generic technological shifts, at least two elements deserve to be further explored. First, the magnitude of the adaptation effect, meaning how important the bias is; second, the direction that the bias has (i.e. it's sign), or the *coherence* of the adaptation (according to Antonelli and Quatraro, 2014).

The Biased Technological Change determinants were addressed in a number of previous works (e.g., Antonelli and Quatraro 2007, 2010, 2014; Kataishi, 2015) achieving a set of common results that worth to be recalled. The first of them is that BTC is a path-dependent variable, related with former decisions regarding resource allocations and specialization patterns. Besides the direct approach consisting in take previous states of the BTC and measure the influence on the current values, the path dependence can also be addressed by comparing the bias with other productivity indicators such as other sector's or technological classes (as in the sector-level analysis conducted in Kataishi, 2015) or a by implementing a ratio between lagged BTC and TFP realizations (as in Antonelli and Quatraro 2014). In any case, the relation of the BTC with the previous states of the economic system raises as an important factor to be taken into account at the moment of explore the BTC behavior.

The output elasticities (OE) have a key role too, specially because they affect the allocation choice by giving a particular return given the characteristics of the technological shock. As was mentioned before, resources can (or cannot) evolve in the same direction than output elasticities. If those evolve together in the direction of an abundant factor then we refer to a positive (negative) bias. From a conceptual point, OE are able to signal whether the relative use of one factor or other is convenient[15] at a given moment, restricting

[15]In the sense that higher output elasticities may imply higher returns from a factor, hence, more demand on its use.

the future allocations and abundance of labor, capital or other production factors. This, of course, is critical on the BTC dynamics.

From a purely theoretical point of view, factor prices affect are strongly related to the elasticities. Particularly, elasticities are calculated assuming CRS production functions and that the Euler's theorem holds[16]. Due to this indirect relation, prices (i.e. wages) may present a different type of influence on the allocation decisions than elasticities, although they are assumed to be strictly related[17]. The effect that price movements have on the BTC will also be considered as relevant in the analysis and explored as both, a determinant and a control variable.

The knowledge dimension is also expected to have an important effect over the Bias, since knowledge nature imply that is embedded in local systems. As is widely underlined on the innovation literature, a key distinction concerning different types of knowledge is worth to mention. On the one hand, radical innovations usually come from a sequence of efforts that are whether originated from science and technology research and applied sciences investments, or from big enterprises that conduce R&D practices. This radical innovations, once widely diffused, may be able to become general purpose technologies. On the other hand, incremental innovations take place at the local level, in which firms adapt and appropriate radical or general purpose innovations to satisfy specific market niche needs. These kind of efforts are related to day-by-day routines that are improved upon the cumulated experience and circulation of knowledge with pairs of a firm's context.

The relation between these two dimensions of knowledge will be addressed in the next section. The BTC, as was mentioned, refers in an aggregated fashion to adaptive processes that take place in particular contexts. On their side, there are different types of variables that may indicate generalized shifts on technology, one of the most frequently used are patents.

There is a rich discussion regarding the role that patents play as an indicator of new knowledge generation (e.g. Trajtemberg, 1987; Pavitt, 1985; Katila, 2000). This indicator is, still, a widely used approximation that allow to explore macro-level tendencies at

[16]Meaning that the elasticities are calculated as $\beta_{i,s,t} = \frac{P_L L}{Y} = \frac{w_{i,s,t} \cdot L_{i,s,t}}{Y_{i,s,t}}$. A complementary way to interpret the a two-factors' CRS approach is that the variations are concentrated in one of the factors (say L). The effect of the remaining elements are contemplated in a raw approach, concentrating in K and α different types of information. The detailed analysis that additional factors may offer is, however, a line of work that apply to the domain of the multi-factor productivity analysis (MFP). Although the last is compatible with the presented framework, it suppose future efforts of development towards an integration of a comprehensive, detailed view and it's formal implementation.

[17]In the econometric exercises, although, this will be represented sorting a number of restrictions in the specification structure that will be noted in the next section.

regional and national level (Acs et al., 2002) and serves as a raw indicator of generalized technologies spreading (Bresnahan and Trajtenberg, 1995) and worldwide relevant innovation activities (Hall et al., 1986).

Technologies that are spread trough codified knowledge -as patents- impact in firms' routines in different ways. Each firm make use of patents according to their objectives, adapting new knowledge to their own routines, giving place to adaptive processes. From a macro perspective, this process can be captured in different ways: on the one hand, patents can lead to an intuition of general technology shocks (that move the isoquants towards cheaper combinations of resources), on the other hand, the BTC indicator can enlight the local reaction to these transformation in the existent production techniques.

Regarding previous insights on this matter, the Bias relation with patents is either strongly negative (Antonelli and Quatraro, 2014) or inconclusively negative (Kataishi, 2015). This is due to the fact that the patent creation affect the diffused techniques and the bias the reaction of the local systems to that new knowledge. In this sense, adaptation processes are not expected to begin or finish every time a new patent is registered or used in an economy. On the contrary, the dynamics of the adaptive processes are a continuum of efforts and routines that doesn't depend, a priori, on the patent creation. So, patents allow the shifts on the isoquants, while the Bias is the adaptive and local response to this process. The dependence of one on the other is, according to previous studies, inconclusive.

Last, knowledge creation, particularly the patenting dynamic, can be associated with a country's resources or, more generally, with its wealth. R&D expenditures will depend on this, in addition to the externalities that may generate a critical number of agents and institutions carrying related activities. This feature present a linkage with the income per-capita figures presented in the last section. On the one hand, the more resources an economy enables toward these activities, the more the probability they have to success in producing new knowledge; on the other hand, the persistence on knowledge creation (of course, resource related in the mid-long term) generates capabilities that determines a technological profile. So, addressing the fact that technology shifts through patents can be related to the economic wealth, the income per capita indicator will be explored as a determinant of the BTC, as a control variable of the shift effects derived from general technologies incursions. As so, the source mechanisms in touch with general technology creation processes are expected to be *in-natura* different from those related with the BTC.

Regarding other determinants of the BTC, some of them won't be considered in this work due to lack of data. The most relevant issue in this sense is related to the R&D efforts. The measurement of variable at the macro level typically take place after the nineties for the majority of the countries, less than the half of the time-window used in this work. This indicator won't be considered in the panel data due to inexistent data for most of the countries, although some of it's variability might be taken into account through the patenting data and it's expected to don't have a relevant impact on the main results.

6 Results

Making use of a set of econometric models, the first issue addressed in this section are the determinants of the Bias Technological Change. Taking into account the previous discussion on this matter and presenting novel elements on the estimation, the first group of models will delve into the bias direction determinants. Additionally, since the BTC can be described as a three states indicator (zero, positive, negative), if values are different from zero then the absolute distance from the null value can be used as an estimation of the amount of bias. Hence, the second set of models will inquire into the connection between the bias intensity and the neutral technology shifts.

In previous sections it was suggested that the BTC is linked with a number of determinants. The following model incorporates the main relations discussed above, intentionally omitting a number of issues related with the econometric specification, specially those connected with simultaneity and reverse causality faults. The reason to do this is to present the basic structure of the model, which will be re-discussed in the next paragraphs. The raw model can be expressed in the following form:

$$A_t^{bias} = \beta_1 \, loe_{(i,t)} + \beta_2 \, y/l_{(i,t)} + [\beta_x \, X_{(i,t)}] + \eta_i + \tau_t + \epsilon_{i,t} \tag{3}$$

Where i, t are subscripts referring to countries i and years t, with i={ 1,13}, t={1973,2005} and:
$loe_{(i,t)}$: stands for Labor Output Elasticities
y/l: income per-capita
X: set of control variables
η_i: country fixed effect
τ_t: time fixed effect

This initial specification is a fixed effects dynamic panel data model, which is able to exploit the strongly balanced structure that the sample has. In fact, η_i and τ_t account for the country and time fixed effects, the latter particularly relevant for long periods of analysis[18]. This raw specification is concentrated on the exploration of two effects: the factor output elasticities and the income per-capita as determinants of the BTC. It is worth to recall that the *pure* BTC indicator takes negatives and positive values, and that the passing from one sign to the other attend to the coherence of the adaptation process (as in Antonelli and Quatraro, 2014). In order to gain robustness of the results, this work will propose a set of models instead of one, making the raw specification the initial staring

[18]Accounting for exogenous shocks that affect all the countries in the sample, such as an international crisis or other global phenomena.

point. The reasons to do this are based on the robustness of the results and the intention is to explore weather the relations are consistent within a variety of formulations. In this sense, the vector $X_{i,t}$ contain a group of indicators that will be selectively included on the specification to explore significant variations on the outcome.

The model as formulated above doesn't consider the fact that some variables have endogeneity issues, not only at the conceptual level, but also by construction. To make the point short, the former model presents the problem of serial correlation since the error terms are linked from one period to the other. This happens specially in cases in which the construction of a variable depends on other terms on the regression (so, there is a violation of the exogeneity assumption that a FE model requires). For instance, the presence of labor elasticity as an independent variable imply *a priori* an incompatibility with the BTC on the other side of the equation, because the first is used to construct the last[19]. If this issue is not taken into account, the relations obtained through the model will not only be spurious, but also the resulting estimations of β_x will be biased.

There are two main approaches to deal with the mentioned problem. The first is to use traditional instrumental variables, incorporating additional information on the regression that allows to capture the variability of the endogenous factor, avoiding the direct correlation with the independent variable[20]. This approach had faced some criticism within the literature due to the necessity of defend the introduced variables at a conceptual level (in addition to the technical dimension) and the risk to incur in spurious correlations. Additionally, it requires to find the particular variables that fit the sample characteristics (32 years and 13 countries) and that accomplish the IV specifications (exogeneity, no correlation with errors, correlation with the instrumented variable, etc.). The second alternative, which is the one applied in this work, is to instrument endogenous variables with a set of lags of their own, as a strategy to avoid potential spurious correlations and reverse causality problems.

Taking advantage on the availability of the past realizations of the regressors, it is assumed that the *t-1* moments are uncorrelated with contemporaneous idiosyncratic shocks on the independent variable. It is also expected that past values of each variable are highly correlated with their contemporary realizations and for time constrain reasons uncorrelated with both, dependent and independent variables contemporary realizations, allowing them to qualify as proper instruments on this model.

[19]And the regression will show an obvious significance because of that construction. This significance, of course, will not be the reflection of an empirical relation, but the consequence of how the variables are constructed.

[20]Of course, these are not the complete conditions to implement an instrumental variable in a dynamic model. See Wooldridge (2010) for further details.

$$A_t^{bias} = \beta_1\, loe_{(i,t-\lambda_1)} + \beta_2\, y/l_{(i,t-\lambda_2)} + \beta_3\, w_{(i,t-\lambda_3)} + \\ + \beta_3\, T.E.P_{(i,t-\lambda_4)} + \beta_4\, \Delta T.E.P._{(i,t-\lambda_6)} + \beta_5\, Pat_{(i,t-\lambda_5)} + \eta_i + \tau_t + \epsilon_{i,t} \tag{4}$$

Where i, t are subscripts referring to countries i and years t, with i={ 1,13}, t={1973,2005} and:

$loe_{(i,t)}$: stands for Labor Output Elasticicities y/l: income per-capita
$[X]$: $w_{i,t}$, $T.E.P_{i,t}$, $Pat_{i,t}$, $growth_i$
$w_{i,t}$: local wages
$T.E.P_{i,t}$: is the proportion of population with tertiary education
$\Delta T.E.P._{i,t}$: patents creation per year
$Pat_{i,t}$: patents creation per-capita
η_i: country fixed effect
τ_t: time fixed effect
λ_x: lag of the variable in years. $\lambda_5 = 1$ represents a lag of one year on the fifth term of the regression. It is expressed as λ_x because each term (variable) have their specific time-lag.

In order to avoid endogeneity issues, a set of time variations were incorporated to the model such that the orthogonality condition $E(\epsilon_{it}|X_{it-\lambda_x}) = 0$ is achieved for the set of regressors X_{it}, by using $X_{i(t-\lambda_x)} = (x_{i1}, ..., x_{it-\lambda_x})$ with $\lambda_x \geq 0$, where λ_x represent time lags. Each variable presents it's own lagging considering the relation it has with the independent variable and with the other regressors. Accordingly, the re-arranged formulation of the model have the form of **Equation (4)**. In such formulation, endogeneity issues are addressed by instrumenting compromised regressors with past realizations of that variables. Each of these variables are lagged in an specific number of years, represented by λ_x[21].

Table 4 shows the results of the regressions carried using the framework presented above, exploring the determinants of the Bias direction (or sign). The table summarize five models that alter the time lags λ_x and selectively include (and exclude) variables to see whether the specification's conclusions are affected or not.

[21] The second column of Table 4 represents the number of years of lag implemented in each model.

Table 4: Dynamic Fixed Effect Models on the Bias Direction determinants.

Variable	λ (lag)	FE(1)	FE(2)	FE(3)	FE(4)	FE(5)
LOE	*1*	.30767288**	.26117984*	.26275519*	.27578383*	.2791132**
Y/L	-	-3.711e-07*	-8.496e-07*	-1.023e-06**	-1.410e-06*	-7.791e-07*
	1			0,0001917	0,0006767	0,0003239
w	*2*	-.00041677	-.00199682	-.00185753		.00038965
	3	.00070776	.00272191*	.00257459*	.00064624	
T.E.P.	*1*	-0,00000526			-0,000006155	
Δ *T.E.P.*	*2*		-0,000005232	-0,000005229		-5.590e-09*
Patents p.c.	*1*		.00670819	.00649841	.00285513	
	2		.00332065	.00352136	.00340625	
_cons		-.15602108**	-.11463721	-.11568707	-.12669465	-.14814135**

Source: Own elaboration. The λ column specify the lags, such that 1 is a one year lag. The significance levels respond to the traditional boundaries: 10%(*); 5%(**) and 1%(***).

The conclusions derived from this set of models indicate that the Bias direction is positively related to the labor output elasticity and negatively related to the income per-capita[22]. This stresses the importance of the specialization patterns at the local level, showing that the higher the output elasticities on labor are, the higher will be the capabilities of a system to adapt to technological shocks (i.e. neutral shifts in the isoquants). On the other hand, countries' wealth works in the opposite direction: the higher the income per capita, the less is expected to be the bias. This relation points that the coherence of the adaptation processes increase as the income per-capita is lower. However, several considerations regarding the sample characteristics can be acknowledged: these countries are the richest in the world and the differences on their income levels doesn't necessarily imply a lack of resources, but depict a production profile oriented or not towards the bias. In other words, the higher the income per-capita (within the richest economies), the higher the probability of a country to be specialized in neutral shifts of the technology, and not in adaptive dynamics. So, a negative association may suggest that some adaptive capabilities are not commonly present in countries with higher $\frac{y}{l}$, fact that can be explained through their specialization patterns, which are not focused on adaptation, but in creation of technological processes. This issue will be specially addressed in the next set of models.

Table 4 also shows that wages are positively related with the BTC in two of the specifications (at 10% of significance). This relation can be explained through the bond between allocations and output elasticities: from a traditional reasoning perspective, the higher the wages, the higher the labor productivity levels are expected. Furthermore, the use of wages serves as an element to validate the LOE related results, because they control for variations

[22]Despite the absence of 1% significance results, the different formulations of the model allow to confirm that the relations found are well grounded.

on the BTC that are explicitly related to price mechanisms. For the case of patents, as was mentioned in the previous sub-section, the non-significance is expected since the bias direction isn't conceptually related to the isoquant shifts, but it's inclusion works both as a confirmation of this intuition and as a control of potential influences of the shift on the BTC. Last, the remaining variables are connected to the education level of a country. The indicators included are the amount of people with tertiary education (plus it's growth over time) and are oriented to control for qualitative factors in the labor force[23]. The relations of these indicators with the BTC are not significant, except for the one on the model 5, in which there is weak negative association with the BTC. This is in-line with the proposed framework, primarily due to the positive linkages that education have with income per capita levels.

To go deeper on the relation between the BTC and the neutral shifts, a second set of models is developed as an alternative approach (**Equation 5**). This set of models inquire about the bias amount, not its direction. The bias amount carry interesting information on the technological trends of the economies. As was mentioned in the theoretical discussion, a zero value of BTC tend to validate the neutrality of technology assumption. The idea behind the next exercise aims to explore whether these two mechanisms, the bias and the neutral shifts, compete with each other. If that's so, then one can think of economies that have more bias as not specialized in technological shifts activities. In other words, this relation explores in a novel way -using BTC- the relation between economies that are, in innovation terms, first movers and followers (the latter, referring to those which adapt what was created in other systems).

In pursuance of the isolation of the BTC intensity, the indicator used as independent variable consist in a module transformation of the bias, such that the negative effect is translated as an absolute variation[24] allowing to interpret the distances this indicator present with respect to the null value. The closer the BTC is to zero, the marginal the effect of it, hence the higher the neutrality of the technological change.

In this case the model is based on dynamic panel data analysis through the General

[23]Of course the use of this variable imply a first specialization level on a professional career (since tertiary is an intermediate step trough a highly skilled formation). There are other indicators that are more restrictive such as number of engineers, PhD graduates, etc. but they are not available for the period analyzed. Yet, the proportion of people with tertiary education serves well to distinguish unqualified workers from the rest, and it is a solid indicator available along the 32 years under analysis for all the countries of the sample.

[24]An alternative indicator is the use of squares. Although some regressions were carried to confirm the tendencies with this alternative, the variability of the Bias is severely affected, not only with respect to it's own movements but also when incorporating the proxy of percentage variations (logs) in the regression. In sum, while this exercise was carried and partially confirm the results (in general with weaker significance), it was discarded due to the lack of sensibility on the bias movements, better captured by the module.

Method of Moments (GMM) estimator (Arellano and Bond, 1991), specifically a two steps System-GMM (Arellano and Bover, 1995; Hall, 2005). This estimator have several advantages when is used with autoregressive models of moving average, such as the managing of errors' heteroskedasticity in order to obtain (the most) efficient estimations. The following set of models have an explicit autoregressive term which, used within a fixed effects framework, may lead to biased estimations if the errors are heteroskedastic. Besides the ability to handle with this issue, the GMM estimator is the most efficient strategy because it uses different sample moments to construct the estimator. The mechanisms behind the construction of the model are the same, taking advantage of the the panel structure and instrumenting variables with lagged terms so to avoid simultaneity and endogeneity problems.

This model, in difference with the previous one, is particularly focused on the relation of patents with Bias Technological Change. Additionally, it explores the relation with income per-capita and the output elasticities. In order to incorporate elements related to the production profiles, two additional variables were included in the analysis: the proportion of low-tech and high-tech[25] output. These indicators may offer a lead to support the idea that the the BTC amount is associated with the technological production profiles. The general specification of the GMM models is as follows:

$$
\begin{aligned}
D_t^{bias} = \beta_1\, log(D^{bias})_{(i,t-\lambda_1)} + \beta_4\, log(y/l)_{(i,t-\lambda_4)} + \beta_5\, log(Pat)_{(i,t-\lambda_5)} + \\
\beta_2\, log(Y_{low})_{(i,t-\lambda_2)} + \beta_3\, loe_{(i,t-\lambda_3)} + \beta_6\, log(Y_{high})_{(i,t-\lambda_6)} + \\
\eta_i + \tau_t + \epsilon_{i,t}
\end{aligned}
\tag{5}
$$

Where i, t are subscripts referring to countries i and years t, with i={ 1,13}, t={1973,2005} and:

$log(D^{bias})$: is the logarithm of the absolute distance of the bias technological change from zero. D^{bias} is the module of the BTC indicator such that[26]:

$$
D^{bias} = \begin{cases} A^{bias} & \text{if } A^{bias} \geq 0, \\ -A^{bias} & \text{if } A^{bias} < 0. \end{cases}
$$

$log(Y_{low})$: share of the GDP from Low-Tech sectors (log).
$log(Y_{high})$: share of the GDP from High-Tech sectors (log).
$log(y/l)$: income per-capita (log)
$loe_{(i,t)}$: stands for Labor Output Elasticities
$log(Pat)_{i,t}$: patents creation per year (log).
η_i: country fixed effect; τ_t: time fixed effect
λ_x: lag of the variable in years. $\lambda_5 = 1$ represents a lag of one year on the fifth term of the regression. It is expressed as λ_x because each term (variable) have their specific time-lag.

Table 5 shows the results of the GMM estimations. At the general level the main results show: first, the strong relevance of the past bias intensity, which stress the path-dependent nature of the BTC; second, the confirmation of an inverse relation of BTC

[25]These indicators are built on the OECD categorization of sectors (OECD, 2011), which were classified using detailed information on the Bias construction as in Kataishi (2015). The inclusion of the intermediate categories -Medium High and Medium Low- were not significant and didn't affected the main conclusions of the models.

[26]Whilst for completeness the first condition specifies that the bias should be equal to zero, there is no empirical value matching such condition at 3 digits detail.

intensity with patenting activities, pointing that there are divergent specialization trends of different technological profiles; third, that these results are in-line with the previous inquiries regarding the BTC relation with the income per-capita.

Table 5: System-GMM Models on the Bias Intensity determinants.

Variable	λ (lag)	GMM (1)	GMM (2)	GMM (3)	GMM (4)	GMM (5)
$log\ D^{bias}$	*1*	.00629227***	.0060798***	.00628534***	.00590552***	-
y/l	*2*	-.00042781*	-.00043665*	-.00042486*	-.00030957*	-.00005351*
$log\ Pat_{pc}$	*2*	-.00231179*	-.0093711**	-.0024264*	-.01299878**	-.0104853**
$log\ y_{low}$	*1*	.00501775***	.00486555***	-	-	-.00165375
	2	-	-	.00509764***	.00280107	-
loe	*2*	ns	-	ns	-	-
$X_{ti}\ controls_1$		*yes*	*yes*	*yes*	*yes*	*yes*
η_i		*yes*	*yes*	*yes*	*yes*	*yes*
τ_t		*yes*	*yes*	*yes*	*yes*	*yes*
$\_cons$		.01702313	.01684888	.01764575	.01818465	-.02102795

Source: Own elaboration. The λ column specify the lags, such that 1 is a one year lag. The significance levels respond to the traditional boundaries: 10%(*); 5%(**) and 1%(***). Note 1: X_{ti} controls include $y_{h}{igh}i, t, \lambda = 1, 2$ and $Pat_{i,t,\lambda=1}$ in which the results show no significance (at 10%). See the Annexes for the full specification of each model. Reference of ns: non-significant. The hyphen means that the variable (or lag) isn't included in the model.

The strong path-dependent nature of the Bias is consistent with the literature, although in this case the relation isn't measured with the common BTC indicator, but with the BTC intensity. The localized efforts are non-reversible and strongly associated with past specialization patterns (Antonelli, 2008; Antonelli, 2006; Robert et. al. 2008), regardless the coherence of the adaptation embodied in the sign of the bias. In all the models in which this variable was included (1-4)[27] the significance was strongly positive, supporting the idea that the bias intensity is associated with previous BTC levels. So, the higher the time an economy specializes on adaptive techniques, the higher the probability to remain in the same situation over time.

Second, the ties with patenting activities are, as expected, inverse to the Bias Technological Change intensity: the higher the BTC distance from zero, the lower the expectations on the patents creation amounts. This is coherent with the theoretical framework discussed above and points that if an economy is specialized in adaptive techniques it is not expected

[27] The reason of the omission in the model 5 was to check if the other conclusions were sustained without the path-dependent term, specially considering the significance this factor has. In this sense, Model 5 confirms direction and intensity of the relation with patents and income per-capita, even if the past reference to the bias is omitted.

to be a technological creator. These results are confirmed in all the models, including model 5 in which the autoregressive term on the bias was intentionally omitted to test the robustness of the other results (given the high significance of the path dependent effect).

Additionally, the income per-capita results are in-line with the first set of regressions (Table 4), confirming the inverse trends with respect to both, BTC direction and intensity. Particularly the results related to BTC intensity (Table 5) show a systematic negative relation of the income with the bias amount, pointing out not only that the richer the country the less is expected to find any type of adaptive behavior, but adding evidence on the patent's related results: if high wealth contexts increase the probability of create knowledge through patents, then the less the resources, the higher the chances to adapt locally knowledge instead of make neutral shifts on production techniques.

Another aspect that supports the direction of the results is related to the technological profile of the economies. The variable Y_{low} capture the share of the GDP belonging to low-tech sectors[28] offering information about the importance of this type of production within each economy. Figures on this matter show a positive and highly significant relation in three of the five models, suggesting that when the complexity of the production system is oriented to low-tech, the probability of having an adaptive behavior is higher. In other words, if an economy have an important low-tech participation, then it isn't expected to be a technological shifter, but a country that adapts itself to technological changes developed somewhere else.

To summarize, the results presented in this section bring evidence on different aspects of the Bias Technological Change. Ordered in two different set of models, the first exercise, based on fixed effects models, confirm previously stated results on the BTC direction determinants appending two critical elements: the importance of the income-per capita of an economy and the key role of the labor output elasticities as indicator of adaptive skills within a production system. The second set of models consist in System-GMM regressions and are oriented to exhibit novel evidence on the Bias intensity (instead of the direction). The corollary of these support the idea that adaptive and localized specialization are associated to economies that present low income per-capita, low-tech sectors specialization and poor performance on patenting behavior. Since the Bias Technological Change is able to measure the local reaction of an economy to external technological changes, the production systems that show strong bias are not expected to be oriented to produce new knowledge, but to use it and to adapt it to their own demand needs.

[28] All prices were calculated using sector level PPP of 2005. The sectoral distinction was made at two digits and the group was arranged according to the OECD categorization.

7 Conclusions

This work shows the importance of the Biased Technological Change both at the theoretical and empirical levels. The theoretical contributions relate the concepts of technological change and it's local aspect with the bias making use of the changing nature of the factor output elasticities as source of economic diversity. From an empirical point of view, the results are based on an original database consisting of a strongly balanced panel-data including 13 developed countries and 32 years of time-lapse. From them, evidence on the bias trends, direction and intensity was discussed, with particular attention on the determinants of these indicators. The main outcomes signal that economies with higher bias are those specialized in adaptive behavior, which are not expected to be neutral technology creators. The direction or coherence of the adaptations are related to the skills of the labor force (using the output elasticities as a proxy of this measure), in addition to the resources that an economy posses.

From a theoretical point of view, the BTC is a fundamental element on the technological change discussions that is often left aside. Since the empirical manifestation of the neutral technological change assumption (made by Solow in 1957) have been proven to be weak, the inquiry on the impact from it's relaxation becomes not only a valid research question, but a clear path to gain comprehention of techonological dynamics. As so, it's complementarity with seminal concepts such as directed technological change and local adaptive behavior place the BTC concept in an element to take into account when discussing long trends technological change and knowledge generation and adaptation. We are in the first steps of exploration on the interpretation and complementarity of the bias with other indicators of technological performance. In this sense, this work offer a continuation of the technological change analysis, and contributes exploring novel interactions with key elements not commonly considered until now.

Two dimmensions of the BTC were explored in this work. The first is in concordance with the traditional analysis of the bias and measures the direction and, hence, coherence of it; the second offers an indicator to explore the intensity of the bias effect. The interaction of these two elements supose a fertile future research field and together offer a coherent approach to analyze local adaptations and technological behaviour. The amount of bias, regardless of it's direction, is a novel element that contributes in the disctintion of technological profiles, specially able to isolate economies that are oriented to neutral shifts on the isoquants, that can be generally understood as radical innovations, from those which adjust their production ways by modifying the isoquant slopes (adaptive or incremental innovations).

Regarding the directionality of the BTC, this works finds it's determinants to be inline with previous works. Additionally, it explores tow main elements: the income per-capita as a raw indicator of the wealth of an economy and labor output elasticities as determinant of adaptive skills. The bias show a recurrent negative relation with the income per-capita, allowing to infer that economies with less resources are better fitted to adapt theirselfs given a technological shock (it is plausible that the reason behind this is that these systems have been recurrently learning from adaptive situations over time, hence they've learned how to better react). On the other hand, the elasticities have a positive influence in the BTC as they grow, meaning that higher workers' skills tend to lead the production system into the *right* direction (or that the adaptation *is coherent* in relation to factors' allocation and available resources, following Antonelli and Quatraro's work).

With respect to the BTC intensity, results show three aspects that are worth to remark. First, the existence of a path dependent nature of the bias amount, pointing that the further from the neutral technological change an economy is, the higher is expected to be the bias effect in the future, regardless the direction of it. Complementarily, the negative relation of BTC with patents confirm both, patents and bias as indicators of neutral shifts and output elasticities, respectively. On top of that, if an economy show a tendency to be specialized in patent creation, then there is a trade-off affecting the bias amount. This is probably one of the most important conclusions of the paper, relating the two main effects of technological change based on commonly used indicators.

Future challenges goes in different directions. From an empirical point of view, there is a need of include developing countries in the analysis in order to see how the bias react. At the moment of the creation of this work the longest time series able to construct the BTC indicator reach the early 90's, making the long trend comparison less robust, as well as the structure of the econometric models. In this sense, the inclusion of other countries with different income and specialization patterns is recognized as a critical step forward. On the theoretical perspective, the generalization of this method in order to be implemented in a MFP (Multi-factor productivity) framework may imply a major breakthrough in the use of the bias as a basic indicator of technological change.

8 Bibliography

Acemoglu D., Autor D., Dorn D., Hanson G. and Price B. (2014). Return of the Solow Paradox? IT, Productivity, and Employment in US Manufacturing, American Economic Review, American Economic Association, vol. 104(5), pages 394-99, May 2014.

Acemoglu, D. (1998), Why do new technologies complement skills? Directed technical change and wage inequality, Quarterly Journal of Economics 113, 1055-1089.

Acemoglu, D. (2002). Technical Change, Inequality, and The Labor Market. Journal of Economic Literature, 40, March 2002: pp. 7-72.

Acs,Z., FitzRoy, F. and Smith, I., (2002). High Technology Employment, nd RandD in Cities: Heterogeneity vs. Specialization. Annals of Regional Science, 6, 269N371.

Antonelli C. (2006). Localized technological change and factor markets: constraints and inducements to innovation. Structural Change and Economic Dynamics 17, pages 224-247, April.

Antonelli C. and Quatraro F. (2014). The effects of biased technological changes on total factor productivity: a rejoinder and new empirical evidence, The Journal of Technology Transfer, Springer, vol. 39(2), pages 281-299, April.

Antonelli, Cristiano and Fassio, Claudio, 2014. Globalization and The Knowledge Driven Economy, Department of Economics and Statistics Cognetti de Martiis. Working Papers 201418, University of Turin.

Antonelli, Cristiano and Quatraro, Francesco, 2007. Shifting the Bias: How to Disentangle Creative Adoption from Radical Innovation. Empirical Evidence from Italy and the US, Department of Economics and Statistics Cognetti de Martiis LEI and BRICK. University of Turin.

Antonelli, Cristiano, 1995. The Diffusion of New Information Technologies and Productivity Growth, Journal of Evolutionary Economics, Springer, vol. 5(1), pages 1-17, February.

Arellano, Manuel and Bond, Stephen, 1991. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, Review of Economic Studies, Wiley Blackwell, vol. 58(2), pages 277-97, April.

Arellano, Manuel and Bover, Olympia, 1995. Another look at the instrumental variable estimation of error-components models, Journal of Econometrics, Elsevier, vol. 68(1), pages 29-51, July.

Bresnahan T.F. J.E. Trajtenberg (1995), General Purpose Technologies: Engines of Growth? Journal of Econometrics 65 (Special Issue, January): 83-108.

Christensen, Laurits R and Jorgenson, Dale W and Lau, Lawrence J, 1973. Transcendental Logarithmic Production Frontiers, The Review of Economics and Statistics, MIT Press, vol. 55(1), pages 28-45, February.

Cristiano Antonelli and Francesco Quatraro, 2010. The effects of biased technological change on total factor productivity: empirical evidence from a sample of OECD countries, The Journal of Technology Transfer, Springer, vol. 35(4), pages 361-383, August.

Cristiano Antonelli, 2004. The Governance of Localized Technological Knowledge and the Evolution of Intellectual Property Rights, Chapters, in: The Elgar Companion to the Economics of Property Rights, chapter 19 Edward Elgar.

Cristiano Antonelli, 2008. Pecuniary knowledge externalities: the convergence of directed technological change and the emergence of innovation systems, Industrial and Corporate Change, Oxford University Press, vol. 17(5), pages 1049-1070, October.

Dasgupta, P., and Stiglitz, J. (1978). Uncertainty, industrial structure, and the speed of RandD. Cambridge (MA), U.S., NBER (National Bureau of Economic Review)

David, P. A. (1975), Technological Choice, Innovation and Economic Growth. Cambridge: Cambridge University Press.

De Loecker, J. (2009). Product differentiation, multi-product firms and estimating the impact of trade liberalization on productivity.

Douglas Todd, 1985. Factor productivity growth in four EEC countries, 1960-1981, Brussels Economic Review, ULB – Universite Libre de Bruxelles, vol. 107, pages 279-325. Economic Review 27, 265-302

Feder, C. 2014. Biased Technological Change. A contribution to the debate. LEI and BRICK. WP 1/2014. Department of Economics. University of Turin.

Habakukk, H.J. American and British Technology in the Nineteenth Century. London: Cambridge University Press, 1962.

Hall, A. (2005). Generalized Method of Moments (Advanced Texts in Econometrics). Oxford University Press. ISBN 0-19-877520-2.

Hall, B.H., Griliches, Z. and Hausman, J.A. (1986). Patents and R&D: Is There A Lag?. International Economic Review, Vol. 27, No. 2, June 1986, pp . 265-284.

Helpman, E. (Ed.), 1998. General Purpose Technologies and Economic Growth. The MIT Press, Cambridge.

Inklaar R. and Timmer M, 2006. International Comparisons of Industry Output, Inputs and Productivity levels: methodology and new results. Intermediate IO Meetings 2006. Sendai, Japan. International Journal of Business Performance Measurement, 2: 180-193

Kataishi, R. 2015. Sector Level Biased Technological Change: Evidence and Implications. Forthcoming.

Katila, R. 2000. Measuring innovation performance. International Journal of Business Performance Measurement, 2: 180-193.

Keller W., 2002. Geographic Localization of International Technology Diffusion, American Economic Review, American Economic Association, vol. 92(1), pages 120-142, March.

Miller E, 2008. An Assessment of CES and Cobb-Douglas Production Functions: Working Paper 2008-05, Working Papers 19992, Congressional Budget Office. RePEc:cbo:wpaper:41195.

OECD, 2011. ISIC REV. 3 Technology Intensity Definition: Classification of manufacturing industries into categories based on RandD intensities. Directorate for Science, Technology and Industry. Economic Analysis and Statistics Division. July.

Pavitt, K. 1985. Patent Statistics as Indicators of Innovative Activities: Possibilities and Problems. Scientometrics 7:77-99. Princeton University, NBER and CEPR.

Robert, V., Pereira, M., Kataishi, R., and Yoguel, G. (2008). The effects of feedbacks on firms productivity growth. Micro, macro, and meso determinants of productivity growth in Argentinian firms.

Solow R. M. (1957), Technical change and the aggregate production function, The Review of Economics and Statistics 39, 312-320.

Trajtemberg, M. 1987. Patents, citations and innovations: tracing the links. NBER WP Series N. 2457. Cambridge, MA.

Wooldridge J. (2010). Econometric Analysis of Cross Section and Panel Data, MIT Press Books, The MIT Press, edition 2, volume 1, number 0262232588, December.