



Effects of commercial and technological integrations on regional agglomeration and welfare outcomes: the case of the European Union

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THÈSE DE DOCTORAT

Effets des processus d'intégration commerciale et technologique sur les bénéfices à l'agglomération : le cas européen

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Effets des processus d'intégration commerciale et technologique sur les bénéfices à l'agglomération : le cas européen

Dans la mesure où ils sont, théoriquement porteurs de gains de bien être pour l'ensemble des partenaires commerciaux, la littérature économique défend pour sa vaste majorité, la poursuite des processus d'intégration régionale. Cependant les tensions causées par l'élargissement des zones d'intégration ont mis en évidence la nécessité d'approfondir l'analyse des effets induits par des formes d'intégration hétérogènes. En effet, dans le cas de l'Union Européenne, les vagues successives d'élargissement ont mis à jour des dynamiques inégalement bénéfiques d'une région à l'autre. L'objet de cette thèse est d'apporter des éléments nouveaux concernant les conséquences d'une intégration commerciale couplée à une intégration technologique sur les phénomènes d'agglomération et de répartition du bien-être entre les régions.

Le premier chapitre pose la problématique de cette thèse en termes de creusement des inégalités spatiales. Sur la base d'outils statistiques issus de l'économétrie spatiale, ce chapitre met en évidence des dynamiques divergentes entre les régions des pays membres de l'Union Européenne (28) sur la période 2000-2016. Il propose comme première hypothèse de travail d'évaluer les effets de deux formes d'intégration (commerciale et technologique) sur les niveaux de bien-être régionaux. Leur valeur explicative au regard des PIB par tête régionaux, est quantifiée via le phénomène d'autocorrélation résultant des réseaux tissés du fait de ces intégrations. Ces premiers résultats ne s'avèrent pas probants mais mettent à jour un fait d'intérêt dans l'existence d'une corrélation négative liant intégration commerciale et intégration technologique.

Dans le deuxième chapitre est abordée la question de l'origine du ralentissement voire de l'arrêt de la croissance pour les régions de la vieille Europe qui ont relativement souffert des processus d'intégration. Ce chapitre utilise des méthodes à la frontière entre les modèles d'Effets Corrélés Communs (qui se rattachent à la famille des modèles de facteurs communs) et l'économétrie spatiale. Les résultats obtenus semblent valider l'hypothèse d'un sur-investissement en R&D pour ces territoires. On montre que

ce résultat, à contre courant d'une vaste littérature, fait écho à des développements théoriques récents dans lesquels une croissance sous-optimale pourrait résulter d'un sur-investissement en R&D.

Le troisième chapitre étudie la littérature qui éclaire les déterminants des gains à l'échange. La Nouvelle Economie Géographique désigne la baisse des coûts de transport comme un élément majeur conditionnant les phénomènes d'agglomération et de répartition des gains de bien-être. La génération suivante de modèles que constituent les cadres croisant Economie Géographique et Croissance (NEGG) introduit une distinction entre intégration commerciale et intégration technologique et permet d'envisager des conséquences distinctes d'une forme d'intégration à l'autre. De récentes avancées théoriques portent des implications testables de cette différenciation au regard des processus d'agglomération. Finalement, une nouvelle génération de modèles spatiaux quantifiables s'appuie sur la mobilité du travail pour appréhender les effets de l'intégration technologique et propose de nouvelles méthodes pour quantifier les conséquences à l'intensification des échanges sur le bien être.

Le dernier chapitre approfondit une implication testable des modèles de type NEGG. Il s'agit d'estimer, au niveau régional, la relation liant l'évolution des processus d'agglomération des activités aux deux formes d'intégration commerciale et technologique. Cette relation est testée dans le cas de l'Union Européenne sur la période récente. Nos résultats vont dans le sens des prédictions théoriques en montrant que l'intégration commerciale participe effectivement de l'agglomération des activités tandis que l'intégration technologique tempère cette dynamique.

Codes JEL : F15, O47, R12

Mots-Clefs : Productivité, Intégration économique, Union Européenne, Economie Géographique, Commerce interrégional, Inégalités régionales, Externalités

Effects of commercial and technological integrations on regional agglomeration and welfare outcomes: the case of the European Union

Broadly, the economic literature supports the idea that deepening regional economic integration benefits all trade partners. However, opposite insights have shed light on the increasing needs for a deeper analysis of the heterogeneous effects of economic integration processes upon territories. In particular, areas of economic integration such as the European Union have kept on enlarging while some elements tend to emphasize unequal gains from one region to another. The object of this PhD dissertation has been to bring in new elements on these issues by discriminating between two different forms of integration, namely, distinguishing a commercial form of integration from a technological form of integration. We investigate the respective impacts of both types of integration on agglomeration outcomes and welfare distribution across regions.

The first chapter lays the problem at the core of this work looking at the entrenchment of spatial inequalities. Using statistical methods from the spatial analysis toolbox, it brings to light diverging dynamics between regions of European Union (EU-28) member states over the period 2000-2016. As a first working hypothesis, we aimed also at evaluating the impact of both commercial and technological forms of integration on regional welfares. We exploit the autocorrelation phenomenon conveyed by those networks to quantify their explanatory share regarding regional GDPs. Our first results fail at enhancing a powerful relationship linking those elements but interestingly we emphasize a negative correlation between both forms of integration over space.

The second chapter investigates the origins of the growth slowdown for regions from the Old Europe that particularly suffered during the last phases of EU integration. In this chapter we make use of recent methods using enhancements at the frontier between Common Correlated Effects models (that root back to Common Factors models) and spatial econometrics. Our results give credit to the hypothesis of over-investment in R&D across those territories. Recent theoretical elements support our results in showing that over-investment in R&D could pair with under-growth paths that is lower than

optimal growth levels.

The third chapter reviews the literature that study the determinants of the gains from trade. The New Economic Geography (NEG) models first designated the lowering of trade costs as a major determinant to agglomeration processes and welfare outcomes. The next generation of New Economic Geography and Growth (NEGG) models introduced the distinction between commercial and technological integrations and allowed to consider impacts that would differ. Recent theoretical advances on this front reached testable implications regarding the relationship between various forms of integration and agglomeration outcomes. Lastly, a new generation of Quantitative Spatial models (QSM) emphasizes the importance of labor mobility, besides capital mobility, as a vector of technological integration between territories and brings in new tools to quantify the spatially uneven impact of economic integration on welfare.

The last chapter pushes further some testable implications of NEGG models. It specifies a relationship between the evolution of agglomeration processes of economic activities across regions and the commercial and technological ties that link regions to their neighbors in a common integration zone. The relationship is tested on regions belonging to the EU-28 over the recent period. We take care of endogeneity issues using tools also combining requirements on the control of spatial autocorrelation issues and nonparametric features. Our main results go along the theoretical statement that oppose the effect of commercial integration that favor spatial agglomeration to the effect of technological integration that temper agglomeration dynamics.

JEL codes : F15, O47, R12

Keywords : Productivity, Economic Integration, EU, Economic Geography, Interregional trade, Regional Inequality, Spillover Effects

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General Introduction

The decade 2010-2020 has marked the advent of a new kind of political leaders that put back on stage nationalism as a solution to the economic turmoil triggered by the crisis of 2008. One can understand the success of those leaders as some evidences of a deep discontent of voters regarding the policies implemented in the last fifty years on the top of which might appear the enforcement of globalization. In the case of the European people, the attentive analyst would have denoted that the principle of some deeper or larger forms of economic integration have been rejected many times in the recent history of the Union. In 1992, the Danish people rejected the treaty of Maastricht a first time and had to re-vote it to make it pass. In 2001, the Irish people voted against the treaty of Nice that aimed to act and set the enlargement of the European Union to the countries of the ex-Soviet bloc. They also had to re-vote it to make it pass. In 2005, the French and the Dutch rejected the European Constitutional Treaty (ECT) that aimed to expand the Qualified Majority Voting to policy areas where the rule of unanimity previously prevailed. The essence of the ECT has finally been imposed under the treaty of Lisbon. In 2008, the Irish rejected that same treaty of Lisbon and had to revote it to make it pass. Finally, in 2016, the people of the United Kingdom voted their Brexit and had to wait 2019 for having it implemented at the end of January 2020. The denial or the inability to have people decisions respected and followed has brought discredit to the ruling classes and participate in the emergence of new forms of liberal governance emphasizing the national preference and rejecting further forms of frontier openness.

Both the many rejections of further integration and the renewal of nationalism in the dominant narrative could be interpreted as symptoms of people uneasiness that has been growing in co-occurrence with wider globalization. One could not ignore the role played by economists in legitimizing and justifying the successive waves of international trade liberalization but the debate has stayed hot as the profession aimed at rigorously quantifying gains and losses of openness. From 1951 that lays the first stone in edifying the European Union, the *terms of trade* approach has been grounding the expansion of the integration logic in Europe and worldwide. The *terms of trade approach*, along the classic trade theory, refers to the existence of comparative advantages based either on technological or factor endowments that nations would benefit to specialize in while

trading in exchange of other supplies they would be less efficient in producing. This supposes that trade between nations is made at no costs and as a consequence, nations should tend to this optimum to maximize their gains. Accordingly, trade agreements have spewed worldwide, next to the World Trade Organization promoting multilateral reduction of trade barriers. In 1957, the treaty of Rome extended the reduction of barriers to factors of production fulfilling expectations of wider gains of efficiency by a closer to optimum allocation of resources to the benefit of all partners.

In the context of the European construction, the public power got assigned two roles. On the one hand, it should lead an industrial policy that supports national industries at the technological frontier to preserve productivity gains, growth, beneficiary terms of trade while ensuring the lowest trade barriers. On the other hand, it should guarantee equality and equity among citizens across its territory in line with the principles that structured many European societies at the end of the WWII.

This definition of the industrial policy comprises a slight paradox that has opposed the French and German conceptions of what should have been/be the role of the State by industries' sides within the European Union. From the end of the WWII until the eighties, France has embodied a *colbertist* vision, legitimizing the role of the State in edifying national champions which benefited from both public and private capitals and were framed into large industrial development projects themselves backed by the State. This vision had few successes among which Airbus which nowadays leads the market of aircraft construction and Galileo, the recently released competitor to the American GPS. However this conception opposed the German's one that rather considers, in accordance to some form of *ordoliberalism*, that the State should only provide the conditions of a free and perfect competition between agents. Accordingly, the public power can concur to the education of the labor force and care for its adequacy to the industrial needs, provide for infrastructures, guarantee the respect of property laws, contracts and patents and ensure the lowering of trade barriers to access foreign markets. The recent treaties deepening the ties between countries within the European Union lay on those last principles ¹and have restricted industrial policies to the support

¹"The frame of [the treaty of] Maastricht reflects the core principles of the ordoliberalism and the

of research and development activities excluding any role of intermediary in industrial cooperations.

Into this restricted field of action, the role of the State still can address the consequences of market failures in research and development. Schumpeter (1911) putted innovation and technological change at the core of economies' dynamics and ever since, a large literature has documented the mechanisms linking the R&D pursued by private agents and economic growth. The theory agrees on the role of States to develop human capital and protect intellectual property of innovations. Based on the existence of market failures, it also justifies more direct incentives to push firms into investing in research and development. Accordingly, knowledge is defined as a public good characterized by partial appropriation : innovation benefit economic agents that do not directly participate into financing research and development activities. This effect creates disincentives to investment in R&D as the private and social yields diverge. Under-investment has been largely studied by the empirical literature that emphasizes the role of knowledge externalities (Hall and al. 2010 [102]). However, the theoretical literature also documented other forms of externalities and failures that could affect firms' behavior. Among them, duplications into R&D activities or rent transfers from old to new innovators could also cause firms to over-invest in R&D. (Montmartin et Massard, 2015 [152])

In a context of budget restrictions imposed as part of the compliance with commitments to the European Union, the question of the allocation of public funds to sustain productivity and competitiveness should be considered in relation with the question of spatial equity and equality that constitutes the second role that falls to the State. Equity is not just a moral principle as emphasized by the principle of *juridic solidarity*² that structured rebuilding of European societies at the end of WWII. Put simply, the principle of *juridic solidarity* specifies that members/citizens must contribute to the common system to the amount of their financial capacity and have the benefits to use

social market economy” M.Jens Weidmann, president of the Bundesbank at the conference in the Institute Walter-Eucken, Frisbourg en Brisgau, February 11th, 2013

²Ni assurance, ni charité, la solidarité, Alain Supiot, Monde Diplomatique, Nov.2014

it according to their needs. For instance in France, the principle leans back the national healthcare system that every citizens could access freely. Somehow the principle of *juridic solidarity* establishes the responsibility of the State in guaranteeing equity between citizens and could be extended to equity between citizens across regional territories. Against this founding principle, policies allowing globalization and sustaining R&D efforts could have induced the entrenchment of regional inequalities.

Spatial analyses show that globalization and localized R&D dynamics participate in some unequal spatial allocation of the factors of growth. Classic trade theory that presided to globalization enforcement worldwide, reasons along a-spatial configurations where the internal geographies of countries are not considered. To this extent, spatial disparities could not be addressed in these frameworks. Conversely models that arose from economic geography brought theoretical foundations to the phenomenon of activities' agglomeration triggered by pecuniary externalities that resulted from the interplay of increasing returns and transport costs (Baldwin and Forslid 2000 [16]). The first generation of economic geography models (Krugman, 1991 [130]) ignore the causality between growth dynamics and the spatial organization of economic activities. Conversely, models that synthesize endogenous growth matters and economic geography appear more suited to analyze the consequences of reduction of trade costs and policies that support research and development activities upon economic growth and regional disparities as they emphasize the link between openness, localization of activities, innovation and growth. (Baldwin and Martin, 2004 [17])

In those models, the interdependency between growth and the localization of economic activities is tied by the hypothesis of knowledge externalities whose spread would be restricted in space. This hypothesis relies on the localized nature of face to face relationships that underlies the spread of knowledge between agents. As a consequence the more localized activities of innovation, the more dynamic the growth engine. Each industrial firm producing an (innovative) good is expected to generate some knowledge externality such that the agglomeration of innovative activities is linked to the agglomeration of industrial activities. To the extent that industrial activities face incentives to locate near large markets where the demand is the highest, a positive causality con-

nects growth and agglomeration. Industrial firms would be incited to locate near the largest markets to exploit increasing returns and minimize production costs while lessening transport costs in serving markets. R&D activities will reduce their production costs by concentrating the closest from the knowledge pool constituted of agglomerated firms. Thus, in this setting, agglomeration participates in reinforcing growth. This, in turn, induces some stronger concentration of activities and factors implying potential divergence processes between regions.

Growth triggers agglomeration to the extent that the area that will benefit the most from growth will ensure its residents to benefit from low (consumption) price indexes. Indeed, the economy of transport costs that firms have realized in concentrating close from the largest market manifests in low prices upon industrial goods varieties for consumers constituting the large market. Conversely residents of 'peripheral' regions will have to settle ever increasing transport costs due the relocation of firms close to the large market. The relative loss is reinforced by the fact that the stronger the dynamic in the 'core' region, the bigger the incentives to migrate activities for those who stayed in the peripheral region. Those elements emphasize a trade-off between growth and equality between regions.

In order to optimize regional situations over this trade-off, studies (Martin (1999) [142] and Riou (2003) [169]) have questioned the role of public policies in trade liberalization (i.e. improving transport infrastructures) and in supporting R&D productivity. Doing so, they found arguments against further commercial integration in showing that lowering transport costs reinforce agglomeration mechanisms and spatial disparities. Conversely, they emphasize the need for technological integration or policies that reduce costs to innovation across regions in opposing the effect of commercial integration on disparities.

Accordingly, one can question the gains from globalization and the role play by the conflicting forces of commercial and technological integrations. A vast literature looks at the gains from lowering trade costs at the national scale while understanding 'integration' as indifferently comprising both forms of commercial and technological integra-

tions. Few studies addresses the interplay of various forms of trade costs as a potential explanation to the literature’s failure to light up the mechanism driving the gains from integration and most keep on reasoning on integration between nations. The twin issue posed by two forms of integration having distinct consequences across regions has not been addressed by empirical studies so far. On the one hand, the interplay between the two forms of integration scarcely arise in studies looking at the agglomeration patterns of industries. Commercial and technological integrations are usually considered as acting in concert to reinforce agglomeration patterns. On the other hand, very recent studies consider the impact of integration on regional disparities. For instance, in the case of the integration of Argentina to international markets during the XIX century, Fajgelbaum and Redding (2014) [77] documents the concentration of manufacturing activities close from the coast where the ratio land prices relative to wages exceed the one in ‘interior regions’ where the agricultural sector dominated. They emphasize the role of investments in both internal infrastructure and technology adoption inducing the conflicting dynamics of the reallocation of workers close from coastal trading posts against the spread of technological progresses to agricultural regions.

To sum up, the complexity of the globalization processes raises questions regarding the effects and the global soundness of policies of integration. The objective of this PhD dissertation is to bring in new elements in order to analyze those questions considering interdependencies that the literature did not considered so far. We shade new lights on the triggers of spatial disparities between European regions by focusing on research and development dynamics and on the differentiated impact of commercial and technological integrations across the Union. To this aim, we mobilized innovative tools from spatial econometrics. Our analysis hinges on 4 chapters :

In a first chapter, we set up the issue at the core of this thesis in updating the representation of spatial disparities between regions across the European Union from 2000 to 2016. The founding contribution made by LeGallo and Ertur (2003) [136] represented spatial income inequalities across European regions before 2000. Ever since new members have been integrated to the Union and have changed regions’ dynamics. Countries from the ex-Soviet bloc entered the European Union in 2004 and doing so

modified the shape of income distribution and the direction of redistribution efforts with consequences for regions from the Old Continent. Many studies have been looking at the convergence dynamics across regions (Battisti and Di Vaio (2008) [21], Debarsy and Ertur (2006)[58], Eckey and Türk (2007)[76], Fisher and Stirböck (2006)[82], Paas and Schlitte (2006)[156]). From results upon the decade 2000-2010, the literature agrees on divergence processes opposing regions from Southern Europe to those belonging to the Blue Banana. According to recent updates, this pattern fades and convergence seems mostly at stake across New Members. The point is that convergence studies consider long term adjustments processes. In this work, we aim at providing the spatial representation of disparities and their evolution from 2000 to 2016. We do so using the Exact Approach that roots back to tools from the Exploratory Spatial Data Analysis (ESDA). Some developments of the Exact Approach allows us to investigate a second point in this chapter. Indeed, as a preliminary test, we confront the hypothesis that the patterns we observe regarding regional incomes might result from the interplay of the commercial and technological forms of integrations. Thus this first chapter aims at addressing the following questions:

Do regions across the European Union kept on diverging during the last two decades that marked great steps of economic integration among European economies ? To which extent could the spatial pattern of income disparities be linked to the two forms of commercial and technological integration ?

To address those questions, we base this work on local measures of spatial autocorrelation to investigate local non-stationarities and bring to light how wealth disparities have evolved in Europe. Spatial autocorrelation measures can be used to represent agglomeration processes and disparities between regions. Among those, Moran's I is a particularly efficient autocorrelation index that justify its extensive use in the literature and our present focus. This index can be understood as a statistic to the extent that it represents a realization from some superpopulation. To infer local Moran's I, several methods are available. First, the "Normal assumption" confronts local Moran's I to a Normal law. Bivand and al.(2009) [26] have shown that this would induce severe errors in presence of autocorrelation. Second, the "randomization approach" assesses

the statistic relative to the set of all possible values that could be obtained by randomly permuting the observed values around the areas. The reliability of the method rests on a trade off between the number of permutations and the calculation burden. A wise choice requires substantial knowledge from the analyst to design properly the experiment and obtain reliable results. The Exact Approach we propose to use in this chapter offers an alternative to randomization methods. By exploiting the spectral decomposition of observed Moran's I, it allows to obtain the local true distributions and exact levels of significance.

Secondly, we exploit further the spectral decomposition of Moran's I in order to compare different definitions of spatial effects. In testing different definitions of proximity based on geographical, commercial and technological distances, we aim at showing how those definitions differ and the explanatory power each imbeds regarding income disparities. We compare classic geographical definitions of proximity under the form of 'contiguity' or 'k-nearest neighbors' spatial matrices to time varying matrices of patent citations to represent knowledge flows and technological proximity in the one hand; and time varying matrices of industrial proximity to represent input and output links, that is commercial proximity, on the other hand.

Regarding the spatial distribution of income disparities, our results go along the main findings of the literature on European convergence. Few central regions of the Old Europe have clearly benefited from integration next to New Members capital cities. Conversely, the last 'decade' (2009-2016) has been detrimental for 'intermediate' peripheral regions. We note a slowdown in the concentration processes starting from 2009. Confronting proximities' definitions we miss to emphasize a great explanative power of commercial and technological forms of proximities regarding the distribution of regional incomes. We raise two potential explanations for this. First, our proximity matrices could be bad proxies for the technological and commercial integrations we intend to represent. Still do they allow us to highlight an interesting point regarding the negative correlation between both forms of proximity across space. Second, the theoretical relationship we test could be more complex and involve nonlinearities we failed taking into account. Next chapters should uncover which issue might have been

detrimental.

In our second chapter, we address the hypothesis that, on average, the growth engine has stopped for regions that are part of the Old Continent which may explain the increasing disparities between core and peripheral regions. Our working hypothesis is that regions from Western Europe being in a situation of over-investment in R&D could explain policies' inefficiency in triggering growth and re-balancing disparities enhanced by agglomeration mechanisms. From a methodological point of view, chapter 2 proposes a refined econometric estimation of a spatially extended growth accounting framework which allows to test for this first explanation. In doing so we bring closer the Exact Approach from the Common Factor methods and their recent extension namely Common Correlated Effects models. Thus this second chapter aims at addressing the following question :

Do regions of Western Europe over invest in R&D such that it would explain that the growth engine stopped for those regions and no longer balance the disparities triggered by agglomeration processes ?

We address this question using a growth accounting accounting framework. Recent enhancements of this frame points to the existence of an omitted variable issue induced by variables' mismeasurements and spatial spillovers. Such omitted elements simultaneously induce strong and weak cross-sectional dependence and indeed, a preliminary analysis based on the estimation of the exponent of cross-sectional dependence provides a clear result in favor of strong cross-sectional dependence. This chapter builds on Eberhardt and al.(2013) [70] which makes a first step toward more reliable coefficients by showing how mismeasurements issues on inputs' aggregates could be handled thanks to common correlated effect methods. Indeed, to the extent that there exist some commonalities between the mismeasured elements across regions, one could control for these handling unobserved common factors. Unobservable common factors whose effects can be heterogeneous across time and space are analyzed as a cross-sectional dependence phenomenon. In this case a multi-factor error structure can be estimated using cross-sectional averages of the independent and dependent variables.

The procedure controls for endogeneity biases arising from the correlation between specified and omitted variables.

In their work, Eberhardt and al. (2013) [70] also intended to account for spatial effects. Yet, Ertur and Musolesi (2016) [75] explained how the cross-sectional dependence phenomenon differs from the autocorrelation phenomena spatial models treat for. On the one hand, cross sectional dependence would consider an omitted phenomena heterogeneously impacting spatial units while spatial models rather address the network effect linking units to one another.

The work we carried out aimed at controlling for both variables mismeasurements and spatial effects. In a first step, we reproduced the two-step approach proposed by Bailey and al. (2016) [14] combining a Common Correlated Effect treatment and a dynamic SAR model. Doing so, we compare CCE to Common Factor (CF) and Spatial Filtering methods. The latter roots back to the Exact Approach and displays a rationale quite close from CCE and CF models triggering our interest in the comparison. In a second step, we implement Yang (2018) [196] spatial GMM estimator. To the best of our knowledge, this is the first time that this estimator is applied to a growth accounting equation.

According to our results on the EU-15, private returns on knowledge are negative and public returns (spillovers) very close from zero. This conclusion takes us back to recent developments challenging the largely admitted idea that countries/regions/enterprises have been under investing in R&D (Comin(2004) [50] ; Montmartin(2015) [151]). Those theoretical studies have shown that over-investment situations are as plausible as under investment cases. Of notice, an important drawback of our approach that could undermine our results is that, to account for knowledge we have been using patents deposits. Those are increasingly beset to strategic deposits issues disregarding the true added value of the patented innovation.

In Chapter 3, we aim at deepening our understanding of the effects of commercial and technological forms of integrations. Chapter 2 emphasizes the missing role of the

growth engine in re-balancing disparities as generated by agglomeration mechanisms but do not properly quantify the interaction between both forms of commercial and technological integrations as the main drivers of agglomeration patterns and regional income distribution. Chapter 3 investigates in depth the literatures that aim at quantifying the role of decreasing trade costs (understood as comprising commercial and technological integrations) in agglomeration mechanisms and welfare distribution. It draws on three generations of scientific progresses : the New Economic Geography (NEG) literature, the New Economic Geography and Growth (NEGG) literature and recent quantitative trade models (QTM). Each of these pieces provides complementary evidence but none gives a straight answer in testing the interplay of commercial and technological integrations. Thus this third chapter aims at addressing the following question :

Do the literatures that address the role of transport costs in shaping activities' agglomeration and income distribution over space emphasize evidences that support the conflicting role of commercial and technological integrations on these outcomes ?

In order to investigate this question, we first review the literature that uses gravity equations to test the link between trade flows and trade costs. Indeed while agglomerating, activities keep on serving peripheral markets and doing so intensify trade flows from the core to the peripheries. As trade costs decrease from high to intermediate levels, we expect trade flows to expand widely. The point is that gravity equations have confronted the so-called *paradox of distance*. The paradox resides in the inability of studies in bringing to light a decreasing coefficient affecting distance costs while the last fifty years have witnessed an explosion of exchanges. Among the five types of propositions Noblet and Belgodère (2010) [153] distinguish to address the issue, we concur with their suggestion that suppose different components of trade costs. Heterogenous variations of components of those costs could have induce outlasting barriers to exchange.

The New Economic Geography and Growth models happen to formalize the conflicting effect of commercial and technological integrations that one can apprehend as some

lowering of transport costs on goods and transfer costs on knowledge. Respectively, the literature on geography of innovation did address the link between agglomeration and Marshallian externalities. To some extent, looking at the impact of pecuniary and non-pecuniary externalities on industrial agglomeration outcomes, those papers have, indeed, considered both forms of integrations under different variables but mostly conclude to a complementary role rather than conflicting forces (Combes and Gobillon (2014)[49]). Still, this literature has been criticized in only considering linear relationships between agglomeration processes and integrations.

Finally, a recent strand of the international trade literature has used complex quantitative (spatial) trade models considering labor movements over space and time (Allen and Arkolakis (2014) [3] and Desmet and Rossi-Hansberg (2018) [61]). Focusing on labor movements, Quantitative Trade Models overcome the tractability issues raised in large dynamic multi-regional settings and allow to obtain solutions to welfare outcomes. Those enhancements could be tied to NEG models to the extent that, as emphasized in Gorin (2016), knowledge externalities are not just "in the air" and should be understood as embedded in people interactions and labor movements. However, this answer is mainly theoretical. Empirically, studies have turned to natural experiments to propose new ways to identify welfare effects out of the restrictive hypotheses of the framework of gravity equations. Those few papers agree that the gain from integration mainly goes to bigger regions with higher employment density but twin forms of integrations have not been strictly investigated so far.

Our ultimate chapter makes an attempt in confronting the role of commercial and technological integrations over agglomeration dynamics across European regions. Theoretically this chapter is grounded on the model developed in Montmartin (2015) [151] that realized a great improvement in formalizing the opposite effect both forms of integrations would have upon both the decentralized and the social planner's decisions regarding the optimal level of agglomeration in a pair of regions. So far this relationship has been emphasized but could not be strictly formalized (Baldwin and Forslid (2000)[16], Martin and Ottaviano (1999)). In supposing a Benassy (1998) [22] type of utility function rather than a CES as in Martin and Ottaviano (1999) [145]

, Montmartin (2015)[151] developed the formal relationship grounding our empirical model allowing us to address directly the question :

Do commercial and technological forms of integrations oppose in triggering agglomeration dynamics of wealth ?

Implementing the specification suggested in Montmartin (2015)[151] , we move from considering agglomeration in the "northern region", in a two-region framework, toward characterizing spatial patterns over the whole European map. Doing so, we suppose that each region constitute a random draw from a stochastic process occurring across space such that each region is to be understood as a particular realization of the general data process.

On the left hand side, we aim at characterizing the nature of spatial configurations (core-periphery or core-core) linking region i to its close neighbors and to do so we use local Moran's I_i as the dependent variable. On the right hand side, we approximated commercial and technological integrations using proximity matrices, as suggested in Chapter 1. On the one hand, we suppose that commercial integration could be proxied by input-output relationships that would induce agglomeration of industries. We measure these using the industrial classification of patent deposits localized at the NUTS2 level and calculating industrial proximity between regions on this basis. On the other hand, technological integration is caught using the paper trail left by patent citations also localized at the NUTS2 level.

Our estimations address potential non-linearities by relying on Generalized Additive models (GAMs). GAMs allows for non-linearities while considering spatial configurations and their evolution over time. Finally, as suggested by Combes and Gobillon (2014)[49], this setting might be undermined by endogeneity issues as there exists strong dynamic relations between independent and dependent variables. In Chapter 3, we made a link between studies looking at agglomeration and studies interested in the effect of infrastructures enhancements. Those last works use outdated infrastructures to instrument potentially endogenous variables. Similarly we propose to use the Ro-

man transportation network to treat for the endogeneity that we expect to arise. Our results uncover evidences suggesting that commercial and technological integrations have conflicting effects on agglomeration outcomes, in accordance with the theoretical prescriptions.

This PhD dissertation brings in new elements of analysis regarding the consequences of commercial and technological forms of integration on agglomeration processes and welfare outcomes. Still, does it embed limits that could constitute avenues for future research. Some potential developments will be sketched in the general conclusion.

Chapter 1

Exploiting Spatial Filtering Methods for Tracing Space-Time Developments : Experiments on Regional Income Disparities in the EU-28

Regional development implies complex space time dynamics of regions that largely depend on territories' interdependencies. Empirically, the presence of spatial structures that impact regions calls for a rigorous assessment of the spatial autocorrelation phenomena. Spatial autocorrelation is strictly defined as "the correlation among values of a single variable strictly attributable to their relatively close locational positions on a two-dimensional surface, introducing a deviation from independent observations assumption of classical statistics". (Griffith (2005) [93]) Thus, spatial autocorrelation measures can be used to represent agglomeration processes and disparities between regions and to quantify the strength of spatial structures linking economic units to one another against the assumption of (spatial) independence.

This article fulfills two objectives : First, it updates the representation of regional income disparities across the 28 European member states. Second, it assesses how important spatial effects have been in explaining those patterns. On the one hand, we aim at updating the spatial patterns of disparities as emphasized in the work of LeGallo and Ertur (2003) [136] while using a slightly alternative measure to the randomized autocorrelation index they worked on. Our interest addresses local measures of spatial autocorrelation to investigate local non-stationarities and bring to light how wealth disparities have evolved on the European territory since LeGallo and Ertur (2003) [136]. On the other hand, we aim at assessing how important spatial effects have been in explaining regional (per capita) GDP disparities and show to which extent some of those patterns can be related to commercial and technological forms of integration between regions.

Among Exploratory Spatial Data Analysis measures, Moran's I is a particularly efficient autocorrelation index that justify its extensive use in the literature and the present choice. This index can be understood as a statistic to the extent that it represents a realization from some superpopulation. In this case, the reality is one possible realization among a universe of possible configurations and inference aims at deciding if the configuration under study can be classified as random or autocorrelated. To infer local Moran's I_i distributions, several methods are available. First, the "Normal assumption" assumes that the statistic of Moran's I follows a Normal law and the re-

alization can be compared to this benchmark. Tiefelsdorf and co-authors [188] explain that, in presence of autocorrelation, the Normal assumption cannot be maintained. Bivand and al. (2009) [26] bolstered this statement and concluded that the induced errors can be severe in presence of autocorrelation. This is due to the finite sample issue that undermine inference on Moran's I. The Normal assumption requires a sample big enough to confront the empiric distribution to an asymptotic Normal distribution. Restricted samples do not meet this criterion and test conclusions are biased. Second, the "randomization approach" (or permutation approach) has been a widely used alternative. The randomization implies to assess the statistic relative to the set of all possible values that could be obtained by randomly permuting the observed values around the areas. A distribution is thus empirically generated and one must rely on pseudo-significance levels to infer. The reliability of the method rests on a trade off between the number of permutations and the calculation burden. The higher the number of permutations, the higher the precision of significance levels but also the higher the calculation burden. A wise choice requires substantial knowledge from the analyst to design properly the experiment and obtain reliable results. The Exact Approach [188] offers an alternative to randomization methods and removes difficulties linked to the choice of the number of permutation. By exploiting the spectral decomposition of observed Moran's I, it allows to obtain the local true distributions and exact levels of significance. This paper presents statistical analyses carried out by means of the Exact Approach.

LeGallo and Ertur (2003) [136] have been using the randomization method to infer spatial patterns in Europe. Their work addressed regional GDP per capita data over 11 European countries ¹ from 1980 to 1995. They brought to light a strong persistence of disparities over time. Regions with high (resp.low) per capita GDP remained geographically close to other high (low) per capita GDP regions. They also emphasized the presence of four important clusters : Portuguese and Spanish regions formed a pocket of poor regions similarly to Southern Italian and Greek regions. Conversely German regions next to Belgium, the Netherlands, Northern France and Northern Italy

¹Denmark, Luxembourg, United Kingdom, Belgium, Spain, France, Germany, Greece, Italy, Netherlands, Portugal

rather formed a cluster of high GDP (per capita) units. This work is an attempt to answer Rey and LeGallo’s call for Exploratory Spatial Data Analysis that would identify new patterns from which “suggestions for new types of theories and hypothesis about the spatial nature of economic convergence may emerge” [168]. We update the spatial patterns LeGallo and Ertur (2003) [136] emphasized using the Exact Approach. For comparability, we also work on regional per capita Gross Domestic Product with both levels and growth rates. We extend the area of study to the Enlarged Europe 28 members over the period 2000-2016. Our results go along the main findings of the literature on European convergence² showing that a divergence process seems at stake between regions. Few central regions of the Old Europe have clearly benefited from integration next to New Members capital cities while, on the other hand, the last decade has been detrimental for “intermediate” peripheral regions.

We put as a working hypothesis that commercial and technological flows between regions have a great impact in regions’ development trajectories. As a consequence, we aim to distinct the impact of trade and knowledge flows on the evolution of disparities by building specific spatial weight matrices. Commercial ties are proxied by alike industrial structures. The hypothesis is that the more similar are regional industrial mixes, the more likely regions share input-output connections and strong commercial ties. Respectively, technological links are proxied by patents’ citations between regions : the more intense the citation pattern, the stronger the technological ties.

On this basis, we exploit Spatial Filtering techniques that are a by-product of the Exact Approach. Indeed, the Exact Approach allows for the decomposition of the spatial autocorrelation phenomena into independent eigenvectors. They represent the map patterns contained in the spatial weight matrix and under this form can be used as additional covariates to filter out the autocorrelation issue from OLS regressions. We aim at quantifying the explanatory share conveyed by those eigenvectors which *de facto* would correspond to the explanatory share of the commercial and technological integrations regarding disparities.

²[Battisti and Di Vaio (2008) [21], Debarsy and Ertur (2006) [58], Eckey and Türrck (2007) [76], Ezcurra and Rapún (2007) [81], Fisher and Stirböck (2006) [82], Paas and Schlitte (2006) [156]]

The rest of the chapter is structured such that Section 1.1 provides further explanations on the Exact Approach and the Spatial Filtering Method. Section 1.2 describes the spatial weight matrices at use in representing disparities and then in estimating commercial and technological integrations. Section 2.3 presents the data and Section 1.4 is dedicated to our results.

1.1 Exact Approach

Even more than their global counterpart, local spatial autocorrelation tests have been found to severely deviate from the normal assumption in presence of spatial autocorrelation. (Bivand and al. (2009) [26]). Tiefelsdorf obtains the true distributions of local Moran's I_i under both the assumption of spatial independence (H_0) and its alternative i.e the occurrence of a spatial process (H_1). Basically, under the hypothesis of spatial independence, p-values provide each region's contribution to the global autocorrelation process. Under the alternative that is assuming a Gaussian autoregressive process (SAR), significance levels measure the statistic variation around the process and reveals local heterogeneities.

1.1.1 Moran's I

Tiefelsdorf's objective has been to provide the true distribution of Moran's I autocorrelation index that happened to be biased in presence of autocorrelation. Moran's I is commonly used as a spatial dependence indicator in a dataset. By defining it as a ratio of quadratic form in some normally distributed regression residuals, one is allowed to express the autocorrelation by the following :

$$I_o = \frac{\hat{\varepsilon}' \cdot \frac{1}{2}(V + V') \cdot \hat{\varepsilon}}{\hat{\varepsilon}' \cdot \hat{\varepsilon}} \quad (1.1)$$

$\hat{\varepsilon}$ are the residuals of a classic regression written $y = \beta X + \hat{\varepsilon}$. In our case, y will state for the regional GDP per capita and X will only be constituted of a constant and countries fixed effects. I_o is the empirical index of Moran and V denote the (usually

row-standardized) spatial link matrix.

To infer under the "Normal assumption" approach, the previous ratio should be standardized and would be expected to asymptotically follow a normal distribution. This will yield the following expression

$$z(I) = \frac{I_0 - E(I)}{\sqrt{V(I)}} \sim \mathcal{N}(0, 1) \quad (1.2)$$

If the moments corresponding to this statistic can be easily obtained under the assumption of spatial independence, it is not the case anymore when supposing spatial dependence. Indeed, the normal assumption is not suitable for small lattices and the Exact Approach allows to circumvent the problem.

1.1.2 The Exact Approach

Under the influence of a spatial process, y is expected to follow a Gaussian spatial process such that corresponding residuals ($\hat{\varepsilon}$) are characterized by an expectation equals to zero and a covariance matrix of the form $\sigma^2 M \Omega M$. M is a projection matrix and the spatial process mainly expresses in the matrix $\Omega = (\varepsilon, \varepsilon')$.

The expression (1.1) of the empirical Moran's can be rewritten from a complex ratio of quadratic form to a simple quadratic form thanks to a transformation of the residuals expression. Residuals can be re-expressed as $\hat{\varepsilon} = M \Omega'^{\frac{1}{2}} \delta$ where $\delta \sim \mathcal{N}(0, \sigma^2 I)$ and allows writing Moran's distribution function, conditional on Ω such that

$$Pr(I_o | \Omega) = Pr \left(\frac{\delta' \Omega'^{1/2} \cdot M \frac{1}{2} (V + V') \cdot M \Omega^{1/2} \cdot \delta}{\delta' \Omega'^{1/2} \cdot M \Omega^{1/2} \cdot \delta} \leq I_0 \right) \quad (1.3)$$

Simplified as

$$= Pr \left(\delta' \Omega'^{1/2} M \left[\frac{1}{2} (V + V') - I_0 \cdot I \right] \cdot M \Omega^{1/2} \delta \leq 0 \right) \quad (1.4)$$

Be H the matrix of normalized eigenvectors of $(\Omega^{1/2} M[\frac{1}{2}(V + V') - I_0.I].M\Omega^{1/2})$, suppose $\eta = H.\delta$, the conditional distribution can be rewritten

$$Pr(I_o|\Omega) = Pr(\delta'.H'.\Lambda.H.\delta \leq 0) \quad (1.5)$$

where Λ is the diagonal matrix of eigenvalues extracted from $(\Omega^{1/2} M[\frac{1}{2}(V + V') - I_0.I].M\Omega^{1/2})$

such that

$$Pr(I_o|\Omega) = Pr\left(\sum_{i=1}^n \lambda_i \eta_i^2 \leq 0\right) \quad (1.6)$$

This last expression is a weighted sum of the χ^2 distributed variables η_i^2 and in this context, Imhof's formula can be applied to calculate the distribution of Moran's.

1.1.3 Spatial Weights Matrices

The previous developments are conditioned by the definition of the spatial matrix V that has been constrained to symmetry by writing $\frac{1}{2}(V + V')$.

Formally V is defined such :

$$V = s_i.B$$

where B is a global spatial binary matrix of the form

$$B = \begin{pmatrix} g_{11} & \cdots & \cdots & g_{1i} & \cdots & \cdots & g_{1n} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{i-1,1} & \cdots & g_{i-1,i-1} & g_{i-1,i} & g_{i-1,i+1} & \cdots & g_{i-1,n} \\ g_{i1} & \cdots & g_{i,i-1} & g_{ii} & g_{i,i+1} & \cdots & g_{in} \\ g_{i+1,1} & \cdots & g_{i+1,i-1} & g_{i+1,i} & g_{i+1,i+1} & \cdots & g_{i+1,n} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{n1} & \cdots & g_{n,i-1} & g_{ni} & g_{n,i+1} & \cdots & g_{nn} \end{pmatrix}$$

and s_i can be defined on a general basis as :

$$s_i = \frac{n}{\sum_{i=1}^n d_i^{(q+1)}}.D^q = \frac{n}{\sum_{i=1}^n d_i^{(q+1)}} \left[diag(d)\right]^q \quad (1.7)$$

where i indexes regions.

In (1.7), D^q is a diagonal matrix that contains d_i^q components representing the degree of linkage of the region i :

$$d = \left[\sum_{i=1}^n g_{1i}, \sum_{i=1}^n g_{2i}, \dots, \sum_{i=1}^n g_{ni} \right]'$$

Different coding schemes can result from the tuning of the q parameter such that :

- *C coding* corresponds to $q = 0$: "globally standardized"
This scheme emphasizes spatial objects with a greater degree of spatial linkage.
- *S coding* corresponds to $q = -0.5$: "variance stabilized"
This scheme even the variation levels of weights of spatial objects. Doing so, it allows to control for the presence of heteroskedasticity in the residuals.
- *W coding* corresponds to $q = 1$: "row sum standardized"
This scheme tends to emphasize small spatial linkage objects, in opposition to a C-coding scheme.

The difference between those options is the parsimony of treatment of spatial weighting heterogeneity. The topology induced heterogeneity stems from the variation in the local linkage degree between regions at the center of the matrix and peripheral ones. The following matrices illustrate respectively the linkage of one peripheral instance and one central instance.

$$B_{i,peripheric} = \begin{pmatrix} g_{11} & \dots & g_{1i} & \dots & \dots & g_{1n} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ g_{i1} & 0 & 0 & 0 & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ g_{n1} & \dots & 0 & 0 & \dots & 0 \end{pmatrix} \quad B_{i,central} = \begin{pmatrix} 0 & \dots & 0 & g_{1i} & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{i1} & \dots & g_{i,i-1} & 0 & g_{i,i+1} & \dots & g_{in} \\ \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & g_{ni} & 0 & \dots & 0 \end{pmatrix}$$

Heterogeneity induces heteroskedasticity while identical variances are required for a spatial process to be stationary and for the Exact Approach to be fully efficient.

1.1.4 Multiple Testing

Under the assumption of spatial independence, controlling for the significance of the local Moran's I requires to take care of the multiple testing issue. *"If multiple hypotheses are tested, the chance of a rare event increases and therefore the likelihood of incorrectly rejecting a null hypothesis increases"*. (Mittelhammer and al. (2005) [149] p73-74). Said differently, correcting for multiple testing reduces the number of false positives. Conversely, in an exploratory phase, correcting too severely for the multiple testing issue might induce missing important outliers (i.e raise the number of false negatives). How severe the correction is depend on the control procedure. Those are usually two folds : On the one hand, the false discovery proportion (FDR) considers the proportion of false rejections among rejected hypotheses. Alternatively, the FWER procedure focuses on the probability that the rejected set contains any errors. As explained by Caldas de Castro and Singer (2006) [36], the FWER approach proceeds very conservative results while the FDR procedures appears as a more parsimonious choice.

Significance levels resulting from the Exact Approach applied on regional GDP (per capita) will be corrected for the multiple testing issue using a "FDR" procedure and taking into account the restricted number of neighbors of each region rather than the total number of regions of the sample.

1.1.5 Spatial Filtering techniques

Spatial Filtering techniques have been an alternative to spatial autoregression methods and aim at taking into account interdependencies between territories, treating for (spatial) autocorrelation. Building on the Exact Approach, Spatial Filtering method decompose variables under study into spatial and non-spatial components and doing so allow using classical regression techniques (OLS or ML) in a framework cleared of (spatial) autocorrelation issues. More precisely, the spatial filtering technique consists in spectrally decomposing preliminary regression's residuals. At first, those residuals contains the autocorrelation phenomena usually aggregated under Moran's I autocorrelation index. From the spectral decomposition of the residuals at use in the computation of Moran's I, one can extract eigenvectors, or so called spatial filters, that retain

the essence of the spatial interdependencies linking units. Griffith (2003) [92] extension builds on the Exact Approach described by Tiefelsdorf (2000) [188] to operate the Spatial Filtering.

Griffith (2003) [92] shows how the eigenvectors in matrix H could be used. When employed as regressors, eigenvectors may endorse the role of proxies for missing explanatory variables. However, for parsimony reasons, one would have to consider a way of selecting the most relevant eigenvectors in extending the original regression framework. Tiefelsdorf and Griffith (2007) [189] suggest to progressively add eigenvectors to the model based on how much autocorrelation is been withdrawn from the residuals. The algorithm they designed stops when the remaining autocorrelation drops below a predetermined threshold. The algorithm runs until no candidate eigenvector reduced the autocorrelation by more than the predefined threshold.

Patuelli and al.(2012) [157] overlay another selection procedure that tight more severely the number of eigenvectors being introduced in the OLS regression. In a first step, eigenvectors are selected on the basis of a minimum $\frac{MI}{\max(MI)}$ value of 0.25 where MI stands for eigenvector's share of Morans' autocorrelation Index. In the second step the statistical significance of each eigenvector is been evaluated by means of a stepwise logistic regression. The threshold condition employed is a 10% level of significance for inclusion and retention of the vector. Finally a backward elimination of regressors is operated through the sequential estimation of the logistic regression model where marginal eigenvectors were excluded if their χ^2 values remained non-significant at the 5% level.

In our case, spatial filtering did not produce a number of eigenvectors that requires such a heavy selection procedure. On the basis of extracted eigenvectors, we proceed to a stepwise logistic regression. We used sequential replacement that is a combination of forward and backward selections. Among the models considered we retain the ones with the lowest Bayesian Information Criterion (BIC) and display the corresponding adjusted R^2 .

1.2 Definitions of proximity

Section 1.1 presented the link between the Exact Approach and the Spatial Filtering techniques. The Exact Approach allows for residuals' decomposition, obtains the corresponding eigenvectors that carry for autocorrelation and computes Exact Moran's I_i . A first part of our results will exploit this to represent spatial patterns of regional income disparities over the EU-28. In representing disparities over the 28 European members territory, we use a 'queen' contiguity matrix computed according to a S coding scheme in order to provide the most neutral representation. Respectively, spatial filtering techniques show how to use the obtained eigenvectors as spatial filters in a regression to quantify the explanative power of spatial structures. A second part of our results will take advantage of this to compare the explanatory share of geographical, commercial and technological representations of spatial ties. The present section strives to provide further details on the proxies for geographical, commercial and technological ties.

We consider three types of spatial weight matrices :

- Geographical proximity is based on geographic contiguity or proximity between regions

According to Tobler's principle, "everything is related to everything else, but near things are more related than distant things". As such, geographical proximity has somehow became the default definition of proximity in spatial studies across regions.

We would retain two definitions of geographical proximity :

- *Shared boundaries matrices* : We consider a "queen" contiguity rule computed according to the C ; W and S coding schemes.
- *Distance* : We retain a definition based on the k – *nearest* neighbors where $k = 50$.

Underlying (the principle of) "geographical proximity", we put as a working hypothesis that some flows may particularly matters in conditioning regions' growth trajectories.

Namely, we point to commercial and technological forms of integrations. We represent commercial proximity based on sectoral proximity between regions. We represent technological proximity based on patents' citations. Matrices' definitions are discussed thereafter.

- Technological proximity is based on the patent citations network

Patent citation networks root back to Jaffe (1986) [120] and have been exploited a lot in regional innovation studies. The basic idea is that knowledge is passed from one firm to another, as scientists/engineers are exposed to one another. A knowledge transfer is operated with a probability that depends on the proximity between knowledge bases. To some extent, the transfer may result in the production of an innovation that then might be patented. At the regional level, the proximity between regions i and j year after year is defined as a matrix

$$\begin{aligned} CitDist &= (d_{it,jt'}) \\ &= \sum_{p \in P_{it}} \sum_{q \in P_{jt'}} \frac{\#Citations_{p \rightarrow q}}{Outcitations_p} \end{aligned}$$

where t is the date of deposit of the patent ³ being cited and t' is the date at which occurs the citation. The number of citations tying patent p to patent q is normalized by the total number of outcitations the patent p generates, as defined by Colino (2016) (p.9) [48]. We work on annual citations matrices. For each year, we consider the backward citations, from 1964 up to the year of interest, made by the patents published this year.

- Commercial proximity is based on proximities between regional industrial structure

The basic idea funding commercial proximity is that, as firms share sectoral and geographical proximity, they may develop preferential partnerships, sharing knowledge, inputs and labor experience over a common or proximate final product. Firms may find an advantage into spatially concentrating to benefit from

³earliest filing date of the patent deposit

tied input-output links. We propose to approximate those ties looking at the spatial concentration of patent deposits while considering the industry the depositor belongs to. Formally, the matrix is built as a Mahalanobis type of proximity matrix that allows considering proximity across sectors of the NACE rev.2.

Let S be the (X, N) matrix where S_{xn} is region n patent share in sector x defined in the NACE rev.2. Defined as such, each column of S contains a region's patent share in one of the X sector. Respectively, each row contains patent class shares across the N regions.

Each column $(S_{\bullet n})$ is normalized such that

$$C_{(X,N)} = \begin{pmatrix} \frac{S_{\bullet 1}}{\sqrt{(S_{\bullet 1})' S_{\bullet 1}}} & \frac{S_{\bullet 2}}{\sqrt{(S_{\bullet 2})' S_{\bullet 2}}} & \cdots & \frac{S_{\bullet N}}{\sqrt{(S_{\bullet N})' S_{\bullet N}}} \end{pmatrix}$$

Each row $(S_{x\bullet})$ is normalized such that

$$R_{(X,N)} = \begin{pmatrix} \frac{S_{1\bullet}}{\sqrt{S_{1\bullet} (S_{1\bullet})'}} \\ \frac{S_{2\bullet}}{\sqrt{S_{2\bullet} (S_{2\bullet})'}} \\ \vdots \\ \frac{S_{X\bullet}}{\sqrt{S_{X\bullet} (S_{X\bullet})'}} \end{pmatrix}$$

Mahalanobis' proximity matrix is defined as

$$ComDist_{(N,N)} = R'_{(X,N)} (C_{(X,N)} C'_{(X,N)}) R_{(X,N)}$$

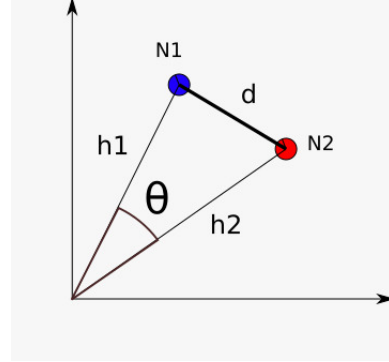
$ComDist$ and $CitDist$ are proximity matrices while spatial filtering requires some "distance" matrix. It helps to consider the relationship between those two concepts from a geometrical side. Basically, in an Euclidean space, distance between N_i and N_j is defined as

$$d_{N_i, N_j} = \sqrt{\sum_i (N_i - N_j)^2}$$

For $i = 1$ and $j = 2$,

$$\begin{aligned} d_{N_1, N_2}^2 &= h_1^2 + h_2^2 - 2h_1h_2 \\ &\Leftrightarrow ||h_1|| + ||h_2|| - 2||h_1|| \times ||h_2|| \cos\theta \end{aligned}$$

To the extent that $N_i.N_j = ||h_i|| \times ||h_j|| \cos\theta$.



Proximity/similarity is to be considered through the inner product $h_1^2 h_2^2 \cos \theta$ such that for $h_1^2 = h_2^2 = 1$ the relationship can be expressed as : $d_{1,2}^2 = 2(1 - p)$. Those developments require that the inner product p would be the same if we consider the distance for N_i to N_j or the distance from N_j to N_i . From this, we calculate the distance matrices at use in the filtering procedure.

Correlation between Technological and Commercial Proximity Matrices

Our matrices are both built using patent information. As a consequence it might arise concerns regarding the extent to which the information being conveyed by each matrix is truly different from the other one and allows to properly distinguish commercial and technological ties. As a first test to the reliability of our proxies, we calculated the correlation between the proximity matrices for each year of our sample (2000-2016).

To do so, we use a multivariate correlogram based on Mantel statistic. Mantel test allows to compare proximity or distance matrices computed for the same objects (European regions) and evaluates the strength of the relationship linking the two matrices. Under its non-standardized format, the statistic is written :

$$r_M = \sum_{i=1}^{N-1} \sum_{j=i+1}^N (D_Y)_{ij} (D_X)_{ij}$$

H_0 states that the proximity/distance matrices D_Y and D_X are not linearly related. H_1 states that the distances among nodes in D_X are related to distances as stipulated in D_Y . Significance will be evaluated based on p-values obtained under the randomization

approach.

1.3 Data

1.3.1 Regional Gross Domestic Product

For comparability with LeGallo and Ertur (2003) [136], we work on regional GDP per capita expressed in Euros from 2000 to 2016. Looking at GDP, one must arbitrate between using Purchasing Power Standards (PPS) data or Euros data. The conversion to purchasing power standards (PPS) is based on national purchasing power parities (PPP) which are regularly calculated and released by Eurostat and spatially harmonize GDPs (per capita) across countries. However those data do not allow comparing regional growth rates as the evolution of national PPP may differ. To this extent we opted for Euros data.

The sample is composed of regions from Belgium, Bulgaria, Czech Republic, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom. We removed some regions from the database as extracted from Eurostat (*nama-10r-2gdp*). We did not keep any NUTS from Switzerland, Island, Liechtenstein, Macedonia, Norway, Turkey and the "Middle East" region as we are primarily interested in the European Union members. Furthermore, we also chose to remove French overseas departments (Guadeloupe(FRA1), Martinique(FRA2), Guyane(FRA3), La Réunion(FRA4), Mayotte (FRA5)), Spanish *Comunidades* of Ceuta (ES63), Melilla(ES64) and the Canarias (ES70), Portuguese Islands of Madeira(PT30) and Los Açores (PT20). Few data were missing for Belgium at the beginning of the panel (2000, 2001, 2002). We interpolated those values.

Table 1.1 provides some summary statistics. Briefly, regional GDPs (per capita) have, on average, increased over the period. 2008 and 2009 have been at odds with this trend. This is likely due to the international financial crisis which started by the summer 2007. Since 2010, regional GDPs (per capita) have been back to an increasing trend. Distri-

bution observations are coherent with stylized facts extracted from the literature [82] : Between 2000 and 2012, the minimum regional GDP per capita has raised by 100%. Not as fast, but at least similarly, the maximum regional GDP per capita in 2016 is 67% higher than in 2000. Conversely, around the mean, from the first quartile to the third quartile, the increase has only been about 40% .

Table 1.1: Summary statistics of regional GDP per capita of the EU-28 from 2000 to 2016 (**Euros**)

	2000	2001	2002	2003	2004	2005	2006	2007	2008
Min.	1300	1400	1600	1700	1900	2300	2500	2900	3200
1st Qu.	11575	12400	13525	14600	15300	16100	16875	17425	17825
Median	21450	22400	22950	23050	24000	24400	25700	26950	26150
Mean	19811	20505	21190	21447	22446	23308	24579	25903	25763
3rd Qu.	25700	25975	26475	26575	28175	28975	30575	31600	31175
Max.	140200	38900	142700	139600	149600	159500	169100	186000	163200
	NA :11	NA :11	NA :11						
	2009	2010	2011	2012	2013	2014	2015	2016	
Min.	3200	3200	3500	3600	3600	3800	3900	4100	
1st Qu.	16900	16875	16425	16150	16325	16625	17075	17275	
Median	24000	24650	25400	25950	25950	26900	28850	28300	
Mean	24109	25087	25753	26317	26436	27282	28612	28549	
3rd Qu.	29175	30975	32425	32750	33050	34150	35475	35375	
Max.	144700	156100	159300	176800	177000	199000	221100	207300	

1.3.2 Patent deposits and citations

The matrices of commercial and technological proximities have been computed thanks to the patent database of PATSTAT (edition autumn 2018). At use in the technological proximity matrix, citations consider references between patents filled between 2000 and 2016 whose inventors located themselves in one of the European Union 28 members. We only considered patents deposited at the European Patent Office as a guarantee of quality of the protected content.

1.4 Results

The following sections provide our results exploiting European regional GDP per capita thanks to the Exact Approach of Tiefelsdorf (2000) [188]. **The following maps are to be read in color.** Section 1.4.1 displays p-values calculated under the spatial independence assumption and corrected of the multiple testing issue. Section 1.4.2 compares the previous results with p-values extracted from computations under the assumption of spatial dependence.

1.4.1 Under the assumption of spatial independence (H_0)

Under the assumption of spatial independence, local Moran's I_i and the p-values attached to those Exact distributions provide each region contribution to the global autocorrelation process. Residuals required to calculate Moran's I_i are extracted from two exploratory specifications respectively for regional GDP per capita levels and regional GDP per capita growth rates. Precisely, we are working on 4-year averages : (2001-2002-2003-2004); (2005-2006-2007-2008) ; (2009-2010-2011-2012) ; (2013-2014-2015-2016). The regressions include country fixed effects in order to control for institutional differences between EU members.

For regional GDP per capita levels

$$\ln(GDP_{capita,i}) = \alpha (1) + \gamma + \varepsilon \quad (1.8)$$

For regional growth rates

$$\frac{1}{T} \ln \left(\frac{GDP_{capita,i}}{GDP_{capita,2000}} \right) = \alpha (1) + \gamma + \varepsilon \quad (1.9)$$

GDPs (per capita) are standardized through the logarithmic transformation ; α is the constant and γ is the vector of country dummies and ε are the residuals.

Legends

Results for regional GDP (per capita) levels and regional GDP (per capita) growth rates are presented on the following maps according to the respective legends :

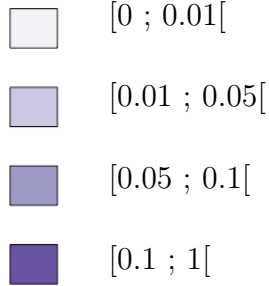


Table 1.2: P-values intervals for regional GDP (per capita) levels

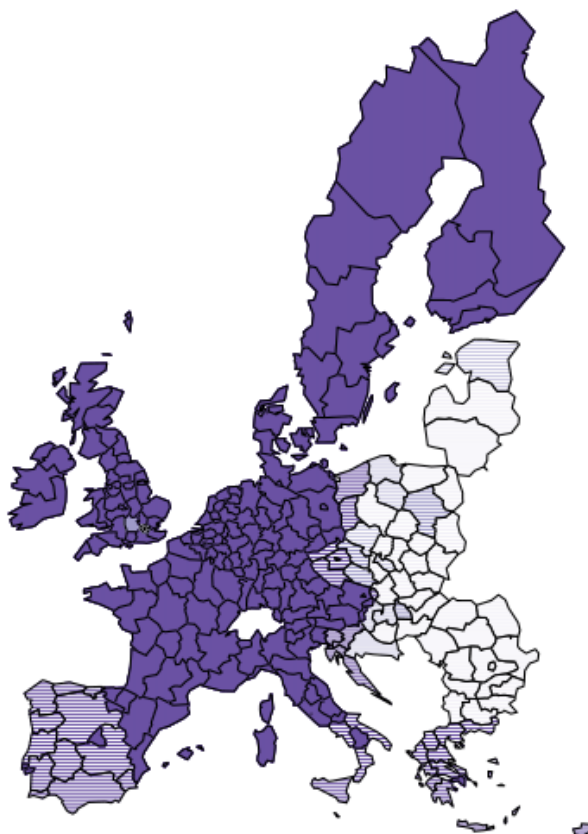


Table 1.3: P-values intervals for regional GDP (per capita) growth rates

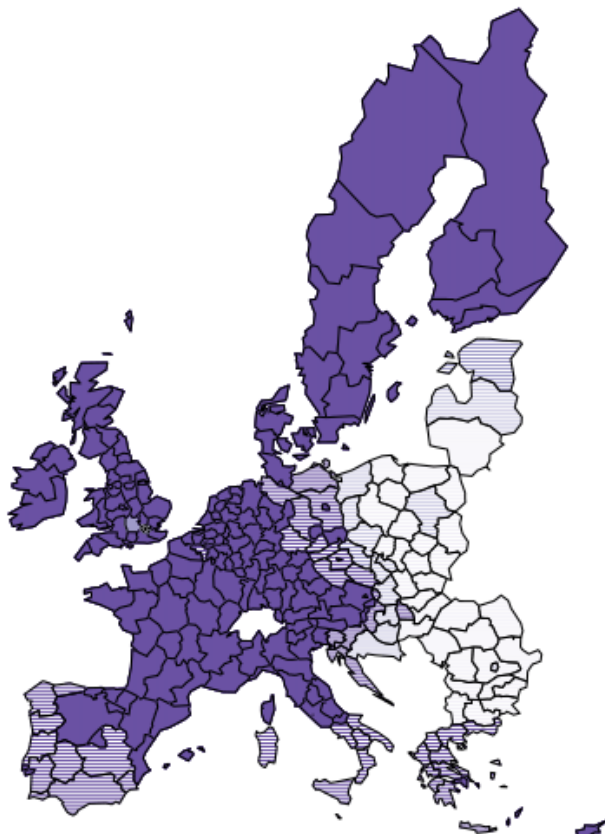
Regional GDP (per capita) levels : The following maps display the significance degree of spatial autocorrelation of the regional GDP per capita levels of European regions. Dark purple indicates low significance of the spatial autocorrelation. Said differently, it spots weakly correlated regions. Conversely light purple represents high degree of significance i.e spatially autocorrelated regions relative to their neighbors. As the strength of the autocorrelation does not indicate whether clusters are positively or negatively autocorrelated areas, hatched areas spot negative residuals in (1.8) i.e clusters under the European mean.

Regional GDP (per capita) growth rates : Figure 1.2 displays the significance degree of spatial autocorrelation for GDP (per capita) growth rates of European regions. Dark blue indicates low significance of the spatial autocorrelation. Said differently, it spots weakly correlated regions. Conversely light blue represents high degree of significance i.e spatially autocorrelated regions relative to their neighbors. As the strength of the autocorrelation does not indicate whether clusters are positively or negatively autocorrelated areas, hatched areas spot negative residuals in (1.9) i.e clusters under the European mean.

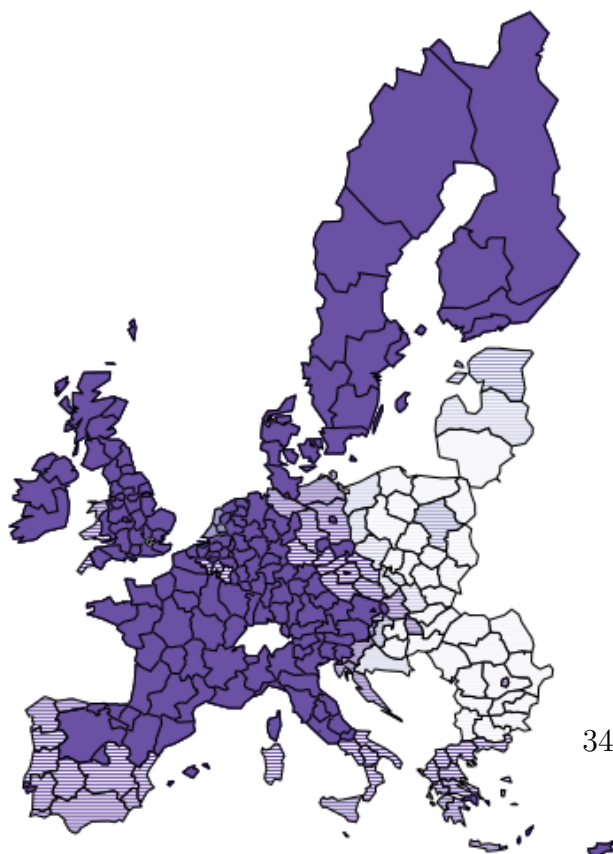
Figure 1.1: Spatial Independence | Regional GDP per capita levels



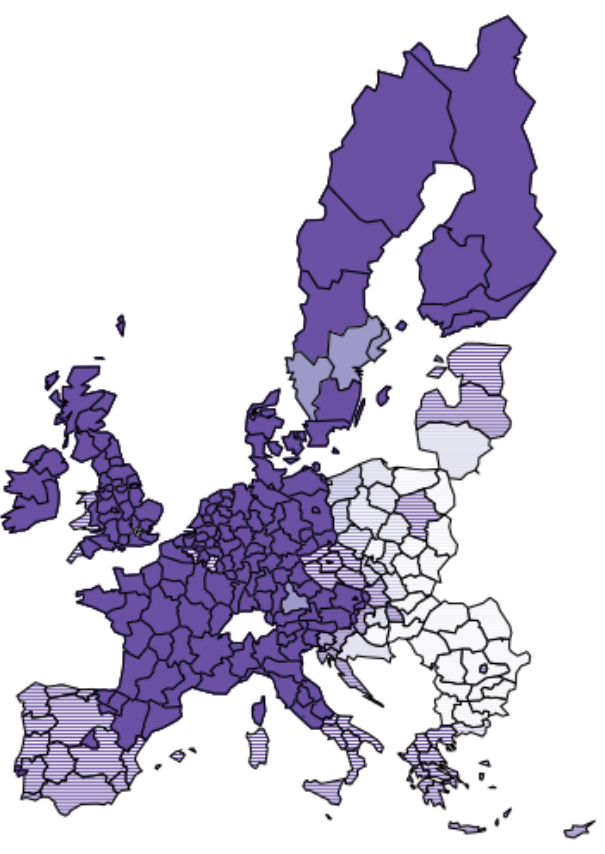
(a) 2001-2004



(b) 2005-2008

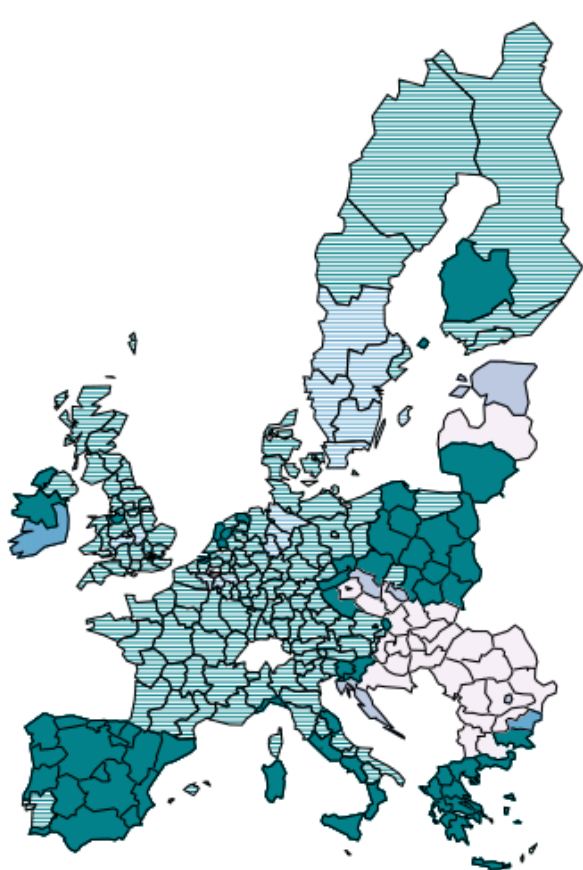


(c) 2009-2012

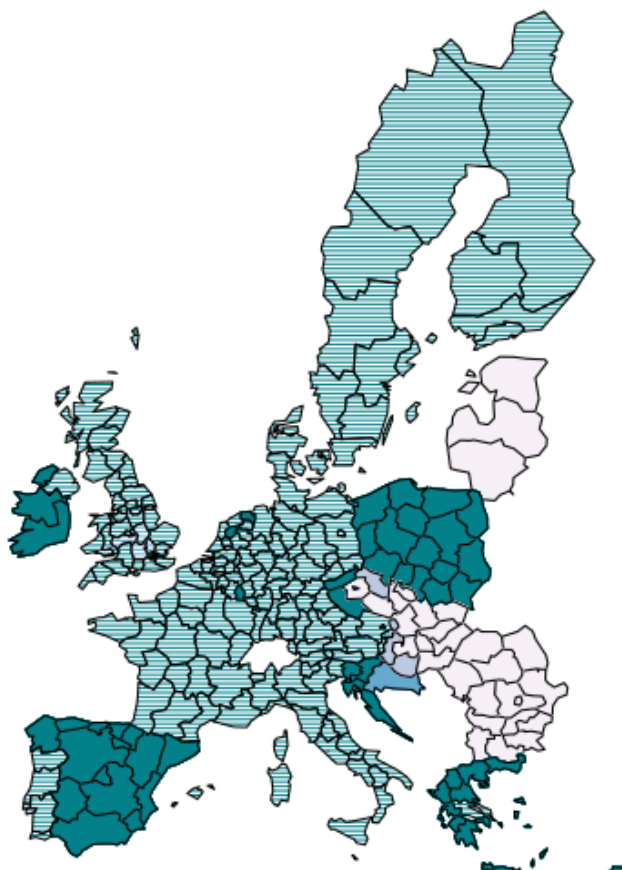


(d) 2013-2016

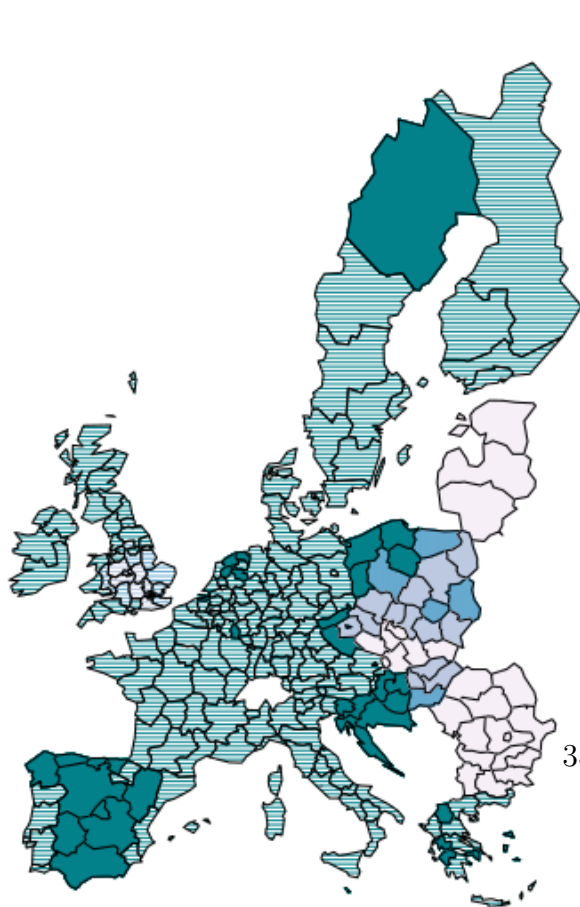
Figure 1.2: Spatial Independence | Regional GDP (per capita) growth rates



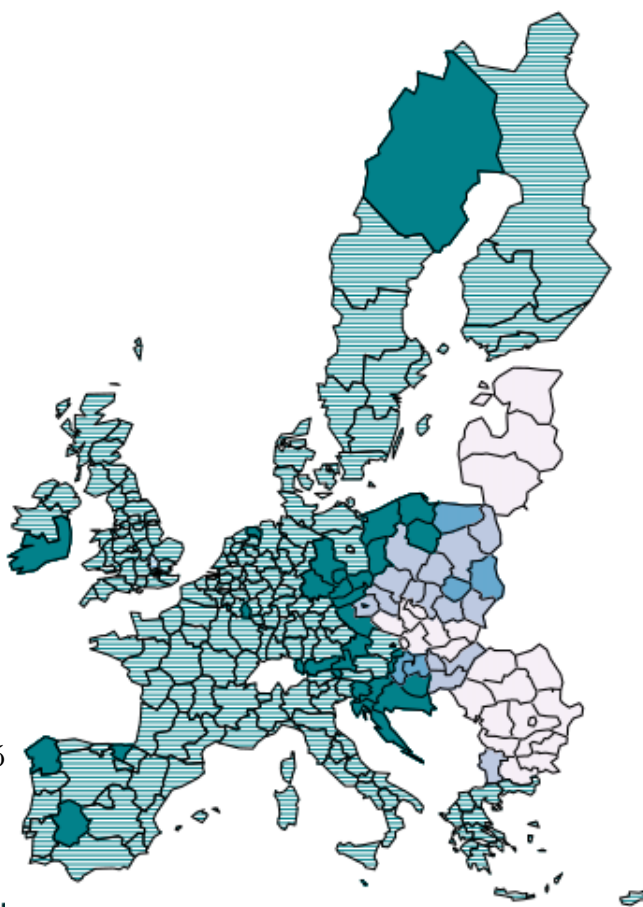
(a) 2001-2004



(b) 2005-2008



(c) 2009-2012



(d) 2013-2016

The most autocorrelated area of the GDP (per capita) level maps is the one spreading over New Members, ex-Soviet Bloc countries, mostly entered in 2004. At the beginning of the period, they have left the Soviet Union for ten years and, as confirmed by growth rates, are in full expansion. The development process has started with Romania, Bulgaria and propagated up North to Estonia, Lithuania, Latvia through Poland and Slovakia. This dynamic left the Hellenic Peninsula apart whose GDP (per capita) levels appears uncorrelated to its neighbors, below the European mean and exhibiting slow growth rates. From Eastern Germany to Eastern Hungary appears a buffer area that did not benefit from New Members dynamic and oscillates around the average of GDP (per capita) levels. The development dynamic of this region seems to have stopped, similarly to its western neighbors but with quite lower GDP per capita levels. On the Western side of Europe, France exhibits over average levels of GDP (per capita) but growth rates have slowdown. Finally, Spain and Portugal GDP (per capita) levels have stayed below the European mean. For few years, some regions have engaged in an over average dynamic which has stopped in 2013.

Briefly concluding about those first results, we should highlight the polarization that took place over the European territory at the beginning of the period on a similar dynamic than what LeGallo and Ertur have been describing for the Western Europe. The core remains intact while the contrast with becoming peripheral regions got wider.

1.4.2 Under the assumption of spatial dependence (H_1)

The previous section has been considering the contribution of each region to the global spatial process. This section presents the results obtained supposing spatial dependence, henceforth measuring the statistic variation around the global process and revealing local heterogeneities. In accordance with the previous sections, we exploit the residuals extracted from :

For regional GDP (per capita) levels	For regional growth rates
$\ln(GDP_{capita,i}) = \alpha(1) + (I_n - \rho W)^{-1} \epsilon$	$\frac{1}{T} \ln \left(\frac{GDP_{capita,i}}{GDP_{capita,2000}} \right) = \alpha(1) + (I_n - \rho W)^{-1} \epsilon$

GDPs (per capita) are standardized through the logarithmic transformation and we are still working on 4-year averages. α is a constant, I_n the identity matrix, ρ the spatial autocorrelation parameter and W a spatial weight matrix.

Importantly, this time, fixed effects have not been added. Indeed, as explained by LeSage and Kelley Pace [137], "in a spatial context, where we only have a single observation for each region, we can treat the vector of intercepts as a spatially structured random effect vector" (p.29) i.e the spatial error model can be used to control for spatial heterogeneity as individual dummies are used in regular panel data analysis.

Results for regional GDP(per capita) levels and regional GDP (per capita) growth rates are presented on the following maps according to the respective legends :

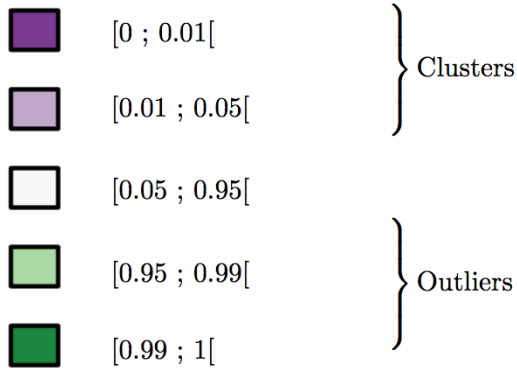


Table 4: P-values intervals for regional GDP (per capita) levels

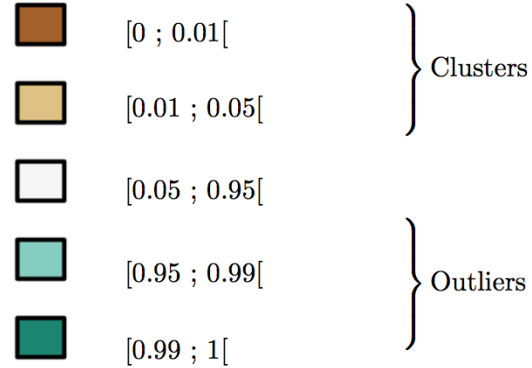
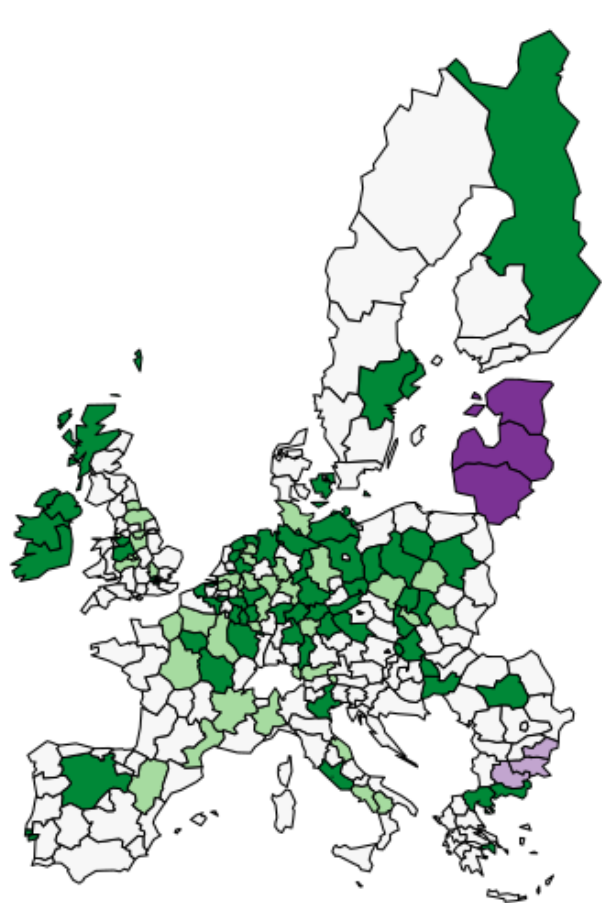
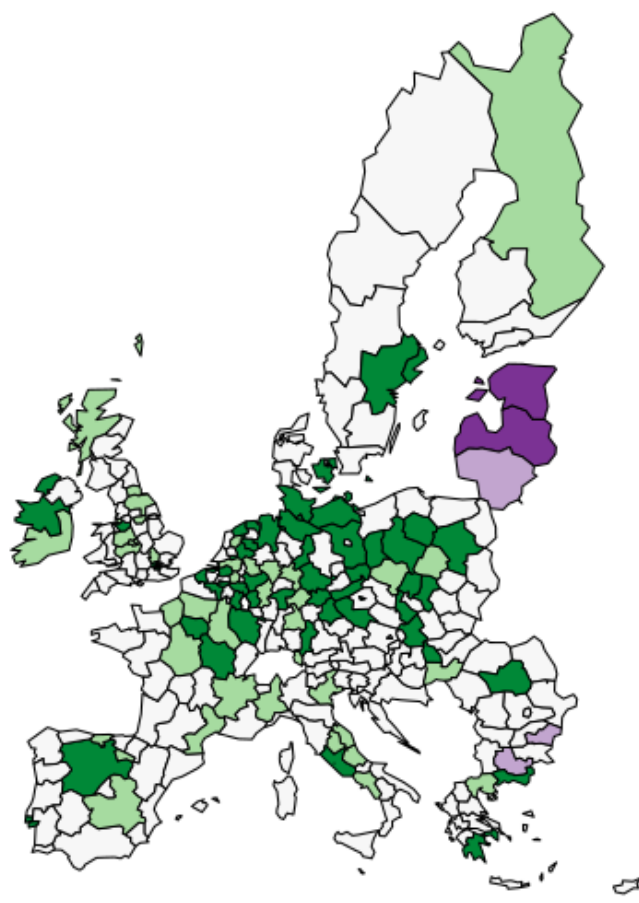


Table 5: P-values intervals for regional GDP (per capita) growth rates

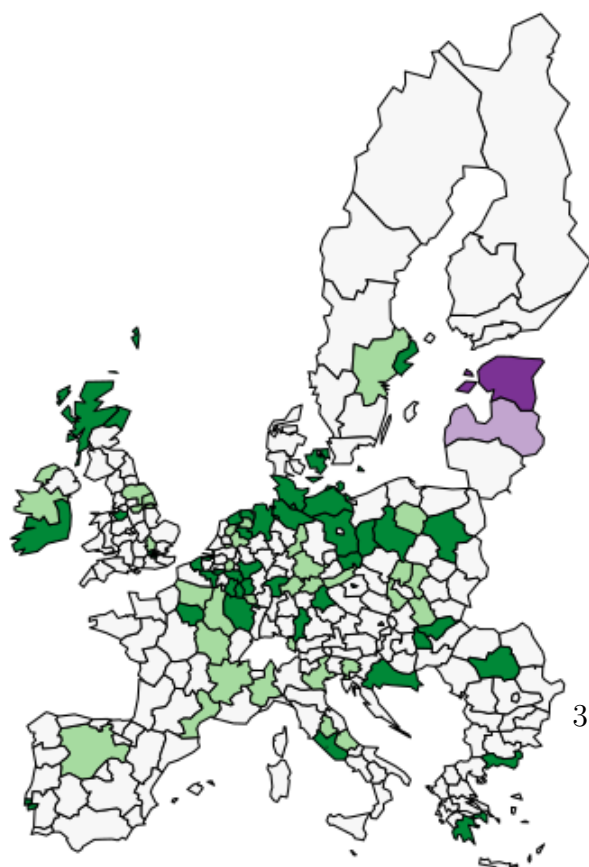
Figure 1.3: Outliers | Regional GDP (per capita) levels



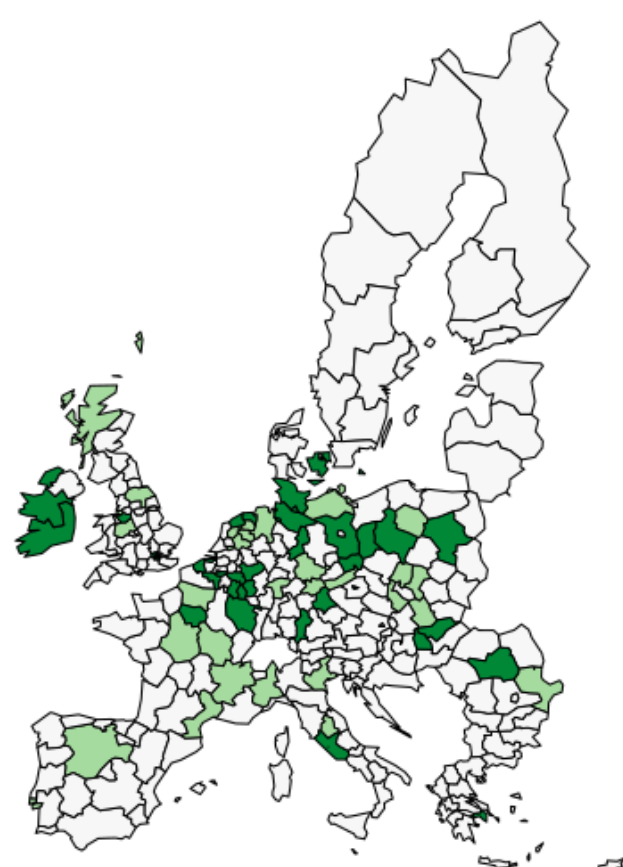
(a) 2001-2004



(b) 2005-2008

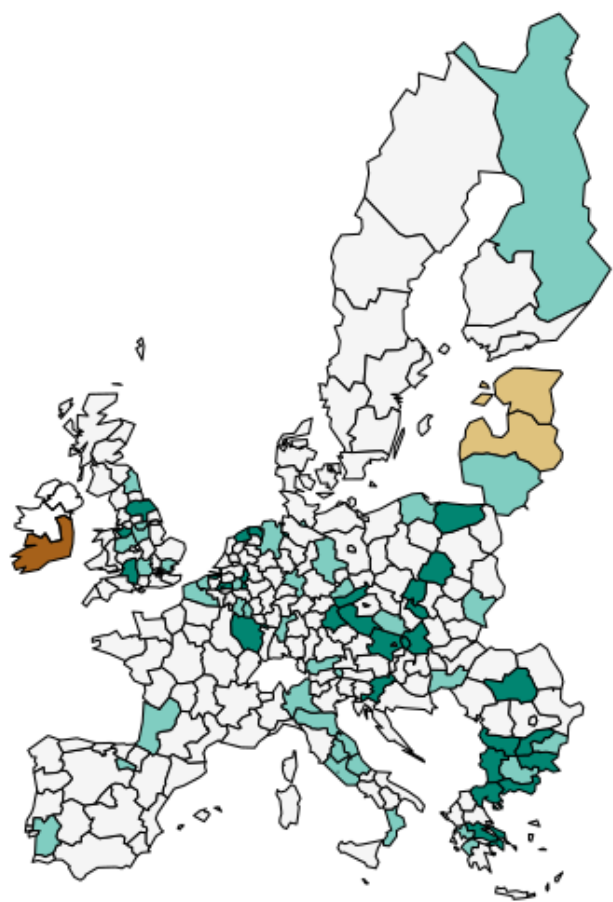


(c) 2009-2012

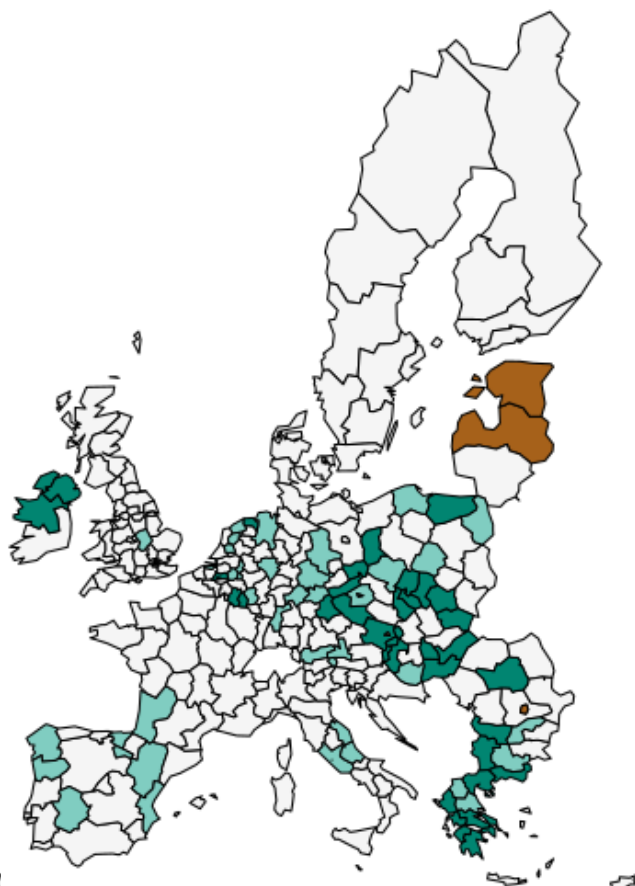


(d) 2013-2016

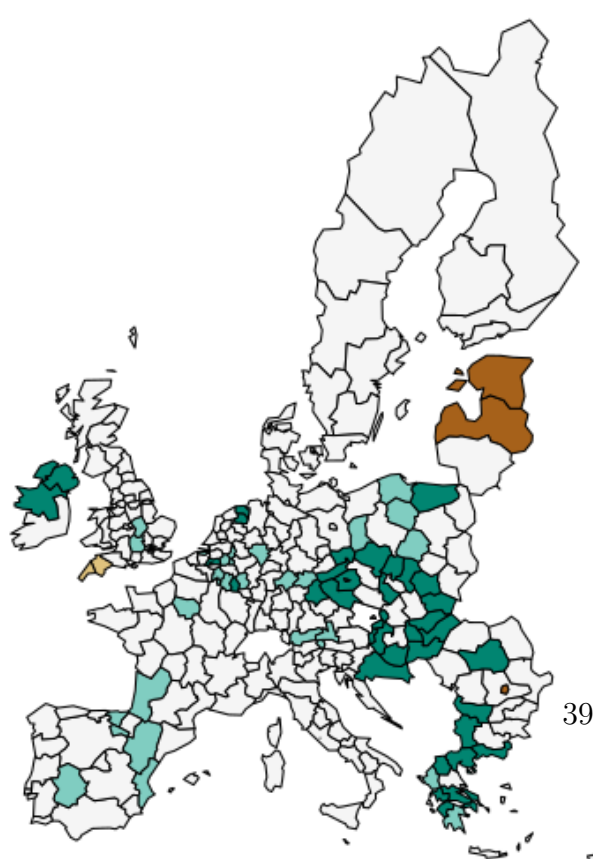
Figure 1.4: Outliers | Regional GDP (per capita) growth rates



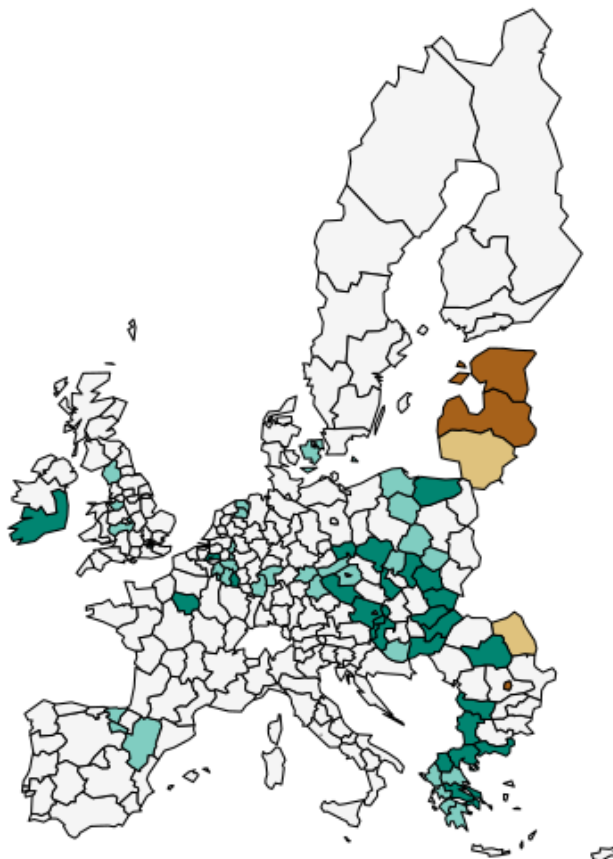
(a) 2001-2004



(b) 2005-2008



(c) 2009-2012



(d) 2013-2016

GDP (per capita) level maps exhibit two clusters of highly homogeneous regions. On the one hand, Estonia, Latvia, Lithuania seems to benefit from a particularly dynamic growth process. They started the decade with below average GDP (per capita) levels and by the end of period still exhibit a cluster of growth. On the other hand, some Bulgarian regions form another cluster of least resilience though. Indeed local Morans' I_i are not significant anymore from 2009 to 2016 and this might simply result from the heterogeneous dynamic one can observe on growth rate maps.

Conversely, numerous outliers scatter across the maps. GDP (per capita) level representations illustrate the polarization pattern over the first half of the decade : few regions, Paris, Roma, Luxembourg, Brussel, strongly appear as outliers, bringing to light a concentration process of wealth at the expense of direct neighbors. However, barely have the stocks been correlated with outstanding growth rates as centers' dynamics differ. First, Paris and the Luxembourg have remained strong and dynamic centers until the end of the period. Conversely, Roma is still concentrating activities but, by the end of the period, its growth rate does not denote an exceptional dynamic anymore. Those maps confirm the polarization dynamic we observed at first but we must notice a slowdown in the concentration processes.

1.4.3 Results on the different proximity approaches

Table 1.4 summarizes adjusted R^2 from regressions using the eigenvectors selected following the procedure in Sect.1.1.5. Adj. R^2 in the case of geographical matrices (contiguity) account for a very large part of the variance in the (log of) regional GDPs (per capita). Of interest, is the comparison with adj. R^2 out of the patent citations (*CitDist*) and the industry proximity (*ComDist*) matrices. Comparatively Adj. R^2 are very low which means that commercial and technological ties have weak explanatory power of regional per capita GDPs. We raise two explanations for this. On the one hand, our measures of commercial and technological proximities might not convey enough information and happen to be bad proxies for the spatial ties we aim at representing. On the other hand, we may have tested for a non-linear relationship, theoretically involving important matters we empirically ignored and that may blur

the link we have been willing to emphasize.

Table 1.4: Amount of variance explained by the selected eigenvectors ($\text{Adj.}R^2$)

	Contiguity C	Contiguity W	Contiguity S	k-nearest	CitDist	ComDist
2000	0.848	0.889	0.854	0.74	0.00159	0.00821
2001	0.839	0.882	0.845	0.734	0.00507	0.00403
2002	0.834	0.88	0.839	0.724	0.0023	0.00234
2003	0.842	0.88	0.844	0.714	0.00088	0.00195
2004	0.840	0.876	0.837	0.707	0.01528	0.00802
2005	0.828	0.856	0.813	0.698	0.00075	0.01162
2006	0.826	0.852	0.835	0.692	0.0035	0.00599
2007	0.809	0.833	0.814	0.672	0.00058	0.00079
2008	0.773	0.796	0.783	0.632	0.00515	$9.830e^{-5}$
2009	0.760	0.775	0.769	0.609	0.00999	0.0404
2010	0.754	0.776	0.773	0.636	0.0026	0.00309
2011	0.749	0.777	0.746	0.646	0.00334	0.00525
2012	0.755	0.779	0.728	0.674	0.00048	0.0013
2013	0.742	0.769	0.721	0.68	0.00101	0.0083
2014	0.740	0.781	0.737	0.684	0.00244	0.00189
2015	0.743	0.781	0.718	0.701	0.00033	0.00258
2016	0.744	0.768	0.696	0.69	0.00722	0.000492

CitDist stands for the technological proximity matrix ; *ComDist* for the commercial proximity matrix computed using NACE.2 classification

Table 1.5 displays Mantel’s correlation coefficient. Bold values represent values being significantly different from 0 (after Bonferroni multiple testing correction). The correlation is evaluated along distance classes that is the correlation between first order neighbors (class 1) then the correlation between second-order neighbors (class 2) An interesting pattern emerges. Both matrices happen to be positively correlated for the first few order neighbors and negatively correlated for further neighbors. This means that, the interaction between commercial and technological flows differ across space.

Table 1.5: Mantel Statistic evaluating the correlation between *CitDist* and *ComDist*

Years	Distance classes											
	1	2	3	4	5	6	7	8	9	10	11	12
2000	0.094	0.112	0.076	0.030	-0.015	-0.035	-0.088	-0.088	-0.092	-0.058	-0.026	-0.016
2001	0.104	0.126	0.092	0.051	0.000	-0.058	-0.092	-0.107	-0.118	-0.078	-0.048	-0.028
2002	0.088	0.103	0.079	0.041	-0.013	-0.054	-0.078	-0.073	-0.096	-0.053	-0.039	-0.021
2003	0.062	0.077	0.064	0.038	0.000	-0.025	-0.055	-0.062	-0.094	-0.061	-0.048	-0.031
2004	0.041	0.054	0.049	0.031	0.005	-0.006	-0.040	-0.056	-0.083	-0.055	-0.034	-0.011
2005	0.076	0.095	0.067	0.038	0.004	-0.023	-0.088	-0.090	-0.092	-0.061	-0.035	-0.008
2006	0.066	0.093	0.079	0.043	-0.009	-0.021	-0.082	-0.082	-0.100	-0.065	-0.036	-0.010
2007	0.062	0.085	0.061	0.015	-0.018	-0.023	-0.044	-0.058	-0.073	-0.053	-0.036	-0.011
2008	0.051	0.077	0.058	0.041	-0.001	-0.014	-0.069	-0.069	-0.080	-0.060	-0.028	-0.026
2009	0.069	0.103	0.085	0.032	-0.005	-0.036	-0.065	-0.086	-0.104	-0.070	-0.042	-0.017
2010	0.073	0.110	0.083	0.041	-0.005	-0.030	-0.071	-0.093	-0.121	-0.077	-0.057	-0.009
2011	0.071	0.108	0.090	0.054	-0.005	-0.019	-0.084	-0.090	-0.122	-0.093	-0.069	-0.030
2012	0.052	0.087	0.067	0.038	-0.002	-0.011	-0.065	-0.079	-0.105	-0.064	-0.046	0.004
2013	0.042	0.070	0.063	0.036	0.004	-0.009	-0.051	-0.071	-0.088	-0.071	-0.039	-0.019
2014	0.055	0.089	0.074	0.039	0.004	-0.026	-0.059	-0.078	-0.098	-0.079	-0.053	-0.020
2015	0.044	0.075	0.066	0.033	0.005	-0.008	-0.067	-0.070	-0.081	-0.065	-0.042	-0.023
2016	0.064	0.095	0.082	0.042	0.013	-0.038	-0.103	-0.098	-0.091	-0.059	-0.014	-0.001

Bold values are values significantly different from 0 when significance has been corrected using Bonferroni multiple testing adjustment

Conclusion

First, this study aimed at uncovering spatial disparities into the European Union over the period 2000-2016. Local Moran's I_i distributions have been obtained from the Exact Approach that allows circumventing Normal approximations. Doing so, it provides an alternative to permutation techniques as used in LeGallo and Ertur(2003) [136]. This revealed some kind of spatial heterogeneity and the co-existence of numerous spatial regimes under the hypothesis of occurrence of spatial process. We should highlight the polarization that took place over the European territory at the beginning of the period on a similar dynamic than what LeGallo and Ertur have been describing for the Western Europe. The core remains intact while the contrast with becoming peripheral regions got wider. Of notice, we observe a slowdown in the concentration processes starting from 2009. The disparities we emphasize raise questions regarding potential issues on the determinants of growth for regions that became peripheral regions in the "Old Europe". Chapter 2 of this dissertation digs further on uncovering potential inefficiencies that would have participated in stopping the growth engine in those regions.

Second, we miss to emphasize a great explanative power of commercial and technological forms of integrations. On the one hand, we suggest that our measures could be weak proxies for commercial and technological forms of integration. On the other hand, we highlight that the theoretical link between regional incomes and integration forces could be more complex than what we initially tested. Still, the comparison of technological and commercial types of proximity has brought to light an interesting correlation pattern between proximity matrices over space. We observe a positive correlation for first few neighbors and a negative correlation for further neighbors. These stylized facts call for further investigations. Chapter 3 points to a wide theoretical literature that links the consequences of freeing commercial and technological flows across regions to the social benefits arising from the occurrence of pecuniary and non-pecuniary externalities. Following, Chapter 4 addresses the relationship between agglomeration and the interplay of commercial and technological forms of integration.

Chapter 2

Spatial autocorrelation augmented
Common Correlated Effects
estimators : What is the fair share
of private returns to R&D ?

It has been broadly accepted that investments in R&D crucially contribute to innovation, future growth and competitiveness of regions. The main reason for this is the non-excludable and non-rival nature of knowledge which implies that knowledge production yields a the combination of some private and public returns. On the one hand, R&D investment returns can be accounted by enterprises and constitute the "private" component of productivity growth. On the other hand, the public component is what the economic literature has designated as "externalities" and its measurement has been much more controversial. Even if a vast corpus attributes an eminent role to the generation of spillovers in long-run growth owing (Hall et al. (2010) [102]), the public-good attributes of knowledge might have adverse implications on the private incentives to invest in R&D. To the extent that firms do not incorporate social returns while evaluating the yield of their effort in research, the non-excludable/non-rival nature of knowledge generate disincentives to investing. As a result, appears a discrepancy between the aggregated level of R&D investment firms endorse and the optimal level of investment the social planner would elect.

In order to mirror this discrepancy, much of the literature that took a close look at the additive knowledge production function (as proposed by Griliches (1979) [96]) has dedicated the bulk of its efforts into accounting for public returns, putting aside mis-measurement issues of capital, labor and R&D inputs at the aggregated level. Our article builds on Eberhardt and al. (2013) [70] that considers more globally the growth accounting framework and makes a first step toward more reliable coefficients on knowledge returns by showing how mismeasurements issues on inputs' aggregates could be handled thanks to common correlated effect methods. To the extent that some commonalities exist between the mismeasured elements across regions, one could control for these using unobserved common factors. Unobservable common factors whose effects can be heterogeneous across time and space are analyzed as a cross-sectional dependence phenomenon. In this case a multi-factor error structure can be estimated using cross-sectional averages of the independent and dependent variables. The procedure controls for endogeneity biases arising from the correlation between specified and omitted variables.

Eberhardt and al. (2013) [70] has been implementing Common Correlated Effects (CCE) models (in the near proximity of common factors models) to obtain refined private returns on knowledge for twelve manufacturing industries in ten OECD countries. However doing so, they also intend to account for public returns indifferently qualified as knowledge or spatial spillovers by the bulk of the literature. Yet, Ertur and Musolesi (2016) [75] explained how the cross-sectional dependence phenomenon differs from the autocorrelation phenomena spatial models treat for. On the one hand, cross sectional dependence would consider an omitted phenomena heterogenously impacting spatial units while spatial models rather address the network effect linking units to one another. This distinction is grounded by the alternative definition to Chudik’s weak cross-sectional dependence proposed by Sarafidis (2009) [177]. To this extent, CCE estimates only provide a partial solution as they only treat for some forms of cross-sectional dependence without addressing network effects.

This chapter aims at implementing an integrated framework assembling CCE and spatial methods in accounting for private and public returns on knowledge at the regional scale in Europe. Following Bailey and al. (2016) [14], we reproduce a two-step approach in combining a CCE estimation and dynamic Spatial Autoregressive model. On this model, we make a first proposition by comparing CCE estimators, Common factors treatments and spatial filtering techniques. Spatial filtering techniques should allow extracting spatial factors assimilable to the common factors. Halleck Vega and Elhorst (2016) [103] already brought closer those techniques. We also aim at experimenting a simultaneous computation of CCE and spatial methods. We implement the recent estimator proposed by Yang (2018) [196] that merge both cross-sectional and spatial treatment in the unified framework of a spatial GMM estimator.

We apply those methods to the case of European regions. Working on annual data, long period time series are not widely available at the regional scale but the sample we will further describe run from 1980 to 2015 and get us close from the minimal threshold of $T = 40$ required for CCE estimators to be fully efficient.

Our computations have brought us closer to the conclusions of over-investment in

R&D. According to our results on the EU-15, private returns are negative and so are public returns (spillovers). It echoes studies that have recently challenged the global consensus of underinvestment in R&D. On the theoretical front, new analyses questioning the existence of firms' underinvestment in R&D have recently been published. On the empirical front, the weakness of returns on R&D, both private and public, has casted doubt on the real value of additional efforts in R&D investments. Still, an important drawback to our approach that could undermine these results is that, to account for knowledge we have been using patents deposits. Those are increasingly beset to strategic deposits issues disregarding the true added value of the patented innovation and, potentially, leading to over estimations of the actual efforts put into R&D activities.

This article is structured as follows : Section 2.1 describes the theoretical framework. Section 2.2 provides further explanations on the empirical frameworks we mobilize. Section 2.3 describes our data and Sections 2.4 & 2.5 detail the implementation on respectively the two-step and one-step procedures. Section 2.5.2 provides the economic results.

2.1 Theoretical Framework

Solow (1957) [183] has laid the theoretical foundation of growth accounting. This seminal paper showed that, under the assumptions of (i) the existence of a stable relation between inputs and output at the economy-wide level of aggregation, (ii) of inputs paid at the value of their marginal product, (iii) of constant returns to scale of factors and (iv) of Hick's neutral form of technical change, output could be expressed as a function of capital and labor inputs augmented by a productivity parameter. The force of this result is that the previous conditions have proved necessary and sufficient to account for countries' growth trajectories.

Formally, the identity can be expressed as :

$$Q_t = A_t F(K_t; L_t)$$

and converted under its growth rate form :

$$\frac{\dot{Q}_t}{Q_t} = \frac{\partial Q_t}{\partial K} \frac{K_t}{Q_t} \frac{\dot{K}_t}{K_t} + \frac{\partial Q}{\partial L} \frac{L_t}{Q_t} \frac{\dot{L}_t}{L_t} + \frac{\dot{A}_t}{A_t}$$

where Q_t is the gross output, A_t is the productivity parameter, K_t and L_t are the production function inputs, respectively, capital and labor and \dot{Q}_t , \dot{K}_t and \dot{A}_t are derivatives according to time (t).

Theoretically, the growth rate of output can thus be divided into its two basic sources whose empirical counterparts might not be so clearly defined. Input growth is linked to the propensity to save while productivity growth is rather attached to the accumulation of knowledge and to the propensity to innovate. Empirically, the distinction is blurred as there exist mutual feedback effects in which an increase in technology causes capital augmentation while capital augmentation generates spillovers, likely to increase productivity. On the top of this, technology is also often embodied in the design of new capital assets which make the distinction even more difficult. Conventional measures of labor and capital contain elements of R&D which are then double-counted: R&D workers are already counted in the total workforce and R&D investments are integrated in the evaluation of the stock of capital. Moreover, since R&D is treated as an intermediate expense and withdrawn from value added calculations, measured value added is to be considered too small by that amount.

Schankerman (1981) [179] discusses the distorting effects of these mismeasurements in a growth accounting framework and show how the double counting of inputs and R&D expenses can be contemplated as an omitted variable issue. In this case, the omission of the share of R&D workers in the total workforce and of R&D investments in the stock of capital induces a downward bias that can not be interpreted as "an excess return" or an over-investment. Actually, the resulting bias may either be negative or positive depending on whether omitted inputs or added value calculations effect predominate. As we will see further, Eberhardt and al.(2013) [70] have shown how relevant econometric techniques handling unobserved common factors allow to control for those issues. Before presenting these developments, let us turn to these issues raised

by social returns in the endogenous growth framework.

The introduction of the endogenous growth framework [171] slightly moved the dichotomy's focus from a distinction between capital and technology to a distinction between types of capital formation. Said differently the dichotomy has moved toward differentiating costless advances in technology, better known as externalities, and other forms of capital augmentation. Externalities or knowledge diffusion appears as a spillover from the stock K_t (that includes R&D and human capital) to the level of productivity.¹

The accounting identity becomes

$$Q_t = A e^{\nu_t} L_t^a K_t^b K_t^\eta \mu_t$$

where μ is an "Abramovitz" term summarizing the other factors (errors and omissions) that affect production, ν is the autonomous rate of productivity change and η is the parameter that accounts for spillovers. On this basis, the corresponding knowledge production function is written such :

$$\frac{\dot{A}_t}{A_t} = \nu_t + \eta \frac{\dot{K}_t}{K_t} + \frac{\dot{\mu}_t}{\mu_t}$$

where \dot{A} and \dot{K} still are derivatives according to time and ν_t became a growth rate effect (relative to the initial observation). The literature that aims at estimating knowledge production functions has usually accounted for private returns on R&D using the share of total turnover devoted to R&D at the firm level and for social returns on R&D using the intensity of R&D expenditures at the sectoral level. According to this methodology, the social returns appear to be much higher than private returns and knowledge spillovers have been found playing a central role in explaining this difference. However, according to Griliches (1992) [97], those estimations might overestimate the role of knowledge externalities because of measurement problems. So far, knowledge spillovers were understood in their "real" definition that is as "ideas borrowed

¹Direct inputs are submitted to constant returns to scale ($a + b = 1$) which then induce total increasing returns to scale.

in-between fields and industries by researchers”. Griliches’ statement addresses the omission of the literature regarding pecuniary externalities that might participate in inflating social returns coefficients. Pecuniary externalities are to be distinguished from knowledge externalities to the extent that they are not directly linked to the free use of knowledge. They rather fall within a price intermediated mechanism according to which some may take advantage of under-priced input acquisitions resulting from the difficulty to determine the real value resulting from R&D activities.

Formally, in this chapter we estimate a growth accounting equation of the form

$$y_{it} = a_i l_{it} + b_i k_{it} + \kappa_i r_{it} + \varepsilon_{it}$$

where lower case letters denote differenced logarithms. For instance : $y_{it} = \log(Q_{it}) - \log(Q_{i,t-1})$ where i indexes regions at the NUTS 2 level and t indexes time. l_{it} , k_{it} and r_{it} respectively account for changes in the labor, capital and R&D stocks. Under this basic form, residuals ε_{it} embed individual and time effects, measurement issues and spatial spillovers.

In a similar setting, Eberhardt and al.(2013)[70] have shown how recent methods have improved the treatment of residuals content. Residual multi-factor approaches assume that the dependence between units (labelled cross sectional dependence) can be characterized by a finite number of unobserved common factors. Those factors are to be assimilated to economy-wide shocks that can affect units on a heterogeneous basis. Typically, Eberhart and al.(2013)[70] corrected for the distorting effects of double counted inputs using this method. Chudik and al. (2015) [43] designate this form of dependence as a *strong* form in which ”correlation between any pair of units does not depend on how far those observations are apart”. This first form is to be distinguished from a *weak* form which rather concerns dependence arising from pairwise correlations across finite subsets of units. Both forms can co-exist and be treated at once as shown in Pesaran and Tosetti (2014) [163].

Ertur and Musolesi (2016) [75] statement comes on top of this first dichotomy. They

consider two forms of weak dependence under the titles of *interactive heterogeneity* that they oppose to a *classic heterogeneity*. Interactive heterogeneity is the result of differentiated feedback effects, caused by interactions facilitated by geographical proximity between units and agents, and requires specific modeling of spatial autocorrelation [59]. This form of dependence is usually the focus of the spatial econometric literature, but, by no means limit to local interactions. Using the example of a Spatial Autoregressive model (SAR), Ertur and Musolesi (2016) [75] show how those models are used to capture the spread of effects across the spatial network and not only local interactions. Briefly, suppose a spatial autoregressive model of the form :

$$y_t = \alpha + X_t\beta + (I_N - \lambda W_N)^{-1}\varepsilon_t$$

where I_N is an identity matrix, W_N is a spatial weight matrix, λ accounts for spatial interactions, ε is an error term.

$(I_N - \lambda W_N)^{-1}$ is called the global spatial multiplier where

$$(I_N - \lambda W_N)^{-1} = I_N + \lambda W_N + \lambda^2 W_N^2 + \lambda^3 W_N^3 \dots$$

and accounts for the spread of random shocks across the spatial network. The diagonal of such a matrix represents the direct impacts of random shocks but also feedback effects which are heterogeneous to the extent that interactions differ between members. Non-diagonal elements account for indirect effects i.e how the shock affects the other nodes of the network. The magnitude of the effect of a random shock will depend on the structure linking network members (given by W_N) and on λ that measures the strength of the interaction between nodes.

The distinction between both forms of weak dependence is grounded by the definition of Sarafidis (2009) [177] that differ from Chudik and al. (2015)[43] 's one. The "interactive" weak dependence corresponds to the case where the conditional covariance linking two spatial units would be bounded.

$$\sum_{i \neq j} |cov(z_{it}, z_{js} | F_{ij})| < \infty$$

where F_{ij} denotes the conditioning set of all time invariant characteristics of individuals i and j . The "classic" weak dependence as defined by Chudik and al. (2015) [43] would rather be written

$$\lim_{N \rightarrow \infty} var \left(\sum_{i=1}^N w_{ij} z_{it} | \mathcal{F}_{t-1} \right) = 0$$

such that a process $\{z_{it}\}$ would be cross-sectionally weakly dependence at time t if its weighted average (at that time), conditional on the set available in the previous period \mathcal{F}_{t-1} , converges to its expectation in quadratic mean as the cross-sectional dimension is increased without bounds for all weights w .

The goal of this paper is to address the untreated issues remaining in the residuals of the growth accounting specification in order to obtain more reliable coefficients on inputs and more particularly on private and public returns on R&D investments. On the first hand, Eberhardt and al.(2013) [70] have proved common correlated effects methods relevant in handling measurement issues as pointed by Schankerman(1981) [179]. Provided that omitted elements display some commonalities across regions, they could be represented through unobserved common factors with heterogeneous factor loadings. On the other hand, pecuniary and non-pecuniary externalities both are the result of some interactions conditioned by the existence of some form or another of transport costs. First, lowering transport costs on goods induces stronger pecuniary externalities. Second, lowering transfer costs on ideas induces wider knowledge externalities. Both are driven by parameters whose evolution has followed some global decreasing trends that could relate to economy wide shocks. Hummels [116] documents the tremendous decrease of transport costs over the last decades and Cairncross [35] famous "death of distance" illustrates how the introduction of high-speed communication technologies reduced costs on the mobility of ideas. To this extent, pecuniary and non-pecuniary externalities would typically enter the category constituted by the *interactive* weak form of dependence and require spatial treatments. Pesaran and Tosetti (2014) [163] has shown how, in the case of simultaneous occurrence of unobserved common factors and spatial autocorrelation, estimation can be carried out by least squares where the observed regressors were augmented with cross section averages and observed common factors (d_t). On this path, the present chapter intends to additionally take into account

interactive forms of heterogeneity under the form of spatial autocorrelation.

2.2 Empirical Framework

In this section, we provide details on the cross-sectional dependence phenomenon (section 2.2.1) and the Common Correlated Effects method (section 2.2.2) at use to correct for it. We compare those with the related Common Factors (section 2.2.2) and Spatial Filtering techniques (section 2.2.3) before turning to spatial models and the one-step approach (section 4.14) that aims at controlling for both classical and interactive forms of dependences at once.

2.2.1 Cross-sectional dependence

Bailey and al.(2016) [14] makes the distinction between the various forms of cross-sectional dependence on the basis of the measure CD developed in Pesaran (2004) [160]. They define the cross-sectional (CD) statistic as

$$CD = \left[\frac{TN(N-1)}{2} \right]^{1/2} \hat{\bar{\rho}}_N$$

where $\hat{\bar{\rho}}_N$ is an estimate of $\bar{\rho}_N$ defined as

$$\bar{\rho}_N = \frac{2}{N(N-1)} \sum_{i=1}^N \sum_{j=i+1}^N \rho_{ij}$$

ρ_{ij} is the correlation index linking units i and j . N gives the number of individuals and T the length of the time series.

$\hat{\bar{\rho}}_N$ converges at a rate $O(N^{2\alpha-2})$. The values of α reveals the intensity of the cross-sectional dependence phenomenon throughout the convergence rate of $\hat{\bar{\rho}}_N$.

α	$[0; 1/2)$	$[1/2; 3/4)$	$[3/4; 1)$
$\hat{\rho}_N$	$O(N^{-2})$ or $O(N^{-1})$	$O(N^{-1})$ or $O(N^{-1/2})$	$\alpha \sim 1 \rightarrow O(1)$

In the first case, $\hat{\rho}_N$ converges quite fast to 0 while when α gets closer from 1, the convergence rate is much slower. In the former case, one addresses a weak form of dependence while in the latter case, one addresses a strong form of dependence.

2.2.2 Factor models and Common Correlated Effects (CCE) estimators

Common factor models and CCE estimators endorse the strong form of cross-sectional dependence.

Factor models build on principal component approaches. As described by Coakley, Fuertes and Smith (2002)[46] and Bai (2009)[10] the typical model is written :

$$y_{it} = \alpha'_i d_t + \beta' x_{it} + \gamma'_i \hat{f}_t + \varepsilon_{it} \text{ for } i = 1, 2, \dots, N \text{ and } t = 1, 2, \dots, T \quad (2.1)$$

where d_t is a $(N \times 1)$ vector of observed common effects ², x_{it} is a $(N \times 1)$ vector of individual-specific explanatory variables and f_t is an (m^*1) vector of principal components. The parameter estimation is a two stage procedure where principal components are estimated from the OLS residuals' regression and then used as observables in the augmented expression. β have been proved consistent for N (individuals) and T (periods) large as long as f_t and x_{it} were uncorrelated.

Pesaran(2006) [161] suggests the Common Correlated Effects (CCE) estimator. The

²including intercepts or seasonal dummies

model becomes :

$$y_{it} = \alpha'_i d_t + \beta'_i x_{it} + u_{it} \quad (2.2)$$

$$x_{it} = A'_i d_t + \Gamma'_i f_t + v_{it} \quad (2.3)$$

$$u_{it} = \gamma'_i f_t + e_{it} \quad (2.4)$$

In its primary version ³, the CCE estimator allows for intercepts and slope heterogeneity, which is of particular interest in a regional and heterogeneous study' context. Similarly to the principle of "factoring out", CCE estimation procedures consists in approximating unobservable common factors as the linear combination of cross sectional averages of both dependent and independent variables (d_t, y_{it}, x_{it}) . Precisely, those averages are weighted under particular "granularity" conditions :

$$\bar{y}_{wt} = \sum_{i=1}^N w_i y_{it} \text{ and } \bar{x}_{wt} = \sum_{i=1}^N w_i x_{it}$$

$$w_i = O\left(\frac{1}{N}\right), \sum_{i=1}^N w_i = 1, \sum_{i=1}^N |w_i| < K$$

where K is a constant, independent of N such that for any N sufficiently large (and as $N \rightarrow \infty$), $Var(z_{wt}) \geq K > 0$. The principal condition is that $w_i = O(1/N)$ as Pesaran allows different types of weights, under this specific requirement. Generally, CCE estimator weighting neutrally attributes a weight of $1/N$ to each unit.

Common factors are identified under a specific "rank condition" :

$$Rank(\bar{C}_w) = m \leq k + 1$$

$$\bar{C}_w = \sum_{i=1}^N w_i C_i \quad \text{and} \quad C_i = \begin{pmatrix} \gamma_i & \Gamma_i \end{pmatrix} \begin{pmatrix} 1 & 0 \\ \beta_i & I_k \end{pmatrix}$$

where m is the number of common factors.

³differently from the successive, aggregated estimator' versions, respectively CCE Mean group estimator (CCEMG) and CCE Pooled estimator (CCEP)

In the adverse case of $m \geq k + 1$, where k is the number of unit-specific regressors included in the model, common factors then cannot be extracted from cross-sectional averages. Still β_i can be consistently estimated under some additional requirements ⁴.

2.2.3 Spatial Filtering

Advances of the "classic" panel data literature have echo Tiefelsdorf (2000) [188], Griffith and Getis(2002) [90], Griffith (2003) [92], Griffith(2008) [94] progresses on spatial filtering (SF) methods.

The SF technique relies on the eigenvector decomposition of the Moran's I autocorrelation index. From a basic regression, Moran's \mathcal{I} are extracted out of estimated residuals and decomposed according to the following :

$$\mathcal{I} = \frac{N}{\iota_N' B_N \iota_N} \frac{\hat{\varepsilon}(I_N - \frac{1}{N} \iota_N \iota_N') B_N (I_N - \frac{1}{N} \iota_N \iota_N') \hat{\varepsilon}}{\hat{\varepsilon}' (I_N - \frac{1}{N} \iota_N \iota_N') \hat{\varepsilon}}$$

where \mathcal{I} is Moran coefficient, $\hat{\varepsilon}$ are regression residuals, I_N is the identity matrix, ι_N are $(N \times 1)$ vector of ones and B_N is the matrix of eigenfunctions each function being the product of an eigenvalue and its corresponding eigenvector.

Extracted eigenvectors are orthogonal and uncorrelated to one another. Largest eigenvalues or eigenvectors accounting for the highest share of autocorrelation represent "global" map patterns ; intermediate eigenvalues rather describe regional patterns while lowest eigenvalues are attached to local map patterns. The linear combination of selected eigenvectors constitute the "spatial filtering" of the variable of interest. Subsequently to the inclusion of the selected eigenvectors in the core of the model, the latter can reliably been estimated thanks to an OLS procedure. Halleck Vega and al. (2016) [103] explains how CCE estimators and SF methods only differ in the definition of granularity. When CCE approach adopts a neutral weighting system ($1/N$ to each unit), spatial filtering methods introduces considerations of spatial proximity.

⁴[that the unobserved factor loadings would be independently and identically distributed across i , and respectively to e_{jt} , v_{jt} and $g_t = (d_t', f_t')' \forall i, j, t$ and uncorrelated with the loadings attached to the regressors (Γ_i) .]

Pesaran and Tosetti (2014) [163] have shown that following cross sectional averages and observed common factors (d_t) augmentations, estimations can be carried out by least squares. Considering that the weak form of dependence left in the residuals require spatial treatments, we now aim at extracting spatial autocorrelation elements. First, Bailey and al. (2016) [14] also propose an empirical strategy in accounting from spatial dependence in factor models' residuals. Second, Halleck Vega and al. (2016) [103] emphasize how the two-stage approach can be condensed into a single step procedure, accounting for both strong and weak forms of dependence at once. The "simultaneous" procedure is found to better account for the dependence between short-term and long-term dynamics. Indeed, first accounting for common factors and then for spatial dependence introduces an artificial exogeneity while both forms of cross-sectional dependences are likely to interact and influence each other's strength. Consequently, the next subsection describe spatial treatments as the second step suggested by Bailey and al. (2016) [14]. In a second time, the one-step approach is developed grounded by Halleck Vega and Elhorst (2016) [103] theoretical argument and Yang (2018) [196] developments.

2.2.4 Spatial considerations and one-step approaches

First paragraph of section 2.2.4 describes developments according to Bailey and al. (2016) [14]. Remaining developments detail the specification of the one-step estimation following the suggestion of Halleck Vega and Elhorst (2016) [103] and the estimator we intend to use on the basis of Yang (2018) work [196].

Bailey and al. (2016)

Having controlled for strong dependence considering both factor and CCE estimators, Bailey and al. (2016) [14] propose a second step estimation. Residuals as extracted from the factor/CCE estimation are analyzed thanks to a dynamic spatial SAR model. Some theoretical reasons support the use of dynamic models in this framework. Indeed, static models do not allow long-run equilibrium relations and omitting lagged variables

could induce mistaking short-run deviations for long-run effects. This intuition is more strictly grounded using panel unit root tests in Appendix 2.7.2 and dynamic treatments are endorsed in spatial treatments.

The (dynamic) SAR spatial model integrate spatial lag(s), temporal lag and spatio-temporal lags of the dependent variable.

$$\hat{\xi}_t = a_\xi + \Lambda_1 \hat{\xi}_{t-1} + \Psi_0 W \hat{\xi}_t + \Psi_1 W \hat{\xi}_{t-1} + \zeta_t \quad (2.5)$$

where $\hat{\xi}_t$ are the residuals extracted from the first-step CCE or factor estimation. W is a row-standardized weighting matrix.

One-step approach : Theory

Halleck Vega and Elhorst (2016) [103] propose a one-step procedure merging Bailey and al.'s CCE and spatial estimations. Decomposing the estimation might induce omitting the existence of interdependencies between the two dependence processes either caught by CCEs or by the spatial treatment while "the mutual structure of regions may have major structural impacts of the national economy on that of its regions while these impacts in their turn may affect the relationships among regions." [103]

The model adapted from the one step-procedure proposed by [103] would be of the form :

$$\begin{aligned} y_t - (\alpha + \beta_1 l_t + \beta_2 k_t + \beta_3 r_t + \alpha_2 \bar{y}_t + \alpha_3 \bar{x}_t) = \\ \alpha_\xi + \lambda_1 [y_{t-1} - (\alpha + \beta_1 l_{t-1} + \beta_2 k_{t-1} + \beta_3 r_{t-1} + \alpha_2 \bar{y}_{t-1} + \alpha_3 \bar{x}_{t-1})] \\ + \psi_0 W [y_t - (\alpha + \beta_1 l_t + \beta_2 k_t + \beta_3 r_t + \alpha_2 \bar{y}_t + \alpha_3 \bar{x}_t)] \\ + \psi_1 W [y_{t-1} - (\alpha + \beta_1 l_{t-1} + \beta_2 k_{t-1} + \beta_3 r_{t-1} + \alpha_2 \bar{y}_{t-1} + \alpha_3 \bar{x}_{t-1})] \\ + \zeta_t \end{aligned}$$

Re-ordered such

$$\begin{aligned}
y_t = & \alpha + \alpha_\xi - \lambda_1 \alpha - \psi_0 W \alpha - \psi_1 \hat{W}_\rho \alpha + \lambda_1 y_{t-1} + \psi_0 W y_t + \psi_1 W y_{t-1} \\
& + \beta_1 l_t - \lambda_1 \beta_1 l_{t-1} - \psi_0 W(\beta_1 l_t) - \psi_1 W(\beta_1 l_{t-1}) \\
& + \beta_2 k_t - \lambda_1 \beta_2 k_{t-1} - \psi_0 W(\beta_2 k_t) - \psi_1 W(\beta_2 k_{t-1}) \\
& + \beta_3 r_t - \lambda_1 \beta_3 r_{t-1} - \psi_0 W(\beta_3 r_t) - \psi_1 W(\beta_3 r_{t-1}) \\
& + \alpha_2 \bar{y}_t - \lambda_1 \alpha_2 \bar{y}_{t-1} - \psi_0 W \alpha_2 \bar{y}_t - \psi_1 W \alpha_2 \bar{y}_{t-1} \\
& + \alpha_3 \bar{x}_t - \lambda_1 \alpha_3 \bar{x}_{t-1} - \psi_0 W \alpha_3 \bar{x}_t - \psi_1 W \alpha_3 \bar{x}_{t-1} + \zeta_t
\end{aligned}$$

$$\begin{aligned}
y_t = & \Xi + (\lambda_1 + \psi_1 W) y_{t-1} + \psi_0 W y_t \\
& + \beta_1 (1 - \psi_0 W) l_t - \beta_1 (\lambda_1 + \psi_1 W) l_{t-1} \\
& + \beta_2 (1 - \psi_0 W) k_t - \beta_2 (\lambda_1 + \psi_1 W) k_{t-1} \\
& + \beta_3 (1 - \psi_0 W) r_t - \beta_3 (\lambda_1 + \psi_1 W) r_{t-1} \\
& + \alpha_2 (1 - \psi_0 W) \bar{y}_t - \alpha_2 (\lambda_1 + \psi_1 W) \bar{y}_{t-1} \\
& + \alpha_3 (1 - \psi_0 W) \bar{x}_t - \alpha_3 (\lambda_1 + \psi_1 W) \bar{x}_{t-1} \\
& + \zeta_t
\end{aligned}$$

$$\Xi = \alpha + \alpha_\xi - \lambda_1 \alpha - \psi_0 W \alpha - \psi_1 W \alpha$$

As explained in Elhorst (2010) [74], such a type of model raises identification issues and has to be downgraded to a 'feasible' form. Yang (2018) provides a fully integrated static estimator in controlling for both cross-sectional and spatial effects. Doing so, though, we have to consider a lighter version of the form:

$$\begin{aligned}
y_t = & \Xi + \psi_0 W y_t + \\
& + \beta_1 (1 - \psi_0 W) l_t + \beta_2 (1 - \psi_0 W) k_t + \beta_3 (1 - \psi_0 W) r_t \\
& + \alpha_{21} \bar{y}_t - \alpha_{22} \bar{y}_{t-1} + \alpha_{31} \bar{x}_t - \alpha_{32} \bar{x}_{t-1} + \zeta_t
\end{aligned} \tag{2.6}$$

One-step approach : Estimator

Yang's GMM estimator [196] integrates both common correlated effects' matters and spatial issues into a single estimate on the basis of a spatial GMM class of estimator

[Kelejian and Prucha (1999, 2010) [124] [125], Lee (2007)[134], Lin and Lee (2010) [139], Lee and Yu (2014) [135]]. The estimator approximates unobserved factors by cross-sectional averages of both dependence and independent variables and then uses it in the construction of the instrumental variables and quadratic moment conditions to solve the endogeneity issue.

The static model she considers is of the form

$$\begin{aligned} y_{it} &= \theta y_{it}^* + \beta \mathbf{x}_{it} + \gamma_i \mathbf{f}_t + u_{it} \\ &= \theta \sum_{j=1}^N w_{ij} y_{jt} + \beta \mathbf{x}_{it} + \gamma_i \mathbf{f}_t + u_{it} \\ \mathbf{x}_{it} &= \mathbf{A}_i' \mathbf{f}_t + \mathbf{v}_{it} \end{aligned} \tag{2.7}$$

where the first term is the spatial lag effect, and \mathbf{x}_{it} are the individual-specific variables (k_{it} , l_{it} , r_{it}). The factor loadings γ_i and \mathbf{A}_i capture heterogeneous impacts of the common effects on cross-section units. u_{it} , v_{it} are the idiosyncratic disturbances respectively attached to y_{it} and x_{it} . This GMM estimator is a first-difference type of GMM. The following simple condition is required to guarantee identification :

$$N^{-1} \text{trace}(\mathbf{W}'\mathbf{W}) > \varepsilon > 0 \text{ for all } N, \text{ including } N \rightarrow \infty$$

where \mathbf{W} is a row-standardized spatial weight matrix.

All of the proposed estimates, that is the two stages least square (2SLS), the best 2SLS and the GMM estimators, are robust to heteroskedasticity and serial correlations in the disturbances.

According to those developments, the implementation strategy we propose works through two main sections. Section 2.4 reproduces Bailey and al.(2016) [14] procedure while Section 2.5 follows the path sketched by Halleck Vega and Elhorst (2016) [103] toward the one-step approach and presents the results obtained from Yang (2018)'s GMM estimator [196]. Before doing so, we describe our data in the following section.

2.3 Data

Cambridge Econometrics Datasets allow us to benefit from data running from 1980 to 2015 all over the 28 European Union Members at the NUTS2 (regional) level. As an output measure, we use Gross Value Added calculated as the "net result of output valued at basic prices less intermediate consumption valued at purchasers' prices deflated to 2005 constant price euros". Intermediate consumption represents the value of goods and services used as inputs to the production process. Labour input is the total hours worked per worker multiplied by employment. Total hours worked are expressed in millions hours.

Capital input, ideally, has to be a measure of current capital services rather than a capital stock (Jorgenson and al.(1967) [122]) and to comply so, we use gross fixed capital formation expressed in 2005 billion euros. Eberhardt and al. (2013) [70] emphasizes their use of double deflated variables in order to provide estimations net of inflation issues. Under single deflation, the growth rate of, say, "real value added in a given industry is taken to be equal to the growth rate of real gross output in that industry". To this extent, single deflation requires a price index (or deflator) for gross output only (not for the inputs as well). Under the double deflation standard, "the growth rate of real value added is measured (roughly) by the growth rate of real gross output minus the weighted average growth rate of real input. Real input is understood as a weighted average of energy, materials and brought in services" (Oulton (2018) [155]). As a consequence, double deflation requires a price index for each of the inputs, together with knowledge of the value of the purchases for each (energy, materials, services). The European Regional Database of Cambridge Econometrics deflates variables using sectoral prices deflators at the national scale for agriculture, manufacturing & energy, construction and services. They constitute region-specific price deflators by exploiting the sectoral structure of each region under the assumption that a given sector has the same price movements across all regions within a country. This does not constitute a proper double deflation as it does not allow to separate prices issues affecting output from those affecting inputs. To this extent, it constitutes a potential downward bias in our results we would have to keep in mind.

Knowledge data have not been extracted from Cambridge Econometrics Dataset and only Eurostat patents counts (publicly available) allowed to trace innovation efforts back to the eighties. CCE models require working on long time series (≈ 40). This has prevented the use of data on R&D expenditures and required data management among which extrapolating work fully described in Appendix 2.7.1 . We have been using "patents applications to the EPO by priority year" which is considered the closest date to the invention and prevent administrative delays to distort annual reports. Crepon, Duguet and Mairesse (1998) [52] stress that innovation output rather than innovation input is supposed to affect productivity. Turning from R&D expenses to patent counts has the disadvantage of narrowing the measure of R&D, excluding capital goods and managerial improvements but reduce exposure to the downward bias and allows working on longer time series. However, even though patent counts have been widely used, they are also known to be very imperfect proxies of innovation undertakings. The first reason is that there exist recurrent differences in the mean value of innovations from a group of patents to another. This makes comparisons of counts a biased measure of innovation efforts between heterogeneous productive apparatus. Secondly, even among groups with similar mean values, the noise in the relationship between patent counts and the value they represent makes it difficult to use them as a reliable proxy to evaluate effective R&D efforts and their consequences. The literature recommends some refinements using renewal fees as an additional indicator of value. However we don't benefit from this additional information and would have to rely on raw patent counts.

To integrate Solow's production function, R&D expenditures must be transformed into an R&D stock. This is commonly done thanks to a perpetual inventory method where the stock of (knowledge) capital is the sum of current and past investments. The rationale is that R&D expenditures takes time to transform into effective innovation and it is the sum of past and current R&D expenditures that matter for productivity more than the current investments. We apply a similar logic to patent counts. In both

cases, R&D is expected to depreciate, establishing a geometric law of motion [115].

$$PS_{it} = (1 - \varphi)PS_{it-1} + Patents_{it}$$

where PS is the stock at respectively t and $t - 1$ and Patents is the flow. φ postulates the depreciation rate that we suppose uniform across regions and constant over time. As noted by Eberhardt and al.(2013) [70], the actual chosen rate is of little relevance as, as long as it does not change dramatically, it will be captured by fixed effects/cross-sectional averages. As we do not dispose from sectoral information, we expect that regional fixed effects will somehow control for productive apparatus changes. Practically, the knowledge stock is thus calculated as

$$\begin{aligned} PS_{i1} &= Patents_{i0} + (1 - \varphi)Patents_{i-1} + (1 - \varphi)^2Patents_{i-2} + \dots \\ &= \sum_{t=0}^{\infty} (1 - \varphi)^t Patents_{i-s} = Patents_{i0} \sum_{t=0}^{\infty} \left[\frac{1 - \varphi}{1 + g_i} \right]^t = \frac{Patents_{i0}}{\varphi + g_i} \end{aligned}$$

where g_i the 3 years geometric moving average of region-specific growth rates (calculated on an annual basis) and φ is fixed to 15% according to Hall and Mairesse (1995)[101].

As a reminder, we work on logarithm differences that is $\% \Delta GVA = \log(GVA)_{it} - \log(GVA)_{i,t-1}$ where i indexes regions at the NUTS II level and t indexes time. $\% \Delta HW$ and $\% \Delta GFCF$ respectively account for Hours Worked and Gross Fixed Capital Formation log changes. Finally $\% \Delta PAT$ addresses changes in regional patent stocks.

The following table displays descriptive statistics about the data :

Table 2.1: Descriptive statistics

	$\% \Delta GVA$	$\% \Delta HW$	$\% \Delta GFCF$	$\% \Delta PAT$
Min.	-0.220886	-0.234917	-0.92941	-2.24459
1st Qu.	0.002074	-0.010327	-0.01888	-0.07221
Median	0.019139	0.004120	0.02019	0.01429
Mean	0.016992	0.002974	0.01648	0.03856
3rd Qu.	0.036339	0.017238	0.06102	0.14545
Max.	0.432202	0.358514	1.04884	3.76662

The proximity between the median and the mean regarding the log changes of the gross value added ($\% \Delta GVA$) denote a weakly skewed distribution. First and third quartiles are close from the central statistics and reinforce this guess. Only the maximum (and the minimum) emphasize the existence of very fast (and respectively very slow) growing regions that appear in sharp contrast with the situation of the bulk. The pattern repeats for the proxies of human capital ($\% \Delta HW$) and the physical capital growth ($\% \Delta GFCF$). The last column regarding patents displays the most heterogeneity and the difference between the mean and the median accordingly denotes a skew distribution.

Original CCE methods as developed in Chudik and al. (2015) [43] requires long time series (≈ 40). Because of this constraint, we focus on EU-15 for which we have the longest series. We now turn to the implementation results. Results on the two-step procedures are gathered in Section 2.4. Results on the one-step procedure are to be found in Section 2.5.

2.4 Implementation results of the two-step procedure

Section 2.4 describes the results while implementing the two-step approach. The procedure follows 4 steps :

1. Evaluate the intensity of the cross-sectional dependence phenomena using CD (or α).
2. In the case of occurrence of some strong form of dependence, proceed to de-factoring of the observations using cross-sectional averages (CCE), Common Factors or Spatial Filtering.
3. Re-evaluate the intensity of the remaining cross-sectional dependence.
4. Treat for the "interactive heterogeneity" with a dynamic SAR model

We detect strong cross-sectional dependence which justify the comparison of three alternative methods : CCE models, Common Factors and Spatial Filtering methods (section 2.4.1). Up to this point, cross-sectional dependence (CSD) tests confirms the remainings of a weak form of CSD that call for spatial treatments in section 2.4.2. Intermediate economic results are displayed in subsection 2.4.3.

2.4.1 Strong form of CSD and de-factoring procedure

To investigate the degree of cross-sectional dependence in gross value added data, we compute the CD statistic as defined by Pesaran (2004) [160] without de-factoring. We obtained $CD_{\% \Delta GVA} = 362.141$ with a 0 p-value. The test outcome suggests a high degree of cross-sectional dependence that could be due to the presence of common factors and justify our use of de-factoring procedures. The α statistic confirms the conclusion : $\alpha_{\% \Delta GVA} = .965$ whose confidence interval is $[.899; 1.03]$. Over .75, one can conclude to the presence of strong cross-sectional dependence which justify the following treatments.

Cross-sectional averages

The strong form of cross-sectional dependence can be modeled using observed (cross-sectional averages) or unobserved common factors (using principal components). In a first instance, using cross sectional averages we compute the following model :

$$y_{it} = \alpha_{it} + \beta_{1it}l_{it} + \beta_{2it}k_{it} + \beta_{3it}r_{it} + \alpha_{2it}\bar{y}_t + \boldsymbol{\alpha}_{3it}\bar{\mathbf{x}}_t + \xi_{it}$$

where $\bar{y}_t = N^{-1} \sum_{i=1}^N y_{it}$ and $\bar{\mathbf{x}}_t = \begin{pmatrix} N^{-1} \sum_{i=1}^N l_{it} & N^{-1} \sum_{i=1}^N k_{it} & N^{-1} \sum_{i=1}^N r_{it} \end{pmatrix}$ account for dependent and independent cross-sectional averages.

Thus, de-factored residuals resulted from the following :

$$\xi_{it} = y_{it} - (\alpha_{it} + \beta_{1it}l_{it} + \beta_{2it}k_{it} + \beta_{3it}r_{it} + \alpha_{2it}\bar{y}_t + \boldsymbol{\alpha}_{3it}\bar{\mathbf{x}}_t) \quad (2.8)$$

x_t have been considered in order to control for some form of dependence between independent variables and the residual term.

Common factors

A second way to account for the strong form of cross-sectional dependence is the factor models. The main issue in this case is to determine the appropriate number of common factors at stake. Bai and Ng (2002)[11] 's information criteria allows to do so. Following the literature (Ertur and Musolesi (2016) [75] App.A), we compute all the information criteria with a particular attention to the IC2 and BIC3 criteria that are expected to minimize the risk of overestimating the number of factors. In our case, IC2 is expected to dominate the other measures.⁵ We allow for a maximum number of 20 factors. The only criteria that indeed, differ from the maximum we have settled are the IC2 and BIC3 which respectively detect 5 and 1 factors. Following the theoretical guideline, we account for 5 common factors in a model of the form :

$$y_{it} = \boldsymbol{\gamma}_i' \mathbf{f}_t + \varepsilon_{f,it}$$

⁵BIC3 perform better when N and T are small or roughly the same size, which is not our case.

where f_t are the unobserved factors and y_{it} have been first-differentiated. As previously (equation 2.8), residuals are obtained thanks to an ordinary least squares regression :

$$\xi_{it} = y_{it} - (\alpha_{it} + \beta_{1it}l_{it} + \beta_{2it}k_{it} + \beta_{3it}r_{it} + \gamma_i f_t)$$

Spatial Filters

The third way to treat for the strong form of cross-sectional dependence is the spatial filtering method.

$$y_{it} = \gamma'_{s,i} (sf)_{s,t} + \varepsilon_{f,it}$$

Once again, the relevant number of spatial filters to be integrated is an issue as the theory is not clear about it. Relevant eigenvectors are selected based on their (absolute) eigenvalues, used a proxy to the share of autocorrelation eigenvectors treat for. Not being very restrictive about this criteria ⁶, we obtain numerous filters. Up to the fifth one eigenvectors are empty for many years and integrating it in the OLS regression would restrict the sample size. To preserve a balanced panel, we limit ourselves to 4 filters.

Residuals' cross sectional dependence

On this basis we evaluate the level of cross-sectional dependence of the residuals respectively extracted from the CCE, the Common Factor and the Spatial Filtering regressions.

⁶Have been excluded eigenvectors with eigenvalues of an absolute value smaller than 10^{-5}

	α	Std.Error	95% Conf. Interval	CD	p.value
CCE Residuals	.378	.024	[.331 ; .426]	2.74	0.006
Common Fact. Residuals	.578	.017	[.545 ; .610]	16.9	0.00
Spatial Filt. Residuals	.775	.0353	[.706 ; .845]	110.17	0.00

Table 2.2: Estimation of Cross-sectional Exponent : α (Bailey and al. (2018)) & CD (Pesaran (2015))

For the reminder $0.5 < \alpha < 1$ corresponds to a strong cross-sectional dependence while the null of the CD test postulates for 'no-cross-sectional dependence'. According to α , the only treatment that performed well enough to withdraw the strongest form of cross-sectional dependence is the Common Correlated Effects model. For both, Common Factor and Spatial Filtering treatments, a strong form cross-sectional dependence remains in residuals. We fail to illustrate the equivalence between CCE methods and Common Factors (and Spatial Filtering) methods Bailey and al. (2016) [14] have been using.

2.4.2 Weak form of CSD and spatial models

Considering that the Common Correlated Effects model has been the best option in treating for the strong form of cross-sectional dependence, we would be using those residuals only in the second part of the procedure namely the spatial treatment(s).

Estimation of spatial connections

The spatial analysis requires computing matrices of spatial connections (W). Classically, we started with matrices of distance based on contiguity measures. Those matrices, noted W_d , are symmetric and identify as 'neighbors regions' lying within a radius of d kilometers. Neighbors regions are notified by 1 for elements (i, j) and (j, i)

while non-neighbors regions are marked 0. Diagonal entries take a value of 0 as it is considered that one region cannot be a neighbor of itself. We considered 3 options in building W_d matrices : a radius of 50 km, a radius of 100 km, a radius of 200 km resulting into W_{50} , W_{100} , W_{200} .

According to Bailey and al. (2016) [14] we also consider a spatial weight matrix based on pair-wise correlations. If the previous W_d did not allow to differentiate positive and negative relationships linking regions, correlation based matrices allow to integrate this information. Using residuals extracted either from the CCE estimation either from the factor estimation, W_ρ is built such

$$\hat{w}_{ij,\rho}^+ = \hat{w}_{ij,\rho} I(\hat{\rho}_{\xi,ij} > 0) \text{ and } \hat{w}_{ij,\rho}^- = \hat{w}_{ij,\rho} I(\hat{\rho}_{\xi,ij} \leq 0)$$

where

$$\hat{\rho}_{\xi,ij} = \frac{\hat{\sigma}_{\xi,ij}}{\sqrt{\hat{\sigma}_{\xi,ii}\hat{\sigma}_{\xi,jj}}} \text{ and } \hat{\sigma}_{\xi,ij} = \frac{1}{T} \sum_{t=1}^T \hat{\xi}_{it}\hat{\xi}_{jt}$$

Under this configuration, each element $w_{ij,\rho}^+$ (of let's say W^+) is the product of the correlation index $\hat{\rho}_{\xi,ij}$ (transformed into 1 if positive) and $w_{ij,\rho}$. $\hat{\rho}_{\xi,ij}$ settled to 1 if it happens to be significant when corrected of the multiple testing issue (using Holm's procedure).

We can quantify the closeness of two types of matrices by looking at the statistical association between them. The symmetry of the matrices allows us to focus on the lower triangular elements. According to Bailey and al., we build contingency matrices of the form

$$\begin{pmatrix} n_{11} & n_{10} \\ n_{01} & n_{00} \end{pmatrix}$$

- n_{11} accounts for the number of times the configuration $W_\rho = 1$; $W_d = 1$ occurs (either W_ρ^+ or W_ρ^-)
- n_{00} accounts for the number of times the configuration $W_\rho = 0$; $W_d = 0$ occurs
- n_{01} accounts for the number of times the configuration $W_\rho = 0$; $W_d = 1$ occurs

- n_{10} accounts for the number of times the configuration $W_\rho = 1$; $W_d = 0$ occurs

$$n_{11} + n_{00} + n_{01} + n_{10} = N(N - 1)/2.$$

The Pearson's chi squared statistic defined as

$$\chi^2 = \frac{1}{2}N(N - 1) \left[\sum_{i,j=0}^1 \frac{n_{ij}^2}{(n_{i.} + n_{.j})} - 1 \right]$$

is leant against a χ^2 distribution, in order to estimate how similar are the matrices. We simply report the χ^2 statistic

	W_{50}	W_{100}	W_{200}
$W_{\rho,CCE}^+$	11.29	9.52	5.13
$W_{\rho,CCE}^-$	100.76	146.61	238.75

The χ^2 statistics are all significant. Matrices denoting positive relationships yields low level statistics compared to negative relationships' cases. The correlation matrices extracted from CCE residuals yields high χ^2 statistic in relation with W_{200} .

Spatial treatments : Dynamic Spatial SAR model

The second step operates the spatial treatment through Dynamic Spatial SAR models. Bailey and al. (2016) [14], have been estimating an heterogeneous spatio-temporal model allowing for coefficients to vary on an individual basis while we restrict ourselves to a "traditional spatial model" where coefficients do not display individual heterogeneity.

Still, do we maintain the heterogeneity based on positive versus negative correlation using the correlation matrices built on de-factored outputs, extracted from 'step one' regressions. Matrices have been row-standardized.

Regarding the dynamic dimension, we limit ourselves to a unit lag order (temporal). Formally :

$$\hat{\xi}_t = \alpha_{\xi}^+ + \lambda_1 \hat{\xi}_{t-1} + \psi_0^+ \hat{W}_{\rho}^+ \hat{\xi}_t + \psi_1^+ \hat{W}_{\rho}^+ \hat{\xi}_{t-1} + \zeta_t^+$$

$$\hat{\xi}_t = \alpha_{\xi}^- + \lambda_1 \hat{\xi}_{t-1} + \psi_0^- \hat{W}_{\rho}^- \hat{\xi}_t + \psi_1^- \hat{W}_{\rho}^- \hat{\xi}_{t-1} + \zeta_t^-$$

\hat{W}_{ρ}^+ and \hat{W}_{ρ}^- respectively are the correlation matrices representing links between regions based on their de-factored outputs such that $\hat{W}_{\rho} = \hat{W}_{\rho}^+ + \hat{W}_{\rho}^-$.

2.4.3 Economic results of the two-step approache(s)

Common Correlated Effects model

Table 2.3: Results on Common Correlated Effects model (pooled)

	Coefficient Est.	Std.Error	z-value	$Pr(> z)$
%ΔHoursWorked	0.3254	0.0335	9.7181	$(< 2.2e^{-16})^{***}$
%ΔGFCapitalFormation	0.1307	0.02312	5.6541	$(1.567e^{-8})^{***}$
%ΔPatentStock	0.00033204	0.00097867	0.3393	0.7344

Residuals	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
	−0.2050	−0.010910	0.0002143	0	0.0112800	0.2660

Total Sum of Squares	9.2777
Residual Sum of Squares	4.0691
HPY R-squared (Holly Pesaran Yamagata [110])	0.48462

Estimates related to input factors are significant, but the coefficient attached to patent stocks is not. This configuration goes along the findings emphasized in Eberhardt and

al. (2013) [70] that did not find significant effects for the knowledge variable. Of interest, summing over our coefficients keeps us far from 1 that is, far from the constant returns assumption usually held and empirically verified in growth accounting framework. We raise two potential explanations : either did cross sectional averages catch a large share of variance, either spatial effects remaining in residuals have important impacts. We turn to spatial regressions to control for the second assumption.

Dynamic Spatial Autoregressive (SAR) model

Table 2.4: Results on dynamic Spatial Autoregressive (SAR) model

	W_{ρ}^{+}	W_{ρ}^{-}	W_{200}
	$\hat{\xi}_t$		
$\lambda_1 \hat{\xi}_{t-1}$	-0.144*** (-11.85)	-0.267*** (-21.84)	-0.121*** (-10.01)
$\psi_0 W \hat{\xi}_t$	0.479*** (9.74)	-10.65*** (-417.42)	0.399*** (21.11)
$\psi_1 W \hat{\xi}_{t-1}$	0.723*** (10.61)	-8.331*** (-131.18)	0.0385 (1.43)
Intercept	0	0	0
Observations	6664		

t statistics in parentheses

*($p < 0.05$), **($p < 0.01$), ***($p < 0.001$)

$\hat{\xi}_t$ are the residuals extracted from the 'Common Correlated Effects' specification. W_{ρ}^{+} is the matrix of positive correlation defined in Sect.2.4.2 ; W_{ρ}^{-} is the matrix of negative correlations defined in

Sect.2.4.2 ; W_{200} is the matrix of geographic proximity. W_{200} identify as neighbors regions lying within a radius of 200 km.

Economically, the residuals $\hat{\xi}_t$ account for the regional output net of classic determinants (labor, capital, knowledge stock) and of omitted variables defined on some form of "classic" heterogeneity. Somehow those residuals thus represent global spatial effects linking regional outputs. All of the estimates are significant at the 1% level. This suggests a reasonably rich temporal and cross-sectional dependence in regional outputs even after stripping them of strong factors.

With regard to the cross section dynamics, contemporaneous positive spillovers effects ψ_0^+ have a smaller magnitude than their negative equivalent ψ_0^- : 0.48 and -10.65 respectively. In both cases, estimates are correctly signed such that positive correlation matrix emphasizes a positive effect of lagged spatial effects and negative correlation matrix enhances negative effects. The strong differential in the magnitude of effects is faded in a joint configuration. Considering the regression that uses W_{200} , ψ_0 appears quite small compared to the strong negative effect at stake in the W_ρ^- configuration. The explanation we provided is that the high number of non-significant positive relationships linking regions fades the negative relationships that dominates when only considering correlation corrected of the multiple testing issue : small magnitude positive relationships outnumber negative ones and fades them completely when aggregating.

2.5 Implementation results of the one-step procedure

2.5.1 Implementation details on the GMM estimator

Table 2.5 summarizes the estimation of model (2.6) based on $W = W_{200}$ that considers neighbors within a 200km radial distance. In columns (1 – 3), the Durbin terms are excluded and the unobserved factors are proxied by cross-sectional averages of both dependent and regressors across all NUTS2 regions. We also introduced national cross-

sectional averages of both independent and dependent variables on a contemporaneous fashion to accommodate the existence of unobservable factors at this scale. The first columns put into evidence the improvements while moving from a 2SLS toward a GMM estimator. The 2SLS estimator provides the right values of parameters but the GMM procedure shrinks variances and brings to light two significant effects. Neighbors' added value growth has a negative impact on one own added valued growth which denotes the existence of some form of competition between regions. The small magnitude regarding the R&D output growth is somewhat coherent with some of the findings presented in Eberhardt and al. (2013) [70].

Our estimations are evaluated regarding how efficiently strong cross-sectional dependence has been withdrawn and regarding the goodness of fit as displayed by \bar{R}^2 . \bar{R}^2 fits in the presence of unobserved factors as suggested by Holly and al. (2010)[110]. It is computed such as :

$$\begin{aligned}\bar{R}^2 &= 1 - \hat{\sigma}_{res}^2 / \hat{\sigma}_{tot}^2 \\ \hat{\sigma}_{tot}^2 &= [N(T-1)]^{-1} \sum_{i=1}^N \sum_{t=1}^T (y_{it} - \bar{y}_{i.})^2 \\ \hat{\sigma}_{res}^2 &= [N(T - k_{cs} - k_d) - k_z]^{-1} \sum_{i=1}^N (\mathbf{y}_{i.} - \mathbf{Z}_{i.}\hat{\boldsymbol{\delta}})' \bar{\mathbf{M}} (\mathbf{y}_{i.} - \mathbf{Z}_{i.}\hat{\boldsymbol{\delta}})\end{aligned}$$

$\bar{y}_{i.} = T^{-1} \sum_{t=1}^T y_{it}$; $\mathbf{y}_{i.} = (y_{i1}, y_{i2}, \dots, y_{iT})'$; $\mathbf{Z}_{i.} = (\mathbf{y}_{i.}^*, \mathbf{X}_{i.} \dots)$ is a $T \times k_z$ matrix of regressors and k_d is the number of observed factors. $\bar{\mathbf{M}}$ is the de-factoring matrix of $T \times k_{cs}$ dimension. For the reminder, $\alpha = .5$ marks the limit between the occurrence of weak ($< .5$) and strong ($> .5$) forms of cross-sectional dependence. We have been walking on this limit which show the relevance of the treatment at stake. According to those measures, columns (4 – 5) provide reliable answers.

Table 2.5: Results on dynamic GMM estimators ; W_{200}

	2SLS	Best 2SLS	GMM (1)	Durbin
[W \times % Δ GrossValueAdded]	-0.126	-0.016	-0.1254***	-0.266***
Variances	(7.9e ⁴)	(11.34)	(4.21e ⁻¹)	(1.18e ⁻¹)
[% Δ HoursWorked]	0.226	0.266	0.226	0.3231
Variances	(1.84e ⁴)	(9.6)	(5.86e ⁻²)	(6.946e ⁻³)
[% Δ GFCapitalFormation]	0.099	0.110	0.099	0.108
Variances	(9.46e ²)	(2.79)	(3.488e ⁻³)	(1.506e ⁻³)
[% Δ Patents]	-0.00055	-0.00014	-0.00055***	-0.00173***
Variances	(2.75e ⁻²)	(6.42e ⁻³)	(3.3e ⁻⁶)	(7.869e ⁻⁶)
[W \times % Δ HoursWorked]				0.178
Variances				(3.856e ⁻²)
[W \times % Δ GFCapitalForm.]				-0.033
Variances				(6.362e ⁻³)
[W \times % Δ Patents]				-0.00277***
Variances				(4.296e ⁻⁵)
National unobserved fact.	Yes	Yes	Yes	Yes
Lag. National unobs. fact.	No	No	No	Yes
Intercept	Yes	Yes	Yes	Yes
CD test statistic	22.23***	0.517	22.141***	-0.349
α	.59	.29	.598	0.397
95% Conf.Int.	[0.55 ; 0.62]	[0.24 ; 0.35]	[0.59 ; 0.64]	[0.368 ; 0.426]
\bar{R}^2	0.567	0.677	0.553	0.557
Observations : N=196	T=35			T=34

About Table 5 :

$\% \Delta \text{GrossValueAdded} = \log(\text{GVA})_t - \log(\text{GVA})_{t-1}$ where GVA means Gross Value Added. $\% \Delta \text{HoursWorked} = \log(\text{HW})_t - \log(\text{HW})_{t-1}$ where HW means Hours Worked such that the variable accounts for human capital. $\% \Delta \text{GrossFixedCaptialFormation} = \log(\text{GFCF})_t - \log(\text{GFCF})_{t-1}$ where GFCF means Gross Fixed Capital Formation such that the variable accounts for physical capital. W is the spatial matrix that define as neighbors regions lying within a radius of 200 km. National unobserved factors and Lagged National unobserved factors are computed using the cross-sectional averages of the dependent and independent variables at the national scale.

Table 2.6: Instruments

2SLS Best 2SLS GMM(1)	(X, WX, W^2X)	
Durbin-GMM	$(X, WX, W^2X, W^3X, \dots, W^{10}X)$	$Z_{(5:T)}$

X designate the vector of explanatory variables displayed in levels (non first-differenced). Z has been defined according to

$$Z = \text{diag}(\tilde{W}_N \text{GVA}_0, \tilde{W}_N \text{GVA}_1, \dots, \tilde{W}_N \text{GVA}_{T-2})$$

$\dim(Z) = (N(T-1) \times T(T-1)/2)$ and $\tilde{W}_N = W_N + W'_N$ where GVA_0 accounts for the vector gathering non-differenced values gross value added in 1980 (t=0).

Care must be taken when interpreting the estimates of independent and Durbin terms as they do not directly points to the marginal effects of variables on added value growth. An important feature in spatial autoregressive models is that a change in an explanatory variable of a unit will affect not only the dependent variable itself but also the dependent variables of other NUTS. In the first instance, one refers to the direct effect while in the second instance to the spillover/ indirect effect. To calculate those

effects, we refer to LeSage and Pace (2009) [137] where

$$Sr(W) = V(W)(I_n\beta_r + W\theta_r)$$

$$V(W) = (I_n - \rho W)^{-1}$$

such that

$$Direct = (1/N) \text{tr}(Sr(W))$$

$$Total = (1/N) \iota'_n Sr(W) \iota_n$$

$$Indirect = Total - Direct$$

To provide for the confidence interval of those effects, we bootstrap the standard errors over 1000 iterations. Those results are displayed in Table 7.

Table 7 displays the direct, indirect and total spatial effects. The most striking result of this table is the negative direct, indirect and total effects on patents. Line 6 of Table 7 displays results for the dynamic, Durbin GMM estimation and we observe that the 3 effects are negative which is further supported by the 95% confidence intervals of those coefficients presented below.

Table 2.7: Average direct and indirect effects

Variables	Direct	Indirect	Total
$\% \Delta HoursWorked$	0.3207853 [0.3212535 ; 0.322993]	0.07539821 [0.07552779 ; 0.0824766]	0.3961835 [0.3975112 ; 0.4044576]
$\% \Delta GFCapitalForm.$	0.1079728 [0.1077938 ; 0.1081812]	0.003924607 [0.002899329 ; 0.004209673]	0.1118974 [0.1108958 ; 0.1121019]
$\% \Delta Patents$	-0.001677091 [-0.0016776 ; -0.001676]	-0.001883453 [-0.001889 ; -0.001880]	-0.003560545 [-0.003565 ; -0.0035563]

2.5.2 Economic results of the one-step approach

The negative sign on patents makes some echoes to recent works in growth theory. Those works address the question of over/under-investments in R&D compared to the optimal level. Comin(2004)[50], Alvarez-Pelaez and Groth (2005)[5] consider that R&D investments were already close from the optimum level and Kumar (2003) [132] shows that situations of over investment are as plausible as situations of underinvestment.

Theoretically, Comin (2004) [50] formalizes two explanations. The first one addresses the role of static production externalities while the second looks at the effects of inter-temporal R&D externalities.

On the one hand, because technology is embodied in the (quality adjusted) capital stock, the higher the efficiency gain yields by an innovation the higher its social value but also the higher the profits reaped by the firm commercializing it. According to a free entry condition on the innovation market, the higher the profits induced by an innovation, the higher the disincentives for potential new entrants. Indeed, the raise of the innovator's markup results in a higher price of the product on the market and, in turn, shrinks competitors' markups. Conversely, strong production externalities and strong social value also imply a higher expected loss due to the depreciation of the market value of the innovations. The faster new technology takes over, the faster final producers will switch from one another, with, as a consequence, "a higher expected capital loss due to the depreciation of the market value of the innovations". To the extent that the first effect dominates the second, strong social value and production externalities result in a lower growth rate of technology associated with a given R&D intensity. At this point the causality is not complete toward appreciating the effect of R&D and externalities on productivity growth. Certainly, the R&D contribution to productivity growth is increasing in the social value of the innovation however, taking into account the adverse effect externalities can have on the growth rate of technology, the R&D contribution to productivity growth happens to be decreasing in the level of production externalities. Comin (2004) concludes that, as a whole, the R&D contribution to productivity growth is inelastic to the level of production externalities.

Turning to the second effect, two features oppose in producing new innovations. Indeed, the knowledge production function is conditioned by two key parameters namely λ which defines the returns on R&D investment and ϕ which defines returns on the knowledge stock. Both λ and ϕ are bounded above by 1 implying diminishing returns on respectively R&D investments and the knowledge stock. In the first case, the 'diminishing return' assumption refers to the existence of some duplication of R&D effort inducing low efficiency and weak productivity growth. As $\lambda \rightarrow 0$, the duplication effect strengthens and returns upon R&D investments diminish. In the second case, ϕ refers to some standing on the shoulders effect that entitles the gains new researchers benefit from in developing their own products using previous research. The 'diminishing return' assumption arises in the extent that as researchers keep on innovate, it becomes more and more difficult to propose something new. Intertemporal externalities exist but might not be so strong such that as $\phi \rightarrow 1$ the returns on knowledge are at their maximum : innovators benefit from previously accumulated knowledge at constant returns. Comin (2004) writes the growth rate of technology as

$$\gamma_A = \frac{\lambda}{(1-\phi)}\gamma_Y \quad \Leftrightarrow \quad \frac{\gamma_A}{\gamma_Y} = \frac{\lambda}{(1-\phi)}$$

where γ_A and γ_Y are respectively the growth rate of R&D activities and the growth rate of output.

According to this equation, the low R&D growth rate (γ_A) he calculates in the US case, indicates that R&D externalities $\left(\frac{\lambda}{(1-\phi)}\right)$ cannot be very large. The rationale is that, for a given λ , if intertemporal knowledge externalities were strong ($\phi \rightarrow 1$), a weak intensity of R&D expenditures at time t would increase TFP growth rates and reduce the costs of research. Agents would be encouraged in increasing their investments in $t+1$ which is in great opposition with how stable the intensity of R&D expenditures has been in the US case. In Europe, according to publicly available data (Eurostat), the average regional investment in R&D has only grown by 2% each year between 2003 and 2015 and should allows us to subscribe to this explanation.

As a final hypothesis to the negative coefficient we obtain on patent stocks⁷, Galor and Moav (2002) [89] suggests an "erosion effect" simply stipulated as "the time required for learning the new technology diminishes with the level of education and increases with the rate of technological change" whose impact has been found of significant importance by Kumar(2003) [132] and Tamura(2006)[187].

This interpretation however, suppose a direct link between the R&D output as accounted by patent counts and R&D investments. Danguy and al.(2009) [56] recall that patenting behaviors results from R&D efforts, research productivity, strategic behaviors and firms' will to appropriate knowledge. The well documented increasing trend to patent according to strategic incentives is a potential explanation to our results. Last decade sharp increase in patent deposits has emphasized the strategic dimension of patent deposits disregarding the true added value of the patented innovation.

2.6 Conclusion

In an already vast literature addressing the growth accounting identity, this article has tried to propose a new estimation controlling for omitted variables issues raised by mis-measurements of aggregated inputs and spatial spillovers. At the core of our interest lies the coefficients on knowledge returns as the positive yields on R&D investments have justified heavy public policies aiming at supporting firms investments and beyond regional/national growth rates.

Yet, conventional measures of labor and capital contain elements of R&D which are double-counted and might alter our conclusions to the extent that, according to Griliches, expenses in R&D should be considered by themselves in a knowledge production function and by extension in a growth accounting framework. Schankerman (1981) has shown how the double counting of R&D inputs and expenses can be considered as omitted variables. In this context, Common Correlated Effects methods have proved efficient in controlling for these, taking into account some form of heterogeneity across 'units'. However, Common Correlated Effects treat for omitted variables under

⁷first difference of the log-linearized patent stocks

the hypothesis that those fall under a cross-sectional dependence phenomenon. However, such a phenomenon is of a different nature from (spatial) network effects and public returns issues as accounted by the literature on the geography of innovation. Statistically, Ertur and Musolesi (2016) have shown that it calls for a different type of treatment as developed by the spatial econometrics literature.

In this chapter we intended to take into account both issues. First, by applying Bailey and al. (2016) two step procedure and, second by implementing Yang (2018)'s spatially, common correlated effects augmented GMM estimator. This drove us to the curbed results that European economies might be over investing in R&D. Indeed, according to our results the 'direct' effect of investing in R&D for a region is negative and so is the spatial indirect effect. The small magnitude of the effects we observe gives credit to the complex procedure we have been through to obtain reliable coefficients, treating for cross-sectional dependence. While these findings echoes a supportive theoretical literature, we could not omit that the fast increasing fashion of patenting could also induce a decreasing 'real' added value embeds in each new deposits. Using R&D expenses, available on long time periods would be of much interest in challenging our results.

2.7 Appendix

2.7.1 Data Management

Cambridge Econometrics dataset

About the series extract from Cambridge Econometrics i.e (i) gross added value, (ii) (physical) capital formation, (iii) hours worked (human capital), most of the dataset has already been cleaned. We simply defined the geographic frontier of the sample along the boundaries of EU-28 excluding Norway and colonial empires' dependencies such as French overseas departments and territories and Spanish islands.

The common factor analysis required a fully balanced panel which imposes withdrawing regions that are part of the ex-Soviet bloc countries. Historically, those information

of those regions has only been collected from 1990 to nowadays. Including them and maintaining the requirement of a balanced panel would induce a too important shrinkage in series' time dimension.

Patent data from Eurostat

About the patent series extracted from Eurostat. We first harmonized those geographic boundaries with those previously defined for Cambridge Econometric' series. The main issue is that patent series stop in 2012 while the dynamic version of CCE estimators require a time dimension as close as possible from 40 periods. On this basis, we thus attempt to reliably extrapolate the data we dispose of. To do so, each NUTS2 represents a time series running from 1980 to 2012 has been extended using Gaussian process (GP) techniques.

The GP approach is a non-parametric approach that finds a distribution over the possible functions that are consistent with the observed data. It begins with a (Gaussian) prior and adapt on the basis of the available information. "A GP assumes that $p(f(x_1), \dots, f(x_N))$ is jointly Gaussian with some mean $(\mu(x))$ and covariance $\sum(x)$ given by $\sum_{ij} = k(x_i, x_j)$ where k is a positive definite kernel function. The key idea is that if x_i and x_j are deemed by the kernel to be similar, then we expect the output of the function at those points to be similar, too".⁸.

GP results have been evaluated regarding more "classic" time series extrapolation algorithms.

The first of them has been Hyndman and Khandakar algorithm for ARIMA models. ARIMA models are some conjunction of autoregressive and moving average specifications. The use of ARIMA models to forecast is 'usually considered subjective and difficult to apply'. Hyndman and al. is a recent solution (there has been several previous alternatives) to implement automatic ARIMA forecasting. First, the model has to be classified into either a seasonal or nonseasonal case. The occurrence of seasonality conditions the necessity of differencing and the value of Akaike information criteria

⁸Kevin Murphy ; Machine Learning: A Probabilistic Perspective

(AIC) for dissimilar levels of differencing are not comparable. Once seasonality has been determined by KPSS unit root test or Canova-Hansen test, and the differencing order estimated, autoregressive and moving average parameters can be chosen to minimize the AIC. The forecasts resulting from each model (one for each region) recursively allow to fit the missing data.

A reliable alternative to ARIMA's models are exponential smoothing models. The two classes of models overlap but are not fully substitutable. For instance, the linear smoothing models are special cases of ARIMA models but non-linear exponential smoothing have no ARIMA counterpart. The other way around many ARIMA models have no exponential smoothing equivalents.

The exponential smoothing models are non-stationary : models with seasonality or non-damped trend have 2 unit roots and otherwise, non-seasonal models with no trend or damped trend have one unit root. Thus if a stationary model is required, ARIMA models are the best option. Furthermore, exponential smoothing models can be non-linear and thus better correspond to series with non linear characteristics including heteroskedasticity.

Extrapolating 2012, we have been able to compare the mean squared error for each algorithm. GP, by far, present the smallest MSE which justify our preference.

Data have been extrapolated from 2012 to 2016 to allow for calculating patent stocks.

2.7.2 Panel unit root tests

We directly jump to second-generation panel unit root tests allowing for cross-sectional dependence that arise as a major bias in first generation tests. The occurrence of some weak form of cross-sectional dependence can be addressed with some simple correction procedures but the presence of strong cross-sectional dependence cause (first generation) test statistics to diverge. Second generation tests handle this issue not only considering individuals' interdependencies as part of residual dependencies. They assume these can be due to the presence of common factors that require some forms of

treatments before testing the presence of unit root in idiosyncratic residuals.

We will take into consideration 4 tests : Bai and Ng (2004) [12] , Moon and Perron (2004) [150] and Pesaran (2003) [159] and Reese and Westerlund (2015) [167] ⁹.

In order to treat for common factors, Bai and Ng suppose a model of the form

$$y_{it} = D_{i,t} + \lambda_i' F_t + e_{i,t}$$

where $D_{i,t}$ is a polynomial function of time, F_t are the common factors, λ_i the attached parameters and $e_{i,t}$ the residual terms. The procedure relies on the fact that common factors estimators can reliably be obtained disregarding the e_{it} being stationary or integrated of order 1 ($I(1)$). Using first-differences in a principal component analysis, λ_i and consequently $e_{i,t}$ can be estimated. Both factors and residuals can then be tested for the occurrence of unit roots using Fisher style tests ($Z_c \sim \mathcal{N}(0,1)$) or Stock and Watson [184] style statistics (MQ_f and MQ_c).

In our case, Z_c statistics are quite high and compared to the Normal distribution allow to conclude to the occurrence of non-stationarity both regarding idiosyncratic components and common factors. MQ_f and MQ_c statistics nuance those first evidences. The statistics suggests that the occurrence of non-stationarity is rather the consequence of such of phenomena primarily impacting common factors rather than idiosyncratic components.

To further investigate the question, we turn to Moon and Perron (2004) [150] who don't allow separately testing for the occurrence of unit roots in common and/or idiosyncratic components. Their set-up considers an autoregressive model with individual fixed effects but where residuals also have a factor structure :

$$\begin{aligned} y_{i,t} &= \alpha_i + y_{i,t}^0 \\ y_{i,t}^0 &= \phi_i y_{i,t-1}^0 + \mu_{i,t} \\ \mu_{i,t} &= \lambda_i' F_t + e_{i,t} \end{aligned}$$

⁹Hurlin et Mignon (2004) [?]

Under the assumptions that the number of factors is known and $e_{i,t}$ are not correlated in the individuals' dimension, one can test the occurrence of the unit root testing $\phi = 1$ under the null hypothesis (non-stationarity) and $\phi < 1$ under the alternative. To do so Moon and Perron define two statistics t_a and $t_b \sim \mathcal{N}(0, 1)$. Working on demeaned data (in accordance with the previous test), our results are in favor of "accepting" H_0 and concluding to the occurrence of non-stationarity.

Finally, Pesaran (2003)'s [159] option doesn't require transforming data. His idea is rather to augment a standard ADF regression with cross-sectional averages aimed at handling the cross-sectional dependence.

$$\begin{aligned}\Delta y_{i,t} &= \alpha_i + \rho_i y_{i,t-1} + u_{i,t} \\ u_{i,t} &= \gamma_i \theta_t + \varepsilon_{i,t}\end{aligned}$$

where $\alpha_i = -\rho_i \gamma_i$ and $\varepsilon_{i,t}$ i.i.d $(0, \sigma_\varepsilon, i^2)$ such that

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + v_{i,t}$$

For each individual i , the estimation allows building the t-statistic $t_i(N, T)$ in order to test for the occurrence of a unit root. Those statistic are aggregated in an average measure such

$$CIPS(N, T) = \frac{1}{N} \sum_{i=1}^N t_i(N, T)$$

CIPS statistic drives us to similar conclusions as the previous tests and idiosyncratic components appear non-stationary.

The main issue raised by CIPS test ¹⁰ is that, in the case of y_{it} being a unit root non stationary process, the law followed by the statistic is highly non-standard which makes implementation complicated. Precisely, it becomes necessary to tabulate critical values for each configuration of (N, T) but also to truncate the test statistics to ensure finite moments. Moreover, the test suppose the same order of integration in common and idiosyncratic components, only testing for the latter. Bringing in advantages of both

¹⁰(and its Sargan-Bhargava style extension by Pesaran and al. (2013))

Bai and Ng’s PANIC procedure and cross-sectional models from Pesaran, Reese and Westerlund [167] apply the PANIC procedure to a cross-sectional augmented model rather than a common factor model. The procedure induces ”rejecting” the null hypothesis of occurrence of a unit root process for the idiosyncratic components while common factors appear non-stationary, as suggested in our primal tests.

In the framework of a dynamic knowledge production, whose core-regressors are at the origin of the non stationary process, it is crucial to exclude the case of a spurious regression, insuring that core-regressors and residuals are not integrated of the same order ¹¹. Pedroni’s [160] test aims at detecting unit roots in the error term of a long-run representation of the form :

$$y_{it} = \alpha_i + \delta_i t + \beta_{1,i} l_{it} + \beta_{2,i} k_{it} + \beta_{3,i} r_{it} + \underbrace{\rho_i \varepsilon_{it-1} + u_{it}}_{\text{tests' object}}$$

under the null hypothesis of stationary residual terms. The test issue 4 statistics v , ρ , t and adf ¹² under both pooled and mean group formats, all $\sim \mathcal{N}(0, 1)$

Stat	Panel	Group
v	-1.93^{**}	
ρ	0.13	2.1^{**}
t	-2.44^{***}	$-3, 13^{***}$
adf	1.06	1.04

To the extent that our setting is closer from a configuration where T is fixed and N more important, our conclusion should more heavily rely on t statistics that gives credit to the null hypothesis of stationary residual terms.

We also consider Westerlund (2007) [194] extension of cointegration tests in panel

¹¹Hurlin et Mignon (2007) [113]

¹²respectively corresponding to a non-parametric statistic under the form of variances ratio, a Phillips-Perron ρ type statistic, a Phillips-Perron t type statistic, a Dickey Fuller t type statistic

ECM¹³ heterogenous representations. Pedroni's allowed for heterogeneous unit root processes from one individual to another. Multiple co-integration tests do not require knowing all of the variables at stake in the co-integration issue and allows detecting several co-integration relations without *a priori* knowing its order.

The framework supposes

$$\Delta y_{it} = \delta_i t + \alpha_i (y_{i,t-1} - \beta_i x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=-q_i}^{p_i} \gamma_{ij} \Delta x_{i,t-j} + e_{it}$$

and the test addresses $\alpha_i = 0$ (no cointegration) under the null. "Panel" and "grouped" statistics respectively requiring homogeneity and allowing for heterogeneity, give credit to the null hypothesis of no-cointegration, in accordance with previous tests.

¹³Error Correction Model

Chapter 3

The conflicting role of commercial and technological integrations in shaping regional agglomeration : a survey

3.1 Introduction

In 1951, grounding the European Union, the creation of the European Coal and Steel Community (ECSC) has found itself at the intersection of the international trade and international relations theories. The necessity to re-build on robust foundations has pushed the logic of the terms of trade approach. It shows how protectionism is a natural Nash equilibrium in countries relations and how partners could improve their situations cooperating. Naturally, countries may find some interests in arising barriers to trade in order to lower imports and enjoy better terms of trade.¹ Incentives, aimed at counterbalancing short term gains to such strategies, are expected to progressively free trade and switch economies to superior equilibria. Accordingly, tied by adverse incentives, partners are spurred to lower their tariffs and non-direct barriers to trade in order to reduce costs in accessing each other markets. The theory has spewed world-wide and resulted in numerous Regional Trade Agreements next to the creation of the World Trade Organization promoting multilateral reduction of trade barriers. During the last seventy years, European Union members have tied even stronger links. In 1957, the treaty of Rome extended the reduction of barriers to factors of production. Those measures were expected to allow economies grasping the dynamic gains to integration. The free circulation of factors of production (capital and labor) should have induced more efficient allocations of resources to the benefit of partners.

Yet, the empirical evidences showing that countries can significantly increase their gains from trade by bowing trade policies are quite weak. For instance, Broda and al. (2006) [29] show that WTO members systematically apply higher custom duties on inelastic goods and thus deviate the Pareto equilibrium. Conversely, Bagwell and Staiger (2006)[9] test the fact that governments use trade agreements to circumvent adverse issues of the prisoner dilemma. They show that the gap between non-cooperative and negotiated tariffs augment with the volume of imports as reported before entering some WTO agreement, giving some credit to the existence of gains. Regarding Europe, Cecchini Report (1988) evaluated the cost of non-Europe (the absence of a single

¹Terms of trade are a price ratio where export prices are expressed relative to import prices. Some increase of the numerator or decrease of the denominator would induce an increase of ratio that is to say better terms of trade for the country whose national income arises.

market in Europe) as ranging between 4.3 to 6.4 % of the 1985 EU GDP. This result mainly stemmed from the reduction of cost due to increasing barriers whose lowering corresponded to a gain of 2.7% (of the 1985 GDP). Long term gains resulting from efficiency improvements thanks to the transformation of the market structure were estimated at 2.1% of the (1985 EU) GDP and expected to represent 3.7% of the GDP by 1992, supposing a perfect integration by then. Critics objected that these estimates were derived from partial equilibrium models which disregard welfare issues induced by the restructuring process and time of adjustment of production apparels.

Still recently, convergence studies at the European scale divide on the dynamic gains resulting from recent integrations. Since 2004, studies brought to light a convergence process for the new entrants but also a polarization process at the expense of non-central regions in the Old Europe (Fisher and Stumper 2008 [82]). New entrants wealth has been rapidly increasing after the integration. Simultaneously, economic resources and geography of production have sharply concentrated in the Old Europe at the benefit of the central area, well-known under the title of "Blue Banana", at the expense of its directly surrounding neighbors. On a political ground, economic tensions parallel the empowering of organizations working against further integration. The Brexit is a tawdry instance but the stream is powerful.

This chapter seeks to address the question of how barriers to exchange have shaped the spatial distribution of welfare. To answer this question, it draws on the New Economic Geography literature and the streams attached to its empirical developments. This chapter connects key contributions in order to shed light on the relation linking transport costs (in general) and welfare. What is lacking is some empirical counterparts to the theory's statement that put transport costs at the core of spatial welfare disparities.

Specifically, the first New Economic Geography (NEG) model (in Krugman 1991 [130]) has introduced, within a general equilibrium framework, the crucial role of transport costs in the mechanisms of economic activities' agglomeration. While it provides welfare insights where the classic theory limits to exogenously rationalizes the distribution of economic activities, the empirical literature has failed into emphasizing the link be-

tween trade flows and trade costs (in general). We detail the many explications that have been raised to address this issue and justify why we concur with those that suppose different components of trade costs. Indeed, this hypothesis happens to be well founded by New Economic Geography and Growth frameworks. Martin Ottaviano (1999) [145] and Baldwin, Martin, Ottaviano (2001) [18] formalized the interplay in reducing transport costs on goods and transfer costs on knowledge. In those models, the spread of pecuniary and non-pecuniary externalities condition the spatial allocation of activities and the welfare outcome. Endorsing the theoretical statement we suppose that to some extent, transport costs on goods and transfer costs on ideas can be accounted for by quantifying the externalities they constrain. The empirical literature has addressed the link between agglomeration and Marshallian externalities to light up the question. Actually, evidences are scarce or undermined by estimation issues. One may find a way out in considering how superficial the treatment of externalities has been so far. Gorin (2016) [91] emphasizes that the knowledge externalities are not just "in the air" and should be understood as embedded in people interactions and labor movements. A recent strand of the international trade literature uses complex quantitative spatial models considering labor force movements over space and time. However, this answer is mainly theoretical. Empirically, studies have turned to natural experiments to propose new ways to identify welfare effects out of the restrictive hypotheses of the framework of gravity equations.

This review is structured along three sections. Section 3.2, subsection 3.2.1 introduces the role of transport costs (in general) on agglomeration and regional welfare from the Old Trade theory to the New Economic Geography frameworks. Subsection 3.2.2 investigates the empirical answer from gravity equations and the paradox of distance researchers faced in evaluating the relationship between agglomeration and transport costs looking at the relationship between transport costs and exchange flows. Section 3.3, subsection 3.3.1 presents the theoretical foundations underlying the hypothesis of two components of transport costs (namely transport costs on goods and transfer costs on ideas) playing in opposite directions upon agglomeration. Subsection 3.3.2 considers the answers of the empirical literature at the regional scale looking at the spread of externalities as flows revealing the level of transport on goods and transfer costs

on ideas. Finally Section 3.4 turns to quantitative spatial models and studies using natural experiments at the methodological frontier toward identifying the gains from integration(s).

3.2 Space and Trade

Grounded on the New Trade Theory, the first generation of New Economic Geography models (NEG) provided an endogenous explanation to disparities and built the foundation that allowed a better understanding of economic geography. The *Old Trade* theory focused on how endowments conditioned international trade. In those frames, first nature advantages explain exchanges and, in an *ad-hoc* way, the repartition of wealth. NEG models introduced a spatial dimension created by the tension opposing transport costs (in general) and increasing returns to scale that conditions market size and the intensity of exchanges between economies. Those models have grounded the central role of transport costs in understanding welfare disparities in a globalized world.

3.2.1 The central role of trade costs in the theoretical relationship linking trade and agglomeration

Initially, *Old trade theory*, which gathers classical and neoclassical strands, ended up to the conclusion that trade was triggered by technology or factorial endowments differences. In *à la Ricardo* version (classical), differences in technology explain discrepancies in relative costs of production and trigger incentives to intersectoral trade. In the Hecksher-Ohlin's version (neoclassical), comparative cost advantage arise from differences in production factor endowments. Under the additional assumptions of constant returns to scale and perfect competition, free trade situation lowers the marginal cost of consumption and overtake the autarky equilibrium. The New Trade Theory (NTT) gives up the inter-sectoral explanation to focus on intra-industry trade i.e the simultaneous export and import of 'similar goods', away from the technological and endowments 'explanations'. In his first NTT paper, Krugman (1979) [128] used the Dixit-Stiglitz framework for two symmetric economies. Doing so he showed that both consumers and producers would gain from exchanges. Exploiting economies of scale for the former goes

hand in hand with varieties' expansion for the latter. In those circumstances, gains from trade arises from profitable specialization in a cost structure, in relative independence with first nature advantages (either technology or endowments' advantages). On the second hand, Krugman (1980) [129] shows how the imperative of transport costs economies induces the development of differentiated industrial goods in proximity of the target market and thus some concentration of production at the benefit of one region. As stated by Anas, Arnott and Small (1998) [6], non-homogeneous space at the roots of comparative advantage theories introduced the relevance of location but only by assumption and without considering interdependence between geography and economics. At this point, the NTT gathered many elements that allowed Krugman to proceed endogeneizing the determinants of industry location and introducing space in international trade theory inducing new insights on the distribution of wealth across territories.

The NEG core model developed in Krugman (1991) [130] has 2 sectors namely agriculture (A) and manufacturing (M), both located into two regions. Both sectors employ a fixed share of workers as the only production factor. In turn, wages are the only source of aggregate income for the consumers that spend either on manufactured or on agricultural products. The agricultural sector produces a homogeneous good, in perfect competition, under the law of constant returns to scale. Conversely, the manufacturing sector is structured according to the Dixit-Stiglitz monopolistic competition, where each firm produces a variety that it partially sells on the domestic market and partially exports. While exporting, the firm must acquit iceberg transport costs calculated as a share of the transported good that is expected to melt away while shipped. The final crucial assumption is that manufacturing workers are allowed to relocate from one region to another (for stability reasons, agricultural ones are not). The workforce mobility (conditioned by real wage differential) allows the demand to shift which drag production toward the most populated area. Indeed, in order to save transport costs, firms will rather locate close from the biggest market. Because of the spatial concentration of many competitors, manufacturing prices will drop, real wages will raise and both will constitute even better reasons for workers to migrate towards the largest region. The model considers three types of equilibrium : the symmetry mix

or complete agglomeration of manufacturing activities in one region or the other. In this frame, transport costs and increasing returns to scale are the variables that give space a dimension and make it crucial. If transport costs are prohibitively high, both regions will evolve in autarky, each producing manufactured and agricultural goods for its own market. When transport costs fall over a certain threshold, the symmetric equilibrium becomes unstable as any firm entering the foreign market triggers workers' migration. Finally, the complete removing of transport costs makes location irrelevant as any markets can be served from any place at no costs.

The great contribution of NEG models has been to tackle the question of how to deal with agents mobility (firms and workers) while endogenizing the size of the market. Transport costs and increasing returns to scale have been proved at the core of the process. However, trade theory deals overall with the question of how international trade conditions the allocation of economic activity and gives few insight on the dynamic of economic growth. On the growth theory side, Solow's seminal model has grounded approaches to the process of growth and somehow integrated distance through some considerations on the existence of heterogeneity. Basically, Solow's model [183] considers that two countries exhibit a convergence process if the one with lower initial income grows faster and finally catch up with its higher income counterpart. Such process occurs under the assumption that returns to capital accumulation are decreasing and that economies share similar characteristics (institutional, behavioral, technological). Mankiw and al. (1992) [141] extension soften the "similar characteristic" assumption by considering convergence clubs that would reach heterogeneous steady states. Premises of location has been introduced into dynamic frames by giving external economies of scale a local dimension. Grossman and Helpman (1991) [99] analyzed localized spillovers in the form of positive knowledge externalities associated with R&D. The limited geographical scale of knowledge spillovers was justified on cultural, political and institutional proximities that thus conditioned how knowledge flows. The authors can thus explain why some groups of countries grow faster and why heterogeneities last. However this conceptualization bears great similarities with how location has been introduced in conditional convergence. In both cases, distance is theoretically stipulated and economic growth is built on *ad-hoc* representations of

space i.e the role of location does not follow from the model itself.

3.2.2 The paradox of distance in gravity equations : the missing relationship between trade costs and trade flows

The next step of our reasoning turns to results of studies looking at how transport costs influence exchange flows. According to the NEG model [130], up to a certain threshold, a decrease in transport costs from prohibitive to some intermediate level should induce agglomeration and increase trade flows between regions. On the one hand, flows from the core to the periphery will densify which corresponds to delivering manufacturing varieties. The other way around, agricultural goods now are almost exclusively produced by the periphery region and have to be sent to the core. The gravity literature has stumbled drawing the law linking trade flows and distance which is used as a proxy for transport costs. Despite the fact that transport costs have been told in great reduction, most empirical gravity models did not obtain evidences of declining distance coefficients and to some authors "it seems appropriate to mention that the effect of distance on trade patterns is not diminishing over time". (Leamer and Levinsohn (1997)) [133] (1387-88)

Several explanations have been considered to address the issue. Those can be classified into five categories (established in Noblet and Belgodère (2010) [153]) we shall present.

Explanation 1 : Interpretation of distance coefficients

The first argument should be made regarding the introduction of multilateral resistance terms following Anderson & van Wincoop (2003) [7]. This seminal contribution starts with McCallum (1995) [147] observation that despite RTA² between the USA and Canada, the national border separating them still tremendously impede trade between American states and Canadian provinces. Anderson & van Wincoop (2003) [7] shows how adding general equilibrium constraints could reduce border effects i.e trade cost effects as accounted by gravity models.

²Regional Trade Agreement

Anderson & van Wincoop (2003) [7] framework relies on Armington (1969) [8] assumption of goods differentiated by their country of origin. Countries are completely specialized in the production of their respective variety which are consumed with homothetic preferences by households. Utility is given according to Constant Elasticity of Substitution function (CES) between varieties :

$$U_j = \left(\sum_{i=1}^N \beta_i^{\frac{1-\sigma}{\sigma}} c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

where c_{ij} is consumption of country i 's products by country j 's consumers. In total, there are N countries (i and j included). β_i introduces asymmetry where consumers express preferences regarding the origin country of the product. The budget constraint is written $\sum_{i=1}^N p_{ij} c_{ij} = Y_j$ where p_{ij} is the price of good. Prices differ only because of iceberg trade costs τ_{ij} between i and j such that prices can be written : $p_{ij} = p_i \tau_{ij}$. The nominal value of an exported variety is

$$X_{ij} = p_{ij} c_{ij}$$

using the result of the utility maximisation under the budget constraint to obtain c_{ij} , we get

$$X_{ij} = \beta_i p_i \tau_{ij}^{1-\sigma} \frac{Y_j}{P_j^{1-\sigma}} \text{ with } P_j = \left[\sum_{i=1}^N (\beta_i p_i \tau_{ij})^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

P_j is the consumption price index. When the number of varieties increases (i.e more countries take part to international trade), the price index decreases and thus raises consumption of each variety. Summing over all consumptions, including the domestic one, and assuming that markets clear (production of traded goods = sales of traded goods at the national scale), one obtains trade flows (in values) as a function of partners' incomes Y_i and Y_j (relative to the global income $Y^w = \sum_{j=1}^N Y_j$) and some multilateral resistances terms Ω_i and P_j .

$$X_{ij} = \frac{Y_i Y_j}{Y^w} \frac{\tau_{ij}^{1-\sigma}}{\Omega_i P_j} \text{ with } P_j = \left(\sum_{i=1}^N \frac{Y_j}{Y^w} \left(\frac{\tau_{ij}}{\Omega_i} \right)^{1-\sigma} \right)^{1/(1-\sigma)} \text{ and } \Omega_i = \left(\sum_{j=1}^N \frac{Y_j}{Y^w} \left(\frac{\tau_{ij}}{P_j} \right)^{1-\sigma} \right)$$

Ω_i is the price index that accounts for the outward multilateral resistance term while P_j is the index stating for inward resistance. The price indices depend on relative income and relative trade costs. For instance, if a country happen to be isolated from the rest of the world, the domestic price index P_j would be high and importations of limited amounts. Because the elasticity of price index to trade costs depends on economic masses, a general raise of trade costs would increase small countries multilateral resistance more than larger countries ones.

Illustrating how omitting multilateral resistance impact results, Baldwin and Taglioni (2007) [19] report Rose (2000) [173] and Rose (2001) [174] results. Both papers estimate a currency union trade effect with a gravity equation. In the first instance, Rose(2000)[173] omits multilateral resistance terms and obtains an effect of +235% that disappear completely in the second instance, which includes multilateral terms. Similarly, when Micco, Stein, and Ordoñez (2003) [148] estimate the impact of the Eurozone's trade area on developed nations, they find that the coefficient is 0.198 without multilateral resistance terms, and is 0.039 accounting for it. The drop is a 4 standard errors difference which is significant.

Coe et al. (2007) [47] proposes a different argument that would induce empiricists to misinterpret coefficients. They rely on Deardoff (1998) [57] and Anderson & van Wincoop (2003) [7] framework to show that distance coefficients are in fact conditioned by the ratio between marginal and average trade costs. In any case the empirical literature would be able to distinguishably account for those costs and catch for their respective evolutions.

The classical gravity model relates bilateral trade to the economic masses (Y_i and Y_j) of partners and trade barriers (C_{ij})

$$Trade_{ij} = (Y_i Y_j)^\alpha C_{ij}^\theta$$

Trade is supposed negatively related to impediments such that $\theta < 0$ but positively related to economic masses ($\alpha > 0$).

In accordance with Deardoff (1998) [57] and Anderdon & van Wincoop (2003) [7], trade barriers must include remoteness measures or multilateral resistance terms to account for trading partners relative distance to the rest of the world. Thus :

$$C_{ij} = D_{ij}^{\beta'} (R_i R_j)^{\gamma'} (P_i P_j)^{\delta'} e^{(\kappa' + \lambda' A_{ij} + \varphi' L_{ij} + \sigma' F_{ij})}$$

D_{ij} is the the geographical distance between trade partners that accounts for transport costs, R_i and R_j are remoteness terms, P_i and P_j are respective populations' sizes. κ is the constant, A_{ij} is a dummy stating for a common border, L_{ij} is a dummy account for a common language and F_{ij} signal trade agreement between partners. ³

So :

$$Trade_{ij} = (Y_i Y_j)^\alpha C_{ij}^\theta = (Y_i Y_j)^\alpha \left[D_{ij}^\beta (R_i R_j)^\gamma (P_i P_j)^\delta e^{(\kappa + \lambda A_{ij} + \varphi L_{ij} + \sigma F_{ij})} \right]$$

Accordingly β i.e the elasticity of trade to distance is the product of the elasticity of trade costs to distance (β') times the elasticity of trade to trade costs (θ).

Under the assumption of homothetic utility functions, Deardoff (1998) and Anderson & van Wincoop (2003) shows that the elasticity of trade to trade costs (θ) depends on the elasticity of substitution between goods ε : $\theta = 1 - \varepsilon$. Rewriting the definition of β yields $\beta = \beta'(1 - \varepsilon)$. The elasticity β' can also be defined as the ratio of marginal costs to average costs such that

$$\beta = (1 - \varepsilon) \frac{\partial C_{ij}}{\partial D_{ij}} \frac{D_{ij}}{C_{ij}} = (1 - \varepsilon) \frac{MC_{ij}}{AC_{ij}}$$

Assuming consumer preferences and other parameters stable, variations of the distance coefficient depends on whether marginal costs (MC) shrink faster than average costs (AC). If marginal costs would decrease more than average costs, the distance coefficient would also decline. Coe and al. (2007)'s [47] first explanation of the paradox of distance reside in the unavailability of data that would allow testing for the evolution of both components of the distance coefficient. Still, do they evoke reasons to believe

³ $A_{ij} = 1$ if partners share a border, $L_{ij} = 1$ if partners share a language, $F_{ij} = 1$ if partners are part of an trade agreement

that marginal costs have decreased faster than average costs and push for further investigations of the question.

Explanation 2 : The geography of growth

Leamer and Levinsohn's (1997) [133] argument emphasizes that, according to the gravity framework, world trade is conditioned by economic masses. The bigger one's mass (the higher the multilateral resistance), the weaker the trade flows. The increasing world trade can thus be explained by the development of US partners' market powers. In the first part, European economies, at the end of the WWII and in a second part, the rise of Asian dragons. Accordingly, distance coefficients have been found constant not because trade costs have not decreased but rather because gravity has spread with the dispersion of economic power.

Carrère and Shiff (2005)[33] formally test for Leamer and Levinsohn's argument. Doing so, they conceptualize the "Distance of Trade" (DOT) as an alternative to the distance coefficient. DOT is defined as an average distance between trade patterns weighted by trade volumes. If one would expect globalization to decrease the distance coefficient, the causality is reversed for the DOT that is expected to increase over time. Similarly to the distance coefficient, a paradox arises as DOT trends have been found either decreasing or at best constant over the last decade. Their explanation for such result relies on an original definition of transport costs. Formally, transport costs are divided into "dwell costs"⁴ (D_wC) and distance costs (DC), both having opposite effects on the DOT.

$$TC = D_wC + DC$$

$$DC = C_m * m$$

C_m is the average cost per kilometer and m is the distance between partners.

Indeed, lower distance costs would raise the incentive to trade with distant partners as total transport costs for these destinations will fall relative to closer partners. On the other hand, lower dwell costs will raise the incentive to trade with neighbors as the fall in total transport cost is relatively higher for shorter distances. If little information

⁴i.e. fixed costs

happen to be available, one can expect last decades' technological progresses to have pushed down dwell costs while fuel prices (C_m), wiggly followed an upward trend. In this frame, Leamer and Levinshon's idea would imply that countries being part of fast growing areas will find beneficial to increase trade relatively more with their direct neighbors thus lowering the DOT. Indeed Carrère and Shiff 's coefficient stresses a significant negative relationship between economic growth of neighbors and the DOT giving some credit to the argument.

In the same vein, Berthelon and Freund (2008) [25] compare an estimated DOT (aggregating actual trade flows) with a theoretical one computed according to a monopolistic competition model where exports fully depends on incomes.

$$DOT = \frac{\sum_{ij} x_{ij}}{X_w} D_{ij} \text{ with } x_{ij} \text{ are exports from country } i \text{ to country } j$$

$$DOT_{theoretical} = \frac{\sum_{ij} x_{ij}^T}{X_w} D_{ij} \text{ with } x_{ij}^T = \frac{Y_i Y_j}{Y_w}$$

Overtime, both trends are positive however the trend of the actual series is not significant. The important difference between these trends can be interpreted as an opportunity cost, suggesting that given GDP movements, average distance of trade should have increased more than what has been observed, implying that the DOT explanation might be insufficient.

Explanation 3 : Regional Trade Agreements (RTA)

Carrère and Shiff (2005) [33] also consider RTA as relevant determinant of the distance of trade. Regional trade agreements are formed on a local basis. Raising intra-bloc exchanges at the expense of extra-bloc trade (trade diversion phenomenon) induces the DOT of members to decrease. However, briefly synthesizing the results of literature, Freund and Ornelas (2009) [85] conclude that most gravity models testing for trade diversion and trade creation bring to light a trade creation phenomenon i.e. an increase in the DOT. As raised by Haveman and Hummels (1998)[104], those estimates are implausibly large and too dependent on sample definitions and variables selection. Magee (2008) [140] makes a sensible effort in refining the definition of counterfactual to pro-

vide more reliable estimates. Classically, gravity model includes two dummy variables. The first one equals 1 if partners are part of an RTA, a positive coefficient implying trade creation. The second equals 1 if partners are not part of an RTA, a negative coefficient implying trade diversion. Conversely, Magee (2008) includes country-pair fixed effects, exporter year fixed effects and importer year fixed effects. The dyad effect picks up what is natural about the trade partners and the exporter and importer year fixed effects capture country specific dynamics. Magee finds that the average effect of RTA is small and that trade creation dominates trade diversion by a (little) one standard deviation. At the product scale, Clausing (2001)[45] and Trefler (2004) [192] agree to conclude that trade creation is the rule rather than the exception in the case of the Canada-United States free trade agreement of 1988. Chang and Winters (2002)[39] findings temper the conclusion showing that, following the implementation of Mercosur, Argentina export prices to Brazil raised while prices of non-members fell.

A meeting point to the two previous arguments is that trade diversion or shrinking of the DOT depends on neighbors' economic power. Neighbors are "natural trading partners" and as such, there is a form of endogeneity of the membership decision or on the trade intensity. Controlling for this effect, Baier and Bergstrand (2007) [13] show that the positive impact of RTAs on bilateral trade becomes more robust and larger ($\times 5$) than when not controlling for endogeneity. Conversely, Fontagné and Zignago (2007) [84] conclude their study on the fact that "a large part of RTA membership's trade effects are simply artefacts" as estimates drastically fell while controlling for endogeneity.

Explanation 4 : The compositional effect

Berthelon and Freund (2008) [25] and Siliverstos and Schumacher (2008)'s [182] argument in explaining the "missing globalization puzzle" relies on the evolution in the composition of export baskets. Basically, the explanation they support is that distance coefficients have heterogeneously evolved over time depending on goods' nature but the composition of export/import baskets would also have changed, resulting in constant distance coefficients at the aggregated level.

Working with disaggregated trade data, Siliverstos and Schumacher (2008) [182] found heterogeneity in the various industries' distance coefficients (three-digit ISIC Rev.2 industries). Their explanation to the constant elasticity of distance at the aggregated level is that there exists a compensation effect that one could investigate looking at the evolution of export/import baskets conditional on distance. Indeed, one would expect that the distance coefficient at the industrial scale would raise as the share of trade at shorter distances increases relative to trade at longer distances. They show that, for agricultural and mining and quarrying products, an important growth in trade at shorter distances has occurred at the expense of trade at longer distances. In the case of manufacturing products, the opposite occurred i.e one observes a slight increase in trade at longer distances. Both trends are thus expected to compensate, resulting in a constant share of trade at longer distances at the aggregate level.

Berthelon and Freund (2008) [25] had a similar idea in investigating a compositional effect. On the one hand, they consider the contribution of trade-share movements (the compositional effect) and on the other hand, the change in distance elasticities among industries (the distance-sensitivity effect).

$$\Delta\gamma_t = \underbrace{\sum_k \Delta s_k \gamma_k}_{\text{compositional effect}} + \underbrace{\sum_k s_k \Delta \gamma_k}_{\text{distance-sensitivity effect}}$$

where γ_k is the distant elasticity of trade of industry k and s_k is the industry k 's share in total exports.

According to their results, the compositional shift has no effect on the increase of the distance coefficient. The evolution of distance coefficients would thus fully be the result of the distance-sensitivity effect. For the authors, the dichotomy is not to be set between industries but between homogeneous goods opposed to differentiated goods. Indeed, the former are more likely to display an increasing importance of distance than the latter and the authors find some (indirect) evidences in favor of this argument : Goods with high initial trade costs (tariffs and transport) i.e rather homogeneous goods, have become more distance sensitive.

Explanation 5 : The various components of trade costs

Grossman (1998) [98] argues that trade elasticities are too important in magnitude to account only for transport costs. Accordingly trade costs should be defined in a broader way than "transport costs" and thus should encompass other components expected to impact trade but while following different patterns.

For instance, Head and Mayer (2013) [105] consider four types of "dark trade costs" :

- Information impediments to trade : distance effects involve informational costs about essential knowledge on product quality or vendor trustworthiness;
- Localized, historically determined tastes : opposing T. Lewitt's argument about the homogenization of preferences, the authors show how, based on history, local tastes persist;
- Persistent colonial legacies : referring to Head and al. (2010) [106], the argument suggests that nearly 60 years after independence waves, trade with the ex-colonizer is very much larger than gravity predictions would suggest, even accounting for policy preferences, common currency, common language and similar institutions;
- History of violence and wars : Martin and al. (2008) [144] find that conflicts lowers bilateral trade between the belligerents by around 40% for the first 3 years after the beginning of hostilities and that trade levels remain significantly lower than the gravity benchmark for the following decade.

Extending the "basic" transport costs function, Brun and al. (2005) [32] make the puzzle disappear. According to their regression, the evolution in the price of oil and infrastructure improvements both accounts for 85% of the change in the elasticity of trade relative to distance. Not yet conceptualized as such, they make a brilliant distinction between "distance related costs" and "distance unrelated costs" that Dias (2010) [62] exploit more deeply. On the basis of an Eaton Kortum type model, he demonstrates how the distinction matters and might be the key to the puzzle. He

supposes an iceberg transportation cost function of the form

$$d = 1 + \alpha + \beta\delta$$

slightly different from Anderson and van Wincoop's version [7] [$d = (1 + \alpha)\delta^\beta$] where δ is the distance between trade partners and β is the unit cost of distance and α is a fixed cost.

Anderson and van Wincoop's version (i.e the classical trade costs function) assumes that all transport costs are related to distance (including tariffs). Dias breaks this assumption and brings to light a complex trade-off. On the one hand, when fixed cost decreases, the relative importance of distance in total trade increases which makes distance more important on trade flows. On the other hand, this lowering also reduces the whole level of transport costs ($d \searrow$) and it acts as if distance barriers were lower. Controlling for both components (distance related and distance unrelated costs), the puzzle disappears suggesting that a decrease in related distance trade costs effectively favors distant and remote partners while a decrease in unrelated distance costs rather favors closer and central partners.

The distinction between fixed and variable costs also triggers the assessment of how the Internet, by supposedly lowering communication costs, have impacted trade. Precisely, Freund and Weinhold (2004) [86] take the "fixed cost" side and ground their analysis on a model with imperfect competition and fixed costs of entry into a foreign market. The Internet is expected to lower these costs as suppliers can find information or advertise their products on a larger scale. The model allows competition to increase as information widest availability triggers strategic incentives for each firm to increase exports to, in turn, prevent other firms to export. This strategic effect is conditioned by distance as it impacts more near firms than distant firms thus enhancing the effect of distance on trade. However, empirically, they find little evidence that the Internet has directly altered the impact of distance on trade. Fink and al. (2005) [80] rather make the assumption that the Internet expansion lowers variable trade costs as communication is required all along the production process through the transmission of

product specification or coordination through the various steps of production. In their case, lower communication costs actually impact trade patterns. Quite intuitively, the impact is larger for complex-differentiated products than for homogeneous ones.

Duranton and Storper (2008) [67] makes a different distinction between the components of trade costs. Precisely, they evolve on the basis of a "machine industry" case i.e of vertically linked industries. As transport costs shrinks, it becomes easier for machine producer to sell to final producers abroad such that they can export better quality equipment. However, this up-grade comes with a transaction cost and the machine producing firm must dedicate some labor resources to adaptation and training of its customer's task force. For intermediate transport costs, the increase in transaction costs due to some quality improvements of exported products inhibits the effect of transport cost lowering. Transport costs have to become quite low for the indirect effect of higher quality export to fade and leave room to denser exchanges. Noblet and Belgodère (2010)'s [153] point is that the previous reasoning could not explain the paradox of distance in the case of low transport costs. They re-write the coordination cost expression expressed as a function of the amount of machine's quality that is lost in transport (φ)

$$\varphi \left[\frac{(1 - \varphi)^{1-\psi}(1 - \psi)}{w} \right]^{1/\psi}$$

$\psi \in]0; 1[$ is the parameter that determines the degree of substitutability between varieties and w is the wage.

Accordingly, supposing very low transport costs ($\varphi \rightarrow 0$) would also make coordination costs null. Noblet and Belgodère's solution is to separate both transport and transaction costs, supposing an additive form

$$\tau = 1 + \theta d + \phi(N; d)$$

where θ accounts for transport costs such that a fall in transport costs would induce θ to decrease and N accounts for the complexity of the production process where coordination costs increase as complexity (N) increases.

They synthesized the matter by the following question : "Should we believe that globalization has the same effect to transport cost and to coordination costs ? Duranton and Storper's argument amounts to answer yes. Noblet and Belgodère have shown that, in the adverse case, the increasing complexity of production processes allowed by the globalization may explain the distance revival.

The explanation of the paradox of distance brought forward by Noblet and Belgodère (2010) [153] emphasizes the key differences between transports costs and coordination costs which are linked to geographical distance. In the next section, we present a second generation of Economic Geography models which introduce knowledge as an economic entity, and doing so emphasize some key differentiation among various components of costs related to distance.

3.3 Growth augmented frameworks without the empirical counterpart

As developed in the previous section, New Economic Geography (NEG) models have introduced the crucial role of transport costs (in general) in the mechanisms of economic activities' agglomeration. However empirical investigations based on the framework of gravity equations have failed into emphasizing a decreasing role of transport costs despite the explosion of exchanges worldwide. Noblet and Belgodère (2010) [153] raises an interesting suggestion in separating transport costs on goods and transfer (/coordination) costs on ideas. Indeed this suggestion happens to benefit from a large theoretical foundation in dynamic frameworks combining space and trade we shall describe at length in subsection 3.3.1. Until recently a reduced form has been missing to allow empirical counterparts to NEGG frames to illustrate the crucial role of transport costs on agglomeration mechanisms and welfare disparities. Empirically, the literature on the geography of innovation made the closest proposition toward understanding the role of transport on goods and transfer costs on ideas in agglomeration mechanisms but happens to be undermined by technical issues. Subsection 3.3.2 will turn to details

on these empirical matters.

3.3.1 Theoretical grounds for the distinction between transport costs on goods and transfer costs on ideas

Endogenous growth models

The distinction between several forms of integration arose with the distinction between level and growth effects of openness in the nineties' literature merging growth and trade theories. The reference model is the AK-type model of Rivera-Batiz and Romer (1990) [170]. They consider two economies similar in technology and endowments. Each has two manufacturing activities (production of consumption goods and production of capital goods) and an R&D industry that creates designs for new types of capital goods. A manufacturing firm needs to hold a patent to its production of good j . The patenting system guarantees a revenue to the researchers equal to the present discounted value of the stream of monopoly rent perceived by the manufacturing firm minus the cost of machines. Up to this point the authors consider two specifications of technology for R&D which may have conditioned the understanding of the consequences of integrations.

The "Knowledge-Driven" model maintains a straight distinction between manufacturing and innovation activities in preventing sectors to require the same factor of production. R&D would use the knowledge stock and high skilled human capital while manufacturing production relies on unskilled labor and physical capital. In this setting, a trade agreement liberalizing exchanges of goods (only) would induce an increase in the level of output without consequences on the economies' balanced growth rate. Specifically, with trade in the specialized capital goods, domestic manufacturers can take advantage of foreign designs and vice versa. For the research sector, opening of trade implies a wider market for its designs with as immediate consequence a doubling of patent prices. To the extent that returns on human capital doubles in both sectors, free trade does not impact the split of human capital between manufacturing and R&D sectors. This implies a higher level of output and welfare but the balanced rate of growth stays the same. Henceforth, one could also consider an opening agreement lib-

eralizing both flows of information and flows of goods. In this case, the rate of growth found itself permanently increased. To the extent that there exists no redundancy between partners' stocks of knowledge, openness doubles them. Such an increase is equivalent to a major gain of productivity for the research sector and would induce a shift of human capital out of manufacturing into research permanently increasing the global balanced growth rate.

This first example shows how the distinction between different types of openness allows to consider and differentiate static from dynamic gains to integration. The second configuration Rivera-Batiz and Romer consider ends up with similar consequences tying flows of goods and flows of ideas. The "lab-equipment" configuration merge the R&D sector and the manufacturing ones. The two sectors share human capital (high skilled and unskilled labor) and capital goods as inputs to their production processes. In this setting, flows of ideas have no effect on production. Opening trade on goods either induces a doubling of patent prices (as in the knowledge driven configuration) either an increase in the interest rate which conditions the long-term remuneration of patents. With a higher interest rate manufacturing profits could not increased and immediate demand for patents plummets. Over time, the increase on the interest rate favors high savings and leads to a faster growth rate of a similar order as a complete integration in the knowledge driven model.

In providing a similar conclusion to the knowledge driven configuration but omitting the separation between flows of goods and flows of ideas, the lab-equipment model may have blurred the consequences of nonlinearities and imperfect synchronization between the different forms of openness. NEGG models integrating space, growth and trade considerations give the full dimension of those issues.

NEGG models

Conversely to NEG models which focus on labor, NEGG frames rely on capital and generate growth by endogenizing its accumulation process. The accumulation process at stake strongly relies on the capital mobility assumption and the distinction between trade costs on goods and transfer costs on ideas. On the basis of Baldwin and Mar-

tin (2004) [17], Martin and Ottaviano (1999) [145] and Baldwin, Martin, Ottaviano (2001)'s [18] models are mobilized to sketch the point.

The basic setup considers two regions both endowed with capital and labor at use in three sectors. The regions are symmetric in terms of preferences, technology and trade costs. The first sector delivers traditional goods which are considered homogeneous. Producing firms are in perfect competition under constant returns to scale. The production function requires one unit of labor to obtain one unit of traditional goods. Importantly, labor stocks are fixed and immobile which prevent NEG type of catastrophic agglomeration scenario induced by labor migration. The second sector delivers manufactured products in monopolistic competition conditions. Each firm produces a unique variety on the basis of one unit of capital (interpreted as a patent or an idea) and some units of labor. Upstream from the manufacturing sector, the knowledge producing sector produces capital in each region. Thus, the marginal cost of the innovative sector corresponds to the fixed cost bore by firms in the M-sector (manufacturing sector). As one unit of capital is required to start a new variety, the number of varieties obviously conditions the number of firms but also the capital stock at the world level.

Depending on the assumption one makes on capital mobility (here is the major difference between Martin Ottaviano (1999) [145] and Baldwin, Martin, Ottaviano (2001) [18]), the stock of capital produced and owned by a region may or may not be equal to the number of firms producing in the region.

When supposing global knowledge spillovers in the innovative sector, the cost of innovation becomes an exogenous parameter governed by a sector-wide learning curve, that is, the marginal cost of producing knowledge decreases as the knowledge stock rises

$$F = wa_I \quad a_I = \frac{1}{K^w} \quad K^w = K + K^*$$

F is the marginal cost of the innovate sector or the fixed cost bore by M-firms to start producing their variety. w is the price of the unique factor of production requires to

produce capital i.e labor's wage and a_I is the labor productivity parameter. Logically, a_I inversely depends on the global knowledge stock K^w (capital stock) constituted by the sum of capital in the North and South (respectively $K + K^*$). The global growth rate is given the dynamic of capital \dot{K}/K .

Let's immediately consider the particular case of localized spillovers, which introduces the "transfer costs on ideas". This implies the following changes

$$a_I = \frac{1}{K^w A} \quad A = s_n + \lambda(1 - s_n) \quad 0 \leq \lambda \leq 1$$

λ measures the degree to which knowledge creation in one region facilitates knowledge creation in the other one. When $\lambda = 1$ the configuration is the global spillovers' one and when $\lambda = 0$, spillovers are fully local. This cost on transfer of ideas weights the share of firms producing in the South ($1 - s_n$) while within each region, spillovers are expected to flows without any constraints (s_n is non-weighted). The marginal cost of producing ideas is impacted as the cost of R&D in one region depends on the location of firms.

Perfect knowledge capital mobility : Martin and Ottaviano (1999)

The perfect capital mobility assumption implies that the initial ownership of capital (s_k) is permanent and both regions have the same incentive to accumulate capital. Indeed, to the extent that the arbitrage condition holds, capital flows freely between regions, profits will stay the same in both regions. Due to localized spillovers, it is less costly to innovate in the region with the highest number of firms or the largest capital stock. Thanks to the absolute capital mobility, the value of capital (its marginal cost) does not differ from one region to the other and innovation occurs fully in the North. In return, the South will be able to repatriate innovations (capital) produced in the North at no cost. This induces that the share of capital in the North (s_k) and the share of firms in the North (s_n) are linked such that when the initial stock of capital is higher in the North than in the South, more firms will be located in the North and all innovations will take place there.

The mechanisms at the core of the model links the three remaining endogenous variables : the growth rate (g , common to both regions), the share of firms producing in the North (s_n) and the share of expenditures in the North (s_e).

- g and s_n : the spatial concentration of firms reduces the cost of innovation and speeds up the accumulation of capital (i.e growth). For a given geography of production (s_n), the more localized spillovers have to be (lower λ), the less regions benefit from partner's innovations, the lower the common growth rate is.
- s_e and s_n : the relation linking the income inequality (s_e) and the geography of production (s_n) is better known as the "Home Market Effect". Basically, it states that a change in the market size (s_e) leads to a more than proportional change in the geography of production. This relation is dependent on the level of trade costs such that lower trade costs will induce an even more unequal geography of production than the income disparity would suggest.
- s_e and g : income inequality is decreasing in the capital's growth rate. As the cost of capital decreases, the growth rate increases but profits being repatriated also induces faster entry of firms in both Southern and Northern markets and shrinks income inequality.

To partially conclude on the role of both types of trade costs : On the one hand, lower trade costs on goods, via the Home Market Effect, would strengthen the concentration of the geography of production and consequently increases the capital accumulation process. On the other hand, less localized technology spillovers would decrease income disparities by the repatriation of capital and the relocation of M-firms (market crowding effect) at the expense of growth. In this context, "the sign of the correlation between growth and agglomeration depends on the nature of the forces at work" ([17]) i.e on the relative intensity between trade costs on goods and transfer costs on ideas.

Restricted capital mobility : Baldwin, Martin, Ottaviano (2001)

Baldwin, Martin and Ottaviano (2001)'s [18] framework is quite similar to Martin and Ottaviano (1999)'s [145] except that the authors drop the perfect capital mobility

assumption. Doing so the value of capital is allowed to differ in the two regions which implies that the marginal cost of capital creation differs between both regions affecting wealth, expenditures and profits differently from one region respective to the other.

In this context, a gradual lowering of trade costs (still over the "catastrophic agglomeration threshold") leads the North to enter a virtuous circle in which its increasing share of capital and its expanding market size reduces the local cost of innovation and promote investment. Conversely, South's wealth diminishes which reduces its market size and shrinks profits for local firms. This prevents them from investing further as the cost of innovation increases. The South only benefits from the Northern expansion through cheaper imported manufactured goods.

If lowering trade costs on goods may foster divergence by accelerating the agglomeration process, lowering transfer costs on ideas is expected to have the opposite effect. By reducing the cost of innovation in both regions, the spread of knowledge spillovers participate in stabilizing the symmetric equilibrium and reduces incentives to agglomerate. Indeed less localized spillovers generate, for a given distribution of capital, a more equal distribution of incomes and expenditures and therefore attract firms in the South.

Baldwin and Forslid (2000)'s "stability map" [16] provides a synthetic representation.

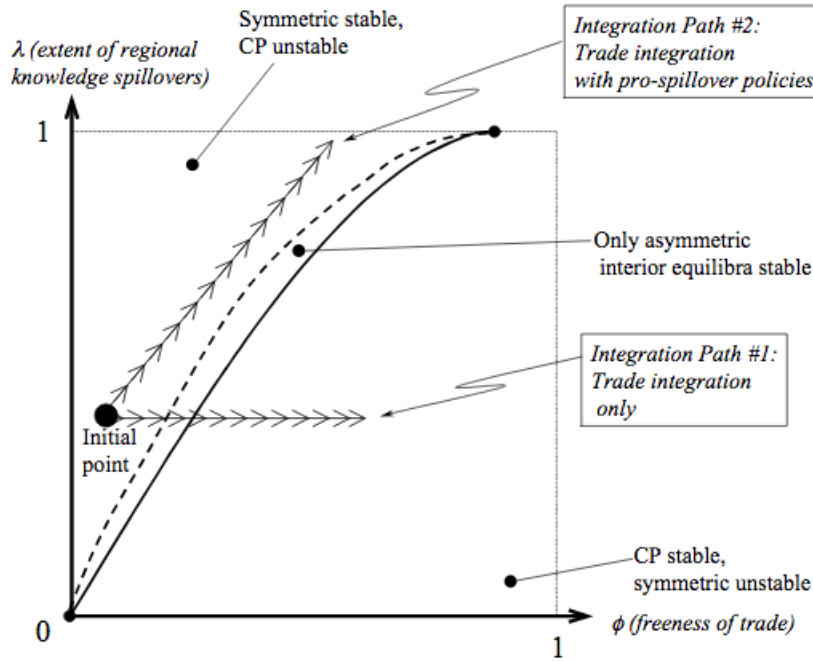


Figure 3.1: Stability map, Baldwin and Forslid (2000) [16]

This shows how equilibria stability is affected by changes in both kinds of 'costs' (λ and ϕ). The curves represent the break and sustain points (thresholds) and draw frontiers between the various types of equilibrium. When nor trade of goods nor spread of ideas are very free (ϕ is low, λ is low), the symmetric outcome is stable. When trade of goods is free but knowledge flows are still restricted, the core-periphery becomes the only stable result.

Toward testable implications : Montmartin (2015) [151]

This conflicting role of trade costs on goods and transfer costs on ideas upon agglomeration outcomes has recently been formalized as a result of a social planner's maximization program. Montmartin(2015) [151] provides an extension to a *à la* Martin Ottaviano (1999)[145] framework. In solving for the social planner optimization problem that maximizes utility for both regions, he shows how the optimal agglomeration outcome formally relates to trade costs on goods and transfer costs on ideas.

The equation we refer to is written :

$$\frac{\partial H}{\partial s_n} = -\frac{\alpha L}{(\sigma - 1)} \frac{(1 - \phi^2)(2s_n - 1)}{[s_n + \phi(1 - s_n)][\phi s_n + (1 - s_n)]} - \frac{2L(1 - \lambda)}{s_n + \lambda(1 - s_n)} + \frac{4\mu L(1 - \lambda)}{\rho\eta}$$

On the left-hand side, the partial derivative of the Hamiltonian (that described the utility maximizing program under constraints) with respect to the level of spatial concentration of manufacturing firms in the core-region (s_n) conditions the optimal level of agglomeration. On the right hand side, three effects distinguish themselves. The 'transport cost effect' accounts for the impact of manufacturing firms' location choice on the global transport cost paid by the two regions of the model. This effect is negative to the extent that as spatial concentration increases, exchanges of goods rise and so do amounts dedicated to transport costs. The second effect is the nominal consumption effect still negative. Indeed, spatial concentration decreases the cost of patent as the innovation sector works under perfect competition. An immediate consequence is to increase the labor devoted to the R&D sector and reduce the labor force allocated to the manufacturing sector dedicated to produce consumption goods. The third (growth effect) represents the pro-growth effect of spatial concentration.⁵

However, those effects are only intermediaries in the relation linking trade costs on goods and transfer costs on ideas. Montmartin (2015) [151] shows how the two parameters (respectively ϕ and λ) induce strictly opposite effects on agglomeration. The only effect being affected by trade costs on goods is the 'transport cost effect'. He finds that the (negative) transport cost effect is decreasing and convex with ϕ which means that as economies integrate their market to one another, the (negative) transport cost effect fades up its disappearance. From that point of view, the optimal level of spatial concentration is the complete agglomeration. Beside, the growth and the nominal consumption effects are conditioned by transfer costs on ideas exclusively. The negative nominal consumption effect is decreasing and convex with λ : as economies integrate

⁵The social planner level of agglomeration integrates considerations on the level of taste for variety (μ) , the elasticity of substitution between varieties (σ) but also the share of differentiated goods in total consumption (α). L denotes the labor force in one region.

($\lambda \rightarrow 1$), the nominal consumption effect shrinks and so does the growth effect that also negatively depends on λ . Thus, on one hand, the social planner has incentives to agglomerate economic activities to benefit from a lower transport cost effect but on the other hand, deeper concentration of activities deprive economies from the benefits of an enhanced growth effect and a reduced nominal consumption effect.

These developments emphasize the interplay of transports costs on goods and transfer costs on ideas upon agglomeration dynamics. However the gap between market and optimal regions' welfare is not only depend on agglomeration but also on growth and R&D investment. Montmartin (2015)'s [151] framework makes clearer which types of inefficiencies induces such gap. Momentarily supposing a fixed spatial configuration, he shows that the effect of an extra variety on the welfare of agents living in the core economy depends on three elements. The first of them is the consumer surplus effect that is the marginal benefit consumers withdraw from consuming the extra variety at initial prices. The second is the profit destruction effect that is the marginal loss of incumbent counterbalanced by the profit gain for new entrants. The third is the "knowledge externalities effect" or the marginal gain/cost for new inventors induced by the patenting of new knowledge. The sum of the three effects actually corresponds to the sum of the under-growth and under-investment in R&D. Activities' agglomeration impacts both conditions to the extent that, under-agglomeration ⁶ increases the potential for situations of under-growth and under-investment in R&D. Testing for a 'welfare equation' that emphasizes the role of those inefficiencies in combination with agglomeration outcomes and determinants could be of interested in providing public institutions with relevant recommendations and tools.

3.3.2 The externality perspective on testing for agglomeration determinants

NEGG frames offer a wider theoretical basis to the distinction between trade costs on goods and transfer costs on ideas towards explaining their role on agglomeration outcomes. Turning to the empirical response, the impact of these costs could be captured

⁶under agglomeration designates an agglomeration level inferior to the optimal agglomeration level

looking at the externalities being constrained.

On the one hand, trade costs on goods impede the Home Market effect and its byproduct. Initially, even a slight difference of capital endowments between partners induces a relocation (destruction/creation) to the wealthiest region and increases expenditures and market size in this region. The HME emphasizes that the relocation effect would be even greater since an expenditure differential would induce a more than proportional change in the geography of production. As previously explained, lower trade costs reinforce the home market effect and triggers agglomeration. The accumulation of capital and the massive entry of firms in the market increase the growth rate and, considering the occurrence of localized knowledge externalities participates in lowering the cost of innovation. To this extent, this mechanism can be brought closer from what Griliches designated as 'pecuniary externalities'. He broadly defined them as the case where "R&D intensive inputs are purchased, from other industries, at less than their full quality price". Indeed, in this situation, the tariffication diverges from an hedonic calculation where prices only reflect firm/industry productivity and do not integrate neighbors/competitors/partners gains of productivity. Yet, those improvements participate in the (total) factor productivity of the system and benefit each of its element in an uncatchable way.

Transfer costs on ideas also affects the cost of innovation, affecting agglomeration the other way around. Lower transfer costs on ideas lessen agglomeration incentives as location becomes less important to innovate and proximity does not overly lower the cost of innovation anymore. According to Griliches' distinction, transfer costs on ideas would rather concern "real" knowledge spillovers. He defines them as "ideas borrowed by research teams of industry i from the research result of industry j ".

Of particular interest, some papers have been testing industrial spatial concentration or firms co-location in relation with industry characteristics associated to the three Marshallian agglomeration mechanisms : labour pooling, knowledge spillovers and input-output linkages. "Long ago, Chinitz (1961) [41] suggested that examining the degree of co-agglomeration of industries depending on their characteristics is another way to test for the presence of agglomeration economies" ([49] p.84) To the ex-

tent that we bring closer industries' characteristics regarding knowledge spillovers and input-output linkages, this literature could light up the distinction between transport costs on goods and transfer costs on ideas at the core of our interest.

Among the first examples, Rosenthal and Strange (2001) [175] proposed to test Ellison and Glaeser (1997) [72] spatial concentration measure of US manufacturing industries against the three channels. Precisely, Rosenthal and Strange (2001) [175] tests a relationship of the form

$$\gamma_{j,m} = \beta X_m + \epsilon_{j,m}$$

where $\gamma_{j,m}$ the concentration index that measures industry m 's concentration at the spatial level j relative to the concentration level of other industries. X_m are industries' characteristics regarding input-sharing, labor pooling and knowledge spillovers. Input sharing is obtained as the manufactured input per \$ shipment and non manufactured inputs per \$ shipment. In the first instance, the more intensive industry's needs in manufactured inputs the higher the gains in spatially concentrating the value chain. Conversely the more intensive in non-manufactured inputs the looser the incentives to spatially concentrate. Labor pooling is estimated supposing that some industries have special skill requirements in terms of workforce. In proxying specialization, the authors use the net productivity, the share of supervisory and support labor and the degree of education. The share of support labor is to be understood such that the the more complex the task, the higher the need for a specialized workforce but also the higher the needs for supervision and support. Ultimately, knowledge spillovers are approximated using the number of new products advertised in trade magazines (in 1982). They also control for natural advantages as an agglomeration force that push industries to localize close to sources of energy, natural resources and water related inputs. Representatively of the studies in the same vein, they found that labour pooling had a positive effect on agglomeration next to knowledge spillovers. Inputs linkages affected agglomeration at the state level but not at a smaller scale.

Ellison and al. (2010) [73] used the degree of co-agglomeration of industries as the independent variable, which is another way to test for agglomeration economies. They

work with industries' pairs studying the role of agglomeration channels in colocation patterns. They obtained results supporting the relevance of the three types of channels. Still recently, Baldwin and al.(2010) [15] extended these studies on the impact of agglomeration mechanisms to the productivity of firms. They combine within production functions, plant characteristics and place-specific features attached to economic performance namely input-output links, labor pooling and knowledge spillovers. They found that input-output links and intra-industry spillovers (proxying for labor pooling) play a major role in productivity at the firm level.

However, this strand of the literature can be considered reaching "conclusions [that] are mostly descriptive". (Combes and Gobillon [49]) This directly stems from weak links between econometric specifications and theoretical models. Second, no robust foundations underlie the choice of explanatory variables nor the *a priori* additive linear relations grounding most specifications. As explained, two industries sharing inputs would have more incentives to co-locate in the case where trade costs are large, thus justifying to interact the input/output linkage variable with some measures of trade costs. Third, these specifications might be undermined by endogeneity issues since there exists strong dynamic relations between independent and dependent variables that the lack of sound theoretical instruments don't allow to prevent.

One should notice that empirical approaches in the geography of innovation have kept a superficial understanding of the black box of knowledge externalities. "Modern approaches [of the geography of innovation] have emphasized the role played by interactions between firms and workers in the innovation process." (Gorin (2016) [91] p.44) Theoretically the NEGG model developed by Baldwin and Forslid (2000) [16] based on the mobility of labor emphasizes qualitatively similar effects than the models we described at length in section 3.3.1. In a similar setting Fujita and Thisse (2002 [87] and 2003 [88]) designed a framework where skilled workers employed in the innovation sector are the beneficiaries of (localized) knowledge externalities. The productivity of the region is tied to the agglomeration of skilled workers. This also has a knock-on effect on the growth process at the benefit of the core region. Those similar results obtained from frames considering the mobility of workers or the mobility of capital

allow us to consider new developments of quantitative spatial models, relying on the assumption of labor mobility, as a relevant way to shed new lights on our matter.

3.4 Space, Growth and Trade

The past decade has witnessed the development of a number of frameworks that can be more closely tied to the data. This section sketches the methodological improvements reached by this literature as promising avenues to light up our question of interest.

3.4.1 Quantitative Spatial Models : computable solutions on the tryptich 'welfare, agglomeration and growth'

The core set up uses a spatial equilibrium framework, where labor is the factor subject to mobility costs. Regions can trade between them at a transport cost. Regions differ in terms of their productivity, the amenities individuals dispose of, and their geography. The key to the tractability of those complex frameworks is that they exploit a gravity structure that is trade flows (migration and commuting flows) depend on iceberg transport (migration, commuting) costs in a log linear fashion. Gravity has the immense advantage of being easily modeled using Ricardian frameworks where locations differ in terms of their productivity in manufacturing differentiated goods. Allen and Arkolakis (2014)[3] made that first step. The gravity based spatial Ricardian model is simple enough to be solved for many locations (more than 2 or 3 in a bounded space), multiple industries and local factors yielding models able to incorporate real-world geography and be quantified using location specific data. However, as in *Old Trade* models, agglomeration here is not actually explained but results from differences in local characteristics. Even when endogenous agglomeration effects are introduced, the models are calibrated (that is parameter values are chosen) to avoid multiple equilibria such that the possibility of endogenous agglomeration fades away. In a first time, we present the foundation that constitutes the model developed by Allen and Arkolakis (2014)[3] to better understand the structure of the recent solutions.

The framework developed by Allen and Arkolakis (2014)[3] combines an economic

and a geographic component. On the one hand, the economic component displays the gravity structure that characterizes the international trade with labor mobility in order to determine the equilibrium distribution of activities across space. On this surface, any topography of exogenous productivity and amenities differences can be considered under the assumption of continuous bilateral trade costs. Congestion externalities are incorporated as a function of population density such that the level of productivity and amenities available is endogenously determined by the population at the location. On the other hand, the geographic component micro-founds the bilateral trade costs supposing that there exists a topography of instantaneous trade costs over a surface. They use methods from differential geometry to characterize the costs in linking any two points in space.

The model combines a gravity structure of trade with labor mobility to provide the conditions for existence, uniqueness and stability of a spatial economic equilibrium. Their world consists of a continuum of locations where each produces a unique differentiated variety of a good. We are in an Armington configuration where goods are only differentiated by country of origin. The new economic geography has supposed that increasing returns to scale generates the cumulative causation (endogeneity of the agglomeration process) and the emergence of multiple equilibria. This model provides the conditions for such occurrence under the assumption of constant returns to scale and Armington differentiation as an alternative to specialization from the love of variety and increasing returns to scale.⁷ The unique production sector consider CES preferences over the differentiated varieties. Trade is costly under the form of an iceberg cost. The world is inhabited by workers who are freely mobile across locations and derive utility from the consumption of differentiated varieties and the local amenity. The later is expected to act as a dispersion force as agglomeration reduces access to the local amenity. Thus, both productivity (A) and amenities (u) may depend on the density of workers such that each is constituted of an exogenous component inherent to the location (\bar{A} and \bar{u}) weighted by the density of workers up to a factor determining how intensively density impacts productivity (α) and amenities (β).

⁷This also can be obtained supposing Ricardian technology differences as in Eaton and Kortum (2002) [69]

$$A(i) = \bar{A}(i)L(i)^\alpha$$

$$u(i) = \bar{u}(i)L(i)^\beta$$

In the 'economic' part of the model, under the assumption of symmetric trade costs, the existence and uniqueness of the equilibrium are conditioned by the partial elasticity of welfare with respect to the population in a location, α and β . When $\alpha + \beta \leq 0$, there exists a unique stable equilibrium as long as dispersion forces are at least as strong as agglomeration forces. For a sum close from 0, the equilibrium is stable but potentially not unique anymore. Conversely when $\alpha + \beta \geq 0$, agglomeration forces take over and induce complete agglomeration in a single location. Conditional on the price index which is partially determined by transport costs, productivity and amenity spillovers (α and β) only change the elasticity of the equilibrium distribution of economic activity to the underlying geography. Precisely, the fraction of the observed variation in incomes $Y(i)$ can be log linearly related to the exogenous productivities \bar{A} and amenities \bar{u} next the price index $P(i)$:

$$\frac{\gamma_1}{\sigma - 1} \ln Y(i) = C_w + C_L + (1 - \beta) \ln \bar{A}(i) + (1 + \alpha) \ln \bar{u}(i) - (2 + \alpha + \beta) \ln P(i)$$

Price indexes are calculated based on the geographic component of the model that aims at estimating bilateral trade costs between any two locations. Estimations are calculated on the case of the continental United States. They use a Shapley decomposition to estimate the expected marginal contribution of the local characteristics (\bar{A} and \bar{u}) and the geographic location to the total variation of observed incomes. Depending on the strength of the spillovers (α and β), at least 20% of the observed variation in income in the United States is due to geographic location suggesting that variation in trade costs greatly matters in the spatial variation of incomes.

An important limit of this first step is that it is a static model in which the patterns in the spatial distribution of growth rates cannot be analyzed. Basically, the problem with introducing dynamics is that the contemporaneous/initial value of the co-state variables do not uniquely determine the evolution of an economy which makes com-

puting and quantifying such models problematic. We use the bright explanation of Rossi-Hansberg (2019) [176] to make this point clear. Think of a firm that is deciding how much to invest in a given location. If the investment implies some form of sunk costs, the firm will try to forecast the return of its investment for now and in the future in order to decide to realize the investment (or not). In any given period, those returns on investment will depend on the market size (according the Home Market Effect) which itself depends on the whole distribution of economic activity worldwide which itself depends on trade costs or more broadly spatial frictions. Evaluating forward returns will then requires to also own those information, for each locations, in the future. Thus, at to this point, one needs to synthesize the whole distribution of spatial characteristics into a state variable. This is particularly difficult/impossible in the case of a spatial model to the extent that firms care more about some locations than others, such that, homogeneity or generality conveyed by few statistics are not enough to describe the evolution of the system. Intractability arises from solving with too numerous state variables.

Some solutions have been raised. One can assumes 'perfect foresight' that is, firms and agents understand perfectly the economy's dynamic of evolution. This setting allows a full characterization of forward-looking transition dynamics to the extent that state variables influence decisions in a log linear way so that future states can be differentiated out. Those frameworks can accommodate any changes into local productivities, amenities or spatial frictions but those changes must be exogenous to population location decisions. Differently, firms and agents can be assumed limited in their 'forward looking' abilities. In this case, agents only look at the present characteristics of the economy to make decisions even though it could also impact the future. The drawback of this option is that any preemptive behavior of policies is discarded. Desmet and Rossi-Hansberg (2014) [60] followed this path. In their model, firms innovate in particular locations and their achievements lead to random technological advances in neighbor or proximate locations. Limited forward looking abilities are embedded in that the yield firms own for their innovations is immediately capitalized in land rents which are submitted to perfect competition. As such firms obtain immediate returns for their innovations and they do not have to consider the future in the investment

decision. Even though innovations do not provide long term gains, it allows firms to win the bid for land at each period and acts as a trigger from innovation and growth. This first setting considered space under the form of a continuum of locations arranged along a line whose representative power of the two-dimensional reality is limited. Still, this model has funded the extension of Desmet et al.(2018) [61] we will describe at length in the following as it introduces migration and trade costs while considering dynamics in a two-dimensional geography.

Desmet and al.(2018) [61] builds on Allen and Arkolakis (2014) and Desmet and Rossi-Hansberg (2014)[60] to study the effect of the geography of development in a dynamic framework while considering the effect of mobility restrictions and transport costs. The model can be sketched in few points.

Each location is unique considering its position relative to the other spatial units. Its geographic location and place in the network tying regions to one another is specific and condition the level of transport costs. Each location is also unique regarding its amenities that make a place attractive or not and its productivity that determines its appeal as a place to produce and work. The distinct levels of labor productivity reflect infrastructures, education systems, capital stocks but also technological know hows. They are endogeneized to the extent that firms invest to improve local technology and infrastructures. Their incentives to do so depends on the local market size which itself depends on the level of transport costs, on the position of the location in the geographic network and on the speed of ideas and innovations through space.

Migration is allowed across and within countries at a cost. It conditions the locations' population density which in turn impact its productivity, incentives to innovate and access to amenities. In this setting, firms in each location produce a variety of goods thanks to the local technology that labor and a local factor they refer to as land. Agents have idiosyncratic stochastic preferences in choosing their living place. The static spatial equilibrium is alike Allen and Arkolakis (2014) [3]'s extended of migration, local factors. Trade is structured à la Eaton Kortum(2002) [69] with heterogenous preferences. The dynamic part re-uses the mechanism brought to light by Desmet and

Rossi-Hansberg(2014) [60] in limiting the forward looking abilities of agents and triggering innovation and growth based on land ownership and market size.

The model concludes that, first, people move to more productive areas. Second, more dense locations will become the most productive since investing in local technologies is more profitable in large markets. Migration restrictions shift the balance between those two effects. If migration are restricted, people stay where they are and today's dense areas (mostly developing countries) will become the most developed parts of the world. Conversely, if migration is unrestricted, today's most productive areas (developed countries) will attract workers and become the most productive-high amenities areas. The correlation between GDP per capita and population density that is nowadays negative will become positive over time. The conflicting role played by transfer costs on ideas opposed to transport costs has not been clearly emphasized but the rationale remains under the assumption that one effectively assimilates migration costs to transfer costs on ideas.

3.4.2 Empirics: Identifying the gains of integration out of the gravity framework

The quantitative model approach takes up the great challenge of rigorously addressing the welfare consequences of market integration considering extended spatial configurations and dynamic effects but the argument has mainly be theoretical. Empirically, identifying market interaction effects in a multi regional setting has remained challenging. The gravity framework has kept on being a widely used approach but as emphasized by Donaldson (2015) [63], unanswered questions remain in considering whether the strong assumptions underlying gravity frameworks allow enough flexibility to provide reliable predictions of the effects of market integration. Recent papers have mobilized the "program evaluation literature" in studying natural experiments in order to handle the identification issue.

In comparing treatment and control groups, researchers have attempted to identify the causal effect of trade integration on welfare under two strong conditions. First,

such methods suppose that the only difference between the treatment and the control groups, after controlling for observable elements among the determinants of welfare, is the difference in trade barriers. This condition is labeled the "uncounfoundedness requirement". The second condition stipulates that the two groups do not interact such that the impact of integration do not report upon the control group. This condition is known under the "stable unit treatment value assumption" (SUTVA).

Among the first studies being published using the program evaluation method, Redding and Sturm (2008) [165] took interest on the effect of the fall of the Iron Curtain in Germany on market access for cities in the near proximity of the new frontier. In a multiregion type of NEG model relying on the structure of a Helpman 1998 [107], they consider two agglomeration forces namely the home market and the cost of living effects and two dispersion forces namely a market crowding effect and a congestion effect. Theoretically, the interplay of those effects induce two central predictions. The first one considers that the relatively larger market loss bore by cities close from the Iron Curtain lead to a reallocation of population toward western German cities. Secondly, this market loss has impacted more deeply smaller than larger cities. The control group is constituted from regions '75 kilometers away' from the fall of the Iron Curtain. The treatment group considers the cities within the strip of land between the Curtain and the '75 kilometers' line. Rather than assuming values from the empirical literature for the model's parameters triggering the four effects at stake, the authors search for the parameters' values for which the decline of cities' size as simulated in the model is as close as possible from the observed data. Doing so, they find plausible (parameters') values giving credit to the hypothesis of a loss of market access expressing itself in the population mobility away from the new border. In a close setting, Brühlhart et al. (2013) [30] considered the impact of the fall of the Iron Curtain on employment and wage growth in Austria. Interestingly, they found that larger towns had larger nominal wage responses but smaller employment responses than smaller towns. Their model does not allow to infer the welfare effects from changes in cities' size but they propose to estimate the differential welfare effect for immobile workers in border towns (control group) compared to interior towns (treatment group). Accordingly, they found a differential of some 31% between the two.

Cosar and Fajgelbaum (2016) [51] rather build around an international trade model in considering the effects of integration on specialization, employment and incomes differentials between coastal and "interior" Chinese provinces. They consider a two-sector economy. Trade is costly and international shipments must transit through international gates located in coastal regions to reach final buyers. Firms use a mobile factor (labor) which tends to agglomerate in coastal regions and reinforce their specialization patterns toward exported oriented industries. They also use an immobile factor that will ground the specialization of interior and poorer regions. When the country opens up to trade, the interplay of international and national trade costs reinforce disparities between regions : the interior region loses due to labor migration toward coastal regions. Efficient national infrastructures are the condition to a better balance of international trade benefits. Somehow the authors also consider market access mechanisms as relevant elements in explaining the spatial pattern under study. They show that, if both comparative advantages and market access are relevant explanations, the former appears of higher importance.

Donaldson (2018) [64] constitutes a key contribution in proposing an estimation strategy that take care of network effects when measuring the welfare gains induced by improvements of transportation infrastructures. Grounding its reasoning on an Eaton Kortum (2002) [69] type of model, Donaldson addresses the whole causality chain linking transport costs embedded in transportation infrastructures and welfare. From a static framework where trade is based on productivities' differentials from one Indian region to the another he obtains four results that will drive the empirical analysis.

1. In the presence of trade costs, price differentials between regions over one homogenous commodity produced in only one place will be equal to the cost of trading such commodity.
2. Bilateral trade flows follows a gravity equation pattern.
3. Welfare as estimated by real income is positively related to railroad network expansion

4. To the extent that the correlation obtained in Result 3 could be induced by many mechanisms, the author demonstrates that the impact of railroad can be explained by the trade-based mechanism developed in his theoretical model.

From Step 1 to Step 4, Donaldson (2018) [64] addresses the causality chain starting with the fall in trade costs calculated at the introduction of the railroads up to its welfare consequences. Step 1 calculates the extent to which railroads drove down trade costs in India. Trade costs can only be obtained in the case where a homogenous commodity was produced in unique place and then traded. The price differentials can be interpreted as a transport cost. In order to draw the impact of the railroads on these costs, Donaldson estimates a mode-specific per unit distance costs and shows that the rail emerges as the cheapest option. Step 2 addresses the consequences of such a reduction of trade costs on trade flows between regions and shows that railroads significantly augmented trade throughout India. The next step investigates to which extent reduced trade costs and expanded trade flows participated in increasing welfare. The author shows that real income was indeed positively correlated to the expansion of the railroad network. Aware that this outcome could result from other mechanisms, Step 4 aims to confirm the role of a trade-based mechanism.

Donaldson and Hornbeck (2016) [65] builds on a gravity setting to look at the effects of the US railroads in terms of counties' market access. An important difference with the previous development is that the authors now have taken care of the issue raised by labor mobility. Rather than being attached to the real income in each county/region, they look at the price of some fixed factor i.e. the price of land. Their results stress that removing all railroads in 1890 would have lowered the total value of US agricultural land by 60,2% which would have represented a loss of 3.22% of the Gross National Product.

Importantly the developments on identifying gains from infrastructures have limited themselves to the considerations on static gains. Fogel (1964) [83] states that assessing the economic impacts of transportation infrastructures depends fundamentally on whether those changes augment the economic activity or induce a reorganization/re-

allocation of resources.⁸ To circumvent the issue, Redding and Turner (2014) [166], in a framework as illustrated in Fig 3.2, proposes to estimate two linear equations. Accordingly, they suppose a sample composed of three regions : a region that received the 'treatment' said has been affected by changes on its transportation costs, a 'untreated' region, close from the first one, but unaffected by changes on transportation and finally, "everyplace else". The outcome of interest is denoted y . The extensive margin generated by the new road is a , the intensive margin or the reallocation of activities from the treated to the untreated region is labeled d . Classic gravity equations estimate the compound effect of both reallocation and growth which amounts to $2d + a$. The solution raised by Redding and Turner (2014) [166] in order to identify both effects suggests to estimate two linearly independent equations respectively addressing reallocation and growth.

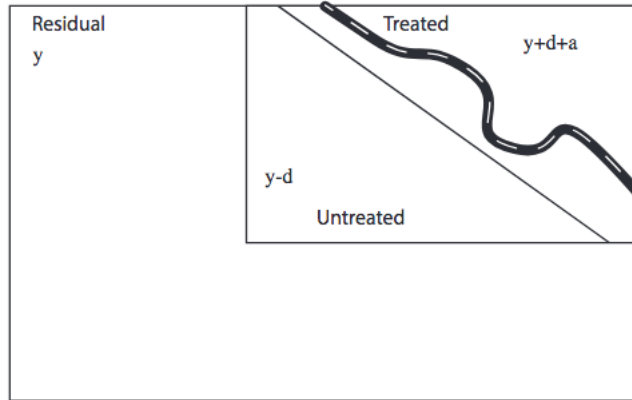


Figure 3.2: Natural experiment framework, Redding and Turner (2014) [166]

Chandra and Thompson (2000) [38] proposed such an estimation distinguishing two equations. The first one predicts the effect of changes in infrastructure on the treated area while the second look at the effect of changes in infrastructure on the untreated area. Doing so, they succeed in separating reallocation and growth effect under the

⁸He considers that the issue is different from the endogeneity problem that typically arise when studying transportation infrastructures. As we explained looking at NEGG models, the problem of distinguish growth from agglomeration issues is complex and would remain, independently from the non-random assignment of observations impacted by changes in infrastructures.

previous assumptions. The authors worked on the effect of interstate highway system for 185 non-metropolitan US counties that benefited from an access to the highway after 1969 (treated) and for 391 neighboring counties that did not (untreated). Over the 24 years that cover their sample, they found a marginally positive effect of highway connection on sectoral annual earnings for non-metropolitan counties. The gain over the 24 years represent a 6-8% increase in total earnings. Conversely, the effect on the 'untreated regions' is evaluated a loss between 1 and 3% in total earnings.

To the best of our knowledge, no study specifically addresses the opposing relationship of trade costs on goods and transfer costs of ideas on agglomeration and welfare patterns. Fajgelbaum and Redding (2014) brings some elements while studying the integration of Argentina to the world market in the late XIX century and considering the impact for regions. Based on a quantitative general equilibrium, they bring to light a complementarity effect of trade openness, infrastructures' development and spread of technological enhancements in the Argentinian countryside. They emphasize a "Balassa Samuelson effect" which means that proximity to trade hubs is associated with high employment density, high land rents relative to wages and structural transformation from agriculture to manufacturing. Conversely agricultural areas benefit from productivity gains and lower land rents relative to wages.

This section has been the occasion to dig deeper on the recent framework that considers the dynamic effects of integration and the welfare gains for many parties in large multi regional settings. Empirically, efforts have directed toward addressing the identification issue by network structure of international trade flows. Those works open avenues of research in rigorously assessing the empirical relevance of our hypothesis concerning the conflicting role of trade costs on goods and costs on the spread of ideas.

3.5 Conclusion

The European Union has been built according to the widespread belief that economic integration would be a vector of wealth and welfare enhancements for trading partners. At the core of this logic, the decrease of barriers to trade should have allowed

economies to reach some higher Pareto equilibrium which pushed national governments to implement policies of openness. However, researchers nowadays show that regional disparities have spurred and if some regions have been net beneficiaries of integration, some seem to have relatively suffered from welfare losses. In this paper, we questioned the role of trade barriers in shaping the new geography of wealth between regions of integrated spaces.

According to New Economic Geography models, agglomeration mechanisms trigger benefits in terms of real wage for core regions but also imply losses for the becoming peripheral region(s). In this frame, agglomeration mechanisms are fully conditioned by the level of transport costs. High transport costs should prevent agglomeration in forcing industries to locate in every market they serve and inhibit trade flows between economies. Conversely, intermediate transport costs should allow agents to benefit from agglomeration and while locating at only one place induce denser trade flows between economies. In a first time, the empirical literature had difficulties emphasizing decreasing transport costs and their impact on trade flows.

As a potential explanation to this, we found evidences coming from different literatures that two components of trade costs could be at play and act in opposite directions. Namely trade costs on goods would trigger agglomeration while transfer costs on ideas would favor economic activities' dispersion. Nowadays, 'integrating' covers both dimensions of commercial and technological integrations and gives much credit to this explanation. In an attempt to find some empirical evaluation of this interplay, we mobilize the literature looking at the impact of infrastructures and externalities spread without finding sufficient answers.

As a final step, we turned to models considering trade costs and mobility of labor in multiregional settings. Indeed recent enhancements from the literature on the geography of innovation think of the mobility of labor as the main determinant of the spread of knowledge externalities. In parallel we investigated the introduction of natural experiments in the literature of international trade as promising avenues of research in quantifying trade costs. Overall the present chapter sketched many avenues of research

and we argue that subsequent works should rely on the methodological enhancements propose by the very recent literature to properly identify effects of openness. Among those avenues, one consists in testing the proposition made by Montmartin (2015) [151] to confront the effects of both forms of integrations upon agglomeration outcomes. We attempt to address this relationship in the ultimate chapter of this thesis.

Chapter 4

The determinants of spatial agglomeration

As economies grow, the spatial distribution of population and productive activities change and tends to agglomerate. If economic growth is somehow a desirable outcome, most governments concerned by agglomeration dynamics have implemented policies to contain the entrenchment of regional inequalities. This mechanism is underpinned by the theoretical literature of the New Economic Geography which emphasizes how concentration of both activities and people tends to spur income inequalities between regions. Those models (Krugman (1991) [130]) show how the agglomeration of productive activities induces a higher demand of labor, higher wages and a higher nominal income for workers moving to the core region at the expense of those remaining in the peripheral area. This concentration also raises the price index for the periphery while it decreases it for the core which, in turn, slows down the (per capita) income convergence between locations. Some empirical studies give credit to this outcome even if the link does not appear as straight forward as the theory would suggest. Precisely, Caselli and Coleman (2001)[34], Kim and Margo (2004) [127] and Kim (2009) [126] describe a diverging process across US regions during the XIX^{th} and early XX^{th} centuries followed by a convergence dynamic. The first phase would correspond to the industrialization of the Northeast regions becoming the manufacturing belt and widening income differentials with Southern regions. The second phase would be linked to the decline in regional specialization at the beginning of the XX^{th} century. Kim (2009) [126] emphasizes an inverted-U-shape pattern more largely documented in the 2009 World Development Report for both developing and developed countries.

Agglomeration is also suspected to influence economic growth. Empirically, evidences are scarce and describe a complex relation. Brülhart and Sbergami (2009) [31] find that greater spatial concentration enhance growth only up to a per capita GDP threshold of \$12.000 ¹. Still does it concern the early stages of development while the positive relationship fades or reverses for more developed countries. Conversely, Crozet and Koenig (2007) [54] find a strong growth promoting effect of agglomeration in the case of Northern European regions between 1980 and 2000. Few models document the triptych constituted by agglomeration, income inequalities and growth but New Economic Geography and Growth (NEGG) models make a step in this direction. In considering

¹in 2006 prices

growth into a New Economic Geography framework, those frameworks get to explain why (innovative) economic activities agglomerate, to which extent firms' concentration enhances capital and knowledge accumulation and finally how does this induce increasing income spatial disparities. Three determinants root those mechanisms namely increasing returns to scale, transport costs and localized knowledge spillovers.

This paper focuses on the relation linking transport costs and localized knowledge spillovers to agglomeration dynamics. Typically, in a NEG framework, trade costs on goods impede the famous Home Market effect (HME) and its consequences regarding income disparities. When trade costs are of a small magnitude, even a slight difference in capital endowments between partners induces a relocation (destruction/creation) toward the wealthiest region and increases expenditures and market size in this region. The HME emphasizes that the relocation effect would be even greater since an expenditure differential would induce a more than proportional change in the geography of production. Low trade costs reinforce the Home Market effect and trigger agglomeration. Conversely, localized knowledge spillovers affect the cost of innovating and impact agglomeration the other way around. Less localized knowledge spillovers/lower transfer costs on ideas lessen incentives to agglomeration as location becomes less important to innovate and proximity does not ease innovation anymore.

Various classifications for the different mechanisms that underpin agglomeration economies have been proposed. "Long ago, Chinitz (1961) [41] suggested that examining the degree of co-agglomeration of industries depending on their characteristics is another way to test for the presence of agglomeration economies" ([49] p.84) Widely studied, Marshall (1890) divides channels of agglomeration into technological spillovers, labor pooling and input-output linkages. In this vein, Rosenthal and Strange (2001) [175] tests industrial spatial concentration or firms co-location in relation with industry characteristics associated to the three Marshallian agglomeration mechanisms.

However, one should consider that this strand of the literature have been sharply criticized. (Combes and Gobillon (2014) [49]). The first critic directly stems from weak links between econometric specifications and theoretical models. Second, no ro-

bust foundations underlie the choice of explanatory variables nor the *a priori* additive linear relations grounding most specifications. Third, these specifications might be undermined by endogeneity issues since there exist strong dynamic relations between independent and dependent variables that the lack of sound theoretical instruments doesn't allow to prevent.

Building on these, we propose another way to test for the presence of agglomeration economies in moving our focus to consider the agglomeration issue at the regional level rather than at the industrial level. To the extent that industries get agglomerated in places, our study consists in a simple change of perspective. We propose to test the relationship linking regional agglomeration outcomes to interregional pecuniary and non pecuniary externalities' flows. Interregional pecuniary and non pecuniary externalities' flows refer to the same phenomena as Marshallian input-output linkages and technological spillovers respectively. Those forces are expected to be constrained by transport costs on goods and transfer costs on ideas respectively. Lower transport costs on goods should allow denser inter-regional pecuniary externalities favoring agglomeration while lower transfer costs on ideas should allow spreading non-pecuniary externalities and temper agglomeration dynamics. The equation we propose is tied to the theoretical developments provided in Montmartin (2015)[151] that extends a NEGG framework and reaches testable conclusions that oppose the effects of commercial and technological integrations in order to explain the intensity of agglomeration processes. We treat for the likely non-linear form of the relation using Generalized Additive Models combined with Control Functions to take care of endogeneity issues.

Section 4.1 develops the empirical equations extracted from Montmartin (2015) [151] that we briefly sketched in Chapter 3. Section 4.2 details how we construct our variables and the underlying reasoning. Section 4.3 develops data matters and descriptive statistics upon our variables. Section 4.4 provides results for preliminary regressions using least squares, two stage least squares and GMM estimations of spatial models. Section 4.5 develops the estimation framework attached to Generalized Additive Models and gives results from those computations. Section 4.6 concludes.

4.1 Theoretical Framework

The theoretical framework we rely on roots back to New Economic Geography and Growth models (NEGG) implementing growth dynamics into New Economic and Geography models (NEG). As stated in Chapter 3, the model of Krugman (1991) [130] opened the path interacting space and trade. Doing so he emphasized the predominant role of transport costs in explaining agglomeration dynamics and their consequences on income disparities. NEGG models introduced capital accumulation upon regional agglomeration issues and showed how knowledge spillovers could play a role in opposing the centripetal forces triggered by low transport costs.

Montmartin (2015) [151] builds on the NEGG framework developed in Martin and Ottaviano (1999)[145] that incorporates an endogenous growth mechanism *à la* Grossman Helpman (1991) [Chap.3] [99] into a Footloose Capital model *à la* Martin and Rogers (1995) [146]. This is a two-region model with initial capital asymmetry which is the only source of nominal income inequality. Trade is subject to transport costs, production benefits from increasing returns to scale, capital flows freely between regions but labor is spatially immobile. In accordance with the NEGG framework, localized knowledge spillovers in the innovative sector pushes productive activities (innovation and manufacturing sectors) to agglomerate and spurs economic growth by widening inventors' access to knowledge while spatially concentrating it. In extending this, Montmartin [151] introduces a Benassy(1998)-type [22] of Constant Elasticity of Substitution (CES) function to redefine the utility equation. This type of CES function allows to disentangle the taste of variety from the elasticity of substitution between varieties.

This setup involves two maximization programs : the first one optimizes utility of a representative consumer in the "Northern region" in the context of a decentralized market economy and the second one considers the solution a social planner would elect in maximizing utility for both the northern and the southern regions.

In the first case, the steady state induces an equilibrium level of agglomeration (s_n) of the form :

$$s_n = \min \left\{ 1, \frac{1}{2} + \frac{1}{4} \frac{\sqrt{(1 + \lambda + \rho\eta)^2(1 - \phi)^2 + 4\eta\rho(1 - \phi^2)(1 - \lambda)(2s_k - 1)} - (1 + \lambda\rho\eta)(1 - \phi)}{(1 - \phi)(1 - \lambda)} \right\} \quad (4.1)$$

where $\phi \in [0, 1]$ denotes freeness of trade and $\lambda \in [0, 1]$ denotes the spread of knowledge externalities. Specifically, as ϕ tends to 0, trade costs are high and prevent exchanges of goods. Conversely, as ϕ tends to 1 integration deepens. Symmetrically, as λ tends to 0 no knowledge externalities spread around while as λ gets closer from 1 technological integration deepens. The equation also integrates considerations on ρ which is the marginal cost of postponing consumption for an instant times η which represents the productivity of labor dedicated to R&D. Ultimately s_k is the initial capital endowment inequality.

This expression emphasizes the forces at play in conditioning the level of agglomeration in a market economy.

- The initial capital inequality s_k constitutes a centripetal force : the wider the capital inequality, the more intense the activities' attraction force towards the core region which is the largest pool of pecuniary externalities.
- Trade integration (ϕ) tends to favor agglomeration dynamics : $\partial s_n / \partial \phi > 0$. As transport costs diminish, firms located in the periphery are increasingly attracted to the core to benefit from pecuniary externalities and scale economies in the near proximity of the largest market.
- Conversely, technological integration (λ) tempers agglomeration dynamics : $\partial s_n / \partial \lambda < 0$. The rationale is that the spread of knowledge externalities between regions supports growth and participate in reducing income inequality across regions.

The second maximization program develops the social planner solution of the model and doing so investigates the optimal level of agglomeration that would maximize the welfare of both regions. Developing the optimal level of agglomeration in the case of

the social planner allows to emphasize the normative power of commercial (ϕ) and technological (λ) integrations.

The optimal level of agglomeration must satisfy

$$\frac{\partial \mathcal{L}}{\partial s_n} = \frac{\partial H}{\partial s_n} + \theta_3 - \theta_4 = 0 \quad (4.2)$$

where \mathcal{L} is the Lagrangian in the maximization program and θ_3 and θ_4 parameters satisfying $\theta_3, \theta_4 \geq 0$. $(\partial H / \partial s_n)$ represents the partial derivative of the Hamiltonian with respect to the level of agglomeration of manufacturing activities in the North region (s_n). In deeper details, the partial derivative of the Hamiltonian with respect to the level of agglomeration (s_n) is itself conditioned by three effects. The equation we refer to is written such as :

$$\frac{\partial H}{\partial s_n} = -\frac{\alpha L}{(\sigma - 1)} \frac{(1 - \phi)^2 (2s_n - 1)}{[s_n + \phi(1 - s_n)][\phi s_n + (1 - s_n)]} - \frac{2L(1 - \lambda)}{s_n + \lambda(1 - s_n)} + \frac{4\mu L(1 - \lambda)}{\rho \eta} \quad (4.3)$$

ϕ still denotes freeness of trade and λ is the spread of knowledge externalities. L is the labor supply of one region. Of least importance for our point, the social planner level of agglomeration also integrates considerations on the level of taste for variety ($\mu \in [0, 1]$), the elasticity of substitution between varieties ($\sigma > 1$) but also the share of differentiated goods in total consumption ($\alpha \in [0, 1]$). ρ is the marginal cost of postponing consumption for an instant times η which represents the share of labor dedicated to R&D.

Montmartin (2015) [151] considers three terms corresponding to the three effects in (4.3) : a transport cost effect, a nominal consumption effect and a pro-growth effect.

- First ratio : The 'transport cost effect' accounts for the impact of manufacturing firms' location choice on the global transport cost paid by the two regions of the model. This effect is negative to the extent that as spatial concentration increases, exchanges of goods rise and so do the amount dedicated to transport costs.

- Second ratio : The second effect is the nominal consumption effect still negative. Indeed, supposing the existence of knowledge externalities whose spread is favored by spatial concentration implies that, as activities concentrate, the cost of producing patent decreases. An additional consequence is to increase the labor devoted to the R&D sector and reduce the labor force allocated to the manufacturing sector dedicated to produce consumption goods. Consumption are thus delayed over time causing an immediate loss at time t in anticipation of higher expected returns at time $t + 1$.
- The third (growth effect) represents the pro-growth effect of spatial concentration. It depends negatively on λ to the extent that, as ideas flow freely between regions, firms find incentives to relocate away from the center slowing down the production of innovations by minimizing the dynamic advantage of concentration in knowledge production.

Trade and technological integrations play a crucial role in rooting those 3 effects. The two parameters, respectively the freeness of trade ϕ and the parameter of externalities' spread λ , induce strictly opposite effects on agglomeration. A strict demonstration should rely on obtaining the optimal level of agglomeration s_n^* in order to solve $\frac{\partial H}{\partial s_n} = 0$ and study the sign of the derivatives $\partial s_n^* / \partial \lambda$ and $\partial s_n^* / \partial \phi$.

Solving $\frac{\partial H}{\partial s_n} = 0$ requires solving a polynomial of third degree of the form :

$$as_n^3 + bs_n^2 + cs_n + d = 0$$

where

$$a = -4\mu(1 - \lambda)^2(1 - \phi)^2(\sigma - 1)$$

$$b = -2(1 - \phi)^2(1 - \lambda)[2\mu(2\lambda - 1)(\sigma - 1) + \eta\rho(\alpha + 1 - \sigma)]$$

$$c = 2(1 - \lambda)(\sigma - 1)[(1 - \phi)^2(2\lambda\mu - \eta\rho) + 2\mu\phi(1 - \lambda)] - \alpha\eta\rho(1 - \phi)^2(3\lambda - 1)$$

$$d = 2\phi(1 - \lambda)(2\lambda\mu - \eta\rho)(\sigma - 1) + \alpha\lambda\eta\rho(1 - \phi)^2$$

This polynomial becomes null in three instances such that the optimal level of agglomeration can be expressed

$$s_n^* = \min\{1, \max\{1/2, s^*\}\}$$

$$\begin{aligned}
s^* &= 2\sqrt{\frac{-p}{3}} \cos \left[\frac{1}{3} \arccos \left(\frac{3q}{2p} \sqrt{\frac{-3}{p}} \right) \right] - \frac{b}{3a} && \text{if } 4p^3 + 27q^2 \leq 0 \text{ and } p < 0 \\
s^* &= -2\frac{|q|}{q} \sqrt{\frac{-p}{3}} \cosh \left[\frac{1}{3} \operatorname{arccosh} \left(\frac{-3|q|}{2p} \sqrt{\frac{-3}{p}} \right) \right] - \frac{b}{3a} && \text{if } 4p^3 + 27q^2 > 0 \text{ and } p < 0 \\
s^* &= -2\sqrt{\frac{p}{3}} \sinh \left[\frac{1}{3} \operatorname{arsinh} \left(\frac{3q}{2p} \sqrt{\frac{3}{p}} \right) \right] - \frac{b}{3a} && \text{if } p < 0
\end{aligned}$$

with

$$p = \frac{3ac - b^2}{3a^2} \quad q = \frac{2b^3 - 9abc + 27a^2d}{27a^3}$$

Obtaining the sign of $\partial s^*/\partial \lambda$ or $\partial s^*/\partial \phi$ implies too complex derivatives to allow for a comprehensive analytical answer. Montmartin (2015) [151] proposes a way to circumvent the issue in considering three cases along $\partial H/\partial s_n$. For the reminder s_n^* (as s_n) evolves in the interval $[0.5, 1]$. H is concave with respect to s_n such

1. When $s_n^* \in]1/2, s^*[$ then

$$\frac{\partial H}{\partial s_n} < 0 \quad \& \quad \theta_3 > \theta_4$$

When the optimum of the concave Hamiltonian is in $s_n^* = 1/2$, the curve left on the interval $]1/2, 1]$ is decreasing such that the derivative $\partial H/\partial s_n$ is negative. It remains so until $\partial H/\partial s_n$ reaches 0

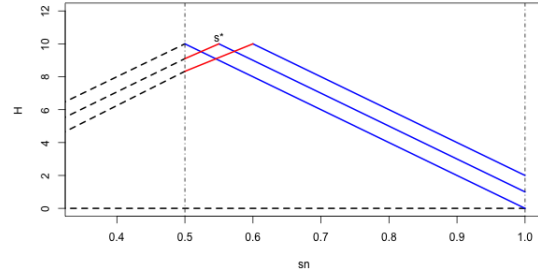


Figure 1 : $\partial H/\partial s_n < 0$ at $s_n^* = s^* \in]1/2, s^*[$

2. In between $1/2$ and 1 , when s_n^* is the point satisfying $s_n^* = \min\{1, \max\{1/2, s^*\}\}$, then

$$\frac{\partial H}{\partial s_n} = 0$$

where s^* is the real solution to the third degree polynomial equation $as_n^3 + bs_n^2 + cs_n + d = 0$ that would solve $(\partial H/\partial s_n) = 0$.

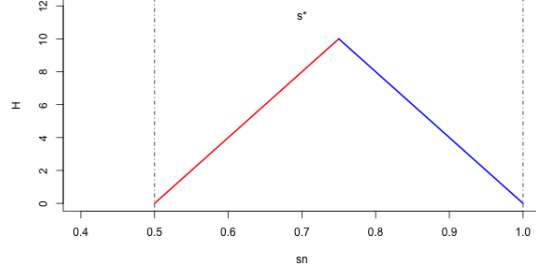


Figure 2 : $\partial H/\partial s_n = 0$ when

$$s_n^* = s^*$$

3. From when $s_n^* \in]s^*, 1]$ then

$$\frac{\partial H}{\partial s_n} > 0 \quad \& \quad \theta_3 < \theta_4$$

When the optimum of the concave Hamiltonian is in $s_n^* = 1$, the curve left on the interval $]1/2, 1]$ is increasing such that the derivative $\partial H/\partial s_n$ is positive. It has been so all over $]s^*, 1]$ that is from the point s^* where $\partial H/\partial s_n = 0$.

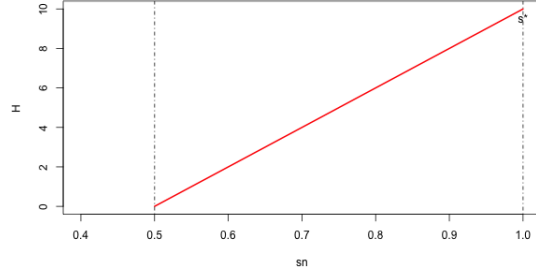


Figure 3 : $\partial H/\partial s_n > 0$ at

$$s_n^* = s^* \in]s^*, 1]$$

Relating back to the full expression of $\frac{\partial H}{\partial s_n}$, the previous configurations correspond to the following cases. Importantly, the pro-growth effect dominates the nominal consumption effect such that the sign of $\frac{\partial H}{\partial s_n}$ depends on the trade-off between the transport costs effect and the pro-growth effect :

- $\frac{\partial H}{\partial s_n} < 0$ requires

$$\frac{\partial H}{\partial s_n} = -\frac{\alpha L}{(\sigma - 1)} \frac{(1 - \phi)^2 (2s_n - 1)}{[s_n + \phi(1 - s_n)][\phi s_n + (1 - s_n)]} > \underbrace{-\frac{2L(1 - \lambda)}{s_n + \lambda(1 - s_n)} + \frac{4\mu L(1 - \lambda)}{\rho\eta}}_{+}$$

- $\frac{\partial H}{\partial s_n} > 0$ requires

$$\frac{\partial H}{\partial s_n} = -\frac{\alpha L}{(\sigma - 1)} \frac{(1 - \phi)^2 (2s_n - 1)}{[s_n + \phi(1 - s_n)][\phi s_n + (1 - s_n)]} < \underbrace{-\frac{2L(1 - \lambda)}{s_n + \lambda(1 - s_n)} + \frac{4\mu L(1 - \lambda)}{\rho\eta}}_{+}$$

Deriving the transport cost effect results in finding that it is decreasing, convex in ϕ such that :

$$\frac{\partial s^*}{\partial \phi} > 0 \Leftrightarrow \frac{\partial H / \partial s_n}{\partial \phi} > 0 \quad \text{and} \quad \frac{\partial^2 s^*}{\partial^2 \phi} < 0$$

This means that as economies integrate, the (negative) transport cost effect fades, up to its disappearance. Respectively the derivative of the nominal consumption effect is also decreasing convex respective to λ :

$$\frac{\partial \left(2L(1 - \lambda) / s_n + \lambda(1 - s_n) \right)}{\partial \lambda} < 0 \quad \text{and} \quad \frac{\partial^2 \left(2L(1 - \lambda) / s_n + \lambda(1 - s_n) \right)}{\partial^2 \lambda} > 0$$

However, to the extent that the growth effect is expected to dominate the nominal consumption effect, the positive derivative (relative to λ) of the former dominates the latter's.

$$\frac{\partial \left(4\mu L(1 - \lambda) / \rho\eta - 2L(1 - \lambda) / s_n + \lambda(1 - s_n) \right)}{\partial \lambda} < 0$$

This leads us to the following conclusion :

- When $\frac{\partial H}{\partial s_n} < 0$ and $s_n^* \in]1/2, s^*[$, it implies that the transport cost effect matters

over the nominal consumption and pro-growth effects.

$$-\frac{\alpha L}{(\sigma - 1)} \frac{(1 - \phi)^2 (2s_n - 1)}{[s_n + \phi(1 - s_n)][\phi s_n + (1 - s_n)]} > \frac{4\mu L(1 - \lambda)}{\rho\eta} - \frac{2L(1 - \lambda)}{s_n + \lambda(1 - s_n)}$$

when $\phi \rightarrow 0$ and $\lambda \rightarrow 1$

A symmetric equilibrium will be favored by a deep technological integration and the ability of knowledge production activities to relocate far from the core region while still benefiting from knowledge externalities. Conversely a restricted commercial integration will prevent firms from agglomerating in maintaining high transport costs on goods.

- When $\frac{\partial H}{\partial s_n} > 0$ and $s_n^* \in [s^*, 1[$, it implies that pro-growth effect dominates both the nominal consumption and transport cost effects.

$$-\frac{\alpha L}{(\sigma - 1)} \frac{(1 - \phi)^2 (2s_n - 1)}{[s_n + \phi(1 - s_n)][\phi s_n + (1 - s_n)]} < \frac{4\mu L(1 - \lambda)}{\rho\eta} - \frac{2L(1 - \lambda)}{s_n + \lambda(1 - s_n)}$$

$\phi \rightarrow 1$ & $\lambda \rightarrow 0$

A core-periphery structure will arise between a region and its neighbors because of the combination of a deep trade integration (low trade costs) and a weak technological integration (high transfer costs). The gains from low trade costs on goods reinforces those from the pro-growth effect.

We synthesize this reasoning in an attempt to test for the conditional relationship between the degree of concentration of manufacturing activities in a region opposed to the two forms of integrations governed by ϕ and λ . We aim at empirically emphasize the interplay of those forces on the regional agglomeration level. Formally, we will estimate the two versions of the agglomeration equation : the one that arise from the maximization program of the decentralized economy and the one that refers to the optimization of the social planner.

The one issued from the market equilibrium in (4.1), is written as,

$$s_n = \hat{f}_1[\phi, \lambda, s_k] , \hat{g}_1[\rho, \eta] \quad (4.4)$$

The one issued from the social planner equilibrium extracted from (4.3), written as,

$$s_n^* = \hat{f}_2[\phi, \lambda, (1 - s_n), L] , \hat{g}_2[\alpha, \sigma, \mu, \rho, \eta, \theta_3, \theta_4] \quad (4.5)$$

where $\hat{f}_{1,2}$, $\hat{g}_{1,2}$ are some empirical functions. In each case, we investigate the relationship tying agglomeration levels (s_n), transport costs on goods (ϕ) and transfer costs on ideas (λ) that constitute the core of our interest. In the empirical estimation, the theoretical optimal level of agglomeration (s_n or s_n^*) are replaced with the empirical realization of the level of agglomeration caught thanks to an autocorrelation index that should give a sense of the role of region n in some center/periphery configuration. The content of \hat{f} are the parameters we expect to be able to empirically proxy while the content of \hat{g} might constitute the residuals and include everything we could not catch. In accordance with the theory, we hope to emphasize that s_n varies positively with ϕ , that is lower transport costs participate in intensifying agglomeration, while s_n varies negatively with λ , that is lower transfer costs on knowledge tempers agglomeration dynamics : $\partial s_n / \partial \phi > 0$ and $\partial s_n / \partial \lambda < 0$ and $\partial s_n^* / \partial \phi > 0$ and $\partial s_n^* / \partial \lambda < 0$

Regions are NUTS2 European regions observed over time t . In extending the two-region setting to the whole map of European regions, we move from a frame opposing agglomeration in the northern region s_n to the southern region $(1 - s_n)$, to a situation where each region i is compared to its neighbors. Doing so we suppose that each region and its close neighbors constitute an integrated area. Each region is conceptualized as a realization from a superpopulation of integrated areas rather than as the elements of a single realization of this superpopulation. However, this setting has two drawbacks: First, we theoretically ignore network effects that would arise from multi-regional configuration (more than two regions). At best could we consider that those network disturbances will induce spatial autocorrelation issues in regression's residuals that we aim at controlling for, in ensuring identification. Second, the empirical framework we

develop, takes no care of the hierarchical issues that still do arise from the overlay of local/regional/national forms of integration.

The following section develops how we constructed our variables to proxy for theoretical parameters. Details on the construction of the dependent variable are displayed in subsection 4.2.1. Details regarding the construction of proxies for ϕ and λ are provided in subsections 4.2.2 and 4.2.3.

4.2 Variables

4.2.1 Co-agglomeration and autocorrelation indexes

Studies looking at Marshallian externalities have used indexes of agglomeration or industries' co-agglomeration to evaluate the degree of spatial concentration of industries. In doing so, they make a strong argument against 'measure of localization' and in favor of measures of industrial concentrations. At first, we can state that an industry with no tendency for clustering, is expected to locate randomly across locations, like "darts thrown randomly at a map". Because the number of plants in any industry could not be so large, random location processes cannot be expected to produce perfectly random patterns. Ellison and Glaeser (1997) [72] take as an example the case of the vacuum cleaner industry in the US. In this case, 75% of the employees work in one of four main plants. Even if these plants would locate separately, only one location would account for the 75% of the workforce in this industry, without it being localized in any meaningful way. Unevenness does not necessarily mean an industry is localized and unfortunately, traditional measures of localization only measure unevenness. (p.2 Duranton and Overman (2005) [66]) So, when looking at the location patterns of industries, the null hypothesis should be spatial randomness conditional on both industrial concentration and the overall agglomeration of manufacturing.

Towards this objective, the index proposed by Ellison and Glaeser (1997) [72] measures

the colocation of industry a with industry b over geographic areas indexed by g .

$$\gamma_{ab}^c = \frac{\sum_{g=1}^G (s_{ga} - \bar{s}_g)(s_{gb} - \bar{s}_g)}{1 - \sum_{g=1}^G \bar{s}_g^2}$$

s_{ga} is the share of industry a 's employment in area g . \bar{s}_g measures the average employment share in region g across industries. The index takes on a value of zero when the industry a and b are located at random and a positive value when the industry a is co agglomerated with industry b . The index is related to the covariance of the area-industry employment shares in the industries a and b . The denominator rescales the covariance to cancel sensitivity to the geographic breakdown (i.e. to the size of the geographic areas).

We aim at transposing the reasoning Ellison and Glaeser (1997) [72] makes in arguing against measures of unevenness in quantifying agglomeration of industries to quantify agglomeration [of industrial activities] at the regional level. In doing so we look at the agglomeration of gross value added rather than the agglomeration of industries *stricto sensu*. Indeed data regarding regional incomes are more widely available over time than industries' revenues or industries' employment shares at the regional scale. We circumvent the flaws of measures looking at "unevenness" in turning to the wide literature that takes interest in quantifying (co-)agglomeration over space and discretized units using autocorrelation indexes. Spatial autocorrelation can be used to represent core-periphery patterns and to quantify the strength of spatial structures linking units to one another. We quantify those structures in Chapter 1 (based on regional GDPs (per capita)) using Moran's I which is a particularly efficient autocorrelation index that justify its extensive use in the literature and the present choice.

In the local definition, Moran's I_i are defined according to a structure very similar to

the (co-) agglomeration index Ellison and Glaeser (1997) [72] propose :

$$I_i = N \frac{\sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

$$= N \frac{(x_i - \bar{x})}{\sum_i (x_i - \bar{x})^2} \sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})]$$

where x_i is the variable of interest for region i whose neighbors are indexed j . \bar{x} is the average across the whole area (265 NUTS II regions). W is a weight matrix. The variance at the denominator is also to be obtained over the whole map.

In the present setting, the interpretation of the local autocorrelation index aims at defining the spatial configuration a region is in regarding its "close" neighbors. For low values of autocorrelation, region i is found dissimilar respective to its close neighbors. The pattern thus tends to a core-periphery configuration. Conversely high values of autocorrelation spot regions of similar levels of gross value added such that the configuration we point to likely tends to a core-core or periphery-periphery configuration.

A negative value of the local Moran I_i emphasizing a core-periphery pattern can result from two instances :

- Either region i is above the global mean such that $(x_i - \bar{x})$ is positive but neighbors are persistently below \bar{x} such that $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})] < 0$
- Either region i is itself below the global mean while its neighbors are over : $(x_i - \bar{x}) < 0$ and $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})] > 0$.

Respectively, a positive value of the local Moran I_i emphasizing a core-core (/ periphery-periphery) pattern can also result from two instances :

- Either region i is above the global mean such that $(x_i - \bar{x})$ is positive and its neighbors are also persistently above \bar{x} such that $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})] > 0$.
- Either region i is itself below the global mean and its neighbors are : $(x_i - \bar{x}) < 0$ & $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})] < 0$.

Certainly does the sign of $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})] < 0$ depends on the weight matrix and more specifically on how distant are regions to be considered as "neighbors". Let's take the example of Ile de France (Paris, France). Paris represents among the highest gross value added in 1990 so, largely above the European mean (\bar{x}). When considering the 5 closest neighbors the local Moran I_i is high and positive since $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})] > 0$. The lowest the variance $\sum_i (x_i - \bar{x})^2 / N$, the strongest the core-core pattern will appear. Conversely, including further neighbors, the local Moran's I_i turns negative as regions below the European average dominate the sum $\sum_{j=1, j \neq i}^n [w_{ij}(x_j - \bar{x})]$. As we change the definition of the area surrounding region i , the nature of the configuration at stake might change. Small kernel would be more precise about the nature of the local configuration while wide kernels will tend to smooth non-stationarities. Economically, each configuration calls for a different hypothesis regarding the scale at which externalities impact the concentration of the gross added value. When supposing 25 nearest neighbors, we focus on relatively local scale. At such scale, core-periphery patterns emphasize even small differences in gross value added across regions; typically differences resulting from local industrial clusters. In such case, forces that trigger the spread of knowledge externalities most likely play a minor role as people are still able to commute on a regular basis. Supposing an ever increasing number of neighbors, differences of gross added values must be bigger to appear as significant differences. In such case, the phenomena we address more likely refer to the globalization process that occurred at the European scale and to technology and absorptive capacities of the regional labor force that condition the spread of knowledge externalities.

In order to ease final interpretation we normalize annual distributions of local Moran's I_i over the range $(1, -1)$ and reverse interpretation of the index. Theoretically, as s_n (the share of manufacturing activities that locates in the North) raises, agglomeration reinforces. Conversely, by definition, a high local Moran's I_i denotes a dispersed pattern. To avoid this discrepancy, we normalize our index along :

$$\text{Normalized } I_i = -2 \times \left(\frac{I_i - I_{min}}{I_{max} - I_{min}} \right) + 1$$

Normalizing allows to reverse the interpretation such that a positive Moran's

I_i now corresponds to stronger agglomeration. Henceforth, negative local Moran's I_i display core-core patterns ($s_n \rightarrow 1/2$) and positive local Moran's I_i display core-periphery patterns ($s_n \rightarrow 1$).

4.2.2 Proxy for transport costs on goods

We re-invest our measure of proximity from Chapter 1 that exploits the patenting colocation patterns to proxy for the regional industrial mix. We already detailed this measure in Chapter 1 and the technical description will be brief. However should we now provide for the economic logic behind this measure. This measure is defined based on the principle that transport costs on goods condition the spread of pecuniary externalities that themselves trigger intra-industry trade. Consequently our measure aims at quantifying the level of inter-regional pecuniary externalities to reveal the level of transport costs.

Investigating the link between trade costs on goods and intra-industry trade, theoretically, 3 configurations are possible :

- In the case where transport costs are prohibitively high, regions live in autarky. To the extent that they both have to produce agricultural and manufacturing goods, regions are "similar". However from one region to another manufacturing "varieties" must differ to trigger trade in a second time. At the point where trade costs are prohibitive, manufacturing mixes should be dissimilar and yet no input-output ties relate regions to one another.
- Moving from autarky to intermediate levels of transport costs, we expect exchanges between regions to intensify based on the input-output links between industries. To some extent, looking from an aggregate point of view, industrial mixes get more and more similar as industries integrate both horizontally and vertically. As integration proceeds the share of intra-industry trade over total trade decreases by the simultaneous decrease of its numerator and increase of its denominator. When reaching a core/periphery pattern, inter-industry trade dominates between regions. Except in the case of complete disappearance of the

industrial sector in the periphery $s_n = 1$, intra-industrial proximity should stay very high.

- Finally when transport costs are very very low, we expect two regions to exhibit again very dissimilar industrial mixes as no pecuniary externalities flow between those regions and agglomeration process has arrived to an end.

We focus on the first linear section of this U-shaped relationship where trade costs are intended in the interval between prohibitive and intermediate levels. We suppose that even with the most fluid connexions both commercial and technological, some barriers remains such as differing languages, historically determined tastes, history of violence and wars. Head and Mayer (2013) [105] advocates those issues as potential explanations to persistent barriers to exchanges. The empirical literature on intra-industry trade have heavily documented a negative relationship between intra-industry trade and distance costs in gravity configurations. Few but famous examples are Bergstrand (1983) [23], Culem and Lundberg(1986) [55], Hummels and Levinsohn (1995) [117], Loertscher and Wolter (1980) [138], Stone and Lee (1995) [186]. Of particular interest, Venables, Ride, Stewart (2003) [193] emphasize the critical role of proximity of supply (and demand) structures in explaining the geography of intra-industry trade. Their reasoning goes along the fact that intra-industry flows embeds a strong geographical concentration : the closest countries tends to exchange significantly more. At play, they found that similarities in countries characteristics (the structure of supply i.e industrial mixes ; the structure of demand i.e love for some varieties) were major determinants. We suppose that, in turn, trade costs significantly conditioned supply structures, especially.

Those empirical digressions ground their approaches on theoretical developments. Bergstrand and Egger (2006) [24] develop both a theoretical and an empirical framework that rationalizes and tests the negative relationship. They consider a two-country, two-sector, two-factor model (similarly to Helpman- Krugman (1985) [108]). One sector produces a differentiated good X under monopolistic competition and the second produces a homogenous good Y. X is expect to be more capital intensive than Y. Across countries, trade is made at cost but exchanges are guaranteed as each firm faces a demand in its domestic market and in the foreign market. They assume that factor

endowments (capital and labor) are fixed in each country i and j . The model allows to express the share of intra-industry trade over total trade (GLI ²) as a function of prices of X and Y (p_{Xi} , p_{Xj} , p_{Yi} and p_{Yj}) and quantities (q_{ij} , q_{ji} , Y_{ij} and Y_{ji}) :

$$GLI = \frac{2 \min\{p_{Xi}q_{ij}, p_{Xj}q_{ji}\}}{p_{Xi}q_{ij} + p_{Xj}q_{ji} + t_Y |p_{Yj}Y_{ij} - Y_{ji}|}$$

t_Y is the transport cost on good Y. At the numerator, the minimum of intra-industry flows between countries i and j . At the denominator the sum of all flows : exports from i to j of X ; exports from j to i of X and net trade of Y. As the intra-industry trade increases, the ratio rises while the opposite occurs when economies specialize and turn to inter-industry exchanges.

The model explores the consequences of a rise in the trade cost on X : $\Delta t_X > 0$. A rise in t_X causes the relative price of X to increase for consumers in country j which then reduces the real income in j . Indeed, due to the love of variety for X, the bulk of X consumed in j is imported which reduce j 's real income and somehow is equivalent to a loss of factor endowments which in turn should raise factor prices in j . However, wages are fixed across i and j so the prices of capital absorb the adjustment : the scarcity of capital in j induces a raise of its rental rate. i is also impacted. Indeed, i is a net exporter of X and, consequently to the fall in demand for X, it faces an excess of supply of capital causing the rental rate to decrease. On net $\frac{wages_i}{rental_i} \searrow$ while $\frac{wages_j}{rental_j} \nearrow$ causing $\frac{p_{Xi}}{p_{Yi}} \searrow$ while $\frac{p_{Xj}}{p_{Yj}} \nearrow$. The widening of relative prices in i and j increases (inter-)industry specialization while diminishing the overall share of intra-industry trade (GLI). This demonstration is supported by an empirical investigation where the authors bring to light a negative relationship between GLI (the share of intra-industry trade) and trade costs (t_X).

Additionally they address the role of differences of factor endowments. They show that wide differences of relative factor endowments $\left(\left| \ln \left(\frac{K_i}{L_i} \right) - \ln \left(\frac{K_j}{L_j} \right) \right| \right)$ tend to exacerbate the decrease of the share of intra-industry trade (\searrow GLI) when trade costs rise. Indeed, as countries display strong differences of relative factor endowments, a

²Grubel-Lloyd index

rise in trade costs of the differentiated good (t_X) leads to even stronger inter-industry specialization and a shrink of the intra-industry trade relative to total flows. Similar enough relative factor endowments guarantee the potentiality for intra-industry trade. We don't expect countries across the European Union to verify situations of large differences of relative factor endowments but the following proposes a rigorous examination of regional relative factor endowments.

From data documenting respectively the gross fixed capital formation and the number of worked hours at the regional scale, we estimate capital and labor stocks at the regional scale along

$$\text{Stock}_{it} = \frac{I_{i,t+1}}{\frac{I_{i,t+1} - I_{it}}{I_{it}} + \delta}$$

Stock_{it} is the stock we aim at obtaining. It can be obtained from the investment in $t+1$ actualized by the growth rate of investment between $t+1$ and t and the depreciation rate δ . We suppose $\delta = 0.15$ that corresponds to a depreciation rate between 6 and 7 %. We average both the capital and the labor stocks across the whole period (from 1990 to 2015) and study the distribution of the relative factor endowments K_i/L_i .

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-70.530	2.284	6.518	6.462	8.797	202

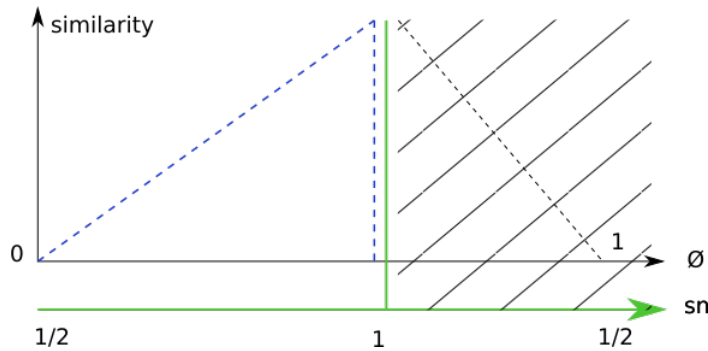
Table 4.1: Distribution of the averaged over time relative factor endowments

We look for outliers at the bottom of the distribution, that potentially could enter the case of relative factor endowments, different enough from the rest of the distribution such that, they would exclusively participate in inter-industry trade. Two regions exhibit relative factor endowments two-standard deviations below the mean : Luxembourg and Western Greece. In the first case, a brutal drop of investment between 1991 and 1992 induces a strongly negative ratio of factor endowments that averaging over time does not smooth nor corroborate. Consequently we consider keeping Luxembourg in the sample. Conversely, Western Greece (EL63) appears as persistently

under-industrialized such that we withdraw that region from our considerations.

To sum up, our reasoning aimed at tying 3 blocks : proximity of industrial mixes to input-output linkages and input-output linkages to levels of trade costs of goods.

As illustrated by the following scheme, we suppose that when trade costs are high ($\phi = 0$), regions are almost in autarky and no input-output linkages tie industries across regions. Varieties are different from one region to another and industrial mixes appear as dissimilar. As trade costs decrease, input-output linkages densify and regions exhibit increasing proximities in their industrial mixes. This relationship is true up to the point right before reaching the case of complete disappearance of the industrial sector in the periphery ($s_n = 1$) as specified along the green axis.



This reasoning aims at drawing a linear and positive relationship between proximities of industrial mixes and freeness of trade ($\phi : 0 \rightarrow 1$) to identify the latter from the former. The findings of the literature that focused on intra-industry trade, both theoretical and empirical, give some credit to this line of thought.

Empirically, working at the 3-digit levels of the industrial classification (NACE rev.2) allows us to consider input-output linkages at the level of intra-industry trade, in accordance with the disaggregation level used in Venables, Ride, Stewart (2003) [193] or

Bergstrand and Egger (2006) [24], for instance. We propose to use the Mahalanobis distance that allows to consider spillovers in a larger definition than the one imposed by finely defined industries. A finely-grained industrial classification could be a too stringent frame to reveal input-output dependencies between industries that share pecuniary externalities. Technically, in a multivariate space that respect the properties of a regular Euclidean space, axes should be orthogonal to one another. This amounts to consider each industry as fully independent from any other. As a consequence the distance between 2 points can be evaluated as a straight line. However, there might exist spillovers across industries which make them not perfectly independent. In this case, the Euclidean distance is not relevant anymore and the Mahalanobis distance accounts better for ties between industries and regions.

Computationally, let S be the (X, N) matrix where S_{xn} is region n patent share in sector x defined in the NACE rev.2. Defined as such, each column of S contains a region's patent share in one of the X sector. Respectively, each row contains patent class shares across the N regions. In order to take into consideration the fact that patents reflect punctual flows of investments more than long-lasting input-output relationships, we propose to sum S_{xn} matrices over 3 years such that $S_{nx,t} = S_{nx,t-2} + S_{nx,t-1} + S_{nx,t}$. $S_{nx,t}$ becomes a Mahalanobis proximity matrix according the following development :

<p>Each column $(S_{\bullet n})$ is normalized such that</p> $C_{(X,N)} = \begin{pmatrix} \frac{S_{\bullet 1}}{\sqrt{(S_{\bullet 1})' S_{\bullet 1}}} & \frac{S_{\bullet 2}}{\sqrt{(S_{\bullet 2})' S_{\bullet 2}}} & \dots & \frac{S_{\bullet N}}{\sqrt{(S_{\bullet N})' S_{\bullet N}}} \end{pmatrix}$	$\left \right.$	<p>Each row $(S_{x\bullet})$ is normalized such that</p> $R_{(X,N)} = \begin{pmatrix} \frac{S_{1\bullet}}{\sqrt{S_{1\bullet}(S_{1\bullet})'}} \\ \frac{S_{2\bullet}}{\sqrt{S_{2\bullet}(S_{2\bullet})'}} \\ \vdots \\ \frac{S_{X\bullet}}{\sqrt{S_{X\bullet}(S_{X\bullet})'}} \end{pmatrix}$
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Mahalanobis' proximity matrix $ComDist$ is defined as

$$ComDist_{(N,N)} = R'_{(X,N)}(C_{(X,N)}C'_{(X,N)})R_{(X,N)}$$

Finally, we compute the closeness centrality that represents the influence a node can have on the flow across the network. Closeness quantifies the average length of the shortest path between a node and the rest of those constituting the graph.³

$$CI_{ComDist,i} = \frac{1}{\sum_j d_{ij}}$$

This index should be interpreted such that : as the centrality index of region i rises, we expect region i to be characterized by low transport costs ($\phi \rightarrow 1$).

4.2.3 Proxy for transfer costs on ideas

On the basis of Chapter 1, our metric will use the dynamic network proximity measure proposed by Colino (2016) [48]. For the reminder, $CitDist$ is approximated such

$$CitDist = (d_{it,jt'})$$

$$d_{it,jt'} = \sum_{p \in \mathcal{P}_{it}} \sum_{q \in \mathcal{P}_{jt'}} \frac{\#Citations_{p \rightarrow q}}{Outcitations_p}$$

where t is the date of deposit of the patent being cited and t' is the data at which occurs the citation. The number of citations tying patent p to patent q is normalized by the total number of outcitations the patent p generates. We work on annual citations matrices. For each year, we consider the backward citations, from 1964 up to the year of interest, made by the patents published this year.

As previously, it could be objected that patents reflect very punctual flows of investment or of externalities. In order to smooth our representation, we sum of annual matrices over 4 years. On the model of $ComDist$, we use $CitDist$ in order to obtain a (closeness) centrality measure giving insights on the degree of openness to knowledge

³We chose closeness over betweenness as betweenness centrality equals 0 for each node in a fully connected graph as we consider here.

flows of each region. As previously, *CitDist* should be transformed from a proximity matrix to a distance matrix and we do so along the same reasoning as in section 4.2.2. However, as a first step, *CitDist* should be transformed into an undirectional matrix. To proceed we add the edges from i to j and j to i in order to preserve strength from both sides of the relationship (without normalizing by 2). We then normalize and transform proximity into distance and calculate the closeness coefficient based on the resulting network. As the centrality index of region i rises in the case of the citation network, we expect region i to be characterized by low transfer costs ($\lambda \rightarrow 1$).

Next section addresses questions regarding data sources, descriptive statistics of main variables and details upon instrumental variables.

4.3 Data

4.3.1 Data sources

The left-hand side variable uses Cambridge Econometrics data on the Gross Value Added for Europe at the regional scale from 1990 to 2015. Gross Value Added is calculated as the net result of output valued at basic prices less intermediate consumption valued at purchasers' prices deflated to 2005 constant price euros.

The right-hand side variables use PATSTAT database (edition autumn 2018). More precisely, we consider patents declared in the European Union member-states between 1990 and 2015.

4.3.2 Descriptive statistics

Dependent variable : Local agglomeration indexes on regional Gross Value Added

We use the regional, Gross Valued Added as a proxy of wealth produced by industries.

	Min	Q1	Q2	Mean	Q3	Max
1990	614.1	7944.3	19871.2	28789.2	36662.5	352683.2
1995	626.8	8108.8	21496.7	30590.5	38660.2	369707.2
2000	796.9	9075.1	25153.3	35281.6	45832.0	421044.6
2005	915.8	10407.3	27844.1	38777.3	49399.4	446805.0
2010	896.1	11897.7	28715.1	40641.2	52578.3	505245.6
2015	937	13967	29040	41584	50987	521185

Table 4.2: Gross Value Added, sampled years in the period (1990-2015)

Table 4.2 shows descriptive statistics of the Gross Value Added for sampled years in the period 1990-2015. Numbers are millions of euros in 2005 prices. Precisely, Gross Value Added is defined by Eurostat as "the net result of output valued at basic prices less intermediate consumption valued at purchasers' prices deflated to 2005 constant price euros. Output consists of the products created during the accounting period. Intermediate consumption consists of the value of the goods and services consumed as inputs in the process of production, excluding fixed assets whose consumption is recorded as consumption of fixed capital. The goods and services may be either transformed or used up by the production process. GVA is calculated before consumption of fixed capital. "

One can notice deep changes in the shape of Gross added value distributions over time. First, the range of the distribution almost doubled from 1990 to 2015 denoting

an ever increasing gap in the production of wealth. Second, the interquartile range also increased a lot from 28718,2 million euros in 1990 to 37020 million euros in 2015. Disparities are not the fact of some outliers on each sides of the distribution but of a general trend. According to the difference between the median and the mean, one can postulate that the bulk of the distribution exhibits relatively low regional GVA and few outliers at the top of the distribution drives the mean up. Getting into much details, among those very high gross added value regions, one can find Ile de France, Lombardia, Düsseldorf, Oberbayern, Cataluna. Conversely, the lowest levels of GVA affect regions from Greece and Bulgaria.

Table 4.3 describes the normalized distributions of local Moran's I_i over time, depending on the number of neighbors one considers through the spatial weight matrix. For the reminder, we normalized annual distributions over the range $(1, -1)$ such that final interpretation gets easier: a negative Moran's I_i now corresponds to least agglomeration ($s_n \rightarrow 1/2$) and a positive Moran's I_i could now correspond to stronger agglomeration ($s_n \rightarrow 1$).

The first line of the table draws the distribution when we consider the 25-nearest neighbors, the second shapes the distribution when we consider the 50-nearest neighbors and so on.... As we raise the number of nearest-neighbors, we might integrate further spatial non-stationarities which explains why the distributions change. Somehow the median appears to stabilize when we consider more than 100 neighbors but less than 250. In those cases, (positive) local Moran's I_i display core-periphery patterns up to almost the third quartile. Core-core configurations (negative) are most represented when considering fewest neighbors and it would of interest to compare settings considering the high spatial non-stationarity at stake.

k	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
25	-1	0.3460	0.5024	0.4511	0.5489	1
50	-1	0.5011	0.6359	0.5978	0.6950	1
75	-1	0.5515	0.6693	0.6328	0.7307	1
100	-1	0.6078	0.7149	0.6794	0.7663	1
125	-1	0.6924	0.7674	0.7419	0.8224	1
150	-1	0.7344	0.7849	0.7665	0.8374	1
175	-1	0.7299	0.7871	0.7640	0.8388	1
200	-1	0.7422	0.7808	0.7571	0.8262	1
225	-1	0.7278	0.7776	0.7423	0.8129	1
250	-1.	-0.3603	-0.2925	-0.3110	-0.2354	1
264	-1	-0.9987	-0.9945	-0.9795	-0.9898	1

Table 4.3: Normalized distribution of local Morans I_i , sampled years in the period (1990-2015)

Proxy for transports costs on goods

Considering the twenty-five years of our sample and all regions, we work with 1.492.332 distinct patents (distinct application ID.).

1990	1991	1992	1993	1994	1995	1996	1997	1998	1999
26.858	26.876	27.145	28.218	30.064	31.843	37.089	41.953	46.117	50.410
2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
53.471	53.186	53.400	54.912	57.772	59.739	60.943	61.131	59.356	59.467
2010	2011	2012	2013	2014	2015				
59.299	60.360	59.926	59.863	60.811	40.575				

Table 4.4: Number of patents declared in European regions (NUTS II) on an annual basis – (1990-2015)

The detailed distribution across industries is to be found in Appendix [4.7.1](#).

We can observe that we work with an increasing number of patents. 2015 is an exception and this most likely reflect the fact that the database was still being filled in 2018. This also explains that we didn't exploit 2016, 2017 and 2018. From the patents being declared at the regional scale, we compute Mahalanobis proximity matrix, its conversion into a distance matrix and the closeness centrality index that characterized each region.

	1990	19995	2000	2005	2010	2015
Min.	0.7071	0.7071	0.7071	0.7071	0.7071	0.7071
1st Qu.	0.8723	0.8981	0.8984	0.8985	0.8985	0.8985
Median	0.9325	0.9476	0.9491	0.9493	0.9493	0.9493
Mean	0.8945	0.9097	0.9113	0.9116	0.9116	0.9116
3rd Qu.	0.9520	0.9675	0.9681	0.9686	0.9687	0.9687
Max.	0.9958	1.0471	1.0496	1.0498	1.0498	1.0498

Table 4.5: Closeness centrality index based on the network transformed from *ComDist*

Table 4.5 displays the distribution of the closeness centrality indexes on sampled years. Considering the cumulative patent deposits over three years has smooth the distribution of centrality indexes but we notice a slight increase in the maximum value emphasizing the fact that some regions gained centrality in the network. According to the definition of closeness centrality, those regions might have diversified and benefitted from increasing input-output linkages owing to lower transport costs on goods.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.7071	0.8776	0.9477	0.9060	0.9661	1.0290

Table 4.6: Distribution of closeness centrality scores (1990-2015)

Table 4.6 displays the descriptive statistics over the whole distribution from 1990 to 2015. The closeness centrality index evolves similarly to ϕ : As centrality raises, the region appears as well connected to the rest of the network. Likely is it characterized by low transport costs such that $\phi \rightarrow 1$.

Proxy for transfer costs on ideas

	1990	19995	2000	2005	2010	2015
Min.	0.7052	0.7055	0.7055	0.7055	0.7055	0.7055
1st Qu.	0.7072	0.7073	0.7073	0.7073	0.7073	0.7073
Median	0.7089	0.7095	0.7095	0.7095	0.7095	0.7095
Mean	0.7101	0.7104	0.7104	0.7104	0.7104	0.7104
3rd Qu.	0.7121	0.7126	0.7125	0.7125	0.7125	0.7125
Max.	0.7246	0.7262	0.7265	0.7265	0.7265	0.7265

Table 4.7: Closeness centrality index based on the network transformed from *CitDist*

Table 4.7 displays the distribution of the closeness centrality indexes on sampled years. The shape of the distribution has remained constant across time. The range is low and the variance of the distribution will remain too. The normalized distribution (0-1) sketched in Table 4.8 confirms that the bulk of the distribution concentrates in a tiny interval. Few regions then appear as outliers and distinguish themselves as central nodes in the "innovation" network.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.7053	0.7072	0.7093	0.7102	0.7122	0.7249

Table 4.8: Distribution of closeness centrality scores (1990-2015)

As previously, as centrality raises, the region appears as well connected to the rest of the network. Likely is it to benefit from low transfer costs such that $\lambda \rightarrow 1$.

Proxies of L and s_k

Theoretically, L is the labor supply of a region. We will proxy this variable using hours worked that is "the number of hours actually worked, defined as the sum of all periods spent on direct and ancillary activities to produce goods and services." Those data have been extracted from Cambridge Econometrics databases, available at the NUTS 2 level.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
27.5	691.2	1089.0	1388.0	1735.0	9405.0

Table 4.9: Distribution of labor supply (1990-2015)

Theoretically, s_k is the initial capital endowment inequality. Using data on gross fixed capital formation, we calculate the capital stock in 1990 along :

$$\text{Stock}_{it} = \frac{I_{i,t+1}}{\frac{I_{i,t+1} - I_{it}}{I_{it}} + \delta}$$

Stock_{it} is the stock we aim at obtaining. It can be obtained from the investment in $t+1$ actualized by the growth rate of investment between $t+1$ and t and the depreciation rate δ . We suppose $\delta = 0.15$ that corresponds to a depreciation rate between 6 and 7 %. Stock in 1990 is an average of years 1989,1990,1991. From this, we compute a Moran's I autocorrelation index to obtain a representation of capital agglomeration regarding the 25 nearest neighbors.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-1.83900	-0.04558	0.03149	0.16710	0.38120	1.48000

Table 4.10: Distribution of the initial capital endowment inequality (1990-2015)

Instruments

Our first measure attempt to proxy for transport costs on goods. Infrastructures constitute another way to do so and the literature that takes this path could provide potentially interesting way to instrument our own variable. Duranton and Turner (2012) [68] exploit the exogenous variation carried by roman road network to solve the endogeneity issue raised in measuring the effect of expanding infrastructures on agglomeration patterns. They suggest that instruments should reflect a region's level of transportation infrastructure some time long ago. Our instrument is built on the basis of the transport network of the Roman world made available by Stanford's geospatial network model (ORBIS) (Scheidel, Meeks and Weiland (2012) [180]). They developed a model that simulate traveling time and costs across the Roman transportation network taking into account terrestrial, fluvial and maritime transportation means. We matched the Roman cities they refer to with the recent regional European configuration. Considering the case where two cities were part of one spatial polygon, we held the closest one from the polygon's barycentre. Thanks to ORBIS, we drew the multi-modal transportation network : for each city being selected, we simulate its ego-network and retain the cost of transporting goods along the cheapest travelling path. From the network we obtain, we calculated a centrality measure that represent how central a city/region used to be in the Roman transportation network.

Our instrument controlling for the endogeneity arising from the patent-citation network *CitDist* involves a transformation of the way we obtain the centrality index for each region. $CI_{CitDist}$ only constitutes a closeness centrality index. The instrument we propose builds on a slightly different computation method developed by Hidalgo and Hausmann (2009) [109] and upgraded in Cristelli and al. (2012) [53]. Hidalgo and al. developed a computational method from country's export basket to obtain a measure of national economies' competitiveness. The more diversified is the national export basket the more competitive the economy. Respectively the more competitive is the exporter, the more complex the product at stake is expected to be. As the algorithm iterates complex products raise the competitiveness score of countries while being exported by competitive exporters enhances the complexity score of a product.

In our case, the goal is to extract the growth potential of a region based on how it is able to benefit from the patent network without consideration regarding the agglomeration of activities. The nonlinear refinements developed in the series of papers starting with Cristelli and al.(2012) [53] should allow us to filter out our matter of interest.

From a matrix M_{is} defined such that

$$M_{is} = \frac{q_{is}}{\sum_j q_{js}}$$

where q_{is} is the number of patents declared in region i ($i \neq j, \forall i \in N$), sector s . Industries have been defined according to WIPO classification. The algorithm constructs F_i and Q_s respectively the growth potential of a region and the complexity score of an industry.

$$\begin{cases} \tilde{F}_i^{(n)} = \sum_s M_{is} Q_s^{(n-1)} \\ \tilde{Q}_s^{(n)} = \frac{1}{\sum_i M_{is} / F_i^{(n-1)}} \end{cases} \quad \begin{cases} F_i^{(n)} = \frac{N_i \times \tilde{F}_i^{(n)}}{\sum_i \tilde{F}_i^{(n)}} \\ Q_s^{(n)} = \frac{N_s \times \tilde{Q}_s^{(n)}}{\sum_s \tilde{Q}_s^{(n)}} \end{cases}$$

$$\tilde{Q}_s^{(0)} = 1 \quad \forall s \quad \text{and} \quad \tilde{F}_i^{(0)} = 1 \quad \forall i$$

Results on first stage estimations comfort us on the reliability of our instruments. We test the hypothesis that our instruments might be weak. To do so, considering that our framework embedded two endogenous variables, the right procedure calls for a Cragg-Donald test confronted to the critical values displayed in Stock and Yogo (2005) [185]. The test statistic we obtain equals 449.1272. In the following tables reporting levels of critical values, we picked the lines supposing 2 endogenous variables and 4 instruments variables since regressions include non-linear versions of our instruments. b is the desired maximal bias of the IV estimator relative to OLS. In order to definitely reject the null hypothesis of weak instruments our test statistic should respectively > 11.04 and > 16.87 . We then are able to reasonably reject their null hypotheses of weak instruments, supposing a 5% relative to the OLS based on the first table and a

5% bias based on the second. ⁴

b	0.05	0.10	0.20	0.30
	11.04	7.56	5.57	4.73

Table 4.11: Critical values for the weak instrument test based on TSLS* bias

b	0.10	0.15	0.20	0.25
	16.87	9.93	7.54	6.28

Table 4.12: Critical values for the weak instrument test based on TSLS* size

Next section develops results for preliminary estimations using parametric estimation techniques: least squares, two stage least squares, GMM estimations of spatial error and spatial lag models. Developments regarding Generalized Additive Models and results obtained in this framework are to be found in Section 4.5.

4.4 Results on preliminary estimations

4.4.1 Estimations considering the decentralized economy

We consider successively OLS, two stage least squares and two stage least squares with an interaction term between the proxies for transport costs on goods and transfer costs on ideas :

⁴See Stock and Yogo (2005) [185] that distinguish weak instruments in the case where the bias of the IV estimator, relative to the bias of OLS, could exceed a certain threshold from the case where the conventional α level Wald test based on IV statistics has an actual size that could exceed a certain threshold. In the first case, instruments would be declared as "weak" if the bias of the IV estimator standardized by the bias of the OLS estimator exceeds a certain threshold. In the second case, instruments would be declared as "weak" if, in the Wald test assessing coefficients, the probability of incorrectly rejecting the null hypothesis (Type I error) is over a certain threshold.

$$\begin{array}{lcl}
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + s_{k,1990} & & \text{(OLS)} \\
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + s_{k,1990} + fe_i + fe_t & | & RR_i + F_{it} + RR_i^2 + F_{it}^2 \text{ (TSLS)} \\
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + CI_{ComDist,it} \times CI_{CitDist,it} + s_{k,1990} + fe_i + fe_t & & \text{(ITSLS)} \\
& | & RR_i + F_{it} + RR_i^2 + F_{it}^2
\end{array}$$

I_{it} is the normalized index of Moran. $CI_{ComDist}$ is our proxy of transport costs. $CI_{CitDist}$ is our proxy of transfer costs on ideas. $s_{k,1990}$ represents the initial capital endowment inequality. fe_i and fe_t are respectively individual and time fixed effects. RR_i is the instrument build on the Roman Road network. F_{it} is the fitness index obtained from section 4.3.2.

In order to analyze the interaction effect, let's sketch the ITSLS model such

$$I_{it} = \beta_1 CI_{ComDist,it} + \beta_2 CI_{CitDist,it} + \beta_3 CI_{ComDist,it} \times CI_{CitDist,it}$$

The net effect of $CI_{ComDist,it}$ is the sum $\beta_1 + \beta_3 CI_{CitDist,it}$. The net effect of $CI_{CitDist,it}$ is the sum $\beta_2 + \beta_3 CI_{ComDist,it}$. Those results are to be found in Table 4.15.

We also consider spatial models in order to control for autocorrelation issues in the error term.

$$\begin{array}{lcl}
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + s_{k,1990} + fe_i + fe_t & & \text{(SEM)} \\
& | & RR_i + F_{it} + RR_i^2 + F_{it}^2 \\
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + CI_{ComDist,it} \times CI_{CitDist,it} + s_{k,1990} & & \text{(ISEM)} \\
+ fe_i + fe_t & | & RR_i + F_{it} + RR_i^2 + F_{it}^2
\end{array}$$

Results are displayed in Table 4.14.

	$CI_{ComDist}$	$CI_{CitDist}$	$CI_{ComDist} \times CI_{CitDist}$	FE	Intercept
K=25					
OLS	0.9267***	-16.461***		No	Yes
TSLs	0.0438	4.9596***		Yes	Yes
ITSLS	-27.7717*	-31.1596*	39.3284*	Yes	Yes
K=50					
OLS	0.8972***	-24.3113***		No	Yes
TSLs	0.0914	0.2856		Yes	Yes
ITSLS	-6.2767	-7.9836	9.0039	Yes	Yes
K=75					
OLS	0.8813***	-24.922***		No	Yes
TSLs	0.0921	-2.2465*		Yes	Yes
ITSLS	1.8604	0.0497	-2.5002	Yes	Yes
K=100					
OLS	0.7622***	-27.3795***		No	Yes
TSLs	0.0227	-1.6988.		Yes	Yes
ITSLS	-8.9164	-13.3065	12.639	Yes	Yes
K=125					
OLS	0.5979***	-27.554***		No	Yes
TSLs	0.0139	-3.0961***		Yes	Yes
ITSLS	-10.8227	-17.1677	15.3219	Yes	Yes
K=150					
OLS	0.4902***	-26.7145***		No	Yes
TSLs	0.0033	-4.5721***		Yes	Yes
ITSLS	1.5349	-2.5833	-2.1655	Yes	Yes
K=175					
OLS	0.5023***	-27.7857***		No	Yes
TSLs	-0.0086	-4.6936***		Yes	Yes
ITSLS	3.6362	0.0392	-5.1533	Yes	Yes
K=200					
OLS	0.3967***	-29.395***		No	Yes
TSLs	-0.0461	-5.1628***		Yes	Yes
ITSLS	-1.8408	-7.4932	2.5375	Yes	Yes
K=225					
OLS	0.2441***	-30.8038***		No	Yes
TSLs	-0.0273	-5.9142***		Yes	Yes
ITSLS	8.9462	5.738	-12.6876	Yes	Yes

Table 4.13: Results on preliminary regressions

	$CI_{ComDist}$	$CI_{CitDist}$	sk_{1990}	$CI_{ComDist} \times CI_{CitDist}$	FE	Intercept
K=25						
SEM	0.6972***	-19.0126***	0.0298***		Yes	Yes
ISEM	-1.8615	-22.5097	0.0297	3.6173	Yes	Yes
K=50						
SEM	0.6856***	-28.6174***	0.006***		Yes	Yes
ISEM	171.2581***	204.3776***	0.0125***	-241.1286***	Yes	Yes
K=75						
SEM	0.7002***	-28.0133***	0.0042***		Yes	Yes
ISEM	186.1231***	225.0821***	0.0116***	-262.1211***	Yes	Yes
K=100						
SEM	0.6521***	-30.1902***	0.0012***		Yes	Yes
ISEM	201.0712***	243.2766***	0.008***	-283.3268***	Yes	Yes
K=125						
SEM	0.5338***	-29.6247***	0.0031***		Yes	Yes
ISEM	187.1571***	224.9477***	0.0082***	-263.8268***	Yes	Yes
K=150						
SEM	0.443***	-28.084***	0.0029***		Yes	Yes
ISEM	165.0414***	196.4679***	0.0067***	-232.6918***	Yes	Yes
K=175						
SEM	0.4473***	-28.7719***	0.0059***		Yes	Yes
ISEM	172.4808***	205.9237***	0.0094***	-243.2021***	Yes	Yes
K=200						
SEM	0.3759***	-30.2808***	0.0062***		Yes	Yes
ISEM	165.8656***	195.4626***	0.0096***	-233.95***	Yes	Yes
K=225						
SEM	0.2593***	-31.3878***	0.0067***		Yes	Yes
ISEM	128.0631***	142.9216***	0.0095***	-180.6735***	Yes	Yes

Table 4.14: Results on preliminary spatial regressions

		Min.	Q1	Median	Mean	Q3	Max.
K25	Com	-0.03	0.04	0.12	0.16	0.24	0.74
K25	Cit	-3.35	3.35	6.11	4.47	6.84	9.31
K50	Com	0.07	0.09	0.11	0.12	0.14	0.25
K50	Cit	-1.62	-0.08	0.55	0.17	0.72	1.28
K75	Com	0.10	0.09	0.09	0.08	0.08	0.05
K75	Cit	-1.72	-2.14	-2.32	-2.22	-2.37	-2.52
K100	Com	-0.00	0.02	0.05	0.06	0.09	0.25
K100	Cit	-4.37	-2.21	-1.33	-1.86	-1.10	-0.30
K125	Com	-0.02	0.01	0.05	0.06	0.09	0.28
K125	Cit	-6.33	-3.72	-2.65	-3.29	-2.37	-1.40
K150	Com	0.01	0.00	-0.00	-0.00	-0.01	-0.03
K150	Cit	-4.11	-4.48	-4.64	-4.55	-4.68	-4.81
K175	Com	0.00	-0.01	-0.02	-0.02	-0.03	-0.10
K175	Cit	-3.60	-4.48	-4.84	-4.63	-4.94	-5.26
K200	Com	-0.05	-0.05	-0.04	-0.04	-0.03	-0.00
K200	Cit	-5.70	-5.27	-5.09	-5.19	-5.04	-4.88
K225	Com	-0.00	-0.03	-0.05	-0.06	-0.09	-0.25
K225	Cit	-3.23	-5.40	-6.29	-5.76	-6.52	-7.32

Table 4.15: Interaction effects on preliminary regressions

	Min.	Q1	Median	Mean	Q3	Max.
Com	0.69	0.70	0.70	0.71	0.71	0.76
Cit	-19.95	-19.34	-19.08	-19.23	-19.02	-18.79
Com	1.19	0.73	0.23	0.01	-0.47	-3.54
Cit	33.88	-7.24	-24.14	-14.08	-28.58	-43.74
Com	1.25	0.75	0.20	-0.04	-0.56	-3.89
Cit	39.74	-4.96	-23.33	-12.40	-28.15	-44.64
Com	1.24	0.70	0.11	-0.15	-0.71	-4.31
Cit	42.94	-5.37	-25.23	-13.42	-30.45	-48.27
Com	1.08	0.58	0.02	-0.21	-0.74	-4.09
Cit	38.40	-6.59	-25.08	-14.08	-29.94	-46.53
Com	0.92	0.48	-0.01	-0.22	-0.68	-3.64
Cit	31.93	-7.74	-24.05	-14.35	-28.34	-42.97
Com	0.95	0.49	-0.02	-0.24	-0.73	-3.82
Cit	33.96	-7.51	-24.56	-14.42	-29.03	-44.33
Com	0.86	0.42	-0.08	-0.29	-0.75	-3.72
Cit	30.04	-9.85	-26.25	-16.50	-30.56	-45.27
Com	0.63	0.29	-0.09	-0.25	-0.61	-2.91
Cit	15.17	-15.64	-28.30	-20.77	-31.63	-42.99

Table 4.16: Interaction effects on preliminary spatial regressions

Table 4.13 displays results using OLS, two stage least squares and TSLS with an interaction effects. Regarding OLS estimations, all coefficients are significant and signed according to theoretical prescriptions. Instrumenting , the coefficient attached to $CI_{ComDist}$ loses its significance but $CI_{CitDist}$ remains and stays well-signed according to the theory. Finally, results from TSLS with interactions are to be analyzed deeper and we refer to Table 15 for this. Of notice, coefficients are not statistically significant in this last case and results on Table 15 should be considered under this light. Interestingly, this is not the case for results of spatial models, integrating interaction effects described in Table 14 and analyzed in Table 16.

Table 15, at lines labelled 'Com', considers the effect of $CI_{ComDist}$ resulting from the addition of $\beta_1 + \beta_3 CI_{CitDist,it}$ at different quantiles of $CI_{CitDist,it}$. Conversely, at lines labelled 'Cit', Table 15 allows to consider the effect of $CI_{CitDist}$ resulting from the addition of $\beta_2 + \beta_3 CI_{ComDist,it}$ at different quantiles of $CI_{ComDist,it}$. If we focus on the respective means of $CI_{CitDist,it}$ and $CI_{ComDist,it}$, we can observe that $CI_{ComDist}$ and

$CI_{CitDist}$ have opposite effects : the effects of commercial integration and technological integration oppose. While commercial integration exhibits a positive relationship with agglomeration, technological integration plays the opposite role in accordance with the theory exposed in Section 1. This conclusion is true on either tables (15 or 16), for small kernels of local Moran's I_i where the number of neighbors is small and we don't smooth spatial disparities too roughly.

4.4.2 Estimations considering the centralized economy

For the case of the centralized economy, we consider successively OLS, two stage least squares and two stage least squares with an interaction term between the proxies for transport costs on goods and transfer costs on ideas. Results are displayed in Table 4.17. Variables are defined as in the previous subsection.

$$\begin{array}{lcl}
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + L & & \text{(OLS)} \\
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + L + fe_i + fe_t \mid RR_i + F_{it} + RR_i^2 + F_{it}^2 & & \text{(TSLS)} \\
I_{it} = CI_{ComDist,it} + CI_{CitDist,it} + CI_{ComDist,it} \times CI_{CitDist,it} + L + fe_i + fe_t & & \text{(ITSLS)} \\
& \mid RR_i + F_{it} + RR_i^2 + F_{it}^2 &
\end{array}$$

As previously, we consider regressions controlling for spatial effects but both under the form of a spatial autoregressive model augmented of a spatial error term this time. Doing so, we test for a form closest from Eq 4.5 in integrating the term $(1 - s_n)$ under the form of WI_{jt} . Results are displayed in Table 4.18.

$$\begin{array}{lcl}
I_{it} = WI_{jt} + CI_{ComDist,it} + CI_{CitDist,it} + L_{it} + fe_i + fe_t & & \text{(SAR)} \\
& \mid RR_i + F_{it} + RR_i^2 + F_{it}^2 + W^5 I_{jt} + W^5 L & \\
I_{it} = WI_{jt} + CI_{ComDist,it} + CI_{CitDist,it} + CI_{ComDist,it} \times CI_{CitDist,it} + L_{it} & & \text{(ISAR)} \\
+ fe_i + fe_t \mid RR_i + F_{it} + RR_i^2 + F_{it}^2 + W^5 I_{jt} + W^5 L & &
\end{array}$$

	$CI_{ComDist}$	$CI_{CitDist}$	L	$CI_{ComDist} \times CI_{CitDist}$	FE	Intercept
K=25						
OLS	0.797182***	-7.297906***	-6.1e-05***		No	Yes
TSLs	0.036744	5.013718***	-4e-06*		Yes	Yes
ITSLS	-28.918109*	-32.581148*	-5e-06*	40.93861*	Yes	Yes
K=50						
OLS	0.717939***	-10.464147***	-9.1e-05***		No	Yes
TSLs	0.059032	0.531868	-2e-05***		Yes	Yes
ITSLS	-11.231063	-14.127146	-2e-05***	15.962809	Yes	Yes
K=75						
OLS	0.698431***	-10.686664***	-9.3e-05***		No	Yes
TSLs	0.060779	-2.008298.	-1.9e-05***		Yes	Yes
ITSLS	-2.915043	-5.872093	-1.9e-05***	4.207447	Yes	Yes
K=100						
OLS	0.576809***	-12.909711***	-9.5e-05***		No	Yes
TSLs	-0.000851	-1.519565	-1.4e-05***		Yes	Yes
ITSLS	-12.532344	-17.790405	-1.4e-05***	17.717994	Yes	Yes
K=125						
OLS	0.408412***	-12.772484***	-9.7e-05***		No	Yes
TSLs	-0.01379	-2.885285**	-1.7e-05***		Yes	Yes
ITSLS	-15.074774.	-22.440407*	-1.7e-05***	21.294384.	Yes	Yes
K=150						
OLS	0.313366***	-12.84938***	-9.1e-05***		No	Yes
TSLs	-0.01835	-4.406893***	-1.3e-05***		Yes	Yes
ITSLS	-1.776406	-6.689546	-1.3e-05***	2.485676	Yes	Yes
K=175						
OLS	0.323311***	-13.800078***	-9.2e-05***		No	Yes
TSLs	-0.029153	-4.537026***	-1.2e-05***		Yes	Yes
ITSLS	0.503193	-3.84583	-1.2e-05***	-0.752672	Yes	Yes
K=200						
OLS	0.212448***	-15.12537***	-9.4e-05***		No	Yes
TSLs	-0.065007	-5.018965***	-1.1e-05***		Yes	Yes
ITSLS	-4.729687	-11.075567	-1.2e-05***	6.595286	Yes	Yes
K=225						
OLS	0.046622**	-15.520193***	-1e-04***		No	Yes
TSLs	-0.050042	-5.741051***	-1.4e-05***		Yes	Yes
ITSLS	5.49208	1.454818	-1.4e-05***	-7.835881	Yes	Yes

Table 4.17: Results on preliminary regressions ; centralized economy

	WI_{jt}	$CI_{ComDist}$	$CI_{CitDist}$	L	$CI_{ComDist} \times$ $CI_{CitDist}$	FE	Intercept
K=25							
SAR	0.0924	0.6351***	-7.955***	-1e-04***		Yes	Yes
ISAR	0.113	-53.045***	-81.1278***	-1e-04***	75.887***	Yes	Yes
K=50							
SAR	-0.3415	0.6151***	-9.7074***	-1e-04***		Yes	Yes
ISAR	-0.2793	97.3689***	122.2067***	-1e-04***	-136.776***	Yes	Yes
K=75							
SAR	-0.6243	0.6552***	-9.506***	-1e-04***		Yes	Yes
ISAR	-0.5669	111.3661***	141.3351***	-1e-04***	-156.5077***	Yes	Yes
K=100							
SAR	-0.3886	0.585***	-11.9112***	-1e-04***		Yes	Yes
ISAR	-0.39	134.757***	170.8634***	-1e-04***	-189.6754***	Yes	Yes
K=125							
SAR	-0.2583	0.4503***	-11.3094***	-1e-04***		Yes	Yes
ISAR	-0.2786	126.3043***	160.1404***	-1e-04***	-177.9174***	Yes	Yes
K=150							
SAR	-0.0665	0.3583***	-11.2605***	-1e-04***		Yes	Yes
ISAR	-0.057	112.5781***	141.6372***	-1e-04***	-158.6437***	Yes	Yes
K=175							
SAR	0.5445	0.364***	-12.1321***	-1e-04***		Yes	Yes
ISAR	0.5542	121.3009***	152.648***	-1e-04***	-170.9668***	Yes	Yes
K=200							
SAR	0.5405	0.2955***	-13.4674***	-1e-04***		Yes	Yes
ISAR	0.5608	113.877***	141.2747***	-1e-04***	-160.5681***	Yes	Yes
K=225							
SAR	0.3793	0.1797***	-13.5233***	-1e-04***		Yes	Yes
ISAR	0.3898	70.7528***	82.6093***	-1e-04***	-99.7677***	Yes	Yes

Table 4.18: Results on preliminary spatial regressions ; centralized economy

		Min.	Q1	Median	Mean	Q3	Max.
K25	Com	-0.04	0.03	0.12	0.16	0.24	0.76
K25	Cit	-3.63	3.35	6.22	4.51	6.97	9.54
K50	Com	0.03	0.06	0.09	0.11	0.14	0.34
K50	Cit	-2.84	-0.12	1.00	0.34	1.29	2.30
K75	Com	0.05	0.06	0.07	0.07	0.08	0.13
K75	Cit	-2.90	-2.18	-1.88	-2.06	-1.81	-1.54
K100	Com	-0.04	-0.00	0.04	0.05	0.09	0.31
K100	Cit	-5.26	-2.24	-1.00	-1.74	-0.67	0.44
K125	Com	-0.06	-0.02	0.03	0.05	0.09	0.36
K125	Cit	-7.38	-3.75	-2.26	-3.15	-1.87	-0.53
K150	Com	-0.02	-0.02	-0.01	-0.01	-0.01	0.03
K150	Cit	-4.93	-4.51	-4.33	-4.44	-4.29	-4.13
K175	Com	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04
K175	Cit	-4.38	-4.51	-4.56	-4.53	-4.57	-4.62
K200	Com	-0.08	-0.07	-0.05	-0.05	-0.03	0.05
K200	Cit	-6.41	-5.29	-4.83	-5.10	-4.70	-4.29
K225	Com	-0.03	-0.05	-0.07	-0.07	-0.09	-0.19
K225	Cit	-4.09	-5.42	-5.97	-5.64	-6.12	-6.61

Table 4.19: Interaction effects on preliminary regressions; centralized economy

		Min.	Q1	Median	Mean	Q3	Max.
	Com	0.48	0.62	0.78	0.85	1.00	1.97
	Cit	-27.47	-14.53	-9.21	-12.37	-7.81	-3.04
	Com	0.90	0.64	0.35	0.23	-0.04	-1.78
	Cit	25.49	2.17	-7.42	-1.71	-9.93	-18.54
	Com	0.98	0.68	0.36	0.21	-0.10	-2.09
	Cit	30.67	3.98	-6.99	-0.46	-9.87	-19.71
	Com	0.98	0.62	0.22	0.05	-0.33	-2.74
	Cit	36.74	4.40	-8.89	-0.98	-12.38	-24.31
	Com	0.82	0.48	0.11	-0.05	-0.41	-2.67
	Cit	34.34	4.00	-8.47	-1.05	-11.75	-22.94
	Com	0.69	0.39	0.05	-0.09	-0.41	-2.42
	Cit	29.46	2.41	-8.71	-2.09	-11.63	-21.61
	Com	0.72	0.39	0.03	-0.12	-0.46	-2.63
	Cit	31.76	2.61	-9.38	-2.25	-12.52	-23.28
	Com	0.63	0.32	-0.01	-0.16	-0.48	-2.52
	Cit	27.74	0.36	-10.90	-4.20	-13.85	-23.95
	Com	0.39	0.20	-0.01	-0.10	-0.30	-1.57
	Cit	12.06	-4.95	-11.94	-7.78	-13.78	-20.05

Table 4.20: Interaction effects on preliminary spatial regressions; centralize eco.

Results on the social planner solution leads to qualitatively similar conclusions as the decentralized economy's case : significant and well-signed coefficients using OLS ; coefficients attached to $CI_{ComDist}$ being non-significant in TSLS regressions and finally, no results appear significantly different from zero while introducing the interaction term.

Results on spatial regressions are more interesting as they exhibit both significant and well-signed coefficients in each configuration. Results accounting for the interaction term are displayed in Table 18 and analyzed in Table 20.

Table 19, at lines labelled 'Com', considers the effect of $CI_{ComDist}$ resulting from the addition of $\beta_1 + \beta_3 CI_{CitDist,it}$ at different quantiles of $CI_{CitDist,it}$. Conversely, at lines labelled 'Cit', Table 19 allows to consider the effect of $CI_{CitDist}$ resulting from the

addition of $\beta_2 + \beta_3 CI_{ComDist,it}$ at different quantiles of $CI_{ComDist,it}$. If we focus on the respective means of $CI_{CitDist,it}$ and $CI_{ComDist,it}$, we can observe that $CI_{ComDist}$ and $CI_{CitDist}$ have opposite effects : the effects of commercial integration and technological integration oppose. While commercial integration exhibits a positive relationship with agglomeration, technological integration plays the opposite role in accordance with the theory exposed in Section 1. This conclusion is true whichever the number of neighbors we consider in estimating agglomeration using the index of Moran's. Once again, this conclusion remains true for small kernels of local Moran's but less true for larger kernels even though the difference between coefficients remains large.

4.5 Challenging linearity

4.5.1 Generalized Additive Models [195]

A generalized additive model is a generalized linear model with a linear predictor (understand the right hand side) built as a sum of smooth functions of covariates.

Linear models can basically be sketched as follows :

$$y_i \sim \mathcal{N}(\mu_i, \sigma^2)$$

$$\mu_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_j x_{ji}$$

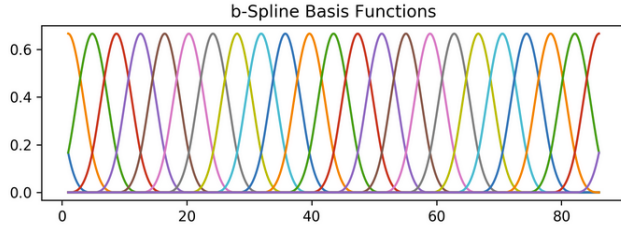
where y_i is a variable to be explained, μ_i is the average of the data generating process and σ^2 its variance. μ_i results from the sum of variables that linearly condition y_i . To break the linear assumption held by the sum, we could classically be adding higher order terms such that

$$\mu_i = \beta_0 + \beta_1 x_{1i} + \beta_{12} x_{1i}^2 + \beta_{13} x_{1i}^3 + \dots + \beta_2 x_{2i} + \beta_{22} x_{2i}^2 \dots \quad (4.6)$$

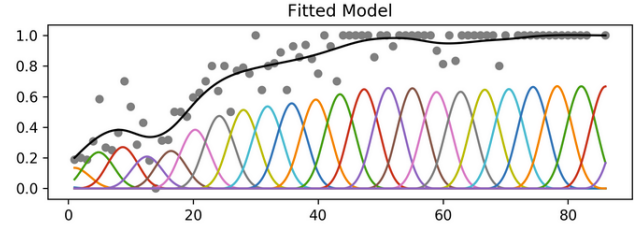
However, first, this solution poses a model selection issue : "where should we stop adding higher terms?". Second, adding ever higher order terms usually induce bad behavior at bounds of interval of definitions ⁵ and don't provide highly optimal solutions.

⁵"runge phenomenon"

The proposition held by Generalized Additive models is to substitute polynomial expansion to basis expansion. From a polynomial expansion that would sketch (4.6) such $y_i = \beta_0 + \sum_j \beta_j x_{ji} + \epsilon_i$, GAMs suggest to estimate smooth functions $s_j(x_{ji})$ instead of linear terms β_j : $y_i = \beta_0 + \sum_j s_j(x_{ji}) + \epsilon_i$. $s_j(x_{ji})$ are called splines and defined $s(x) = \sum_{k=1}^K \beta_k b_k(x)$ where b_k are basis functions times some coefficients β_k to be estimated. Indeed, GAMs estimate the coefficients β_k at each point x_i for some chosen basis function. As a consequence it allows to catch for local behaviors when polynomial expansion imposes wiggleness to the whole data generating process.



Splines formed from basis functions



Splines formed from weighted basis functions

In estimating a GAM model β are obtained in maximizing the penalized log-likelihood written as $\mathcal{L}_p(\beta) = \mathcal{L}(\beta) - \frac{1}{2}\lambda\beta^T S\beta$. \mathcal{L} is the log likelihood and the second part $\frac{1}{2}\lambda\beta^T S\beta$ penalizes the estimation for its wiggleness. In $\beta^T S\beta$, S is the penalty matrix and can be presented under a more intuitive form as $\beta^T S\beta = \int_{\mathbb{R}} [s'']^2 dx$, that is the sum of splines' second order derivatives that typically account for wiggleness. λ are coefficients to be optimized in order to fit at best the data generating process at the lowest cost (wiggleness). In estimating, one can either aim at minimizing out sample error and then λ is a classic parameter. This is the reasoning called by generalized cross validation or AIC methods of estimation. Otherwise, one can consider λ as a prior on the basis coefficients and this is the way Random Effects Maximum Likelihood estimation endorses it.

Most of the smooth functions only allow for univariate smoothing of the form $f_1(x_{1i})$ and not for bivariate smooths of the type $f_3(x_{1i}, x_{2i})$. In order to be able considering

the interaction between transport and transfer costs variables, solutions for bivariate smooths divide between thin plate regression splines and tensor smooths. Thin plate regression splines suppose isotropy and to this extent are sensitive to linear rescaling of single covariates that could occur under a change of measurement units. Since they make the assumption of scale invariance, such issue does not affect tensor smooths.

The model is to be estimated using the penalized iteratively re-weighted least square algorithm (PIRLS) that consists in a slight modification of the iteratively re-weighted least square algorithm used to fit generalized linear models. The PIRLS takes some care of the random effects integrated when moving from a generalized linear models (GLM) to a generalized linear mixed model (GLMM) and provides an analytically tractable solution to the likelihood estimation. The procedure is no conceptually different in the case of Generalized Additive Models (GAM) whose objective of the optimization problem is similar to a GLMM's one.

Still do we face a number of identification problems that GAM models don't endorse by themselves. First, data limitations preclude meaningful estimates of the fixed parameters included in (4.3) namely α , σ , ρ and η . We consider the role of those effects as fixed and capture it in regional fixed effects (r_i). Second, our setting face endogeneity issues arising from both the fact that our measures of transport and transfer costs might reflect agglomeration patterns on the one hand and from the presence of autocorrelation in our residuals due to omitted elements being spatially correlated. Dealing with endogeneity issues within a nonparametric framework is challenging and at the research frontier in econometrics.

The solution we propose relies on the control function approach as developed in Newey, Powell and Vella (1999) and Blundell and Powell (2003) [28]. Broadly consider a model such

$$\begin{aligned} y &= g(x, z) + \epsilon \\ x &= \Pi(z) + u \end{aligned}$$

where g and Π_0 are functions of x and z respectively endogenous regressors and their

instruments. ϵ and u are residuals constrained to the extent that

$$E(\epsilon|u, z) = E(\epsilon|u) \quad (4.7)$$

$$E(u|z) = 0 \quad (4.8)$$

If $\Pi(z)$ was linear in z , condition (4.7) would imply z being independent of u while condition (4.8) would require $z \perp \epsilon$. In a nonparametric configuration, Newey and al. (1999) show that identification is guaranteed when there is an exact, nonadditive functional relationship tying (x, z) and u . This constitute a weaker assumption than the strict independence suggested in the linear case. As an estimation procedure, they propose a two-step approach. The auxiliary nonparametric regression is first computed on the model of $x = \Pi(z) + u$ and then \hat{u} are reinvested in the structural equation.

As evoked, our case requires three auxiliary regressions to address the issues of spatial autocorrelation and endogeneity of the transport and transfer costs proxies.

In a parametric setting sketched $y = X\beta + \varepsilon$, spatial effects are dealt substituting X and ε such ⁶

$$y = (I - \delta W)^{-1} X\beta + (I - \delta W)^{-1} \varepsilon$$

$$\leftrightarrow$$

$$y = \delta W y + X\beta + \varepsilon$$

Because of the feedback effects between y and its spatial lag term, Wy and the residuals ε are correlated. Kelejian and Prucha (1998)[?] proposed a 2SLS procedure where Wy would be regressed on a set of instruments built from the spatial lags of the strictly exogenous variables. The fitted values would then be used in place of the endogenous variable. Accordingly, in a nonparametric setting, Basile and al. (2010) [20] proposed to estimate an auxiliary regression of the form $Wy = g(Z) + v$ where Z are constituted of the first order spatial lags of all exogenous variables. To the extent that g is an exact, nonadditive functional relationship of v , this first step guarantees the treatment of the endogeneity simply adding a smooth function of \hat{v} in the structural equation.

⁶where W is a spatial weight matrix, and δ the parameter of spatial externality

In addition to the autocorrelation issue, we suspect that our proxies are not independent from the level of agglomeration observed and that reverse causation could be at work.

From the instrument variable built on the Roman road network, we propose an auxiliary regression of the form :

$$CI_{ComDist,it} = g_1(RR_i) + v_{1,it}$$

where $CI_{ComDist}$ is the centrality index obtained from ComDist proximity matrix and RR_i a centrality measure calculated based on how each region i locates in the network built from the roman road infrastructure.

Symmetrically, we propose for $CI_{CitDist}$ an auxiliary regression of the form :

$$CI_{CitDist,it} = g_2(F_{it}) + v_{2,it}$$

4.5.2 Results on non-linear estimations

Fits of first stages

$$CI_{ComDist,it} = g_1(RR_i) + v_{1,it}$$

```

1 Family: gaussian
2 Link function: identity
3
4 Formula:
5 CL_Com ~ s(C_RR, bs = "ad", k = 110)
6 + te(X, Y, Time, d = c(2, 1), bs = c("ds", "tp"),
7     k = c(130, 130, 25))
8 Parametric coefficients:
9             Estimate Std. Error t value Pr(>|t|)
10 (Intercept) 0.592574    0.001805   328.4   <2e-16 ***
11 _____
```

```

1 Approximate significance of smooth terms:
2           edf Ref.df    F p-value    | k-index p-value
3 s(C_RR)      62.57    76 25.1 <2e-16 *** | 0.726    0
4 te(X,Y,Time) 49.03    122 79.5 <2e-16 *** | 0.00764    0
5
6 R-sq.(adj) = 0.665    Deviance explained = 67%
7 -REML = -2939    Scale est. = 0.02244    n = 6890

```

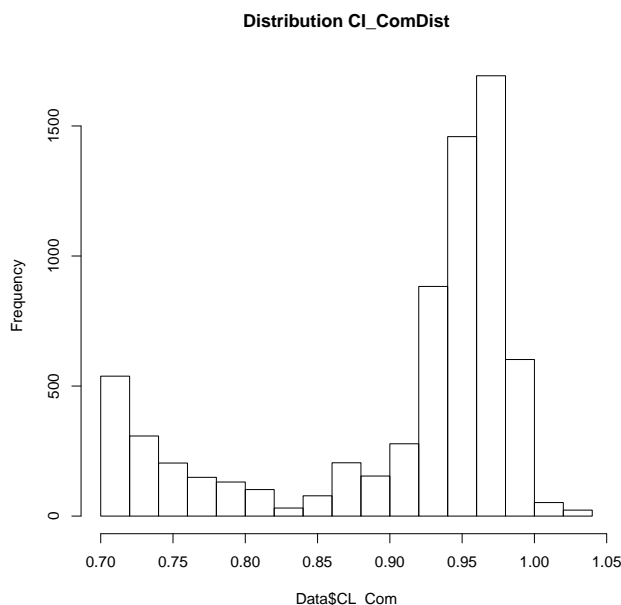


Figure 4.1

The shape of the distribution of $CI_{ComDist}$ (Figure 4.1) tends to a Gaussian. Of notice, it exhibits a fat tail on the left hand side. Still did we opt for a gaussian family function and a neutral (identity) link function as family function. Allowing expressively for fat tails didn't bring much in terms of deviance being explained.

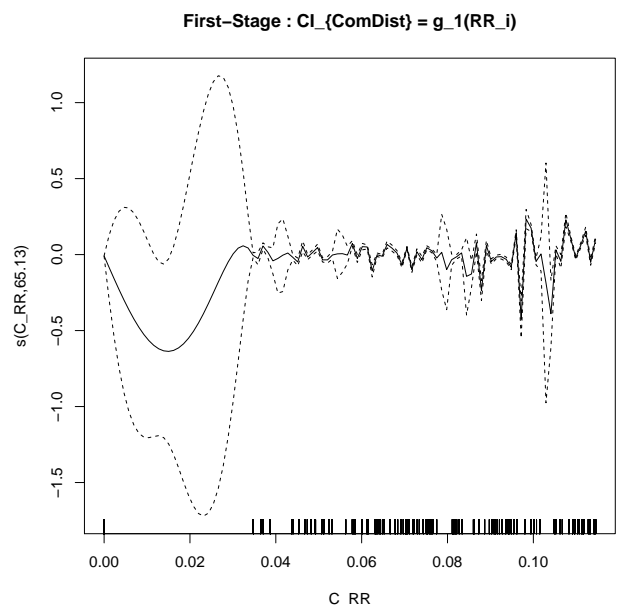


Figure 4.2

Results appear satisfying : 67% of the deviance is being explained throughout this regression and the instrument based on the Roman transportation network has an effect significantly different from zero. We use an adaptative spline to fit this variable to handle the absence of values between 0 and 0.3474. We modeled the spatial structure

over using a Duchon spline and a thin plate bases. The Duchon spline is particularly suited for fitting spatial structure. It is common to model spatial structures using the Markov Random Field Smooths. However this fit ended up to smooth considerably our explaining variable and presented very wide confidence intervals than our final choice does not exhibit.

$$CI_{CitDist,it} = g_2(F_{it}) + v_{2,it}$$

```

1 Family: gaussian
2 Link function: identity
3
4 Formula:
5 Cit ~ s(Fit, bs = "tp", k = 110) + te(X, Y, Time,
6 d = c(2, 1), bs = c("ds", "tp"), k = c(130, 130, 25))
7
8 Parametric coefficients:
9             Estimate Std. Error t value Pr(>|t|)
10 (Intercept) 7.102e-01  1.343e-05   52869   <2e-16 ***
11 ———
12
13 Approximate significance of smooth terms:
14             edf Ref.df      F p-value      | k-index  p-value
15 s(Fit)       99.52   109 251.35 <2e-16 *** | 0.717  0
16 te(X,Y,Time) 47.32   121  13.96 <2e-16 *** | 0.152  0
17 ———
18
19 R-sq.(adj) =  0.888   Deviance explained =  89%
20 -REML = -36661   Scale est. = 1.2433e-06   n = 6890

```

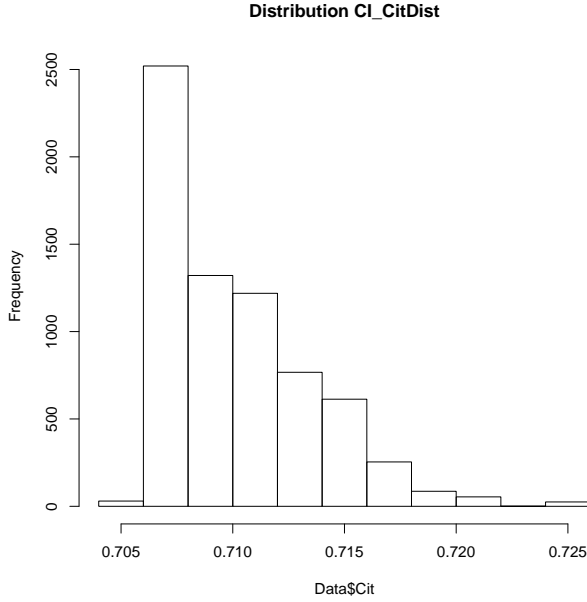


Figure 4.3

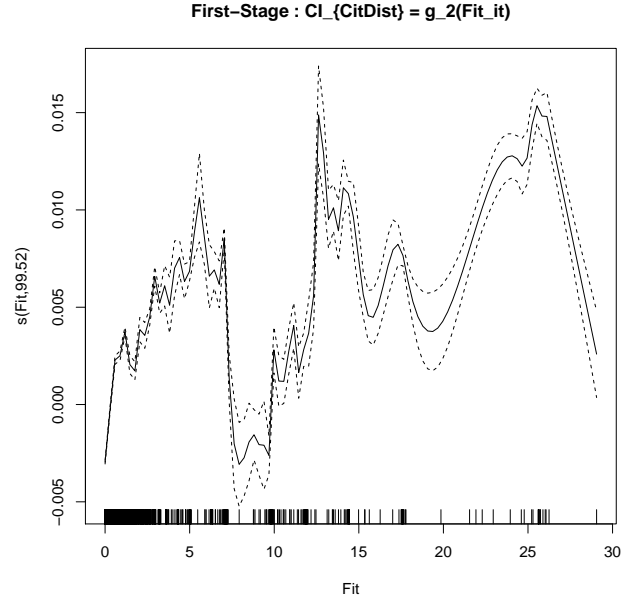


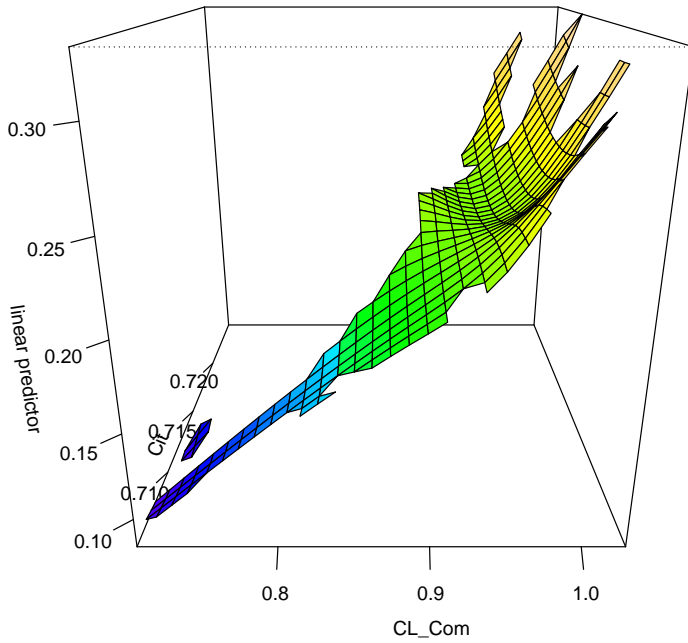
Figure 4.4

The distribution of $CI_{CitDist}$ is complex : the large tail calls for a Poisson like distribution between the left hand extremum deviates from this type of distribution. We fit a Gaussian and results appear satisfactory : 89% of the deviance is being explained and the instrument based on the fitness indicator developed by Cristelli and al. (2012) [53] which has an effect significantly different from zero. Classically, we used a thin plate spline to fit this variable. The k-index is not very close from 1 but the attached p-value indicates that it is significantly different from zero : we had enough degrees of freedom to fit properly.

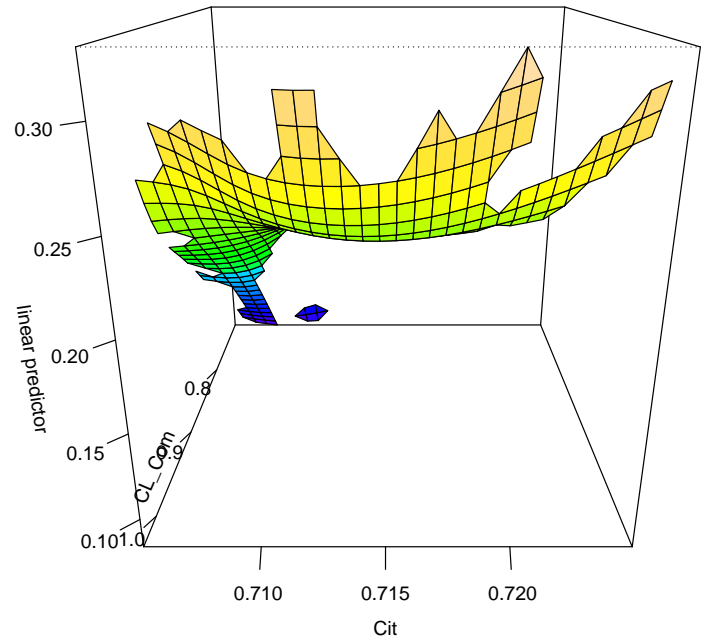
The decentralized setting

Parametric regressions shaded light on the fact that small kernels of local Moran's I_i provided for more interesting results since they caught more precisely for local information while large kernels induced too rough smooths. This section and the following section describing results on the centralized economy only consider k-nearest neighbors when k=25 to k=100.

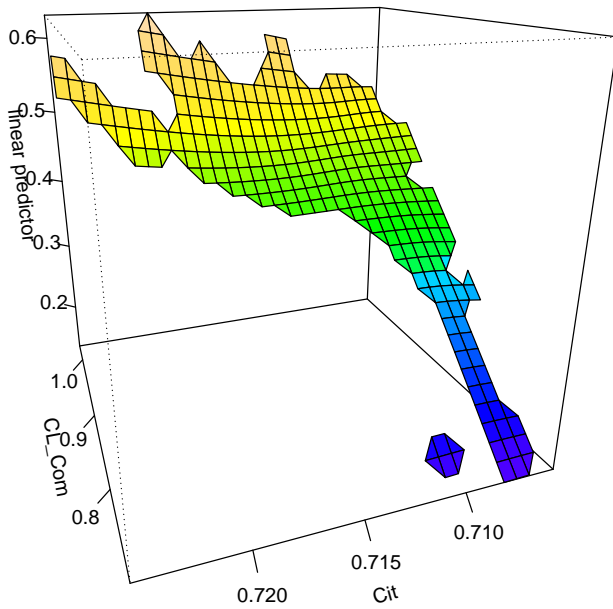
Figure 4.5: Interactions effects ; GAM ; decentralized economy



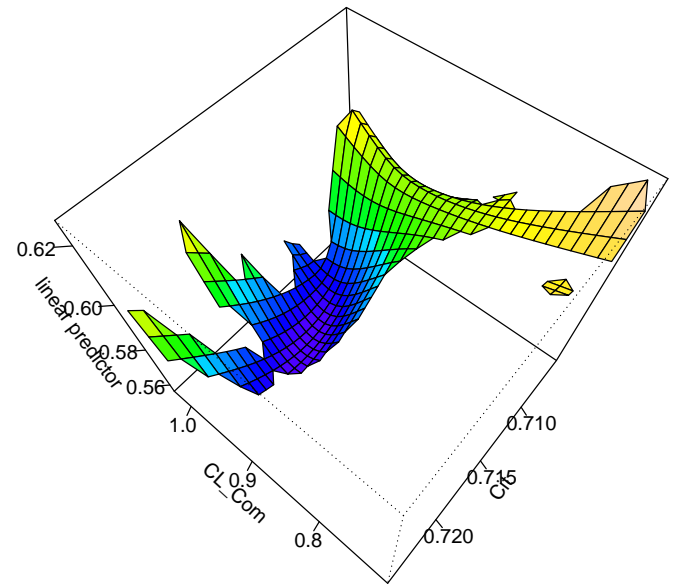
(a) K=25 ; View 1



(b) K=25 ; View 2



(c) K=50



(d) K=75

	Effective.DF	Reference.DF	F	p-value
K=25				
Interaction Eff.	11.9274	13.8398	4.4998	0
Deviance explained	0.9959		REML	-19658.6226
K=50				
Interaction Eff.	10.8791	12.8321	11.2903	0
Deviance explained	0.9983		REML	-22928.1921
K=75				
Interaction Eff.	13.6149	15.4195	12.239	0
Deviance explained	0.9983		REML	-22838.5949
K=100				
Interaction Eff.	14.15	16.0073	12.6109	0
Deviance explained	0.9988		REML	-23931.3845

Table 4.21: Control statistics on the previous GAM computations

Fig 4.5 displays the graphical representation of interaction effects extracted from the computation of the GAM models for small kernels of local Moran's I_i ($k=25$, $k=50$, $k=75$). Surfaces are the result of a 5% interpolation based on our data.

Subfigures (a) and (b) are two views from the same surface. In (a), the effect of the variable $CI_{ComDist}$ appears strongly positive, favoring local agglomeration processes in accordance with what the theory predicts. (b) is a 90° rotation of the surface in (a) so that we better consider the effect of $CI_{CitDist}$. The effect follows the shape of parabola : negative from low to intermediate values of λ and slightly positive in a second time. Conclusions are quite alike when we consider a slightly larger kernel in $K = 50$. The prediction radically change when we consider a larger kernel in $K = 75$. The effect of $CI_{ComDist}$ becomes mostly negative and exhibits a slight non-linearity for high values of centrality. The effect of $CI_{CitDist}$ now exhibits a strong non-linearity and a very negative slope. We found identical patterns for all large kernels.

Economically, we raise two points. First, the positive effect of $CI_{ComDist}$ that represents the theoretical parameter ϕ seems to play a positive role at relatively local scale. We control for the spatial structure of our data, such that those findings are not driven by the occurrence of spatial autocorrelation. Thus, the opposition in sign of both variables occur at small scales, not up to the 50th -nearest neighbors. Second, at larger scale, our variables rather tend to co-vary : intermediate values for both proxies of λ and ϕ play against agglomeration and high values play in favor of.

The centralized setting

	Effective.DF	Reference.DF	F	p-value
K=25				
Interaction Eff.	12.3266	14.1948	53.3778	0
L	13.7789	16.2356	5.2539	0
$1 - s_n$	23.9994	24	790180.3398	0
Deviance explained	1		REML	-45926.258
K=50				
Interaction Eff.	14.8987	16.6142	65.8874	0
L	12.9265	15.5019	6.8957	0
$1 - s_n$	24	24	39709733140681.8	0
Deviance explained	1		REML	-106628.419
K=75				
Interaction Eff.	15.3131	16.9664	52.9555	0
L	6.5602	8.6326	11.6803	0
$1 - s_n$	23.9991	24	1529633.3124	0
Deviance explained	1		REML	-51281.687
K=100				
Interaction Eff.	3.8492	4.5521	19.3097	0
L	13.3643	15.8861	12.9148	0
$1 - s_n$	23.9025	23.9988	21171.7154	0
Deviance explained	1		REML	-38264.9339

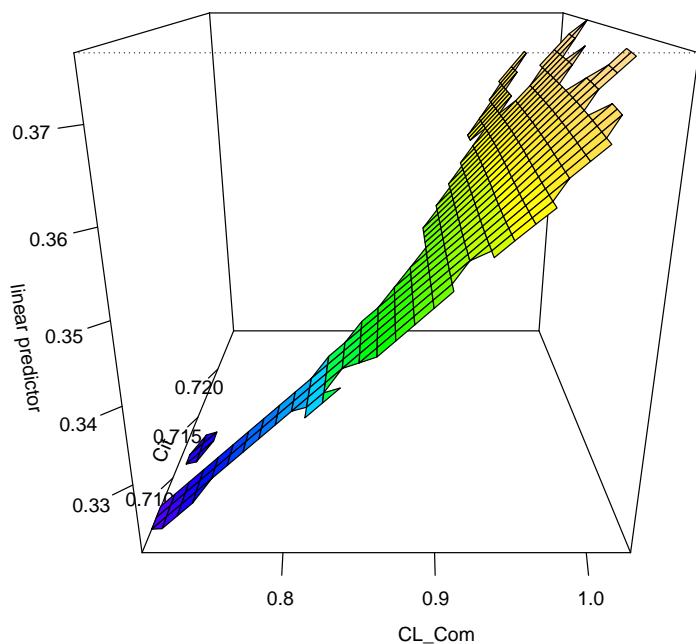
Table 4.22: Control statistics on the previous GAM computations

Fig 4.6 displays the graphical representation of interaction effects extracted from the computation of the GAM models for small kernels of local Moran's I_i , in the case of the centralized economy. Surfaces are still the result of a 5% interpolation based on our data.

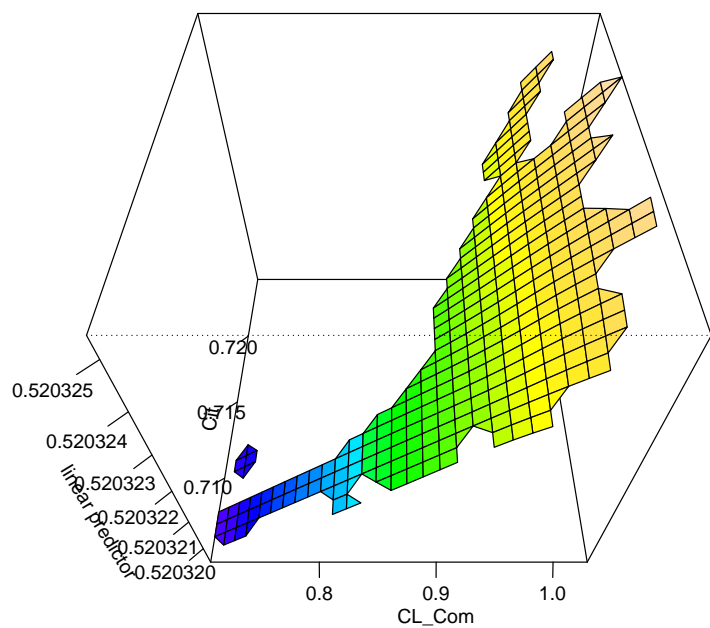
Qualitatively, the conclusions are similar for the 3 subfigures (a), (b) and (c) : for small kernels (25 up to 75), the effect of the variable $CI_{ComDist}$, that accounts for the

theoretical parameter ϕ , is strongly positive. This indicates that low transport costs on goods effectively favors agglomeration at a local scale. Conversely, technological integration does not seem to have a significant effect. Deepest investigations exhibit a slightly negative effect for the highest values of centrality indexes (low transfer costs on ideas).

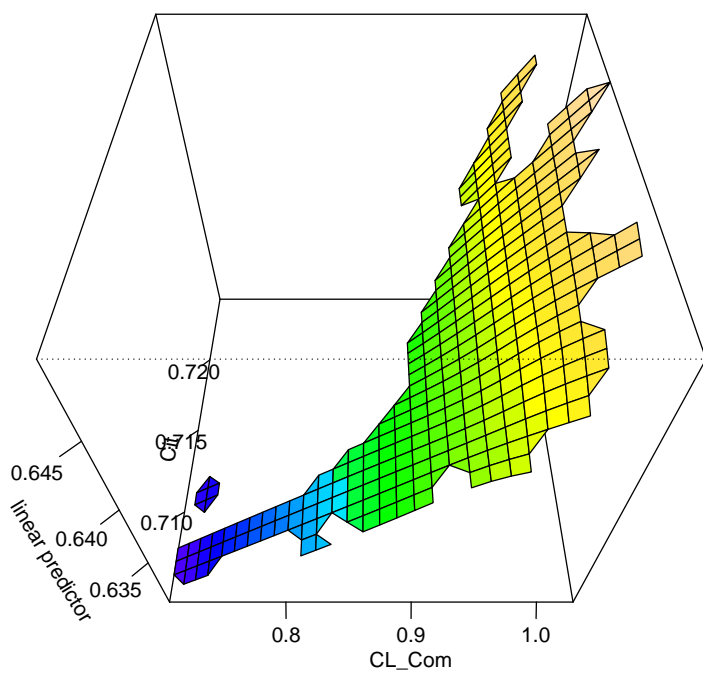
Similarly to regressions in the case of the decentralized economy, the prediction reverse for large kernel ($K=100$) : the effect of low trade costs on goods play negatively on agglomeration dynamics. Technological integration still does not exhibit a significant effect.



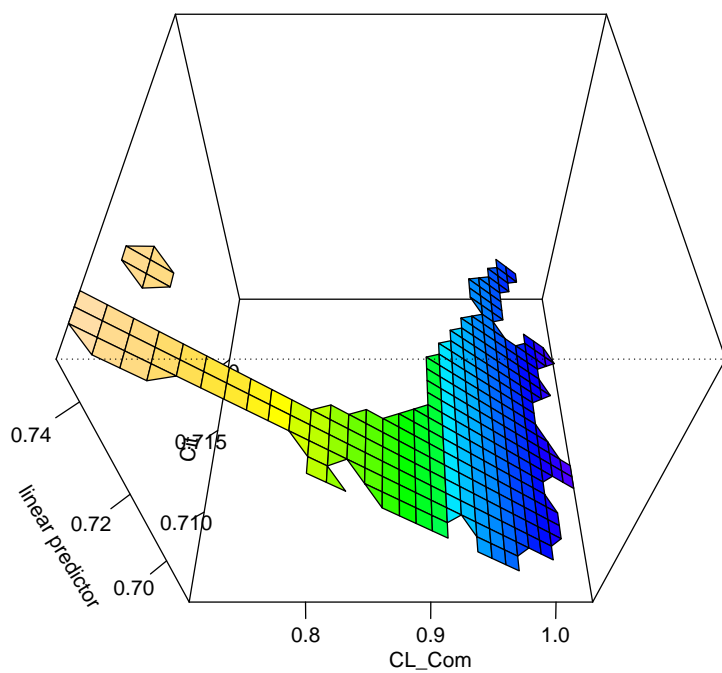
(a) K=25



(b) K=50



(c) K=75



(d) K=100

Figure 4.6: Interactions effects ; GAM ; centralized economy

4.6 Conclusion

This chapter makes an attempt in addressing the sharp criticisms raised by Combes and Gobillon (2014) [49] against the framework conditioning industries' agglomeration outcomes to Marshallian externalities. We slightly shift the issue from considering agglomeration of industries to focus on agglomeration across space, at the regional level. Doing so allowed us to rely on the theoretical framework provided by Montmartin (2015) [151] that condition agglomeration to two parameters namely transport costs on goods and transfer costs of ideas. Transport costs on goods and transfer costs on ideas are expected to be forces that constrain the spread of pecuniary and non-pecuniary externalities that themselves relate to what some others call input-output linkages and knowledge spillovers respectively.

Based on this reasoning, we proposed original proxies for pecuniary and non-pecuniary externalities. On the one hand, we proxied pecuniary externalities thanks to centrality index that give region's exposure to input-output flows between spatial units. Those flows have been calculated using proximity between industrial mixes, as represented by patterns of patent deposits. Accordingly the more exposed a region to pecuniary externalities, the lowest the transport costs it will be affected by. Respectively, we have been proxying exposure to non-pecuniary externalities using a centrality index based on a network building from patents citation patterns. Based on a 'control function' identification strategy using parametric and non-parametric estimation methods we emphasize that the forces at stake play opposite roles in accordance with the theory : the proxy for transport costs is affected by a positive coefficient meaning that lower transport costs tends to reinforce agglomeration dynamics while the proxy for transfer costs on ideas is affected by a negative coefficient meaning that lower transfer costs temper forces that drive the concentration of activities.

This work opened (at least) two opportunities for improvement : On the one hand, recent literature has proposed to approximate transport costs using infrastructures and travel speeds. This could alleviate the complex reasoning underlying the proxy we used for transport costs. On the other hand, we chose to pursue a 'control function' identifi-

cation strategy but it could have been different. Recent work on identification provides us with hypotheses that could seem reasonable in our framework. Attached to those new identification strategy, even more performant estimation technics (handling heteroskedasticity better than would GAM models) could have been put in place namely instrumental variables in quantile regressions in their parametric and non-parametric forms.

4.7 Appendices

4.7.1 Patents per industry

The industrial classification has a hierarchical structure such that industries labeled "23.1", "23.3", "23.4" and "23.5" are embedded in "23". As a consequence, some licensees might have filled their patents in both "23" and "23.1". We didn't correct for this nor did we extend the cases where "23.1" only has been documented. In the first instance, we didn't restrict the patent to industry "23.1" exclusively as licensees might have considered as also relevant a broader definition of their innovation. One might have considered that her innovation in glass and glass products (23.1) could be extended to clay building materials (23.3) or porcelain and ceramic products (23.4). Deleting "23" would have erased such ties. Respectively we didn't extend every case where one strictly specified "23.1" or "23.3"... toward considering "23" - "23.1" or "23" - "23.3". Indeed, this would have lead to consider stronger ties than existing between patents licensed in "23.1" and "23.3".

The distribution of patents across industries is displayed in the following barplot and industries' labels are specified thereafter.

Barplot : Patents per industry

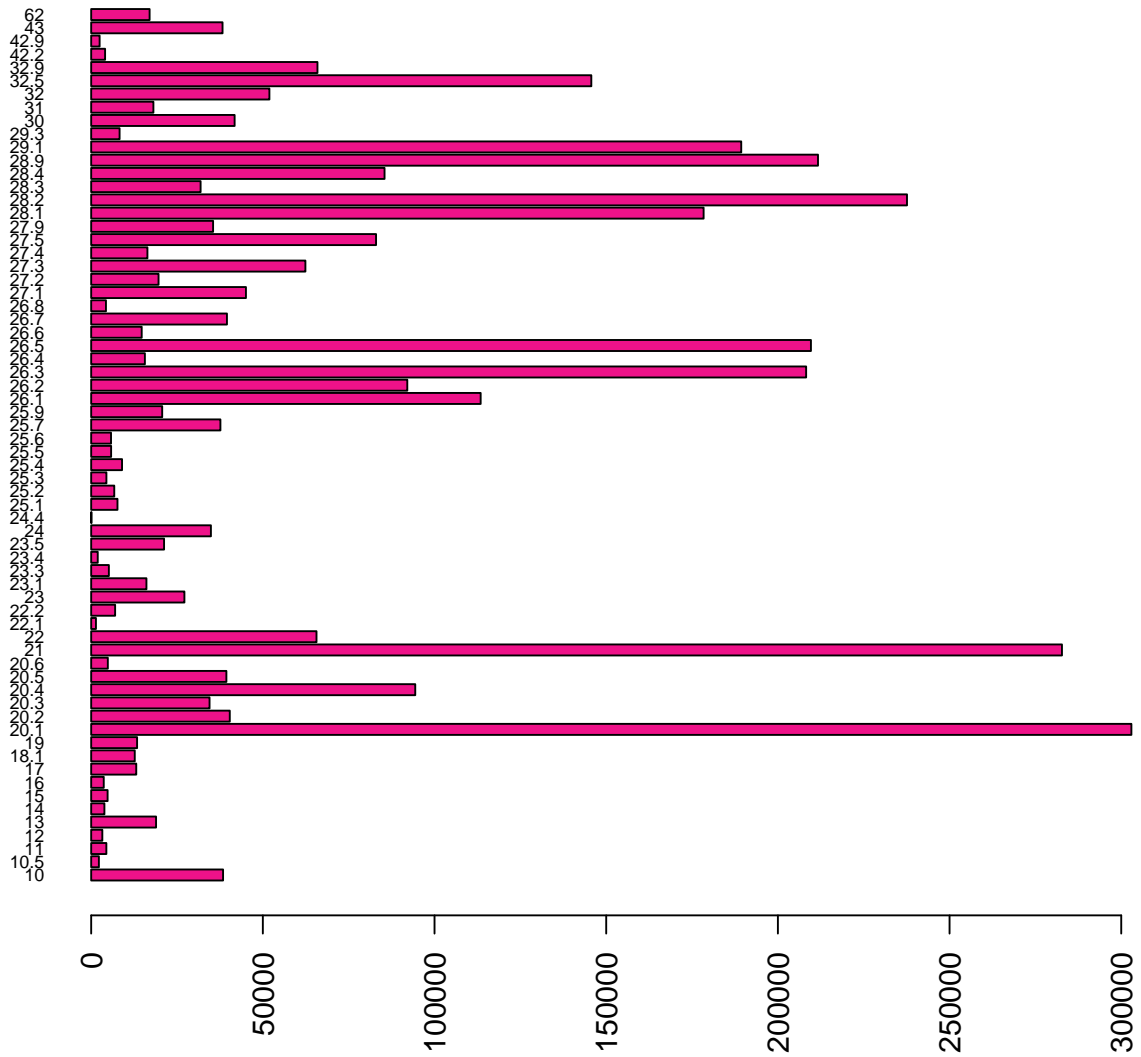


Table 4.23: Industries' titles

10	Manufacture of food products
10.5	Manufacture of dairy products
11	Manufacture of beverages
12	Manufacture of tobacco products
13	Manufacture of textiles
14	Manufacture of wearing apparel
15	Manufacture of leather and related products
16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
17	Manufacture of paper and paper products
18.1	Printing and service activities related to printing
19	Manufacture of coke and refined petroleum products
20.1	Manufacture of basic chemicals, fertilizers and nitrogen compounds, plastics and synthetic rubber in primary forms
20.2	Manufacture of pesticides and other agrochemical products
20.3	Manufacture of paints, varnishes and similar coatings, printing ink and mastics
20.4	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations
20.5	Manufacture of other chemical products
20.6	Manufacture of man-made fibres
21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
22	Manufacture of rubber and plastic products
22.1	Manufacture of rubber products
22.2	Manufacture of plastics products
23	Manufacture of other non-metallic mineral products
23.1	Manufacture of glass and glass products
23.3	Manufacture of clay building materials
23.4	Manufacture of other porcelain and ceramic products
23.5	Manufacture of cement, lime and plaster
24	Manufacture of basic metals
24.4	Manufacture of basic precious and other non-ferrous metals
25.1	Manufacture of structural metal products
25.2	Manufacture of tanks, reservoirs and containers of metal
25.3	Manufacture of steam generators, except central heating hot water boilers
25.4	Manufacture of weapons and ammunition

25.5	Forging, pressing, stamping and roll-forming of metal; powder metallurgy
25.6	Treatment and coating of metals; machining
25.7	Manufacture of cutlery, tools and general hardware
25.9	Manufacture of other fabricated metal products
26.1	Manufacture of electronic components and boards
26.2	Manufacture of computers and peripheral equipment
26.3	Manufacture of communication equipment
26.4	Manufacture of consumer electronics
26.5	Manufacture of instruments and appliances for measuring, testing and navigation; watches and clocks
26.6	Manufacture of irradiation, electromedical and electrotherapeutic equipment
26.7	Manufacture of optical instruments and photographic equipment
26.8	Manufacture of magnetic and optical media
27.1	Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus
27.2	Manufacture of batteries and accumulators
27.3	Manufacture of wiring and wiring devices
27.4	Manufacture of electric lighting equipment
27.5	Manufacture of domestic appliances
27.9	Manufacture of other electrical equipment
28.1	Manufacture of general — purpose machinery
28.2	Manufacture of other general-purpose machinery
28.3	Manufacture of agricultural and forestry machinery
28.4	Manufacture of metal forming machinery and machine tools
28.9	Manufacture of other special-purpose machinery
29.1	Manufacture of motor vehicles
29.3	Manufacture of parts and accessories for motor vehicles
30	Manufacture of other transport equipment
31	Manufacture of furniture
32	Other manufacturing
32.5	Manufacture of medical and dental instruments and supplies
32.9	Manufacturing n.e.c.
42.2	Civil engineering
42.9	Construction of other civil engineering projects
43	Specialized construction activities
62	Computer programming, consultancy and related activities

General Conclusion

In a context of economic turmoil, where disparities between territories exacerbate at both the local/national/ supra-national scales, political agenda keeps on presenting globalization processes as a key solution to sustain economic growth and welfare gains. This might be quite surprising for the attentive observer given that already, early models of the Economic Geography literature, nuanced this broad statement in showing that some regions could suffer from integration processes as core-periphery configurations arise. Those models shaded light on the mechanisms driving increasing disparities and exposed how spatial concentration of activities is triggered by the interplay of increasing returns to scale in manufacturing activities and transport costs. In those configurations, low transport costs allows firms to exploit increasing returns to scale by both concentrating production and serving markets at low/no costs. The introduction of growth considerations by the next generation of models, brought to light the role played by the spread of non-pecuniary externalities across space in tempering the dynamics of activities' agglomeration. NEG models showed how decreasing costs on the transfer of ideas between regions could help in mitigating agglomerations forces favored by low transport costs on goods. This dissertation took interest in developing the empirical counterpart to those theoretical statements looking at the effects of commercial and technological integrations on regional agglomeration and welfare outcomes in the case of the European Union.

Our first chapter set up the issues at the core of this thesis : Do regions across the European Union kept on diverging during the last two decades that marked great steps of economic integration among European economies ? To which extent could the spatial pattern of income disparities be linked to the two forms of commercial and technological integrations ? To address the first question, we considered to which extent regions of the European Union kept on diverging during the recent period between 2000 and 2016 in the wake of the dynamics emphasized by studies focusing on the nineties. We did so using the Exact Approach that roots back to tools from the Exploratory Spatial Data Analysis (ESDA). Our results showed that few central regions of the Old Europe have clearly benefited from integration next to New Members capital cities. Conversely, the most recent period seemed to have reinforced the entrenchment of disparities with "intermediate peripheral regions". Some further developments of the Exact Approach

allowed us to investigate the second question namely to which extent the patterns we observed in a first instance have been conditioned by commercial and technological forms of integration. We missed to emphasize a great explanative power of commercial and technological forms of proximities. We raised two potential explanations for this. First, our proximity matrices could be bad proxies for the technological and commercial integrations we intended to represent. Second, the theoretical relationship we tested in opposing regional per capita GDP to proxies of either form of integrations, could be more complex and involve theoretical nonlinearities we failed to take into account.

The second chapter addressed the hypothesis that the growth engine has stopped for regions that are part of the Old Continent which may explain the increasing disparities between core and peripheral regions. Our working hypothesis was that regions from Western Europe were in a situation of over-investment in R&D and this could explain policies' inefficiencies in triggering growth and re-balancing disparities enhanced by agglomeration mechanisms. To address this hypothesis, we proposed a refined econometric estimation of a spatially extended growth accounting framework. Econometrically, Eberhardt and al. (2013) [70] showed how Common Factor and Common Correlated effects' models (CCE) can be used to handle the omitted variable issue that undermined reliable results in such type of estimations. Yet, Ertur and Musolesi (2016) [75] explained how the cross-sectional dependence at the core of CCE models differ from the autocorrelation phenomenon and therefore require a special treatment. Our work aimed at controlling for both common factors and autocorrelation issues using in turns the two-step approach proposed by Bailey and al. (2016) [14] and the spatial GMM estimator developed by Yang (2018) [196]. Our results showed that private returns on R&D for regions on the EU-15 are negative and public returns very close from zero. Theoretical studies have shown that over-investment situations are as plausible as under-investment cases and tend to confort our result at odds with most of the empirical literature addressing the question of over/under investment in the growth accounting framework.

Chapter 3 aimed at deepening our understanding of the effects of commercial and technological forms of integrations. Chapter 2 emphasized the missing role of the

growth engine in tempering disparities triggered by agglomeration processes but did not properly quantify the interplay between the commercial and technological forms of integration. Chapter 3 developed in depth the literatures that consider the role of transport costs in shaping activities' agglomeration and income distributions in order to emphasize elements that would support the rationale opposing the effects of both forms of integration. In order to investigate the question, we first reviewed the literature that uses gravity equations to question the link between trade flows and trade costs. While agglomerating, activities keep on serving peripheral markets from the core region and trade flows should intensify between trade partners. As trade costs decrease (from high to intermediate levels), we thus expected flows to densify rapidly. In fact, the empirical framework of gravity equations has confronted the 'paradox of distance' in the inability of studies to emphasize a decreasing coefficient affecting distance costs while worldwide trade flows soar. In reviewing potential explanations to this puzzle, we gave a particular attention to studies suggesting that heterogeneous variations of components of trade costs could have induced outlasting barriers to trade. Indeed, this suggestion found echoes in the theoretical frameworks integrating growth mechanisms in Economic Geography settings. NEGG frameworks model the conflicting role commercial and technological integrations might play on agglomeration and welfare outcomes. Empirically, few studies have considered both forms of integration looking at the role played by the spread of pecuniary and non-pecuniary externalities in the (co)-agglomeration patterns of industries. In the wake of the study of Rosenthal and Strange (2001)[175] most conclude to a complementary role played by the spread of both forms of Marshallian externalities on agglomeration outcomes at the industrial level. This framework has been criticized by Combes and Gobillon (2014) [49]. First, those equations miss robust theoretical foundations, justifying the forces involved in the specification. Second, most papers relying on this framework hold an assumption of linearity while estimating the specification. Additionally, strong suspicions of endogeneity might be raised against this framework and most of the time, those have lightly addressed. Chapter 4 makes an attempt in addressing those points.

Chapter 4 reframed the question of agglomeration raised by "Marshallian specifications" into a New Economic Geography and Growth model. Doing so, our interest

moved from agglomeration patterns of industries to agglomeration patterns conceived along a spatial dimension. Theoretically, we relied on the NEGG model developed in Montmartin (2015) [151] that provides for the conditional expression of the levels of agglomeration at equilibrium in cases of some decentralized and centralized economies. In both cases, commercial and technological integrations were expected to play opposite roles : on the one hand, lower transport costs favors the agglomeration of activities toward the becoming core in order to benefit from pecuniary externalities and minimize costs by producing in the near proximity of the largest market. Conversely, lower transfer costs on ideas tempers this dynamic in allowing innovative activities to locate further from the core while remaining fully efficient. Empirically, we tested for the relationship linking agglomeration outcomes to parameters of commercial and technological integrations. We made innovative propositions in proxying for those parameters. Transport costs on goods and transfer costs on ideas are expected to be forces that constrain the spread of pecuniary and non-pecuniary externalities. As a consequence we aimed at quantifying flows of externalities as proxies for costs that should restrict them from flowing freely across regions. In estimating we relied on Generalized Additive models in order to alleviate assumptions of linearity "Marshallian specifications" used to maintain. We addressed the endogeneity issue in proposing a new instrument using information about the transport network at the age of the Roman empire as suggested by the literature that proxies transport costs using infrastructure network. Imposing linearity or alleviating it, we obtained comforting results regarding theory.

This work brought in some elements that helped to question the distinct roles of commercial and technological forms of integration on agglomeration dynamics at the regional level of Europe. Certainly, considering how broad this subject remains, we have only been brushing on many interesting aspects of the matter and some deserve deeper attention and further research.

A first opportunity of improvement should focus on extending the GMM estimator used in Chapter 2 and developed by Yang (2018)[196], toward considering a dynamic specification, introducing a lag of the dependent variable. Sarafidis (2012)[178] already demonstrated that such specification can be considered when common factors happen

to be present in the errors. His dynamic GMM estimator remains unbiased even in this case. Merging both propositions from Yang (2018)[196] and Sarafidis (2012)[178] could be of interest toward considering dynamic effects that likely arise in many specifications among those growth accounting frameworks.

A second opportunity of improvement should improve the identification strategy developed in Chapter 4. We have been relying on a control function model to guarantee identification but it only is one path among many. Recent developments have been considering non-separable models as a way to break the additivity assumption held on errors in most econometric models. In following the literature building on Imbens and Newey (2009)[119] up to the frontier that represent the works of Torgovitsky (2015)[190] or Gunsilius (2018)[100], we could, under reasonable hypotheses, guarantee identification in our framework. Researchers feeding this line of research have also been developing estimation strategies relating to instrumental quantile regression holding parametric hypotheses (Chernozhukov and Hansen, 2006)[40] or considering non-parametric settings (Horowitz and Lee, 2007)[111]. It could of interest to extend the present work to strategies guaranteeing identification and alleviating the additivity assumption of the error term.

A third opportunity of improvement could focus on the variable we used to proxy for commercial integration. In order to represent transport costs on goods we have been supposing that those could be proxied by interregional flows of pecuniary externalities that arise from input-output linkages. Empirically we used proximity in industrial mixes to draw a network linking regions and spot the degree of centrality for each region as a proxy for openness. This measure implied numerous assumptions, first, on the interval of definition of transport costs we can consider empirically, second, on the determinants of proximities between industrial mixes across regions. Measures using data about transport infrastructures could be interesting options to pursue in alleviating too strong assumptions. For instance, Donaldson (2018)[64] uses a measure of "lowest-cost route effective distance". In his paper, bilateral trade costs are modeled using a graph representation of space (nodes and edges) and some estimation of the cost of traveling along each arc. Nodes are finely distributed points in space, edges

are connections made thanks to either mean of transportation (rail, road, river ...) whose per unit distance costs differ from one another and are estimated using price differences (Donaldson (2018)[64]) or relative travel speeds (Ahfeldt, Redding, Sturm and Wolf (2015)[2]).

Another stream of developments could get some interest in considering that both migration and innovation dynamics are quantitatively important in shaping agglomeration outcomes. Embodying pecuniary externalities in migration flows could open interesting avenues toward considering technological integration by means of the literature interested in the role of skilled mobility in the geography of innovation. Some recent computable models has paved this way among which the few models we have reviewed in the last developments of Chapter 3 but no empirical study investigates the role of the interaction between mobility patterns and commercial integration on agglomeration outcomes.

Finally, this line of research evaluating the role of trade costs on agglomeration and welfare outcomes has remained very dynamic. On the basis of the computable models described in Chapter 3, recent developments merging network and general equilibrium models have recently succeeded in endogeneizing transport investments while evaluating the implications for the spatial equilibrium distribution of economic activity. We precisely refer to Falgelbaum and Schaal (2020)[?] following Alder (2019) [1], Felbermayr and Tarasov (2015) [?] and Allen and al. (2019) [4]. The implications of those models will obviously call for some innovative empirical counterparts in the wake of studies using natural experiments or other refined identification methods in order to guarantee strong results.

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