Specialization Patterns Through Biased Technological Change

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Preliminary Version

1 Introduction

This work is developed as a contribution to the study of productivity growth using Total Factor Productivity (TFP) to asses technological change in broad periods of time. TFP measurement entails multiple processes, and this paper will be particularly focused on the Biased Technological Change and it's implications on conceptual and empirical aspects.

The main contributions of this paper are, on the first place, use the Biased Technological Change (BTC) concept to explain long-term specialization patterns by bringing a novel interpretation of the indicator. Second, is to show the dynamics of the BTC at a sectoral level. Finally, to explore the determinants of the BTC. The main results show that the specialization patterns are path dependent and that the use of this kind of bias is a key element in the analysis of innovation cycles and economic trends.

The TFP measurement is acknowledged as a standard tool that allows to interpret in a very synthesized way the effects of technology on the productive structure of an economy. The mechanism behind it's functioning is based in calculate differences between a theoretical expected value of productivity and the actual value observed in the economy. Since the theoretical model considers technological change as exogenous, the residual derived from contrasting theoretical and empirical levels of productivity offer an idea on how much the technological structure has been modified from one period to another. Over the last 50 years, the measurements of the TFP evidence a clear upwards tendency, suggesting that technological improvement is one of the main reasons of global growth.

Since the early works of Cobb-Douglas (1928), Douglas(1971) and particularly Solow (1956; 1979), the TFP methodology became a standard procedure on technological change measurement. Studies using this approach proliferated during the 70‘s and they prevail until our days with very few changes with respect to the original setup.

The application of TFP based methodologies was developed on different aspects over the past decades. On the one hand, the relaxation of the main assumptions derived from the use of a Cobb-Douglas production function with constant returns to scale were modified to include increasing returns to scale and non-multiplicative production relations (Dasgupta and Stiglitz, 1978; Krugman, 1990; Crepón, Duguet, & Mairesse, 1998; Raval, 2011). This methods are, in comparison, more flexible and accurate for particular situations than the traditional approach, although they are heterogeneous in their formulations (*in natura*) and clearly fit to micro and sector specific analysis instead of macro aggregated models.

On the other hand, one may find the efforts surrounding the original model, mainly focused on diminish the amount of Solow's residual, giving birth to the empirical use of factor expanded production functions and multifactor productivity (MFP). This current maintains the restrictions of CRS, but incorporates the role of intermediate inputs and capital-labour heterogeneities, among other improvements (Ark et.al., 2008; Mas et.al., 2008; Timmer et.al, 2007; Mas and Quesada,2005). As a mirror of the case above, the MFP approach applies the same production function to the analysis of multiple sectors, being a relatively less-flexible model to analyse particular situations.

Each of these perspectives show it's own strengths and weak points, whilst nowadays both are still in use to conduct productivity related research, it is a matter of focus and objectives of a research the choice of one or another. The strengths of each model, at least at a very general level, are quite clear: the MFP is focused on long trends and macro comparisons while the increasing returns to scale and non-multiplicative models are specific for certain sectors in a particular period of time, with low power on inter-sectoral comparability.

This work will be subscribed on the macro aggregated perspective and it will expose long trend dynamics comparing several sectors of a group of countries. The reason behind the use of a CRS Cobb-Douglas production function it is merely for simplicity and clarity of the main point of the work. Future developments should incorporate the implications of the Biased Technological Change in more complex functional forms.

The rest of the paper will be organized as follows: the next section will develop the Biased Technological Change from a theoretical perspective. The third part will be focused on the characterization of the data used. The fourth section will be dedicated to the econometric models and the results, and finally, the last section will elaborate the final remarks.

2 Theoretical Background

The study of Total Factor Productivity (TFP) dynamics has been intensively studied since the early works of Solow (1956) and Cobb-Douglas (1928). After the seminal contributions of Griliches (1967, 1968, 1979) and Acemoglu (1998), the interpretation on the role of factors in TFP dynamics, specially regarding the effect of knowledge diffusion in labor and capital became a central research topic within economics.

The analysis of the determinants of Technological Change (TC) represented a challenge from it beginnings. The traditional approach considered that exogenous forces affected technological change. It is known, however, that specialization, as in the Smithian tradition, affects productivity levels, and hence the technological dynamics. Through sectoral trends, it can be seen that input prices of some activities perform different across time and countries, implying that specialization is an important element of productivity dynamics. The effect of becoming specialized on a set of tasks can be seen in the factor's input prices, which iteratively change with the technological trajectory of each economy and determine future resource abundance structures and specialisation cost opportunities. The more specialized one economy is, the higher the returns of the output elasticities for that particular specialization pattern.

According to the traditional Solow's vision (Solow, 1979), technological change dynamics can be identified by the calculation of the difference between a theoretical model that calculate the (expected) outputs according to the use of certain amount of factors, and the actual value that one find in the real performance of that economy. The difference between the two estimations (Solow's "A_t") offers a very generalized and aggregated idea of the technological change over time: the gap existent from the expected output to the actual value of it implies technical modifications on the factor's use, and hence technological change. This method calculates the so called Solow's residual, which is the mentioned difference, pointing a raw but extremely potent indicator of technological dynamics.

A technological shock may affect the movement of the isocuants in two ways: the parallel translation and, our focus, the modification of the slopes. According to the traditional theory (Solow, 1979) the effect of new technologies impact on the isocuants moving them in parallel directions towards the origin. This make the factors produce more with the same resources or be cheaper to produce the same output. But when technical improvements take place the isocuants slopes are also subject to change, since the new improvement imply new prices relations, and hence factor's output elasticities modifications (effect dodged by the assumption regarding the neutrality of technology towards factors' output). The process that explores the measurement and behaviour of the isoquant's slopes variations is denominated Biased Techological Change (Antonelli, 2002; Antonelli, 2010; Antonelli and Quatraro, 2010; Antonelli and Quatraro, 2014), and will be the main focus of this work.

The TFP calculation consists in the empirical application of the Solow's residual measurements. The derivation of this indicator will relay on trans-log transformations of the production function (Christensen, Jorgerson and Law, 1973), mainly because of its benefits regarding the simpler calculations and a direct interpretations of its results. Departing from the raw Cobb-Douglas macro approach $Y = AL^{\alpha}K^{\beta}$ for, the trans-log derivation of the production function becomes $log(A_{i,s,t}) = log(Y_{i,s,t}) - \alpha_{i,s,t}log(L_{i,s,t}) - \beta_{i,s,t}log(K_{i,s,t})$ with i, s, t representing country, sector and time variations. The elements considered in the Cobb-Douglas representation are the typical Y as output (gdp), L as labor, K, α and β as the output elasticities and A as the residual.

Following the traditional methods on TFP calculations, the output elasticity is not estimated within the model, but calculated with available data assuming that $\alpha_{i,s,t} = \frac{P_L L}{Y} = \frac{w_{i,s,t}.L_{i,s,t}}{Y_{i,s,t}}$, with w as wages of the labor force (i.e. total compensations over total persons engaged) and α as the equivalence between the marginal productivity of labour and the factor's prices.

If technological shocks affect not only the total amount of output by a given amount of factors but also the returns that each factor have, then the Solow's TFP doesn't consider the complete effect of a technical change because the biases of the output elasticity changes are not accounted.

The Bias Technological Change calculation (Antonelli and Quatraro, 2010; Antonelli and Quatraro, 2014; AQ now on) consists in developing a two-step index. First, a derivation of one that fixes the effect of output elasticities across time (called "total technological change" in AQ) that will be denominated Fixed Returns Technological Change (FRTC).

The Fixed Returns Technological Change derivation can be expressed in the trans-log form $log(A^{FRTC}_{i,s,t_n}) = log(Y_{i,s,t_n}) - \alpha_{i,s,t_0} log(L_{i,s,t_n}) - \beta_{i,s,t_0} log(K_{i,s,t_n})$. This index fixes the output-elasticities at t_0 to isolate the variations of factors and output over time t_n. The result of it consists in an estimation of the technological change as if the factor's output-elasticities remained fixed in the period considered, allowing an explicit ceteris-paribus analysis of the TFP variation.

Then, the Bias Technological Change consists in the difference between the FRTC and the Solow's traditional TFP. The conceptual reason for implementing the difference is that the Bias objective is to account for the impact that transformations in the factor's output elasticities have on productivity levels. Since the Solow's indicator doesn't consider this effect and the FRTC is meant to the complete effect of other changes but the bias, then the difference between the second and the first isolates the problem of our interest as $(A^{FRTC}_{i,s,t_n}) - (A^{Solow}_{i,s,t_n}) = (A^{Bias}_{i,s,t_n})$.

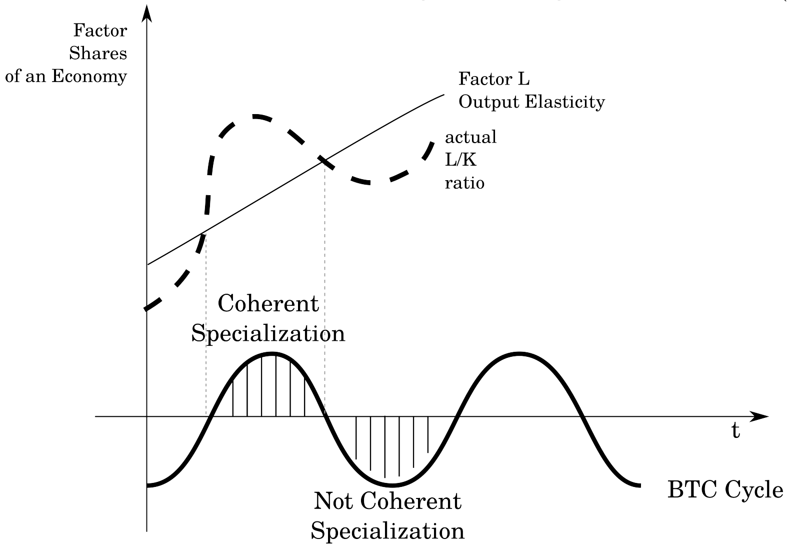
Interpreting the Biased Technological Change

One of the main contributions of this work lies on a novel interpretation of the Biased Technological Change. This section will develop the traditional understanding of this indicator to arrive to the new proposition that links BTC with Estructural Change.

The concept developed by Antonelli and Quatraro (2010, 2014) is centered on the relations among factors, output elasticities and productivity. In this sense, the interpretation is commited to the ratio of capital and labour over timeand the output elasticity of the factors (which is reduced to one factor since the complementary relation derived from the CRS). Hence the focus of the interpretation consist in the $\frac{K}{L}_t$ trend in comparison with the returns derived from $\beta = 1 - \alpha$, where α stands for the labour output elasticity.

The Biased Technological Change indicator contain it's strongest explanatory feature within it's sign. A positive BTC can be interpreted as a *coherent* (Antonelli and Quatraro, 2014) relation between the factor's ratio and their output elasticities. On the other hand, negative values represent the opposite: a *non-coherent* relation between these mentioned variables. Last, it is worth to mention that a zero-value is an empirical *meta-impossibility* but it is exactly the case in which the traditional Solow's indicator doesn't have a bias, meaning that technological change is neutral.

Figure 1. The Biased Technological Change Interpretation (Traditional).



The nominal amount of the Biased Technological Change indicator doesn't lead to any particular assessment, mainly because it is a difference of indexes, but also due to the fact that the value of the Bias vary over time. This variation makes difficult to stablish an ex-ante maximum or minimum within each BTC Cycle and lead to an impossibility to attribute any particular connotation to a nominal intensity of the Bias. As said, the key aspect to take into account is it's sign.

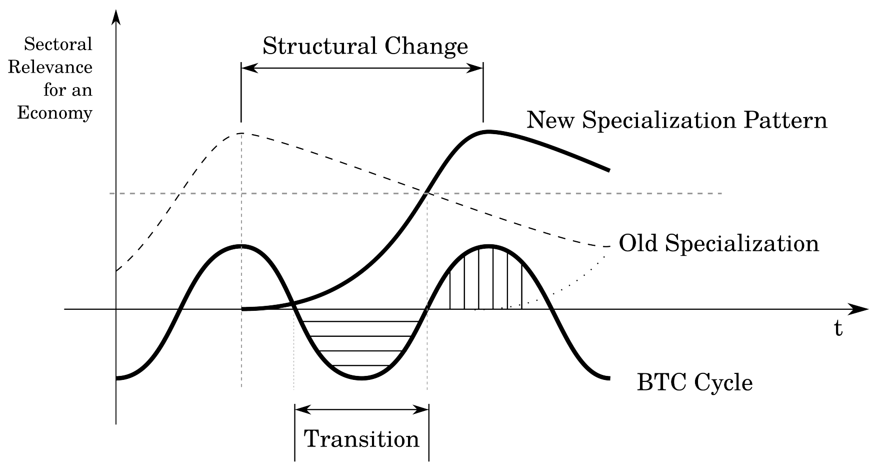
Under this scenario the optimal outcome in terms of efficiency leads to the use of abundant factors with increasing output elasticities. In fact, under a pure neoclassic frame, there is no place for a negative bias: both theoretically and empirically a negative bias show a clear inefficient allocation of resources. The "right" choice is to allocate the economic activities in factor-abundant and output-increasing sectors. It's worth to remind that by doing this, the period-per-period allocation is increasingly restricted according to the initial factor endowments allocations[1].

[1] Although this differs from the Ricardian perspective due to the output elasticities element, in this point the conditional effect of the initial endownments represent an important aspect of the bias dynamic.

The main issue consist in the evidence, that suggest that the negative bias exist in almost every country of the sample. Whilst theoretically the negative bias is inefficient and temporary, the empirical data show that is a regular situation, capable to be found in any economy.

In order the disentangle additional explanatory power from the biased technological change it is necessary to go beyond it's dual interpretation based on efficient vs. non-efficient allocations. When an economy learn and innovate, or even adapt their productive structure, the process of specialization is gradual and the results may be seen after a certain period of time. Each novel specialization process imply inefficiency in the resource allocations: at an schematic level there is a change from an activity they were specialized on to a new activity that is new. This is by nature an inefficient process. Every creation of a new sector suffers this condition, and particularly this may happen if an economy search to re-define their technological specialization towards sectors that they didn't dominated. The Biased Technological Change is an instrument that is able to offer some insights about these processes.

Figure 2. Biased Technological Change as Structural Change Indicator.



An accentuation of the economic structure derived from the initial endowments may show a positive BTC over time. But if economies change their specialization in order to become leaders (as in the Schumpeterian Cycle), then inefficiency takes over.

A positive BTC imply that the economy is coherent with it's productive structure (factors abundance and returns), a negative that it is not. Although this remain as the main concept of the BTC, the contribution of this work intend to underline an additional perspective. If the economic structure is deriving resources to a sector that wasn't present (enough) in the economy, then the trend observed by the Bias show a not coherent use of the resources cause the former specialization is not being accentuated, but replaced by other activities and productive patterns.

Each time an economy derive resources from traditional activities to sectors that wasn't their main source of productivity, the Bias will show negative values. This doesn't mean that the economy is necessarily going in the wrong direction, but that it's sectoral specialization is changing. Hence, structural variation towards new specialisation patterns generate inefficiency on relative factor allocations, but this inefficiency is not a sign of wrong choice (a priori[2]). A negative bias can be interpreted as an indicator of transition associated to structural change, whilst a positive bias as an signal of a deep specialization with respect to the previous resources and their exploitation.

The Bias Technological Change measures coherent allocations with respect to the output elasticities, but by doing that is addressing other processes that occur simultaneously such as the structural change. The specialization around certain productive structures or the structural change towards new sectors are dynamics that the Bias reflect on the relative allocations measurement through it's sign.

[2]In order to evaluate that, there is a need to incorporate some valuation indicator on the sectors that are gaining participation. One indicator purely based on the technological aspects could be the patents per sector, but depending on the definition of structural change, many other indicators may be used. The issue of the evaluation of the technological change direction will not be addressed on this work.

3 Data and methodology

Using the mentioned framework, this paper will calculate the amount of Bias Technological Change over four technological typologies for the 19 sectors and 16 countries considered in the period 1973-2005. The sources used to construct the database are several: first, the KLEMS database for the basic indicators in order to obtain the TFP and Biased Technological Change estimations; second the World Development Indicators (WDI) for patents and other control variables; third, the Groenningen Productivity level database (GGDC) for relative pricing adjustments considering sectoral level discrimination (Inklaar and Timmer, 2006) for the Gross Output and, indirectly, the wages. The result of the integration of these sources is an strongly balanced panel data with specific information on the countries considered from 1973 to 2006.

Among the 19 manufacturing sectors, 4 groups are built from the OECD Technological Instensity Classification (ISIC, Rev. 3 - 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 of High to Low tech are merely descriptives, while within the econometric models all the exercises will be carried using sector level details.

Regarding the country-level comparisons, the TFP dynamics show different behaviour for each broad technological class (see Annexes: Figure 1). From a global perspective, the TFP levels have been increasing during the period considered. Particularly, those sectors categorized in higher technological classes are more productive and show higher growth rates. In concordance with previous literature (e.g. Lipsey and Carlaw, 2004), high-tech sectors are systematically above in terms of productivity for the majority of the countries considered.

A complementary tendency can be observed in the averages of output-elasticities trends (see Annexes: Table 1), as α levels growth as the technological level increases. This suggest that the techniques alterations over time impact positively on the technological use of the labour, as the extensive literature on Skill Biased Technological Change propose (e.g. Baller and Reens, 2013).

The differences among aggregated productivity levels and labour productivity was extensively addressed by the literature in the last decades (eg. OECD, 2011). There are some economies in which the levels of labour productivity in a particular technological class is relatively different from the others, delimiting an specialization patters. This is generally associated with a type of labour (highly skilled) and a type of predominant sector level activities (Research and Development intensive).

Regarding the Biased Technological Change, the tendency show that there is an heterogeneous behaviour over time. Particularly, some countries (like the Nordic ones) show less variability on their patterns, while others such as USA, UK, Italy and Germany, show a higher variation (See Table 2 and Figures 2 series on the Annexes).

From a methodological aspect, it is worthy to mention that the Bias trends shouldn't necessarily show notorious cycles over time. This, as said in the previous section, may be linked to the speed in which each economy is transforming it's structure and to the direction of that change. For instance, there are some countries that show negative bias for all the technological levels considered during an important part of the period (as U.S.). This particular behaviour can be attributed to the sector-level aggregations and the sector average calculation process that "covers" the out-layer cases. In fact, when one look at the detailed sectoral level, the economies with recurrent sectoral negative Bias, by definition, have to have a positive bias in some of their sectors. This is so for machinery and food for the case of United States. From a theoretical-empirical integration aspect, it is worth to say that the panel data used was balanced in order to show continuity of the traditional sectors (existing in the 70's) for the whole period (1973-2005). Hence, the newest and more detailed information was ommited in order to prioritize the long-term trends and a balanced panel for the econometric exercises. As a consequence of this, there is an hypothetical case (since it doesn't happens in this sample, although it might happen in other dataset) in which all the sectors of an economy have negative bias for a long period: this should be due to the late specialization on new sectors (previously inexistent) that are not contemplated in the old statistics, generating an ommited effect of the positive bias.

One of the novelties of this work is to show how the BTC dynamics are different by sector classes (Annexes: Table 2 series), since this comparison wasn't carried out until the exercise that this work is proposing. In terms of the dynamics across time, each technological class evidence a specific trend. Generally speaking, there is a trade-off dynamic among technological classes in which the countries that have a positive BTC in a given technological group, tend to show other classes with inverse bias values. As was mentioned above, this could be due to the effect of specialization patterns, that can eventually lead to complementarity among sectors but the further is the technological class, the higher is expectation of an inverse Bias effect with respect to the specialized sector.

4 Empirical Strategy and Findings

In order to explore the econometric modelling, a two different alternatives are explored. The exercise consist in the comparison of an ARMA - Fixed Effect model and a GMM optimal estimators model to provide consistent results. Both models are computed to solve endogeneity problems due to the reverse causality existent among the variables. The strategy adopted was to lag the set of independent variables and to include the auto-regressive terms with two lags within the ARMA-Fixed Effects structural equation. The use of the GMM efficient estimator is a complement that intended to deal with the dynamically autoregressive, heteroskedastic, Low T, Low N condition of this calculations. The potential (non-measurable) systematic clustered heteroskedasticity errors on the data can be also confronted with this method.

Taking into account the previous modelling within the literature (Antonelli and Quattraro, 2010, 2014), the determinants of the Bias comprehend a group of market related variables, such as the wages and a group of factors linked to the technological dimension (particularly patents). In addition to that, two key elements were tested in this work: the existence of path dependence on the factor's use (specialization) and the inverse effect due to a meta-substitution effect in terms of sector's compositions.

Preliminary results suggest that the ARMA-FE model and GMM model goes in the same direction. Although they are heavily work in progress at the moment, the first results supports a number of ideas: first, that patents are not determinants of the BTC, element that seems coherent with the theoretical approach, which shows that the "patents-effect" should be present mainly on the Solow's technological change determination. Second, that the path dependence matters. As the specific sector's and the technological class of belonging cumulativity are proxies of specialization patterns, preliminary results show strong positive significant relations in both models. Last, the sectoral structure is significative on the BTC behavior, while changes in structure towards a particular activity tends to accentuate the Bias Technological Change.

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$$\begin{aligned} A_{bias} = C + \beta_{1_1} A_{bias(i,c,t-1,2,3)} + \beta_{1_2} A^{c}_{bias(i,s,t-1,2,3)} + \beta_{2_1} te_{it-1,2,3} + \\ + \beta_{2_2} T_{it-1,2,3} + \beta_3 w_{it-1,2,3} + \beta_4 X_{it} + \eta_t + \tau_i + \epsilon_{i,t} \end{aligned} \tag{1}$$

Where C represents the constant, A_{it}, A^{c}_{it} stand for the bias of the current sector and technological class for the period t, country i, sector s and technological class c. Additionally, i refers to tertiary education level, T for technological level measured in patenting by year t and w for wages, and X is a vector of control variables at country level . On their part, η_t, τ_i, $\epsilon_{i,t}$ consider the impact of the fixed and time effects and the structural error on the regression.

The structure of the model is due the strategy implemented to avoid potential endogeneity issues because of the auto-regressive nature of the framework. Particularly, this formalization makes use of lagged instrumental variables focused to avoid causality feedbacks. By doing this, different time levels restrict the regression from *t-1* to *t-3*.

Particularly for the High Tech technological class,

The results show that consistently for both models the Bias of the high-tech sectors depend on the previous cumulative experience on that sector class or, in other words, in the path-dependence effect of each economy. The higher the experience, the higher is expected to be the Bias. For the particular case of the High-Tech sectors, we can observe a trade off effect instead

Table 1: Fixed Effect and GMM models for High Tech Technological Class

		Fixed Effects	GMM
Tertiary Ed	Lag 1	0.398	0.223
		(1.22)	(1.11)
Patents	Lag 1	0.00343	-0.000553
		(0.46)	(-0.49)
Wage	Lag 1	0.0341	-0.0000652**
		(1.57)	(-3.91)
	Lag 2	-0.0594*	0.000120***
		(-2.74)	(6.14)
	Lag 3	0.0235	-0.0000545
		(1.14)	(-2.04)
BTC High Tech	Lag 1	0.793***	0.891***
		(8.00)	(11.41)
	Lag 2	0.198	0.138
		(1.88)	(1.22)
	Lag 3	-0.161	-0.100
		(-1.47)	(-0.95)
BTC MidHigh Tech	Lag 1	0.134	0.119
		(1.22)	(0.93)
	Lag 2	-0.340*	-0.375
		(-2.48)	(-2.04)
	Lag 3	0.120	0.173
		(1.66)	(1.99)
BTC MidLow Tech	Lag 1	-0.271*	-0.285**
		(-3.04)	(-3.34)
	Lag 2	0.184	0.272
		(1.36)	(1.75)
	Lag 3	-0.000189	0.0360
		(-0.00)	(0.34)
BTC Low Tech	Lag 1	0.0314	0.131
		(0.19)	(0.72)
	Lag 2	0.113	0.118
		(0.53)	(0.61)
	Lag 3	-0.0117	-0.156
		(-0.06)	(-1.04)
_cons		0.178*	0.0370
		(2.22)	(0.70)

of a complementarity with respect to the mid-high technology class. There is significant relation with respect to the sectors with lower technological intensity.

In consonance with the previous results on the literature, the relation that the bias have with the patenting level is expected to be not-significant. The reason for this is the the traditional TFP takes over of the knowledge generation effect, while the Bias is concentrated on how the available resources are used in relation with the productive structure.

Table 2: Fixed Effect and GMM models by technology class

Variable	Lag	FE high	FE mhigh	FE mlow	FE low	gmm high	gmm mhigh	gmm mlow	gmm low
Tert.Educ.	L1.			+*					
Patents	L1.								
Wages	L1.		-**	-**		-**			
	L2.	-*	+**	+**		-**		+**	
	L3.		-**	-**	+*			-**	
BTC_high	L1.	+***				+***			
	L2.								
	L3.								
BTC_medhigh	L1.		+**				+**		
	L2.	-*			-*				
	L3.								+**
BTC_medlow	L1.	-*		+***	-*	-**		+***	-**
	L2.								
	L3.								
BTC_low	L1.				+***				+***
	L2.								
	L3.								
_cons		+*		+*	+**		+**		

Last, the relation that the Bias present with factor prices tends to be significant, although it doesn't show a clear direction. This could be due to the dynamic that wages have on productivity, as it is known that often lower wages not necessarily imply a restriction on the use of the available resources, but the contrary (specially in the application of liberal measures, and only observing the short term). This results point in the same direction than the previous works on the subject (Antonelli and Quatraro, 2014) meaning that the role that relative factor prices relations have on the technological specialization patterns is particularly relevant. The lesser the wages, the higher is expected to be the bias for a particular technological class. This is so in the High-tech sector only, while in the others the sign of the relation depends on the lag one consider.

5 Conclusions

The main subject of interest of this work is to complement the TFP studies by making use of additional information that can be derived from the available data. In order to do so, the concept of Biased Technological Change acquire particular relevance.

The BTC trends are different by sector, country and time. For the period analysed the trends of BTC differ according to each economy's history and structure. This can be attributed to the different specialization patters and prices relations of the factors.

The interpretation of the Biased Technological Change goes beyond a dual evaluation related to the coherence. In addition to that interpretation, it can also be useful to understand sectoral specialization patterns. In this sense, because of the learning process associated with the use of new technologies, a negative bias imply a modification on the specialization trend, which carry a non-coherent use of the resources available in the economic structure. Each time a new specialization take place, is unavoidably unneficient. On the other hand, a positive bias imply a profundization of the specialization pattern that the economy had in the past, responding to the same group of productive activities.

Regarding the determinants of the bias, the results are consistent with previous works. On the one hand, the determinants are different from those which explain the traditional TFP dynamics, in particular regarding the role of patents, which in general doesn't show a significant relation (or even a negative one). This is due to the bias nature, that is based on resource allocation instead of science and technology activities. On the other hand, the results show the importance of the path dependence effect for the Bias, with a systematic role of the previous periods of BTC on the present one, even in different technological classes.

Due to the sector-level detail explored in the dataset used, this work address the specialization meta trade-off that takes place when the Bias is negative in one sector. In these cases, at a theoretical level, if a sector show a negative bias, at least other sector should exhibit a positive one. Or in other words, the BTC allow to see how the sectors compete with each other at the moment of resource allocations.

To conclude, it is important to mention that the theoretical developments regarding the Bias and it's implications are able to be measured and tested. This process can be carried out without any new data collection process, meaning that the currently available data is useful to calculate the BTC at different aggregation levels.

Last, the implications on the interpretation that one can make from the available data entail important consequences if one consider the effect of the Biased Technological Change, such as a deeper understanding of catching up processes and specialization patterns. Further developments to understand the BTC dynamics under a framework of Multi-Factor Productivity entail a theoretical, analytical and empirical challenge worthy to be faced in future works.

6 Bibliography

Ark, B. van, O'Mahony, M. and Timmer, M.P. (2008), "The productivity gap between Europe and the U.S.: Trends and causes", Journal of Economic Perspectives, vol. 22(1), pp. 25–44

Acemoglu D., 1998. "Why Do New Technologies Complement Skills? Directed Technical Change And Wage Inequality," The Quarterly Journal of Economics, MIT Press, vol. 113(4), pages 1055-1089, November.

Acemoglu D., 2000. "Labor- and Capital- Augmenting Technical Change," NBER Working Papers 7544, National Bureau of Economic Research, Inc.

Acemoglu D., Johnson and Robinson (2004), "Institutions as the Fundamental Cause of Long-Run Growth," Handbook of Economic Growth

Acemoglu D., 2010. "When Does Labor Scarcity Encourage Innovation?," Journal of Political Economy, University of Chicago Press, vol. 118(6), pages 1037 - 1078.

Antonelli, Cristiano (1997). "Percolation processes, technological externalities and the evolution of technological clubs", Empirica, Vol. 24, num. 1-2, January

Antonelli, Cristiano. (2007) "The system dynamics of collective knowledge: From gradualism and saltationism to punctuated change", Journal of Economic Behavior & Organization, Vol. 62 215–236, 2007.

Antonelli, C. (2007). Technological knowledge as an essential facility. Journal of Evolutionary Economics, Vol.17, Nº 4, Agosto de 2007.

Antonelli, Cristiano (2011). Handbook on the economic complexity of technological change. Edward Elgar, Chetenham.

Antonelli Cristiano, 2013. The economics of technological congruence. Department of Economics and Statistics Cognetti de Martiis. Working Papers 201306, University of Turin.

Antonelli C., Quatraro, F. 2014. The effects of Biased Technological Changes on Total Factor Productivity: A Rejoinder and New Empirical Evidence. GREDEG Working Paper. University of Nice Sophia Antipolis.

Balleer and Reens (2013). Skill-Biased Technological Change and the Business Cycle. The Review of Economics and Statistics, MIT Press, vol. 95(4).

Bartelsman, E. J., Haltiwanger, J., & Scarpetta, S. (2008). Cross Country Differences in Productivity: The Role of Allocative Efficiency. Cambridge (MA), U.S., NBER (National Bureau of Economic Review)

Boskin, M., & Lau, L. (2000). Generalized Solow-Neutral Technical Change and Postwar Economic Growth. Cambridge (MA), U.S.

Crepón, B., Duguet, E., & Mairesse, J. (1998). Research, Innovation, and Productivity: an econometric analysis at the firm level. Cambridge (MA), U.S., NBER (National Bureau of Economic Review)

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

Duguet, E. (2003). Innovation height, spillovers and TFP growth at the firm level: Evidence from French Manufacturing. Economics of Innovation and New Technology, 13(1-2), 106–112.

Feder, Christoph, 2014. "Biased Technological Change: A contribution to the debate," Department of Economics and Statistics Cognetti de Martiis. Working Papers 201404, University of Turin.

Fisher, Franklin M and Solow, Robert M and Kearl, James M, 1977. "Aggregate Production Functions: Some CES Experiments," Review of Economic Studies, Wiley

Blackwell, vol. 44(2), pages 305-20, June.

Griliches, Z. (1979), Issues in assessing the contribution of research and development to productivity growth, Bell Journal of Economics, 10, 92–116.

Griliches, Z. (1991). The Search for R&D Spillovers. Cambridge (MA), U.S. NBER

Hall, Robert and Jones, Charles (1999), "Why Do Some Countries Produce So Much More Output perWorker than Others?,"Quarterly Journal of Economics, 83-116.

Hall, B. H., Griliches, Z., & Hausman, J. A. (1983). PATENTS AND R&D: SEARCHING A LAG STRUCTURE. Cambridge (MA), U.S., NBER (National Bureau of Economic Review)

Krugman, P. (1990). INCREASING RETURNS AND ECONOMIC GEOGRAPHY. Cambridge (MA), U.S.

Lipsey and Carlaw, (2004). Total Factor Productivity and the Measurement of Technological Change. The Canadian Journal of Economics / Revue canadienne d'Economique Vol. 37, No. 4 (Nov., 2004), pp. 1118-1150 Published by: Wiley. Article Stable URL: http://www.jstor.org/stable/3696125.

Martin L. Weitzman, 1998. "Recombinant Growth," The Quarterly Journal of Economics, MIT Press, vol. 113(2), pages 331-360, May.

Mas, Matilde and Javier Quesada (2005), ICT and Economic Growth in Spain 1985-2002

Mas, Matilde, Carlo Milana and Lorenzo Serrano (2008) Spain and Italy: Catching up and falling behind. Two different tales of productivity slowdown

Perez, C. (1986)."The new technologies: An integrated view" Jul, 1986

Perez, C. (1983). "Structural Change and Assimilation of New Technologies in The Economic and Social Systems" Oct, 1983

Perez, C. (2009).Technological revolutions and techno-economic paradigms Jan, 2009

Quah, Danny, 1993. "Empirical cross-section dynamics in economic growth," European Economic Review, Elsevier, vol. 37(2-3), pages 426-434, April.

Raval, D. (2011). BEYOND COBB-DOUGLAS: ESTIMATION OF A CES PRODUCTION FUNCTION WITH FACTOR AUGMENTING TECHNOLOGY. Cambridge (MA), U.S., NBER (National Bureau of Economic Review)

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

Solow, R. (1957). Technical Change and the Aggregate Production Function. The Review of Economics and Statistics, 39(3), 312–320.

Solow, R. 1979. "Alternative Approaches to Macroeconomic Theory: A Partial View," Canadian Journal of Economics, Canadian Economics Association, vol. 12(3), pages 339-54, August.

Solow, Robert M., 1987. "Growth Theory and After," Nobel Prize in Economics documents 1987-1, Nobel Prize Committee.

Timmer, Marcel, Mary O'Mahony and Bart van Ark (2007), The EU KLEMS Growth and Productivity Accounts: An Overview, March 2007

7 Annexes

Table: BTC values at country level for 2005

BTC for High Tech Sectors		BTC for Mid-High Tech Sectors		BTC for Mid-Low Tech Sectors		BTC for Low Tech Sectors	
Finland	0,2588431	Australia	0,1032339	Finland	0,0852395	Finland	0,0815533
Australia	0,1208218	Denmark	0,0429426	United Kingdom	0,0611306	United Kingdom	0,0289376
Denmark	0,0555285	Netherlands	0,0162143	Netherlands	0,0248647	Spain	0,0238482
United Kingdom	0,0274878	France	0,0136268	Australia	0,0239456	Australia	0,0232899
Japan	0,0263787	Japan	0,0057055	Spain	0,0232379	Japan	0,0214199
Germany	0,0171946	Italy	0,001846	Belgium	0,017621	Korea	0,010029
France	0,0152616	Korea	0,0016354	Japan	0,0149806	Belgium	0,0078278
Korea	0,0014341	Germany	0,0015709	France	0,0134472	Netherlands	0,0065911
Spain	-0,0023444	Finland	-0,0005584	Korea	0,0087859	France	-0,0126639
Belgium	-0,0158158	Belgium	-0,0022822	Germany	-0,0114972	Denmark	-0,0130407
Italy	-0,02715	Spain	-0,0173432	Denmark	-0,0131516	Germany	-0,027937
Netherlands	-0,0856211	United Kingdom	-0,0609391	Italy	-0,026381	Italy	-0,0570867
United States	-0,1142452	United States	-0,0671418	United States	-0,185166	United States	-0,1357625

Table 3: General Description by sector's technolgical level and country

Country	$\mathbf{A}^{\mathbf{Solow}}_{\mathbf{High}}$	$\mathbf{A}^{\mathbf{Solow}}_{\mathbf{low}}$	α_{high}	α_{low}	**AV**
Australia	1.029095 (0.04)	1.019783 (0.02)	.7611892 (0.10)	.6679908 (0.07)	87.82 (24.00)
Austria	1.013285 (0.02)	1.012029 (0.01)	.7774077 (0.08)	.6986536 (0.08)	91.49 (19.03)
Belgium	1.014507 (0.02)	1.016044 (0.01)	.7416166 (0.03)	.6378198 (0.02)	92.47 (14.39)
Denmark	1.013601 (0.02)	1.012157 (0.01)	.7777828 (0.08)	.7079545 (0.02)	97.27 (10.67)
Spain	1.04974 (0.07)	1.036309 (0.04)	.6653023 (0.06)	.5728817 (0.04)	92.04 (22.01)
Finland	1.031736 (0.04)	1.03165 (0.04)	.5972933 (0.14)	.6095666 (0.06)	95.99 (25.83)
France	1.014495 (0.03)	1.018418 (0.02)	.7111405 (0.04)	.6229139 (0.03)	92.66 (17.97)
Germany	1.008527 (0.03)	1.010413 (0.01)	.7467293 (0.05)	.6729525 (0.02)	115.8 (10.52)
Ireland	1.043263 (0.14)	1.014259 (0.07)	.4697167 (0.09)	.439921 (0.07)	90.31 (43.74)
Italy	1.034093 (0.06)	1.034524 (0.05)	.6195079 (0.04)	.5551646 (0.05)	85.91 (17.85)
Japan	1.000274 (0.02)	1.000542 (0.01)	.577064 (0.04)	.4961445 (0.03)	88.61 (16.81)
Korea	1.009833 (0.02)	1.008553 (0.01)	.4938315 (0.07)	.5506201 (0.06)	71.07 (46.78)
Netherlands	1.014194 (0.04)	1.013777 (0.01)	.9011989 (0.10)	.6323223 (0.03)	90.12 (20.70)
UK	1.030718 (0.05)	1.031191 (0.04)	.6866772 (0.05)	.6770142 (0.03)	91.94 (15.76)
United States	1.015779 (0.02)	1.017056 (0.02)	.6525807 (0.01)	.5922616 (0.06)	89.18 (24.95)

Figure 1. TFP trend by country and technological class.

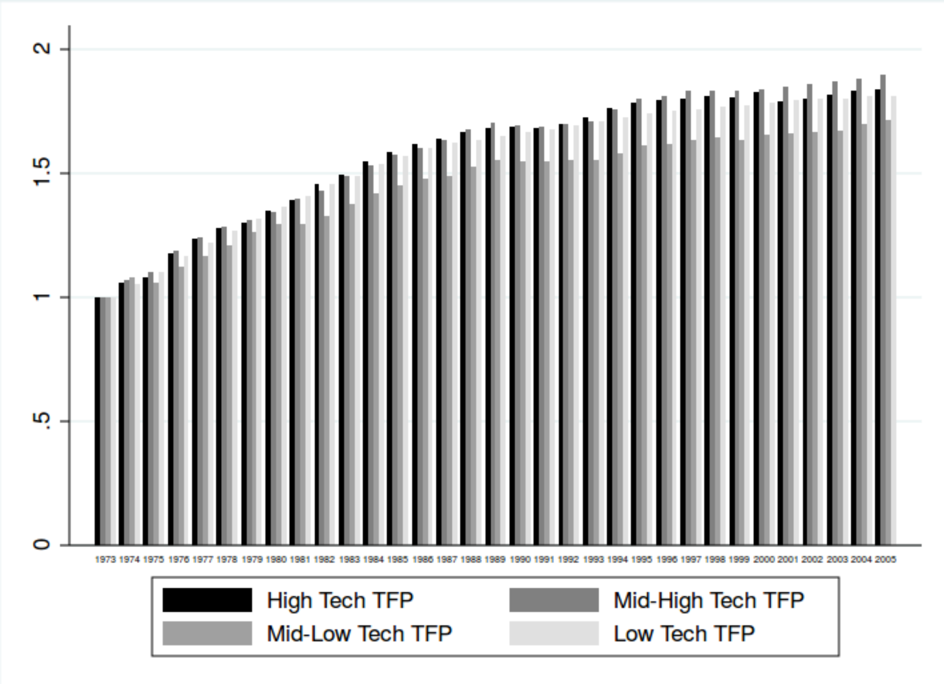

Figure 2.a. BTC trend by country for High-Tech technological class.

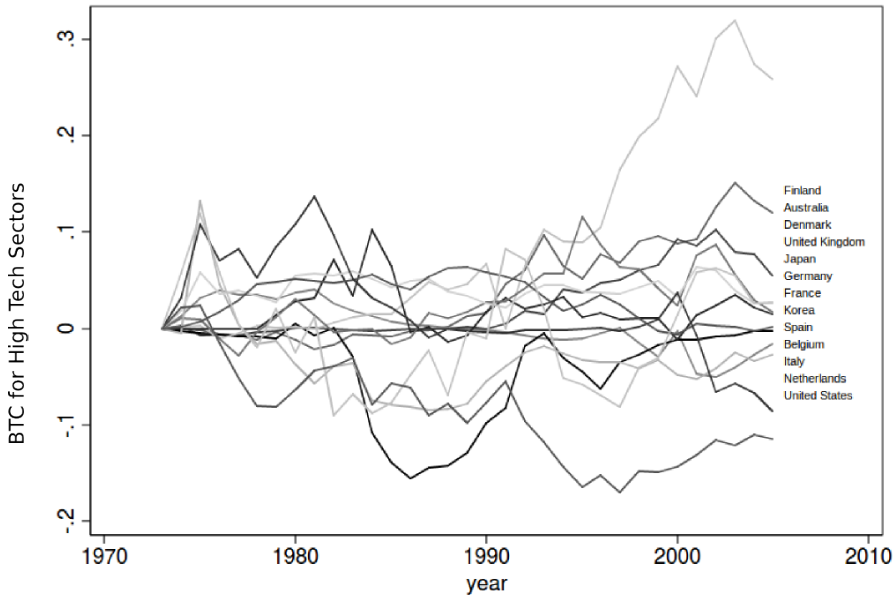

Figure 2.b. BTC trend by country for Mid-High-Tech technological class.

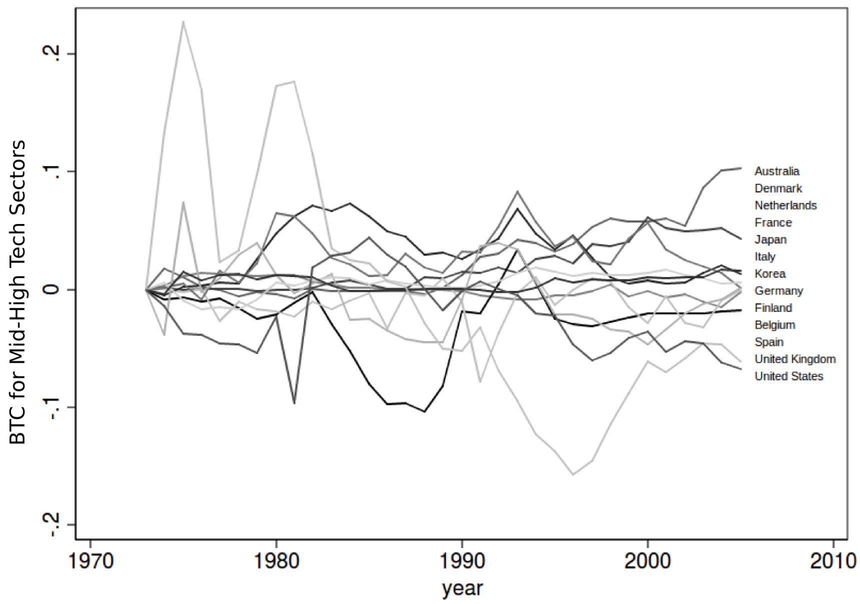

Figure 2.c. BTC trend by country for Mid-Low-Tech technological class.

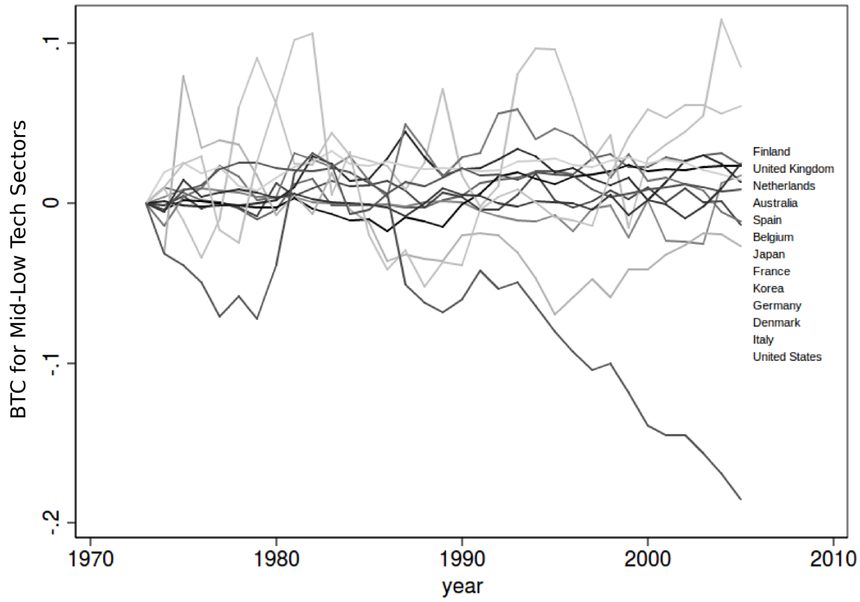

Figure 2.d. BTC trend by country for Low-Tech technological class.