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DIRECTED TECHNOLOGICAL CHANGE AND TECHNOLOGICAL CONGRUENCE: A NEW FRAMEWORK FOR THE SMART SPECIALIZATION STRATEGY

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Directed technological change and technological congruence: A new framework for the smart specialization strategy[1]

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ABSTRACT. Technological congruence implements the analysis of directed technological change showing how the match between the relative size of outputs' elasticity and the relative abundance and cost of production factors has powerful effects on total factor productivity (TFP). Smart specialization strategies can rely upon technological congruence to support the introduction and diffusion of new directed technologies characterized by the best mix of factors relative cost -as determined by pecuniary externalities in the regional factor markets- and output elasticity. The evidence of 278 European regions in the years 1980-2011 confirms that the levels and the changes in technological congruence, brought about by the introduction of directed technological changes, have significant effects on the levels and the changes of TFP. The key policy implication is that the optimal S3 policy mix should not only look at the history of local industrial or technological specializations, but it should also take into account the pecuniary externalities that characterize local factor markets to promote technological changes directed to augmenting the output elasticity of the cheaper regional production factors.

JEL Classification: O11, O30.

KEY WORDS: S3; Directed technological change; Technological congruence; Local factor markets; Pecuniary externalities; Output elasticity; Total factor productivity.

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1 Introduction

Smart specialization strategy (S3) is attracting increasing attention by policy makers to articulate a new framework of regional and innovation policy. The S3 approach combines in an original frame innovation and regional policies suggesting the need to implement a new framework of regional policy measures aimed at strengthening and improving local economic conditions by leveraging the structural characteristics of the regional economy (Foray et al., 2009). According to the S3 regional policy should rely upon a bottom-up selective innovation policy directed at supporting the introduction of innovations that impinge upon the local stock of technological knowledge and competence and use intensively the factors that are more abundant in the local factor markets (Aghion et al., 2011).

So far, the S3 has received more attention by policy makers than by economic analysis (Foray, 2015; Radosevic et al., 2017). Much literature has worked to strengthen the theoretical foundations of the S3 grafting the results of the investigations about the role of regional branching (Boschma and Gianelle, 2014). This approach stressed the importance of relatedness in the evolutionary dynamics underpinning the emergence of new industrial and technological activities out from the array of existing local activities. The regional branching literature has provided large evidence showing that regions will stay close to their existing capabilities when moving into new products and technologies (Boschma and Frenken, 2011).

In this framework, the central role of relatedness in the process of regional diversification is considered as a pillar of the S3 approach (Boschma, 2014). Smart specialization emerges as an outcome of the regional branching process, in which the proximity or relatedness to the existing structure of local competences constrains the direction of possible diversification avenues (Boschma, 2017; Colombelli et al., 2014).

This paper aims at contributing the theoretical foundations to the S3, by articulating its relationship with the notion of technological congruence. This latter stresses the importance of localized learning dynamics and the accumulation of competences in local contexts characterized by specific conditions of factors' markets (David, 1975; Abramowitz and David, 1996). The technological congruence approach related to regional technological diversification refers to the capacity to introduce new biased technologies that can take advantage of the pecuniary externalities that characterize existing factor markets' conditions, in terms of factors scarcity and relative costs.

The emphasis on the structure of local economic activities therefore makes the technological congruence approach suitable to fruitful combination with the S3 approach and its theoretical foundations grounded in the economic geography literature.

Using a dataset of 278 European regions in the years 1980-2011, we confirm that the levels and the changes in technological congruence have significant effects on the levels and the changes of total factor productivity (TFP). The policy implication is that the S3 policy mix is efficient as long as it not only stimulates the development of development trajectories based on the exploitation of cumulative local learning dynamics, but it also includes specific technology policies aiming at increasing the output elasticity of the cheaper factor at local level. Such effort would provide the S3 approach with a stronger background that enables to widen its scope of application and implement its selection procedures. In this sense, the notion of technological congruence provides a parallel and yet complementary perspective on S3, as compared to the regional branching approach.

In the rest of the paper section 2 articulates the relationships between S3, related diversification and technological congruence. Section 3 presents the hypothesis. Section 4 provides the empirical evidence. Section 5 summarizes the main results of the analysis and elaborates the policy implications.

2 Theory

The standard notion of economic growth was not able to capture the role of regional heterogeneity (Krugman, 1991; Blanchard, 1997; Acemoglu and Dell, 2010). In recent years, the regional branching approach has been applied to explain how the regional endowment of production factors impacts on the introduction of innovations (Boschma and Frenken, 2011a; Montresor and Quatraro, 2017).

The strong consensus and the widespread attempts to use the S3 as a basis to articulate a new framework to support inclusive growth at the European level with a bottom-up approach able to identify and select the activities that are able at the local level to yield faster growth of output and productivity, requires an effort to implement its theoretical foundations. Like we will articulate in the following subsection, the analysis of the mechanisms of related diversification and regional diversification and regional branching that have made a first important step to provide an analytical framework to S3. Building upon these results we propose an additional and complementary step to strengthen the economic foundations of the S3 approach.

The notion of technological congruence, based upon the analysis of the pervasive role of pecuniary externalities, i.e. the persistent variety of factor costs across regions, and their role in directing the introduction of biased technological change can contribute this endeavor (David, 1975; Abramowitz, 1986; Antonelli, 2016).

2.1 Related diversification and regional branching

The concept of smart specialization shares the main principles of the construction of regional advantages, which requires regions to identify technology-based development patterns, drawing upon knowledge, variety and policy platforms (Oughton et al., 2002; Asheim et al., 2011; Boschma, 2014). In turn, the construction of regional approach identifies "related variety" as the main driver of diversification and industrial branching at the regional level (Boschma, 2011; Boschma and Frenken, 2011b).

Technical or cognitive proximity amongst sectors or technologies shapes regional development trajectories in such a way that competences accumulated over time are likely to create dynamic irreversibility, engendering path-dependent diversification dynamics (Boschma et al., 2013; 2014; Colombelli et al., 2014; Essletzbichler 2015; Montresor and Quatraro, 2017).

The regional branching approach has therefore provided a fertile ground to understand the theoretical underpinnings of S3, and to elaborate the argument at the regional level (Boschma and Gianelle, 2014; Balland et al., 2018). In this context, the interplay between regional idiosyncratic features and the ability of local agents in engaging in successful learning processes is considered key to drive regional diversification patterns towards the valorization of the local competences accumulated over time (McCann and Ortega-Argiles, 2015). A wide of body of empirical literature has eventually shown that related diversification is positively associated with regional economic performances.

The extension of the resource-based view of the firm to the regional domain allows to better appreciating the impact of relatedness in the elaboration of regional diversification strategies (Lawson, 1999; Quatraro, 2009; Neffke et al., 2018). Smart specialization involves therefore the capacity to leverage the existing regional resource base to support the development of new economic and technological activities. Regional resources are in turn highly idiosyncratic, non-substitutable, inimitable, rare and valuable. Competences emerging out of localized learning are mostly specific to sectors and technological domains, and therefore hardly useful for activities that are loosely related to existing bundle of regional activities. For this reason, the dynamics of emergence of new activities in regional contexts is featured by path-dependence leading to related diversification patterns.

The constraining role of regional economic and technological history is a distinctive feature of the regional branching approach, which provides a valuable background to the discourse on S3. Similarly, the concept of technological congruence blends economic and technological aspects, suggesting that regions able to leverage technologies that are able to identify and take advantage of the sources of pecuniary externalities in local factor markets, in terms of relative scarcity, are more likely to be featured by better economic performances.

The concept of relatedness gains new meaning, concerning the fitness degree between the factor intensity required by the new technologies and the one actually observed in the regional economies. In the next section we will present the main ingredients of the technological congruence theory, and discuss more explicitly its relationship with the related diversification theory and the bearing on the S3 approach.

2.2 Technological congruence

As stressed in sub-section 2.1, related diversification and regional branching gained momentum as a theory explaining regional diversification dynamics, and its relationship with regional economic performances. The technological congruence theory complements and integrates the analysis of related diversification as it focuses on the role of factor markets while the latter concentrates its attention on the industrial composition of local economic systems. The analysis of technological congruence allows to identifying the effects of the matching between the local endowments of production factors and the direction of technological change on regional output and productivity growth. This sub-section provides the basic tools to appreciate the effects of technological congruence on productivity dynamics and articulate our working hypothesis that the direction of technological change is a powerful factor that should become the target and the tool of a S3 policy mix able to support the introduction of biased innovations better able to match the pecuniary externalities that stem from the factor endowments specific to each region.

The analysis of the relationship between the direction of technological change and the relative abundance of factors in local markets enables to implement the analysis of the related diversification and hence to contribute the endeavor shared by a large literature to articulate solid theoretical foundations for the S3.

Technological congruence is an important factor in economic growth both at the firm and the aggregate level. From a theoretical viewpoint, technological congruence elaborates upon and extends the directed technological change framework. Within this strand of analysis, not only the rate but also the direction of technological change is no longer regarded as an exogenous. On the contrary, economic forces play a central role in determining its characteristics including its direction that is far from being neutral (Acemoglu, 2002; 2003; 2010).

Increasing empirical evidence has recently documented the strong directionality of technological change. The new evidence has shown that the output elasticity of factors is far from stable at the aggregate level as it varies considerably across time and countries, as well as at the disaggregate level across firms, regions and industries (Krueger, 1999; Hall and Jones, 1999; Caselli and Coleman, 2006; Caselli and Feyer, 2007; Comin and Hobijn, 2004).

Technological congruence is the result of the endogenous introduction of biased technological change induced by the changing conditions of factor markets. It is the result of a process of augmented factor substitution where technological change is biased towards the reduction of the intensity of the production factor that are relatively more expensive and its substitution with a more intensive use of the factors that are locally more abundant and hence cheaper (Antonelli, 2003, 2012, 2016).

Technological congruence is the result of a meta-substitution process where technical substitution is augmented by the introduction of technological change directed at increasing the output elasticity of the factors that can yield pecuniary externalities because they are locally cheaper. Technological congruence enables higher levels of dynamic efficiency as it has direct and clear effects on the levels of TFP. In the Appendix, we provide the analytical demonstration that technological congruence, defined by the matching between the slope of both the isoquant and the isocost, has direct effects on output levels: an increase of output elasticity of the cheaper factor induces an increase of productivity growth.

The actual effects of technological change when it is directional, as opposed to neutral, depend upon the specific conditions of local factor markets. The effects of directed technological change are not universal but contingent upon the specific local conditions to which they apply. The introduction of a new technology characterized by strong shift and non-neutral effects can vary across countries and regions that have heterogeneous factor markets. A new technology can be superior in a region and actually inferior in another. A new capital-intensive technology with a strong shift effect can be superior to existing ones in a capital abundant region, but actually inferior in a labor abundant one.

From the viewpoint of the analysis of adoption and diffusion of technological innovations the notion of technological congruence, and the understanding of its effects on TFP, implements the idea that firms choose the most appropriate technology from a library of technologies -- this idea underpins the meta-frontier literature, where the output shortfall associated with choosing the wrong technology is referred to as a meta-technology ratio. The notion of technological congruence implies that new technologies can no longer be ranked along an objective order. As a consequence, delayed adoption can be rational. Agents located in a labor abundant country may have no interest to adopting a capital-intensive technology although its shift effects are relevant (Comin and Hobijn, 2004).

From the viewpoint of the introduction of new technologies, the notion of technological congruence, and the understanding of its effects on TFP, contributes another aspect of the economics of innovation and new technologies. Here there is not a library of technologies, but, on the opposite a binding set of relative factor markets conditions that induce the direction of technological change. Technological congruence provides solid foundations to understanding the variety of directions of technological change across countries and regions with differentiated factor markets. Regions characterized by capital abundance have a clear incentive to generate new technological knowledge and introduce technological innovations that make an intensive use of the factor locally abundant. This aspect has been little appreciated by the 'appropriate technology' literature. Yet it contributes to understanding the persistence of differentiated technological paths of regions. The notion of technological congruence helps understanding: (i) why the direction of technological change across regions is inherently heterogeneous; (ii) the pervasive role of pecuniary externalities as a source of incentives to guide the technological bias.

As suggested by Aghion et al. (2011), the directed technological change approach is useful for EU policy as it induces structural changes in the economy, i.e. it describes an innovation process, and it selects specific policies for the regional heterogeneity of endowment, i.e. the policies that are tailored to exploiting the regional endowment of factors. The focus on the matching between direction of technological change and the levels of pecuniary externalities specific to each region provides the tools to implement the smart specialization concept, since it shows how the introduction of directed technological change enables to take advantage of the structural heterogeneity of regional factor markets that has been shaped by the local history of specialization and related diversification.

The new proposed framework based on technological congruence and that based on related diversification and regional branching contribute two different and yet complementary layers of analysis. The regional branching framework uses network analysis at the industrial level to establish proximity relations amongst economic activities. Vice versa, the technological congruence framework uses macroeconomics analysis at the regional level. Successful industrial branching takes place when it impinges upon high levels of technological congruence and the search for technological congruence enables to identify the industrial branching that offers the best matching between pecuniary externalities in local factor markets and the direction of technological change.

3 Hypothesis

The hypothesis of this work is that the levels of technological congruence are the cause of the bias components of TFP. The more intensively a system (and an agent) is able to use the production factor that is locally cheaper and the larger the levels of

TFP. The larger is the difference between the slope of the isocost and the slope of the isoquant and the larger are the levels of technological congruence, the larger will be the levels of TFP.

Some scholars identify a set of indicators enables to disentangle the bias and the shift (neutral) effects of the introduction of technological change (Antonelli and Quatraro, 2010; 2013; 2014; Zuleta, 2012; Sturgill and Zuleta, 2017; Feder, 2018a; 2018b). To identify the bias effects of the introduction of biased technological change and to distinguish them from the shift effects of technological change, we use the procedure of Antonelli (2016).

This tool enables to test the hypotheses about the effects of the introduction of biased technological changes that affect the levels of technological congruence: (i) the increase of the directional component of TFP will be larger the larger is the bias of technological change in terms of the increase of the output elasticity of the production factor that has become less expensive; (ii) the larger is the reduction (increase) of the slope of the isocost and the larger is the increase (decrease) of the reciprocal of slope of the isoquant, and the larger will be the rate of increase of TFP.

Our hypotheses can be synthetized and formalized as it follows. Let A_B be the effect of the directed technological on the TFP; r and w the capital rental and the labor cost, respectively; and α and β the output elasticity of capital and labor, respectively. Formally we want to test if the following functions (called f and g) are decreasing:[2]

(1) $A_B = f\left(\frac{w}{r} - \frac{\alpha}{\beta}\right)$ with $f' < 0$;

(2) $\frac{dA_B}{A_B} = g\left(\frac{d(w/r)}{(w/r)} - \frac{d(\alpha/\beta)}{(\alpha/\beta)}\right)$ with $g' < 0$.

The empirical validation of the hypotheses makes an important contribution to implement the theoretical foundations of a new selective and yet inclusive European policy framework based upon S3 as it shows that regions should elaborate a selective support to technological change favoring the introduction of innovations that make the most intensive use of the production factor that are locally more abundant.

The following sections describe the data and the methodology implemented to test our hypothesis on the European evidence, at the regional level.

[2] See the Appendix for a more elaborated demonstration.

4 Data and Methodology

The main working hypothesis of this paper is grounded on the effects of technological congruence on TFP, proposing that it is in particular the cause of its directional component.

In order to provide an empirical assessment, we implement an econometric analysis articulated at the regional level. The data are drawn from the Cambridge Econometrics' European Regional Database (ERD), which is a highly disaggregated dataset across both sectoral and sub-regional dimensions. Eurostat's REGIO database is the primary source of data for the ERD but is supplemented with data obtained from AMECO, a dataset provided by the European Commission's Directorate General Economic and Financial Affairs (DG EcFin).

The variables included in the database allow for the calculation of the different productivity indexes, by implementing a standard growth accounting approach based on the assumption that the regional economy can be described by an aggregate Cobb-Douglas production function (Solow, 1957; Zuleta, 2008; Antonelli at al., 2017).

In particular, we used the regional GDP as an output measure. Output elasticities are calculated moving from labor output elasticity, which is obtained as the share of labor income in total production:

$$\beta_{i,t} = \frac{w_{i,t}L_{i,t}}{Y_{i,t}} .$$

The ERD provides data on Compensation of Employees, which can be used to this purpose. By assuming constant returns to scale, we derive the output elasticity of capital:

$$\alpha_{i,t} = 1 - \beta_{i,t} .$$

To finalize the calculations, we also used data on regional Employment and on Gross Fixed Capital Formation.

For all the variables but employment, the ERD provides deflated data taking the 2005 as base year. Table 1 shows the geographical coverage of the dataset.

>>> INSERT TABLE 1 ABOUT HERE <<<

Based on these data, we implemented the empirical exercise on an unbalanced sample of 278 regions spread over the 28 European countries. The 77% of the regions are observed over the whole-time span (32 years), while the remaining 23% is observed starting 1990 (1991 for 6 German regions), i.e. over 22 years.

The panel data nature of our dataset calls for the implementation of appropriate econometric estimators. In particular, we estimate the impact of the mismatch between factors' relative cost and output elasticity on the bias component of productivity, by using the fixed effect estimator. The structural model takes therefore the following form:

$$(3)\ y_{i,t} = \alpha + \beta x_{i,t} + \sum_{k=1}^{K} \gamma_{k,i,t} z_{k,i,t} + \sum_{t=1}^{T} d_t + \sum_{i=1}^{N} \varphi_i + \varepsilon_{i,t}\ .$$

where $y_{i,t}$ is the dependent variable, while $x_{i,t}$ is the focal regressor. According to equations (1) and (2):

$$y_{i,t} \equiv \begin{cases} A_B \\ \frac{dA_B}{A_B} \end{cases}; \qquad x_{i,t} \equiv \begin{cases} \frac{w}{r} - \frac{\alpha}{\beta} \\ \frac{d(w/r)}{(w/r)} - \frac{d(\alpha/\beta)}{(\alpha/\beta)} \end{cases}.$$

The econometric specification also includes a set of k control variables $z_{i,t}$, for $k = \{population, man\_share\}$, time dummies and region-specific effects.

Table 2 provides a summary of variables definitions, along with the main descriptive statistics.

>>> INSERT TABLE 2 ABOUT HERE <<<

5 Econometric results

5.1 Testing for a panel unit root

The test of the basic hypothesis of this paper rests on the econometric estimation of the effects of a mismatch between relative factors' cost and output elasticity on the directional component of TFP. Since the dataset involves European regions observed over a long-time window, there can be problems related to the presence of a unit root in the variables.

Actually, unit roots can affect regression results giving rise to spurious results. To minimize this risk, we first examine whether the variables in equation (3) exhibit a unit root. We perform a panel unit root tests proposed by Im et al. (2003) (IPS) and a Fisher-type test based upon the Phillips-Perron (PP) statistics (Phillips and Perron, 1988). Other tests are available, like the one implemented by Breitung (2000) or the one elaborated by Levin et al. (2002), but they are not suited to test unit root in unbalanced panels. The joint interpretation of the PP and the IPS tests should allow us to safely derive a conclusive result on the presence of unit roots.

>>> INSERT TABLE 3 ABOUT HERE <<<

Table 3 summarizes the results of the panel unit root tests. The tests include a constant term and, in the case of growth rates of the dependent variable and of the focal regressor, a time trend. The results suggest that with the only exception of population (P), for the others variables we can reject the null hypothesis of a unit root, and therefore we can proceed with our estimations by assuming stationarity, as P is a control variable entering only a few models.

5.2 Determinants of directed technological change

Table 4 shows the Spearman correlation coefficients amongst the variables used in the empirical analysis, while Table 5 reports the results of the econometric estimations carried out on the levels of biased technological change. The first column reports a very baseline version of the model, including the current difference between relative costs and the ratio between output elasticities of factors as an explanatory variable, plus time and region-specific fixed effects.

The coefficient of our focal regressor is negative and significant, suggesting that as $x_{i,t}$ decreases, i.e. as $w_{i,t}/r_{i,t}$ gets smaller than $\alpha_{i,t}/\beta_{i,t}$, the biased component of TFP becomes larger. This is due to the fact that the difference between the two components of $x_{i,t}$ is smaller the larger the increase of $\beta_{i,t}$ ($\alpha_{i,t}$) following a decrease in $w_{i,t}$ ($r_{i,t}$). Therefore, we observe that the function f in equation (1) decreases, i.e. $f' < 0$.

>>> INSERT TABLES 4 AND 5 ABOUT HERE <<<

Column (2) of Table 4 shows instead the results of the estimations obtained by considering the lagged value of our focal dependent variable, i.e. $x_{i,t-1}$. As for the previous model, time and region-specific fixed effects are also included. The coefficient on the focal regressor is once again negative and significant, consistently with the previous estimation and supporting the robustness of the result.

Columns (3) and (4) alternate again regression with current and lagged level of x respectively, but also controlling for the regional share of manufacturing employment and population levels. The coefficient of $man\_share_{i,t-1}$ is positive and significant, while that on population (P) appears to be negative and significant. While the effect of this latter variable is to be interpreted cautiously, the result may suggest that smaller regions are not fully able to shape the direction of technological efforts, as they are more likely to be adopters or importers of new technologies, while larger regions command an adequate level of resources and competences to impress upon the direction of innovation activities.

When we move to the focal regressor, the coefficient is still negative and significant, implying that when new technologies involve the increase of the output elasticity of the less expensive factor, i.e. when x is small, the biased component is large.

So far, we have estimated the former version of the model based on the levels of the dependent variable and the focal regressor. It would also be interesting to look at the dynamic version of the relationship, i.e. to investigate the impact of the rate of change of x on the rate of change of the biased component of TFP. The result of these estimations is reported in Table 6.

>>> INSERT TABLE 6 ABOUT HERE <<<

Columns (1) and (2) report the results of estimations including the actual and the lagged rate of change of x, respectively. Consistently with the expectations and the previous results the coefficient is negative and significant. The bias component decreases when there is a mismatch between relative costs and output elasticities of factors. In columns (3) and (4) we introduce the control variables, the signs of which are still in line with the previous estimations, although the coefficient of the lagged level of P now is not significant. The sign and significance of coefficient of the focal regressor is instead very persistent.

We finally perform four more regressions in columns (5) to (8) that include the level of x, both current and lagged, instead of its rate of change. In these last estimations the coefficient of P is again statistically significant. Across the different specifications the coefficient of the focal regressor is persistently negative and significant, suggesting that evidently the results are robust to different specifications.

The results of our empirical analysis confirm the strong and effective results in terms of TFP of the matching between the direction of technological change as accounted by the output elasticity of the two basic factors and their relative cost in the local factor markets. More detailed work based upon a sales production function, including, next to capital and labor, the relevant intermediary factors would make it possible to show the role of pecuniary externalities. The implementation of an extended frame of the technological congruence approach would, in fact, enable to identify the positive effects of the introduction of technological change directed at increasing the output elasticity of the intermediary factors that for institutional, historic and structural are characterized by cost levels that are below average –equilibrium- ones.

6 Conclusions

The S3 approach has attracted considerable interest by policy makers as an innovative framework able to match the selective support of regional and research policy with the bottom up identification of the activities that are more likely to contribute the growth of output and productivity at the regional level. S3 enables to pick the local winners reducing the risks and shortcomings of centralized policy interventions. The original articulation of the S3 approach missed a solid theoretical background. The analysis of the regional dynamics of related diversification and industrial branching has considerably enriched the economic foundations of the S3 approach. This paper has provided and articulated a complementary level of analysis with the notion of technological congruence showing the powerful effects on TFP of the matching between the direction of technological change and the characteristics of local factor markets. The evidence of the European regions confirms the direct effects on the levels and the rates of increase of TFP of the levels and the rates of change of technological congruence. Building on these bases, the paper makes a contribution both to the S3 and to innovation policy.

The analysis of the technological congruence articulated by this paper and the strong empirical evidence contributes to articulate and deepen the theoretical foundations of the S3 that aims at directing a large array of public policies, ranging from research and innovation policy including regional and industrial policies to support the new activities that are closer to the structure of the endowments of each region. The identification of the effects of technological congruence and of its roots in the induced technological change and technological congruence approach provides the S3 with a twin set of tools: pecuniary externalities and directed technological change.

Innovation policy has paid far more attention to fostering the rate of technological change than to guiding its direction. Technological change is far from neutral and the selection of its direction has important effects on the growth of output and productivity when it is able to identify and to match the sources of pecuniary externalities that characterize the local factor markets. Pecuniary externalities are in turn endogenous to the system as they are – to a large extent- the by-product of the local history of industrial specialization and related diversification. The selective support to a direction of technological change that is able to increase the use of the inputs that are locally cheaper can become an important policy tool that blends regional and innovation policies.

This set enables policy makers to implement their strategies by means of the identification of the regional factor markets that are characterized by relative abundance. The analysis of technological congruence enables to call attention on the relevance of pecuniary externalities as a mechanism that contributes to stir the introduction of directed technological changes. Policy makers at the regional level can rely upon of the relative costs in the wide range of intermediary factor markets as a reliable device that enables to stir and yet select the direction of technological change.

According to the results of the theoretical and empirical analysis carried on by this paper, S3 can generalized, implemented and empowered not only by the support to the analysis of mechanisms of related diversification and industrial branching at the regional level, but also by means of the systematic search of the sources of pecuniary externalities and the selective support to the introduction and adoption of new technologies whose mix of factors is able to take advantage of the relative abundance of intermediary factors augmenting the matching between their relative cost in the factor markets and their output elasticity in the production process.

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Table 1 - Data availability by time and regions

Country/Regions	Years available	All regions available excluding
Belgium (BE)	1980-2011	BE10, BE100, BE310, BEZ, BEZZ and BEZZZ
Bulgaria (BG)	1990-2011	BGZ, BGZZ and BGZZZ
Czech Republic (CZ)	1990-2011	CZ0, CZ010, CZ020, CZ080, CZZ, CZZZ and CZZZZ
Denmark (DK)	1980-2011	DK0, DK050, DKZ, DKZZ, DKZZZ
Germany (DE) Except (DE3, DE4, DE8, DED, DEE and DEG)	1980-2011	DE50, DE60, DE600, DEC0, DEF0, DEZ, DEZZ AND DEZZZ
DE3, DE4, DE8, DED, DEE and DEG	1991-2011	DE30, DE300, DE80, DEE0, DEG0
Estonia (EE)	1990-2011	EE0, EE00, EEZ, EEZZ and EEZZZ
Greece (GR)	1980-2011	GR30, GR300, GRZ, GRZZ and GRZZZ
Spain (ES)	1980-2011	ES120, ES130, ES220, ES230, ES30, ES300, ES620, ES630, ES640, ES70, ESZ, ESZZ and ESZZZ
France (FR)	1980-2011	FR10, FR30, FR910, FR920, FR930, FR940, FRZ, FRZZ and FRZZZ
Ireland (IE)	1980-2011	IE0, IEZ, IEZZ and IEZZZ
Italy (IT)	1980-2011	ITD10, ITD20, ITZ, ITZZ and ITZZZ
Cyprus (CY)	1990-2011	CY0, CY00, CY000, CYZ, CYZZ and CYZZZ
Latvia (LV)	1990-2011	LV0, LV00, LVZ, LVZZ and LVZZZ
Lithuania (LT)	1990-2011	LT0, LT00, LTZ, LTZZ and LTZZZ
Luxembourg (LU)	1980-2011	LU0, LU00, LU000, LUZ, LUZZ and LUZZZ
Hungary (HU)	1990-2011	HU10, HUZ, HUZZ and HUZZZ
Malta (MT)	1990-2011	MT0, MT00, MTZ, MTZZ and MTZZZ
Netherlands (NL) except 3NL23	1980-2011	NL230, NL310, NLZ, NLZZ and NLZZZ
NL 23	1986-2011	
Austria (AT)	1980-2011	AT130, ATZ, ATZZ and ATZZZ
Poland (PT)	1990-2011	PLZ, PLZZ and PLZZZ
Portugal (PT)	1980-2011	PT150, PT20, PT200, PT30, PT300, PTZ, PTZZ and PTZZZ
Romania (RO)	1990-2011	ROZ, ROZZ and ROZZZ
Slovenia (SI)	1990-2011	SI0, SIZ, SIZZ and SIZZZ
Slovakia (SK)	1990-2011	SK0, SK010, SKZ, SKZZ and SKZZZ
Finland (FI)	1980-2011	FI20, FI200, FIZ, FIZZ and FIZZZ
Sweden (SE)	1980-2011	SE110, SEZ, SEZZ and SEZZZ
United Kingdom (UK)	1980-2011	UKF30, UKK30, UKM50, UKN0, UKZ, UKZZ and UKZZZ
Norway (NO)	1980-2011	NO0

Table 2 – Variables definition and descriptive statistics

Variable	Definition	N	Mean	Min	Max	Sd	Skewness	Kurtosis
$\boldsymbol{y}$	Biased component of productivity	8171	11,836	-14,341	177,486	15,064	3,175	22,447
$\boldsymbol{d(y)/y}$	Rate of change of the biased component	8171	1,031	-73,972	182,357	9,502	7,690	132,307
$\boldsymbol{x}$	$(w/r) - (\alpha/\beta)$	8171	0,255	-3,468	63,931	2,776	9,461	137,973
$\boldsymbol{d(x)/x}$	$d(w/r)/(w/r) - d(\alpha/\beta)/(\alpha/\beta)$	8171	8,348	-4,512	99,912	6,142	2,193	24,336
$\boldsymbol{Man\_share}$	Log of employment share in manufacturing	8171	-1,741	-4,116	-0,786	0,487	-1,073	4,708
$\boldsymbol{P}$	Log of Population levels	8171	7,130	3,215	9,382	0,872	-0,741	4,589

Table 3 – Unit root tests

	IPS statistics	PP statistics
$\boldsymbol{y}$	-4.2403***	8.8170***
$\boldsymbol{d(y)/y}$	-14.9431***	6.0082***
$\boldsymbol{x}$	-9.2763***	16.9540***
$\boldsymbol{d(x)/x}$	-7.3335***	4.0366***
$\boldsymbol{Man\_share}$	-6.4469***	3.4675***
$\boldsymbol{P}$	12.4169	-0.5422

Asymptotically standard normal distributed test statistics. Starred statistics are significant at 1%. Automatic selection of lags based on AIC criteria for the IPS statistics. 3 lags included for the calculation of the PP statistics.

Table 4 – Correlation matrix

	$\boldsymbol{y}$	$\boldsymbol{d(y)/y}$	$\boldsymbol{x}$	$\boldsymbol{d(x)/x}$	$\boldsymbol{Man\_share}$	$\boldsymbol{P}$
$\boldsymbol{y}$	1					
$\boldsymbol{d(y)/y}$	0,3373*	1				
$\boldsymbol{x}$	-0,2720*	-0,3715*	1			
$\boldsymbol{d(x)/x}$	0,1641*	0,1952*	-0,0904*	1		
$\boldsymbol{Man\_share}$	-0,3279*	0,0057	-0,0921*	-0,1634*	1	
$\boldsymbol{P}$	-0,7588*	-0,1069*	-0,1698*	-0,0154	0,2296*	1

Starred coefficient is significant at 5%.

Table 5 – Econometric results (I)

	(1)	(2)	(3)	(4)
x	-0.6817***		-0.6531***	
	(0.0173)		(0.0175)	
x_{t-1}		-0.6100***		-0.5757***
		(0.0175)		(0.0173)
Man_share_{t-1}			1.4896***	1.2351***
			(0.4237)	(0.4310)
P_{t-1}			-20.9968***	-21.8090***
			(1.3951)	(1.4173)
_cons	17.2527***	14.9979***	171.3672***	175.9390***
	(0.3885)	(0.3989)	(10.0044)	(10.1671)
N	8171	7895	7895	7895
R^2	0.190	0.161	0.214	0.188
adj. R^2	0.159	0.127	0.182	0.155
AIC	50479.8856	48462.4887	47953.0692	48211.5933
BIC	50711.1611	48685.6562	48190.1847	48448.7088

Dependent variable: $y = A_B$
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 – Econometric results (II)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$d(x)/x$	-0.1245***		-0.1101***					
	(0.0244)		(0.0227)					
$[d(x)/x]_{t-1}$		-0.1070***		-0.1048***				
		(0.0227)		(0.0228)				
x					-0.1052***		-0.0980***	
					(0.0124)		(0.0119)	
x_{t-1}						-0.0950***		-0.0926***
						(0.0115)		(0.0116)
Man_share_{t-1}			0.7570***	0.7514***			0.7993***	0.7536***
			(0.2890)	(0.2893)			(0.2874)	(0.2877)
P_{t-1}			-1.7084*	-1.6934*			-0.4373	-0.4999
			(0.9446)	(0.9448)			(0.9464)	(0.9462)
_cons	0.8797***	0.4582*	15.3388**	15.2132**	1.5868***	1.3214***	7.1085	7.4117
	(0.2675)	(0.2408)	(6.7833)	(6.7843)	(0.2782)	(0.2621)	(6.7871)	(6.7872)
N	8171	7895	7895	7895	8171	7895	7895	7895
R^2	0.013	0.013	0.014	0.014	0.019	0.019	0.020	0.020
adj. R^2	-0.025	-0.027	-0.026	-0.026	-0.019	-0.021	-0.020	-0.020
AIC	45069.3974	41882.0192	41872.5877	41875.1288	45021.7610	41834.1745	41826.4222	41830.6219
BIC	45300.6728	42105.1868	42109.7032	42112.2442	45253.0364	42057.3420	42063.5377	42067.7374

Dependent variable: $d(y)/y = d(A_B)/A_B$
Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix - Technological congruence and output levels

The aim of this appendix is to provide the analytical demonstration that technological congruence, defined by the matching between the slope of the isoquant and the slope of the isocost, has direct effects on output levels. The larger is the difference between the two slopes and the larger are the output levels.

Our approach differs from the well-known concept of cost allocative efficiency (CAE) (i.e., choosing factor quantities so that marginal rates of technical transformation are equal to relative factor costs) because we assume explicitly that the production function, and specifically the output elasticity of the factors, can change because of the introduction of biased technological change directed at increasing the output elasticity of the factor that is locally cheaper (Hjalmarsson et al., 1996).

The standard Cobb-Douglas production function seems a suitable and effective starting point. The Cobb-Douglas specification, in fact, accommodates explicitly, with α and β, the output elasticity of the production factors and enables to analyze their changes made possible by the introduction of biased technological innovations. The standard Cobb-Douglas takes the following format:

$$(A1)\ Y(t) = AK^{\alpha}L^{\beta}.$$

where K denotes the amount of capital and L the amount of labor.

The cost equation is:

$$\text{(A2)}\ C = rK + wL\ .$$

Firms select the traditional equilibrium mix of factors according to the slope of the isocosts given by ratio of labor costs (w) and capital rental costs (r) and the slope of isoquants. The equilibrium condition is:

$$(A3)\ \frac{\partial Y/\partial L}{\partial Y/\partial K} = \frac{w}{r} \rightarrow \frac{\beta}{\alpha}\,\frac{K^*}{L^*} = \frac{w}{r}\,.$$

From (A3), in equilibrium it must be:

$$\text{(A4)}\ L^* = \frac{r\beta}{w\alpha}K^*\ .$$

The optimal mix of productive factors that entails total costs equal to C can be obtained as the solution of the following system:

$$(A5) \begin{cases} L^* = \frac{r\beta}{w\alpha} K^* \\ C = rK^* + wL^* \end{cases}.$$

The solution of (A5) gives:

$$(A6) \begin{cases} L^* = \frac{C\beta}{w} \\ K^* = \frac{C\alpha}{r} \end{cases}.$$

Substituting (A6) in (A1), we can express the level of output that can be achieved at cost C:

$$(A7)\ Y^*/C = \left(\frac{\alpha}{r}\right)^{\alpha} \left(\frac{\beta}{w}\right)^{\beta}.$$

To show the effect of α on the level of productivity let us derive (8) with respect to α:

$$(A8)\ \frac{d(Y^*/C)}{d\alpha} = \frac{Y^*}{C} ln\left(\frac{\alpha w}{r\beta}\right) = \frac{Y^*}{C} ln\left(\frac{K^*}{L^*}\right).$$

From the previous expression, we have that:

$$(A9)\ \frac{d(Y^*/C)}{d\alpha} > 0 \Leftrightarrow K^* > L^*.$$

Condition (A9) is the necessary and sufficient condition for $d(Y^*/C)/d\alpha > 0$. If $w > r$ and consequently $K^* > L^*$, an increase of α induces an increase of Y, given the production cost.

Three qualifications are useful here. First, our mathematical presentation takes into account only production processes that can be approximated by means of a Cobb-Douglas production function. In other functional forms of the production function, like the translog, output elasticities are functions of the data, so they vary across observations, but the coefficients of the function are constant (the same applies to linear and quadratic functions). Yet the Cobb-Douglas production function is widely used as the general case and especially in growth accounting. Second, it is indeed difficult to imagine a firm where it is meaningful to consider differential changes in technologies. At the aggregate level because of the myriad of specific product and production processes, our assumptions are far less unrealistic. Consistently the standard analysis of induced technological change at the aggregate levels builds on these assumptions (Ruttan, 1997; 2001; Acemoglu, 2002; 2003; 2010). Third, our mathematical presentation includes extreme cases that at the firm level may seem unrealistic. It is clear that the equilibrium condition (A3) is only true if we rule out boundary solutions. Their inclusion in the analysis would not affect the results.

We have shown that output levels are influenced by the introduction of biased technological change. This result is important as standard growth accounting is able to identify only the effects of the introduction of neutral technological changes that produce a shift in the map of isoquants, does not accommodate the effects of the introduction of biased technological change and is not able to distinguish the two effects. Figure A1 helps to make our result better clear.

>>> INSERT FIGURE A1 ABOUT HERE <<<

Figure 1 represents the two extreme positive cases: 1) with the full line that exhibits the case of perfect matching when the isoquant is steep ($\beta > \alpha$), hence the technology in place is capital intensive, with an output elasticity of capital larger than the output elasticity of labor; and the isocost is flat ($w < r$) hence wages are smaller than capital user costs, and 2) the dotted line that exhibits the case of a steep isocost ($w < r$), hence capital user costs are lower than wages, and a flat isoquant ($\beta < \alpha$), with a labor intensive technology where the output elasticity of labor is larger than the output elasticity of capital. In both cases the technology in place exhibits the maximum levels of technological congruence and output levels are largest. In all the cases comprised between these two extremes, output levels are lower. Hence the introduction of biased technological changes can increase output levels. In economic terms this amounts to saying that Y is larger when either a capital-intensive technology is at work in a capital abundant factors market, or a labor-intensive technology is at work in a labor abundant factor market. The introduction of biased technological change affects the levels of output and hence of total factor productivity. We can term these effects as bias effects. Bias effects can be both positive or negative. They are positive when technological change increases the levels of technological congruence and negative when technological change reduces the levels of technological congruence.

The analysis implemented so far relies upon a value-added production function that includes only the basic factors: capital and labor. It can be generalized to a sales production function that includes, next to capital and labor, relevant intermediary factors. The latter is most appropriate to explore the actual scope of application of smart specialization strategies as it enables to identify the specific factor markets that make possible to access not only the basic factors available at a cheaper cost, but also the intermediary factors characterized by relevant pecuniary externalities. The S3 can consequently reframed as the set of innovation policies that are able to stir the introduction of biased technological changes directed at making the most intensive use of the factors that enjoy pecuniary externalities in the regional factor markets

Figure A1 - The matching between the slope of isocosts and isoquants