Romanian Journal of Regional Science
Vol. 16, No. 1, Summer 2022

DOES GENDER MATTER FOR RELATED AND UNRELATED VARIETY? A SECTORAL, SPATIO-TEMPORAL ANALYSIS FOR THE ITALIAN PROVINCES

Barbara Martini[a]

[a] University of Rome Tor Vergata, Department of Enterprises Engineering

Address: Viale del Politecnico 1, 00133-Rome -Italy

E-mail: barbara.martini@uniroma2.it

Biographical Note

Barbara Martini PhD is a researcher at the Department of Enterprise Engineering of the University of Rome Tor Vergata. Her main research interest lies in the following areas: resilience, spatial econometrics and gender in regional science. She teaches Statistical Methods in Economics and Gender & Inclusion. She also teaches International Economics (3563) and Macroeconomic Principles (1101) at Temple University Rome. She has a bachelor's degree in Economics (University of Rome Tor Vergata *cum laude*). She spent one year at the Groningen University (Erasmus Program), where she studied Advanced Econometrics and Operational Research. She holds a PhD in Economics from Tor Vergata University. She is a member of AISRe, ERSA and SIE.

Abstract

The paper investigates if and how knowledge spills between and within sectors when gender is considered. The data show that females and males are concentrated in different sectors. This different concentration can be a source of different proximity and cognitive distance between gender, and, therefore, the knowledge spillovers can be hindered by this different distribution due to the "gender barriers". Furthermore, they have different skills and capabilities that can impact skill relatedness connectivity. This "gender diversity" can make the labour market stickier and more polarized. Another two dimensions will be considered: sector composition and spatial spillovers. The latter aims to investigate if and how spatial units under consideration (provinces) are affected by their neighbors and vice versa. An SDM (Spatial Durbin Model) will capture the spatial spillovers. The analysis will be carried out at the Italian provincial level over 2012-2017. The results highlight that labour growth can be influenced by gender distribution within and between industries.

Keys words: Variety, growth, spatial econometrics, provinces, Italy.

JEL classifications O18, R11, R19

1. Introduction

Gender[1] is acquiring an increasing interest in several disciplines. In the economic field, the first contributions date back to the late 1970s, and they were focused on pay-gap (Aigner et al., 1977; Becker, 1985; Abbot and Beach 1994; Altonji and Blank 1999). Furthermore, Hakim (2000) used preference to explain females' behaviour and choices between employment and family work. Outset from this pioneering contribution, a growing body of economic literature aims to investigate the different behaviour of females and males in the job market and their consequences on gender segregation[2] (Alesina et al., 2011; Olivetti and Petrongolo 2016; Ngai and Petrongolo 2017; Hall et al., 2019; Petrongolo and Ronchi 2020). However, despite this increasing interest in including gender in the economic analysis of the contributions in Regional Science are still limited (Hirschler 2010; Pavlyuk 2011; Noback et al., 2013), and Evolutionary Economic Geography (EEG) has not yet considered them.

Evolutionary Economic Geography -EEG (Boschma 2004; Boschma 2005; Boschma 2007; Boschma 2009; Boschma and Frenken 2009a; Boschma and Frenken 2009b; Boschma and Martin 2007; Frenken and Boschma 2007; Martin and Sunley 2001; Simmie 2005) deals with the uneven distribution of economic activities across space, and it focuses on the historical process that produces these patterns. Furthermore, it aimed to understand why industries concentrate in the space, how networks evolve, and why some regions grow more than others, using three key concepts: proximities, capabilities and routines, and industries relatedness.

Proximities play a central role in understanding interactive learning and innovation (Boschma 2005), and five forms of proximity can be identified: cognitive, social, institutional, organizational, and geographical. These proximities influence the diffusion of knowledge and, consequently, innovation. Gender differences in social behaviour have been explained by the social role theory (Eagly 1987; Eagly and Wood 2012) in accordance to which females and males behave differently due to the roles they are engaged in, which are usually associated with diverse requirements (Eagly et al., 2000). Moreover, they have different skills and capabilities and different behaviour in the structure of social networks and their attitude toward them (Collischon and Eber 2021, Van Emmerik 2006, Brashears 2008). For example, females focus on ties that provide friendship and emotional support, while males focus on job-related information. These different attitudes can impact skill-relatedness connectivity, proximities, capabilities, routines, and, consequently, the diffusion process

[1] Following the definition provided by the World Health Organization, gender is used to describe the characteristics of women and men that are socially constructed. At the same time, sex refers to those that are biologically determined. For example, people are born female or male but learn to be girls and boys who grow into women and men. This learned behaviour makes up gender identity and determines gender roles.
[2] EIGE https://eige.europa.eu/thesaurus/terms/1304

of knowledge and they can be an obstacle or an advantage in social proximity. Furthermore, females and males have different attitudes in sharing the same knowledge base and expertise that they may learn from each other -cognitive proximity-. However, if and how cognitive proximity can be affected by gender is neglected in the literature. EEG considers organizational routines (Nelson and Winter 1982) as a unit of analysis (Boschma and Frenken 2011). Firms broadly differ in their capabilities, strategies, and routines (ter Wal and Boschma 2007), and these differences can affect the diffusion process of knowledge and the innovation process. However, Nelson and Winter's routines assume homogeneity of human capital (Eberl 2018), but individuals are not homogeneous in organizations. The difference in values, beliefs, preferences can also depend on gender. Consequently, organizational routines can have different performances due to gender.

The core question in EEG studies is whether firms learn more from local firms in the same industry –regional specialization- or from local firms in other industries – regional diversity-. This concept is known in the literature as industry relatedness. In other words, are the most innovative and fast-growing regions sectoral specialized or diversified? (Iammarino 2011). Jacobs' concept of externality -externalities generated by different industries- has been used to answer this question. Industry-relatedness is captured through the decomposition of diversity measure (Frenken et al., 2007) based on the Shannon index (1948), which has the characteristics of being decomposable. The diversity (Variety) can be decomposed into diversity between sectors (Unrelated Variety-UV-), at a higher level of aggregation (usually 2-digits), and diversity within the sectors (Related Variety-RV-) at a lower level of aggregation (commonly 5-digits). The higher is the Related/Unrelated Variety, the lower is the concentration between and within industries. According to Frenken et al., (2007), the higher the number of industries that are technologically related, the more learning opportunities there are for local firms because firms will be beneficial for knowledge spillovers more than a set of unrelated industries, the more will be the contribution to regional growth. Regional diversity, by contrast, will prevent the risk of unemployment following the portfolio theory. Specialized regions are less sensitive to a sector-specific shock because the probability to be hit is lower. Nevertheless, such a shock will be more likely to damage a large part of the economy when hit. Diversified regions, by contrast, have higher chances to be hit by sectoral specific shocks, but the shock will damage a small part of the economy (Boschma 2015). For this reason, the higher is the Unrelated Variety, the lower is the impact on unemployment.

Gender differences are identifiable in the Italian provinces, where the highest percentage of females is employed in the capital-intensive service sector while the lowest is in high tech manufacturing. Nevertheless, there are some niches in manufacturing, such as textiles, in which the female share is more than 80%. Moreover, females mainly concentrate on education and human health among the capital-intensive service. If knowledge spillovers are sources of regional economic growth and depend on proximity, how does knowledge spill between and within industries if gender is considered?

So far, we have highlighted that industrial composition, complementarity, proximity, and knowledge spillovers can foster innovation and enhance labour growth according to EEG theory. Nevertheless, females and males are employed in different industries, and they can share different levels of complementarities captured by different values of within and between diversity measured through Related and Unrelated Variety. Our first question is:

Q1. Do females' have higher Related/Unrelated Variety? In which sector(s)?

Related and Unrelated Variety have an impact on labour growth. As previously highlighted, regional diversity - captured by the Unrelated Variety- protect regions from sector-specific shock. Furthermore, Related Varieties foster innovation and, consequently, labour growth. Nevertheless, if the Unrelated/ Related Variety measures differ by gender, and, being all the other things equal, regions can be more (less) exposed to external shocks. This different degree of exposure to shock will depend on the value of Related and Unrelated Variety by gender. This consideration led to our second question:

Q2. Which is the RV and UV impact for females and males on labour growth?

So far, Unrelated and Related Variety has been explored under two dimensions: gender and sectors. Our last question will regard spatial spillovers. Literature has often considered geographical units isolated, and much attention has been devoted to the spillover effects inside the geographical units. However, geographical proximity can play a role. Spatial analysis allows us to explore the impact of a change in Related/Unrelated Variety in the observation unit under consideration and the neighbours. The impact of (Un)Related Variety of labour growth can be enhanced if sectors are connected through spatial spillover. Our analysis will consider a third dimension: spatiality. Hence, our third question is:

Q3. Does geographical proximity matter and create spatial spillovers that vary in gender?

The novelty of this article can be summarized as follows. First, the relationship between Related/ Unrelated Variety for females and males and labour growth will be investigated to what extent Related/Unrelated Variety for females and males has different magnitude and impacts on labour growth. To our knowledge, this is the first contribution to exploring this topic. Second, the literature focuses on internal spillover i.e. in the same spatial unit. However, geography can be a source of spatial spillovers, and appropriate techniques are needed to consider them. Previous studies (Cortinovis and van Oort 2015 and Caragliu et al., 2016) have used spatial autoregressive with autoregressive error (SARAR) model. Nevertheless, not much attention has been dedicated to direct and indirect effects as a source of local and global spillovers. In contrast with them, our approach will be based on a Spatial Durbin Model (LeSage 2014), which includes spatiality both on the dependent variable and the covariates. As LeSage and Pace (2009, pg. 33) pointed out, Spatial Durbin regression models exploit the complex dependence structure between observation (provinces). Because of this, the parameters estimate contains much information on the relationship between the observations. A change in a single province will affect the province itself (direct effect) and potentially other provinces indirectly (indirect effects). Furthermore, this model allows us to explore the global spillovers, i.e. the analysis will involve the neighbours and higher order of neighbours, including the impact of a change in RV and UV for females and males in the observation unit under consideration. In doing so, special attention will be dedicated to indirect effects.

The paper is organized as follows. The following section summarizes the literature on related and unrelated varieties and their impact on labour growth. The data used and some descriptive features are presented next, followed by the empirical investigation. The last section concludes and discusses policy implications.

2. Literature review

Evolutionary Economic Geography considers proximity (Boschma 2005) and knowledge spillovers as sources of regional economic growth, and regional diversification is crucial in creating new growth paths and offset stagnation (Boschma and Gainelle 2014). However, Variety would support innovation "when variety is 'related', in a technological sense or market sense" (Content and Frenken 2016, p. 2099), and cognitive proximity plays a fundamental role (Nooteboom, 2000). Sufficient knowledge spillovers for innovation will not exist in cases where cognitive distance is too large (i.e., regional diversity is too high). In this case, knowledge has difficulties being reorganized (Aarstad et al., 2016). Knowledge spillovers between related industries facilitate the recombination of pieces of knowledge in entirely new ways and, thereby, innovation. Knowledge will only spillover from one industry to another when the sectors complement shared competencies. The crucial point is the right balance between cognitive distance and proximity, allowing for innovation and interaction. Summing up, diversity is essential for innovation and creativity, but the right balance between cognitive distance and proximity allows for innovation and interaction.

Frenken et al., (2007) measure diversity is based on the concept of entropy developed by Theil (1972). The entropy decomposition proprieties allow decomposing the diversity index into related (RV) and unrelated (UV) variety. According to Frenken et al., (2007), the higher the number of industries that are technologically related, the more learning opportunities there are for local firms because firms will be beneficial for knowledge spillovers more than a set of unrelated industries, the more will be the contribution to regional growth. Regional diversity, by contrast, will prevent the risk of unemployment by the portfolio theory.

Focusing on employment growth, the contributions of Frenken et al., 2007, Boschma Iammarino 2009, Bishop and Gripaios 2010, Hartog et al., 2012, Mameli et al., 2012, Cortinovos and Van Oort 2015, explore the relationship between employment growth and Related/Unrelated Variety obtaining mixed results. In some cases, the Related/Unrelated Variety positively impacts employment; in some other cases, it has a mixed or negative impact. These contributions differ from several points of view. First, the spatial scale is different, varying from Nust 3 in Frenken et al., (2007), Boschma Iammarino (2009), Nuts 4 (LLMA) in Hartog et al. (2012) and Mameli et al., (2012), Nuts 2 in Cortinovos and Van Oort (2015) and UK sub-regions in the study of Bishop and Gripaios (2010). Second, RV and UV are calculated using different digit levels. In some studies, Related Variety is calculated at the 5- digit level and Unrelated Variety is based on the 5-digit falling in the 2 digits; in some other studies, Variety is considered at the 4 digits or the 3 digits. Furthermore, the results are obtained using different estimation strategies. The approach followed by Frenken et al., (2007), Boschma Iammarino (2009), Bishop and Gripaios (2010), and Mameli et al., (2012) is a cross-sectional approach based on OLS regression. Hartog et al., (2012) use a dynamic panel data approach, and the estimations are obtained through a GGM method. The different approaches in calculating the Related/Unrelated Variety, the different spatial units, and different estimation methods make the results not comparable. Furthermore, not considering a crucial variable such as gender could represent a limit to the results obtained so far.

Literature highlights that sectoral composition plays an important role in creating knowledge spillovers, and not all industries are the same in terms of knowledge externalities (Audresch and Feldman 1996). Starting from Combes (2000), which pointed out that sectoral specialization and diversity can have a different impact on manufacturing and services sectors, a growing body of literature highlighted the importance of sectors in exploring the relationship between related Variety and regional growth, especially between manufacturing and services sectors (Blien and Suedekum 2005, Paci and Usai 2008, Quatraro 2010, Bishop and Gripaios 2010, Mameli et al., 2012). Sectoral composition acquires even more importance if gender is included in the analysis. Females and males are not employed in the same sectors, and they do not share the same competencies, skills, and knowledge. These differences can have a different impact on knowledge spillovers and, consequently, labour growth.

Knowledge spillovers can be affected by geographical proximity, but geographical proximity is not necessary or sufficient (Boschma 2005). Furthermore, there may not be reciprocity in the process. Knowledge can spill from spatial unit A to spatial unit B without spilling from B to A

(Balland et al., 2014). Moreover, if knowledge spills from A to B, this process can impact B labour growth, which will impact A labour growth. Literature focused mainly on spillovers in the spatial unit, while spillovers can also have spatial dimensions, i.e., the spillover created in the neighbourhood can influence the spatial unit under consideration and *vice versa*. Appropriate spatial analysis techniques capture the spatial proximity dimension.

In contrast with linear regression models, the spatial regression models exploit the complex dependence structure between observations (LeSage and Pace 2009, p. 33). Linear regression parameters have a straightforward interpretation, as they measure the partial derivative of the dependent variable to the explanatory variable. This interpretation arises from linearity and the assumed independence of observations in the model. In spatial regression models, the estimate parameters contain a lot of information on the relationship between the observations. For example, a change in a single province will affect the province itself (direct effect) and potentially other provinces indirectly (indirect effects).

3. Dataset, sectoral classification, and descriptive features

We aim to investigate Related/Unrelated Variety along two dimensions: sub-group and gender summarized by a two-way table as displayed in Figure 1. RVF_{Sn} and UVF_{Sn} represent the females' related and Unrelated Variety in sub-group *n*, while RVM_{Sn} and UVM_{Sn} are the males' Related/Unrelated Variety in sub-group *n*. By row, we can explore the Related/Unrelated Variety by gender in different sub-groups, and by column, we investigate the Related/Unrelated Variety in the same sub-groups by gender.

Figure 1. Related/Unrelated Variety by Gender and Sub-group

		Sub-groups			
		Sub-group 1	Sub-group 2	….	Sub-group N
Gender	Female	RVF_{S1} UVF_{S1}	RVF_{S2} UVF_{S2}	RVF… UVF…	RVF_{SN} UVF_{SN}
	Male	RVM_{S1} UVM_{S1}	RVM_{S2} UVM_{S2}	RVM… UVM…	RVM_{SN} UVM_{SN}

The impact of knowledge spillover and growth by sub-groups has been widely explored in the literature (Paci Usai 2008 Bishop and Gripaios 2010, Cortovis and Van Oort 2015, Hartog et al., 2012, Mameli et al., 2012). The results highlight that sub-groups can impact knowledge spillover and growth differently and Related Variety effects on growth are confined to specific sub-groups. Nevertheless, the gender impact of knowledge spillover has never been explored in the literature.

Including gender in the analysis, it is not a mere theoretical exercise. Stylized facts (Par. 3.2) highlight that females and males work in different sectors and that these sectors are different in terms of proximity. Furthermore, proximity can impact knowledge networks and, consequently, innovation and labour growth.

3.1. Building the dataset

Our dataset is based on the Statistical classification of economic activities in the European Community, NACE_Rev.2, provided by the Italian National Statistical Institute (ISTAT) at the provincial level for 2012-2017 at a 5-digit class. Unfortunately, these data are not available for females and males. Nevertheless, data by gender are provided at the regional level at the 3-digit class. For obtaining a dataset at a 5-digit level, at the provincial scale, that has a composition of males and females as representative possible; we will proceed as follows. The regional dataset can easily obtain the percentage of females and males at 3-digit class (percF, percM) in each region. The weight of sector *i* at 3-digit class in province *P* belonging to region *R* is given by:

$$w_{Pi} = \frac{E_{Pi}}{E_{Ri}}$$

where E_{Pi} is the employment in 3-digit class in sector *i* in province P and E_{Ri} is the employment in region R (to which the province P belongs) in 3-digit class in sector *i* with $\sum_{P=1}^{N} w_{Pi} = 1$ with N=numbers of provinces in the region. The number of males and females employed in sector *i* at 3-digit class in province P will be equal to:

$$M_{Pi} = w_{Pi} * PercM * E_{Ri}$$

$$F_{Pi} = w_{Pi} * PercF * E_{Ri}$$

To obtain the females and males employees at 5-digit class in province P we calculate the employment sectoral weight at 5-digit class with respect to the 3-digit class:

$$w_{Pj} = \frac{E_{Pj}}{E_{Pi}}$$

where *j* represents the 5-digit class and $\sum_{j=1}^{M} w_{Pj} = 1$ where M is the numbers of 5-digit class falling in the i 3-digit class. The number of males and females employed in sector *j* at 5-digit class in province P will be equal to:

$$M_{Pj} = M_{Pi} * w_{Pj}$$

$$F_{Pj} = F_{Pi} * w_{Pj}$$

3.2. Stylized Facts

Females and males are not employed in the same industries. According to the Nace2_Rev industries definition (Table 1.A), Figure 2 summarizes the share of females and males in each 1-digit level industry in Italy:

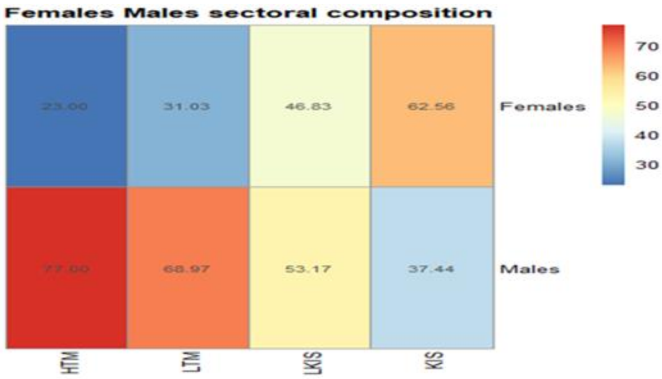
Figure 2. Females and Males share by 1-digit industry in Italy; Average 2012-2017

Source: our elaboration on Istat data

The highest share of males is in the industry (B-E) and construction (F). Nevertheless, services (G-S) display differences in females/males' share. For example, in transportation and storage (H), the females' percentage is 20%, while the health (Q) females' share is 81%. Industries will be grouped following the European Union classification, based on NACE Rev.2. The manufacturing is split into two sub-groups: High and Medium Technology Manufacturing (HTM), and Low Technology Manufacturing (LTM). Services are also split into two sub-groups: Knowledge Intensive Services (KIS) and Low Knowledge Intensive Service (LKIS), as reported in Table 2.A[3]. The share of females and males in Italy by sub-groups is depicted in Figure 3.

[3] Under this classification, some groups belonging to the same divisions are classified as KIS and others as LKIS. The approach followed by Frenken (2007) is based on a pre-given hierarchical classification as provided by NACE Rev.2. To maintain this hierarchical classification unchanged, sector G, H, I, L, S will be considered low knowledge-intensive services, while J, K, M, N, P, Q, R, will be considered knowledge-intensive services.

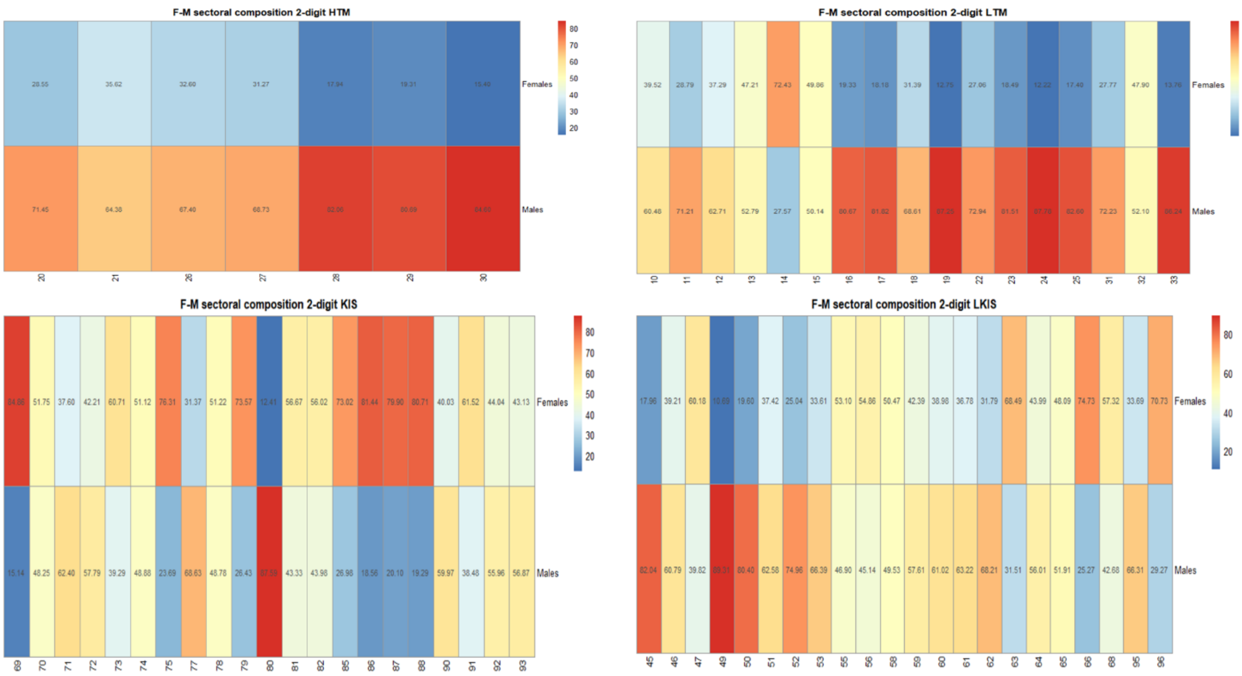
Figure 3. Females/Males' percentage by sub-groups; Italy; Average 2012-2017



Source: our elaboration on Istat data

In the High and the Low Tech-intensive Manufacturing sub-groups, the males' share is more than 69%. By contrast, the females' share is higher than 62% in the Knowledge-Intensive Service. Finally, the Low Knowledge-Intensive Service is equally distributed between females and males. As previously highlighted, exploring the sub-groups composition by gender can be misleading. Among sub-groups, there are some industries at the 2-digit level in which the females' share is very high and some others in which it is low, as depicted in Figure 4.

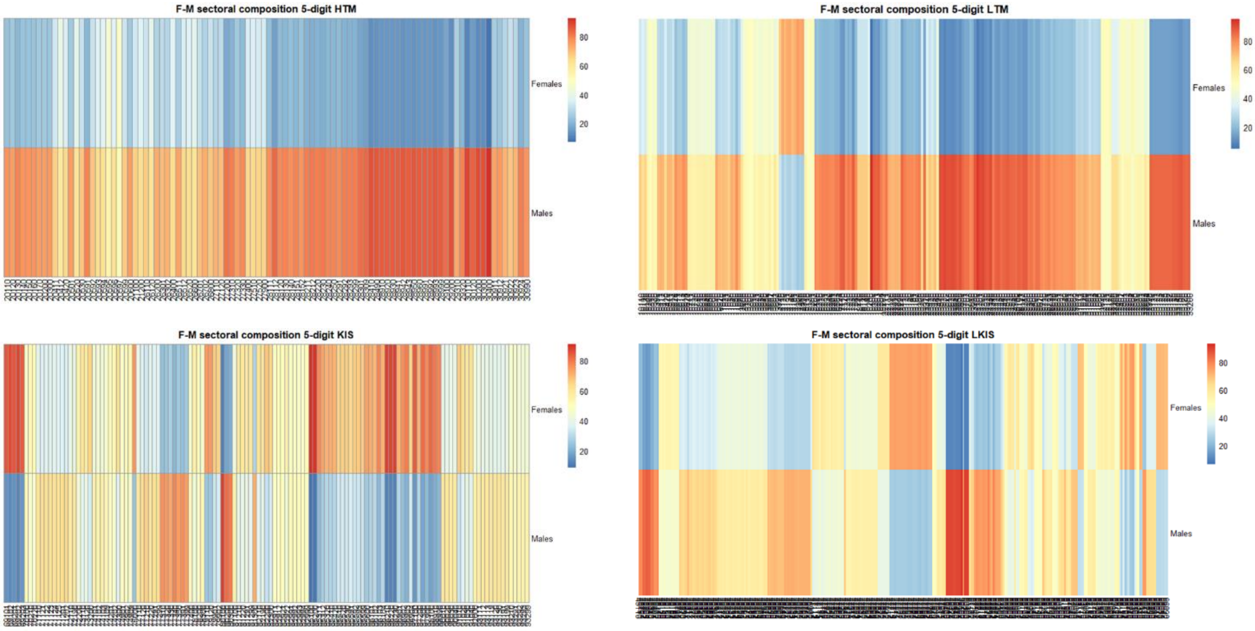
Figure 4. Females/Males' share by sub-groups at the 2-digit level; Average 2012-2017



Source: our elaboration on Istat data

Employees in the HTM sub-group are mainly males. However, at the 2-digit level, a female share of some industries (20-21; 26-27) is between 28-31%, while, in some others (28-30) it is between 15.4-18%. In the LTM sub-group, males' share is higher than females'. Nevertheless, there are some female niches in the textile sector. The distribution between 2-digit of females and males in the KIS sub-group is diversified, but there are some females' clusters, such as Health and Educations (85-88) in which females' share is higher than 80%. Finally, the LKIS sub-group is diversified as the KIS sub-group, but, in contrast with it, there are no females' clusters. The females' males distribution among 5-digit industries is depicted in Figure 5.

Figure 5. Females/Males' share by sub-groups at 5-digit level; Average 2012-2017



Source: our elaboration on Istat data

The situation appears remarkably clustered in HTM and LTM sub-groups where females and males are very concentrated at the 5-digit. However, a different picture emerges, taking into consideration service. KIS sub-group display females' clusters while, in the LKIS sub-group, females and males are more scattered. In conclusion, stylized facts highlight that females and males are employed in different sub-groups, and there are differences at the 2-digit and the 5-digit level between gender. Gender and sub-groups display differences in labour growth, as depicted in Table 1.

Table 1. Average labor growth (2012-2017) by gender and sub-groups

	Females	**Males**		**Females**	**Males**
	KSI			**HTM**	
Mean	0.02	0.039	Mean	0	0.002
Std. Dev.	0.019	0.023	Std. Dev.	0.07	0.068
Min	-0.019	-0.051	Min	-0.229	-0.207

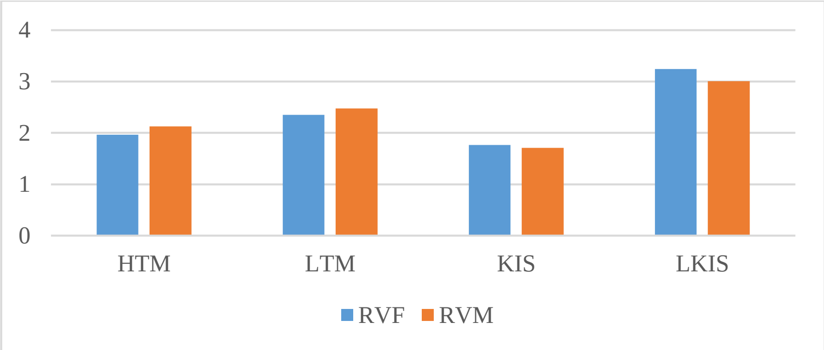
Max	0.117	0.14	Max	0.454	0.575
	LKSI			LTM	
Mean	0.001	0.009	Mean	-0.017	-0.011
Std. Dev.	0.017	0.018	Std. Dev.	0.024	0.021
Min	-0.037	-0.022	Min	-0.147	-0.092
Max	0.13	0.147	Max	0.12	0.113

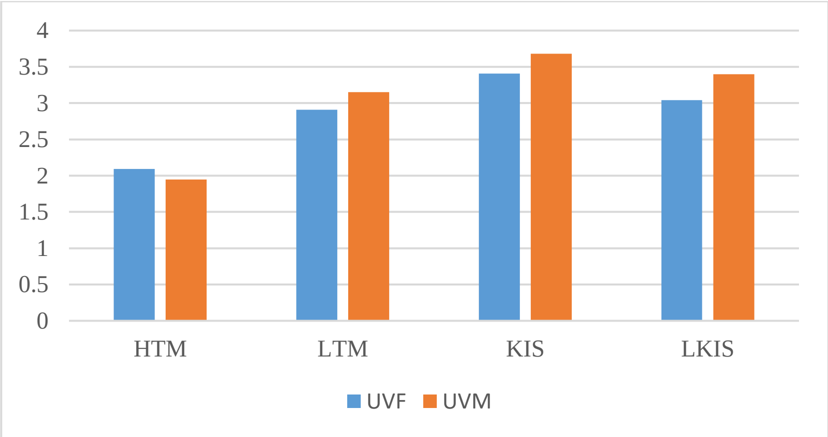
Source: our elaboration on Istat data

3.3. Related and unrelated Variety by sectors and gender

Related and Unrelated Variety based on Frenken et al., (2007) are discussed in Appendix 2. The values of RV and UV for females and males are summarized in Figure 6 (data are provided in Tables 3.1A-3.2A in Appendix 1).

Figure 6. RV-UV by sub-groups; average over Italian provinces;





Source: Our elaboration

By the diversity measures, the higher is RV (UV), the lower is the concentration. By Figure 1, the results can be read by column- comparing the RV(UV) for females and males in the same sub-group-, or by row- comparing RV (UV) for females (males) in different sub-groups-. Our analysis highlights that RV for females is higher than males' RV in service sectors, where females are less clustered while lower in manufacturing. According to the previous results, RV highlights that females are more concentrated in a few manufacturing industries while more scattered in services. Exploring the results by columns, RV's highest value for females is in the LKIS sub-group while the lowest is in the KIS sub-group. The same result holds for males.

In conclusion, RV varies from sub-group to sub-group. The highest value is in the LKIS sub-group for both genders, and the lowest is in the KIS sub-group. This result aligns with the literature and underlines that the results differ by sub-group. Furthermore, within the same sub-group, RV varies by gender. This result is a novelty in literature and highlights the importance of gender as a critical dimension. UV is always lower for females than males in all sub-groups but HTL. Exploring the results by columns, the highest UV value for females is in the KIS sub-group while the lowest is in the HTM sub-group. The same result holds for males. This investigation allows us to answer to:

Q1: Do females' have higher (Un)Related Variety? In which sector(s)?

RV(UV) is different for females and males in the same sub-group. RV is lower for females in the manufacturing sub-group and higher in the services sub-group. The result is in line with the descriptive analysis: females are less concentrated in services. Moreover, females display an Unrelated Variety lower than males apart for the HTM sub-group. To manage the remaining questions, we will use an empirical investigation and it will be presented in section 4.

4. Methodology and empirical results

The first step of the analysis involves a panel data model for 2012-2017, considering the labor growth as a dependent variable and RV, UV, and population density as covariates. This approach is standard in the literature (Frenken et al., 2007, Mameli et al., 2012). Following the research design previously described, our analysis moves along two dimensions: sector and gender; consequently, regressions will be replicated for each sub-group and gender. Furthermore, regressions will be replicated by sub-groups without considering gender for comparison reasons. The equations being estimated are:

$$Labour\ growth = \alpha_i + \beta_1 RV_{it} + \beta_2 UV_{it} + \log(popden) + u_{it} \quad (1.1)$$

$$Female\ labour\ growth\ = \alpha_i + \beta_1 RVF_{it} + \beta_2 UVF_{it} + \log(popden) + u_{it} \quad (1.2)$$

$$Male\ labour\ growth\ = \alpha_i + \beta_1 RVM_{it} + \beta_2 UVM_{it} + \log(popden) + u_{it} \quad (1.3)$$

with i=1..107; T=5.

We estimated the panels both with fixed and random effects. The Hausman test highlights that a fixed effect model must be used. In standard, not spatial econometric models, each geographical unit is independent of neighboring units, and disturbances are cross-sectionally independent by assumption. In the presence of cross-sectional dependence, which could be induced by a common factor and/or spatial dependence, the standard estimators for panel data (FE and RE) are inconsistent.

Pesaran CD test (Pesaran 2004) can test for cross-section dependence, especially when T is small, and N is large. The estimation results in Appendix 1 (Table 4.A) highlight cross dependency, i.e. all units in the same cross-section are correlated. Following the literature (Lacombe & LeSage 2018), a spatial panel technique is advised if panel estimation highlights cross dependency.

We start by specifying a general spatial model. It can be described through the following equation:

$$y = \rho Wy + X\beta + \theta WX + u$$

$$u = \lambda Wu + \epsilon$$

where y is nx1 vector, W is a nxn weight matrix that contains elements consisting of 1/m_i or 0 where m_i is the number of contiguous units to unit *i*[4]. The scalar parameter ρ measures the strength of spatial dependence on the endogenous variable, with $-1 \leq \rho \leq 1$, with zero indicating spatial independence. x is a nxk matrix of covariates, and β, and θ are kx1 vectors measuring spatial dependence on the explanatory variables. Finally, λ is a kx1 vector that accounts for possible spatial dependence on the unexplainable error component. If $\lambda = \theta = 0$ the model is a spatial autoregressive model (SAR). If $\rho = \theta = 0$ the model is a Spatial Error Model (SEM). If $\theta = 0$ the model is a Spatial Auto-Regressive with Auto-Regressive error model (SARAR) or SAC. If $\lambda = 0$ the model is a Spatial Durbin Model (SDM) and, finally, if $\rho = 0$, the model is a Spatial Durbin Error Model (SDEM).

Literature (Piras and Prucha 2014) highlighted that the common use of pre-test strategies for model selection probably ought to and replaced by estimating the most general model appropriate for the relationship being modelled. Furtheremore, Jaya and Ruchjana (2016) proved that the better estimate of the spillover effect is the SDM model. This result is also in line with LeSage (2014) "the literature places too much emphasis on the SAC specification because of its theoretical econometric interest. Practitioners can safely ignore this specification as it has numerous drawbacks in applied use. It is argued that only two specifications, the SDM and SDEM, should be considered by regional science practitioners" (LeSage 2014 pg. 30).

Previous studies (Cortinovos and Van Oort 2015 and Caragliu et al., 2016) have used spatial autoregressive with autoregressive error (SARAR-SAC) model. Nevertheless, the best model for our

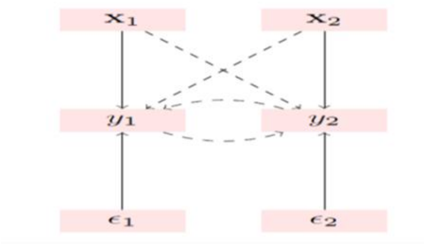
[4] W is a contiguity matrix. The islands are connected using the shipping maps provided by Istat. Consequently, Rome is connected with Olbia and Cagliari; Napoli is connected with Cagliari, Genova is connected with Olbia and Messina is connected with Reggio Calabria. The results obtained using distant matrix remain unchanged. Le Sage e Pace (The Biggest Myth in Spatial Econometrics, Econometrics 2014, 2, 217-249) showed that direct and indirect effects of SAR and SDM models are very stable/similar across different choices of m (the number of nearest neighbours) and r (the distance decay parameter r).

data, following the previous discussion, is an SDM model with fixed effects, described by the following equation:

$$y = \rho W y + X\beta + \theta W X + \varepsilon$$

In spatial models, the least-squares interpretation is not valid because spatial dependence expands the information set from neighboring units. SDM model considers such spatiality through the introduction of Wy and WX. The dependent variable y represents the labour growth at the provincial level, while the explanatory variables X are RV, UV, and the population density for each province. In the SDM model, a change in labour growth also depends on the labour growth from neighboring provinces captured by the spatial lag vector Wy and the characteristics of neighbouring provinces represented by WX. Interpreting the results is not straightforward, and, as noted in LeSage and Pace (2009), the proper marginal effects that need to be interpreted are not the β parameters. Estimating an SDM model gives three different effects: direct, indirect, and total effects. (a detailed explanation is provided in Appendix 3). The direct effects measure how a change in an explanatory variable in province *i* affects the dependent variable in province *i*, plus any feedback effect. The indirect effects measure how changes in the explanatory variable associated with province *i* cumulatively impact the dependent variable in all other *n-1* provinces. The total effects are the sum of the direct and indirect effects. Direct and indirect effects can be summarized through Figure 7.

Figure 7. Direct/ indirect effects in SDM model



Source: Golgher and Voss (2016)

Following the SDM model, the direct effects are represented by the solid line, the effect that a change in covariates in province 1 has on the dependent variable in province1, while the indirect effects in the SDM model are represented by the dotted line, where X_1 represents the covariates in province 1 and Y_2 represents the dependent variable in province 2. The indirect effects obtained by SDM capture the impact that a change in covariate in province 1 has in province 2 and the feedback effect, i.e, the effect of the change of dependent variable in province 2 on the dependent variable in province 1. While direct, indirect, and total effects can be calculated for each observation unit, LeSage and Pace (2009) have recommended that scalar summaries of the effect estimates be used. Therefore, we present the average direct, indirect, and total effect for each explanatory variable in our estimation.

The estimated model is summarized in equation 2.1-2.3

$$lbg = \alpha_i + \rho Wlgb + \beta_1 RV_{it} + \beta_2 UV_{it} + \theta_1 RV_{it}W + \theta_2 UV_{it}W + \log(popden) + u_{it} \quad (2.1)$$

$$lbgF = \alpha_i + \rho WlgbF + \beta_1 RVF_{it} + \beta_2 UVF_{it} + \theta_1 RVF_{it}W + \theta_2 UVF_{it}W + \log(popden) + u_{it} \quad (2.2)$$

$$lbgM = \alpha_i + \rho WlgbM + \beta_1 RVM_{it} + \beta_2 UVM_{it} + \theta_1 RVM_{it}W + \theta_2 UVM_{it}W + \log(popden) + u_{it} \quad (2.3)$$

The results for each sub-group are presented in the Appendix 1 (Table 5.1A-5.4A).

In paragraph 4.1 we will explore total effects, while in paragraph 4.2 we will investigate the direct and indirect effects highlighting the spatial spillovers' role.

4.1. Total effect

To investigate the results, we will start by analyzing the total effects summarized in Table 2.

Table 2. Total Effect; SDM model

SDM model Fixed Effects Dependent variable Labour growth/ Females labour growth/ Males labour growth												
TOTAL EFFECTS												
	HTM			LTM			KIS			LKIS		
	Total	Females	Males	Total	Females	Males	Total	Females	Males	Total	Females	Males
UV	0.171 (0.124)	-0.311* (0.027)	-0.683*** (0.000)	-0.964 (0.000)	-0.480*** (0.000)	-0.627*** (0.001)	0.355** (0.002)	0.321** (0.001)	0.237* (0.012)	-0.146 (0.585)	-0.107 (0.664)	-0.215 (0.378)
RV	-0.089 (0.41)	-0.582*** (0.000)	-0.991*** (0.000)	0.198 (0.151)	0.348*** (0.000)	0.094 (0.515)	-0.376*** (0.000)	-0.196* (0.039)	-0.502*** (0.000)	-0.664*** (0.000)	-0.572*** (0.000)	-0.635*** (0.000)
lpop	-0.162 (0.842)	0.699 (0.551)	-0.054 (0.959)	0.453 (0.395)	0.911 (0.071)	0.582 (0.324)	0.206 (0.66)	0.0288 (0.952)	0.861 (0.121)	-0.664 (0.221)	-0.878 (0.111)	-0.165 (0.789)
P values in parenthesis legend: * p<.05; ** p<.01; *** p<.001												

Source: our elaboration

The high-tech manufacturing (HTM) highlights a non-significant relationship between UV and labour growth if we consider the Total dataset (no gender differences). This result is also obtained in previous studies (Frenken et al., 2007, Quatraro 2010, Hartog et al., 2012, Cortinovis and van Oort 2015). Moreover, there is a non-significant relationship between RV and labor growth. This finding is in line with the ones obtained by Caragliu et al., (2016) at the sectoral level using a spatial estimation technique. Different results are obtained, taking into consideration gender. Both RU and UV display a significant negative sign for females and males with a different magnitude. Since the total effects are the sum of the direct and indirect effects, the coefficients' magnitude will be discussed in the paragraph dedicated to analyzing the spatial spillovers. For now, our attention will be focused on the sign of the relationship.

Unrelated Variety captures the diversity between industries, and, according to the portfolio theory, it can be considered a strategy to protect the region from asymmetric shock and, consequently, protect the labor market from unemployment. Our results highlight a negative relationship between Unrelated Variety and labor growth in the HTL sub-group. An increase in diversity will have a negative impact on labor growth. This result is intriguing because it holds when females and males are considered disjointly. In the HTL sub-group, the share of females at the 2-digit level varies from 15.4% to 31.7% among industries. Moreover, HTL sub-group, as previously highlighted, is composed of two different clusters. The first one (Division 28-30; Manufacturing of machinery and equipment, motor vehicles, and other transport equipment) is a male cluster in which female share is low, and a second one, (Division 20, 21, 26, 30) in which the females' share is slightly higher. This fragmentation can hinder the spillover effect between industries. Consequently, an increase in UV cannot protect the labor market from external shock. Furthermore, females and males do not share the same skills and capabilities and are not employed in the same industries. These differences impact skill relatedness connectivity. Finding new jobs in related industries can be hindered due to different skills and capabilities based on gender, making the labor market stickier and hampering the recombination between unrelated knowledge. Unrelated industries share proximity only apparently, but they can be disconnected in terms of social and cognitive proximity due to gender. As far as RV is concerned, it has a negative impact on labor growth both for females and males: an increase of diversity within an industry prevents the Jacobs externalities and has a negative impact on labor growth. The descriptive analysis highlighted that HMT sub-group has a remarkable variance in females and males within the 5-digit sectors. The highest share of males (97.5%) is in 30400- manufacturing of military fighting vehicles-, while the lowest percentage (52%) is in 20597- manufacturing of electrochemical products. Although they are closely based on the Nace2_Rev 2-digit and 5-digit classification, the industries highlight a high social and cognitive distance in terms of gender.

In the Low intensive Manufacturing sub-group (LTM), the results in terms of total effects highlight a negative relationship between UV and labor growth and a positive e significant relationship between RV and labor growth only for females. In the LTM, females are more concentrated in some industries at the 2-digit level, as highlighted with the descriptive analysis. An increase of UV (between diversity) means that industries are less connected at the 2-digit level. This lower connection-level can increase the distance in cognitive terms. Moreover, females' industries are less concentrated in the 5-digit level. Therefore, an increase in terms of Related Variety (within diversity) positively impacts females' labor growth.

In KIS sub-group, UV for females and males is positive and significant. This sub-group is more inhomogeneous than manufacturing because it contains several industries at the 1-digit level (M to R). The descriptive analysis highlighted two female clustered industries at the 1-digit level: education (P) and health (Q). Females and males are spread out between 2-digit industries in the remaining ones. A situation in which females and males are less polarized between industries favors cognitive proximity and knowledge spillovers. Consequently, an increase in Unrelated Variety (between diversity) enhances labor growth and can protect females' and males' employment from external shocks. Nevertheless, the results highlight a negative relationship between RV and labor growth. Even though females and males are not very concentrated at the 2-digit level, they are clustered at the 5-digit level, as the descriptive analysis highlighted. This situation hinders the cognitive proximity and, consequently, Jacobs' externalities.

Sub-group LKIS displays differences in terms of females/males between industries. For instance, industry G — wholesale and retail trade; repair of motor vehicles and motorcycles-, is composed of three industries at the 2-digit level: Wholesale and retail trade and repair of motor vehicles and motorcycles (45), Wholesale trade, except motor vehicles and motorcycles (46) Retail trade, except motor vehicles and motorcycles (47). These industries at the 2-digit level are very different in terms of the shares of females and males that make them up. In wholesale and retail trade and repair of motor vehicles and motorcycles (45) the females' share is less than 18%, while in Retail trade, except motor vehicles and motorcycles (47), females' share is greater than 60%. An increase in UV does not impact labor growth due to the industry's composition. Finally, RV has a negative impact on labor growth. This result is the consequence of the 5-digit industries composition. Females and males are spread out between industries but are clustered within the 5-digit industries. Therefore, an increase in Related Variety does not enhance labor growth.

The results previously discussed can be used to answer to our second question:

Q2: Which is the RV/UV impact for females and males on labor growth?

The RV and UV impact on females and males' labor growth varies between sub-groups and females and males in the same sub-group. A more in-depth analysis in terms of magnitude will be provided using the direct and indirect effects. Nevertheless, the results highlight that diversity (within and between) will impact labor growth. This difference is due to the gender distribution among the 2-

digits and the 5-digits industries. If females (males) are very clustered at 2-digit (or 5-digit) level, an increase in between/within diversity will negatively impact labor growth. Clustering hinders cognitive proximity, and consequently, knowledge does not spill from one industry to the other.

Nevertheless, clustering is based on gender, and this clustering process can result from culture, social values, different skills, and capabilities. How and why these clusters formed is behind the scope of this paper. First, however, they need further investigation to understand better if and how they can impact knowledge creation and diffusion.

4.2. Spatial spillover

The results regarding the direct and indirect effects for model 2.1-2.3 are reported in Appendix 1 and summarized in Table 3.

Table 3. SDM Direct-Indirect effects

SDM model Fixed Effects dependent variable Labour growth/ Femal labour growth/ Male labour growth DIRECT/INDIRECT EFFECTS												
	HTM			LTM			KIS			LKIS		
	Total	Females	Males	Total	Females	Males	Total	Females	Males	Total	Females	Males
Direct												
UV	-0.16*** (0.000)	-0.83*** (0.000)	-0.80*** (0.000)	-0.27*** (0.000)	-0.17*** (0.000)	-0.25*** (0.000)	-0.09 (0.08)	-0.06 (0.22)	-0.08 (0.07)	0.001 (0.99)	-0.13 (0.16)	0.049318 (0.53)
RV	-0.07 (0.08)	-0.49*** (0.000)	-0.69*** (0.000)	0.044 (0.31)	0.10** (0.004)	-0.04 (0.35)	-0.30*** (0.000)	-0.31*** (0.000)	-0.28*** (0.000)	-0.29 (0.000)	-0.30 (0.000)	-0.29 (0.000)
lpop	-0.60 (0.27)	-0.17 (0.88)	1.55 (0.06)	0.32 (0.27)	0.16 (0.61)	0.38 (0.21)	-0.001 (0.10)	0.01 (0.97)	-0.20 (0.56)	0.06 (0.79)	0.07 (0.76)	0.06 (0.83)
Indirect												
UV	0.33*** (0.000)	0.52*** (0.000)	0.12 (0.25)	-0.70*** (0.000)	-0.31** (0.002)	-0.38* (0.017)	0.45*** (0.000)	0.38*** (0.000)	0.32*** (0.000)	-0.15 (0.53)	0.02 (0.92)	-0.26 (0.23)
RV	-0.02 (0.811)	-0.10 (0.275)	-0.30** (0.006)	0.15 (0.177)	0.24** (0.003)	0.14 (0.243)	-0.08 (0.287)	0.12 (0.166)	-0.23*** (0.000)	-0.38*** (0.001)	-0.28* (0.023)	-0.35** (0.009)
lpop	0.43 (0.611)	0.87 (0.548)	-1.60 (0.172)	0.13 (0.799)	0.75 (0.131)	0.20 (0.722)	0.21 (0.659)	0.02 (0.969)	1.06 (0.057)	-0.73 (0.145)	-0.95 (0.059)	-0.22 (0.699)
P values in parenthesis legend: * p<.05; ** p<.01; *** p<.001												

Source: our elaboration

In the HTL sub-group, results describe different pictures to those obtained, exploring the total effects. The direct effects of UV are negative in all three cases under consideration. An increase in diversity in a province *i* will have a negative impact on labor growth in the same province. This result holds for females and males. Nevertheless, indirect effects highlight a positive relationship between labor growth and UV in all the datasets and females. An increase in UV in province 1 will positively impact the labor growth of neighboring provinces and on the labor growth in province 1 itself through the feedback effects. Geographical proximity matters and creates spatial spillovers that are different by gender. The impact of UV on labor growth for females is in terms of magnitude lower than males due to the indirect effect that mitigates the impact. RV has a negative and significant sign for females and males in direct effects. For males, the situation is strengthened by RV's negative and significant impact on labor growth in terms of indirect effects. In the LTM sub-group, the UV is negative in direct and indirect effects both for females and males. The magnitude of UV in terms of direct effect is lower than indirect effects. The negative impact of an increase of UV (between diversity) in province 1 has an impact not only via direct effect but is reinforced through indirect effects. RV is significant and positive only for females, and the magnitude is higher for indirect than the direct effect. The result highlights that increasing RV (within diversity) will impact each province and its neighborhood and that the feedback effects play an important role. The UV is positive and significant only for indirect effects in the KIS sub-group, while the direct effects are not significant. RV has a negative sign in terms of direct effects while it has a positive sign, but not a significant sign of indirect effects for females. Moreover, the indirect effects of RV are negative and significant only for males. This result highlights that an increase of within diversity has a negative impact on labor growth for females and males, but, in the case of males, this effect is reinforced by the indirect effects. Finally, in the LKIS sub-group, we find a negative relationship between labor growth and RV only if we consider the indirect effect.

The results previously discussed can be used to answer our third question:

Q3: Which is the role played by the spatial spillovers?

Spatial spillover plays an important role in mitigating or hampering the effects of Related and Unrelated Variety on labor growth. For females, the spatial spillovers, if significant, mitigate the negative impact of RV and UV. These results lead us to conclude that geographical proximity matters and create spatial spillovers that vary in gender.

5. Conclusion

EEG considers knowledge spillovers as a source of regional economic growth. Nevertheless, gender is not included in the analysis. Social and economic literature highlighted that females and males have different approaches to innovation, inter-industry collaboration, sharing knowledge and social relation, job preferences. These differences impact knowledge transmission and are amplified when females are males are concentrated in different industries. Our analysis pointed out that females and males are employed in different industries, affecting the Related, and Unrelated Variety measures and our results show that RV and UV measures differ between sub-groups and by gender in the same sub-group. Consequently, labour growth can be influenced by gender distribution within and between industries. Finally, Related and Unrelated Variety produce spatial spillovers.

The results open a new scenario regarding policies devoted to increasing females' participation in the labour market. Females are more concentrated in some industries than others. Therefore, increasing the females' employment in an industry where the females' share is already high increases gender segregation and increases the females' concentration within or between industries. Nevertheless, this higher concentration may not affect knowledge spillover and labour growth. Consequently, policies should be addressed in reducing gender segregation in some industries. However, as Borrowman and Kasen (2020) pointed out, tackling industry occupation is not easy. Females' industry occupation depends on several interrelated variables such as education, culture, welfare. Even though females have a higher schooling rate, many follow humanistic studies, but the job market requires more and more STEM competencies and females are less prone to undertake STEM studies. This phenomenon's motivation is complex and involves role models, cultural dimensions, and female mental barriers. The cultural dimension plays an important role. Females in Italy still have a higher opportunity cost in working than males due to childcare activities and home duties. Finally, the welfare state is essential. Increasing daycare and full-time schools' programs would help females decrease the opportunity cost of working.

Policies should be dedicated to increasing females' participation in the labour market and removing the social and cultural obstacles that prevent females from doing jobs in which they are segregated. In this context, policy should favour programs for young females in STEM disciplines and programs dedicated to acquiring new competencies for women who already work. Moreover, enhancing some sectors to the detriment of others can increase the gender gap. In this perspective, especially for the Recovery Plan in Italy, a gender evaluation is essential.

References

Aarstad, J., Kvitastein, O. A., and Jacobsen, S. E. 2016. Related and Unrelated Variety as Regional Drives of Enterprise Productivity and Innovation. A Multilevel Study. *Research Policy, 44*(4), pp. 844-856. doi:https://doi.org/10.1016/j.respol.2016.01.013

Abbot, M. G., and Beach, C. M. 1994. Wage Changes and Job Changes of Canadian Women: Evidence from the 1986-1987 Labor Market Activity Survey. *Journal of Human Resources*, *29*(2), pp. 429-460.

Aigner, D. J., and Cain, G. G. 1977. Statistical Theory of Discrimination in Labor Market. *ILR Review, 30*(2), pp.175-187.

Alesina, A., Giuliano, P., and Nunn, N. 2011. Fertility and the Plug. *NBER*(16718).

Altonji, J. G., and Blank, R. 1999. Race and Gender in the Labor Market. In *Handbook of Labor Economics* pp. 3143-3259.

Audresch, D. B., and Feldman, M. P. 1996. R&D splillovers and the Geography of innovation and Production. *The American Economic Review, 86*(3), pp.630-640.

Balland, P.A., Boschma, R., and Frenken, K. 2015. Proximity and Innovation: From Static to Dynamics. *Regional Studies, 49*(6), pp.907-920. doi:10.1080/00343404.2014.883598

Becker, G. 1985. Human Capital, Effort, and the Sexual Division of the Labor. *Journal of Labor Economics, 3*(1), S33-S58.

Bishop, P., and Gripaios, P. 2010. Spatial Externalities, Relatedness and Sector Employment Growth in Great Britain. *Regional Studies, 44*(4),pp. 443-454. doi:10/1080/033400802508810

Blien, U., and Suedekum, J. 2005. Local Economic Structure and Industry Development in Germany, 1993-2001. *Economic Bullettin, 17*(5),pp. 1-8.

Borrowman, M., and Klasen, S. 2020. Drivers of Gendered Sectoral and Occupational Segregation in Developing Countries. *Feminist Economics, 26*(2), pp. 62-94.

Boschma , R., and Iammarino, S. 2009. Related Variety, Trade Linkages, and Regional Growth in Italy. *Economic Geography, 85*(3), pp. 289-311. doi:10.1111/j.1994.8287.2009.01034.x

Boschma, R. 2015. Towards an Evolutionary Perspective on Regional. *Regional Studies, 49*(5), pp.733-751.

Boschma, R. A. 2004. Competitiveness of Regions from an Evolutionary Prospective. *Regional Studies, 38*(9), pp.1001-1014.

Boschma, R. A. 2005. Proximity and Innovation. *Regional Studies, 39*(1), pp.61-74.

Boschma, R. A. 2007. Path Creation, Path Dependence and Regional Development. In J. Sammie, and J. Carpenter, *Path Dependence and the Evolution of City Regional Development* pp. 40-55. Oxford Brookes University, Oxford.

Boschma, R. A. 2009. *Evolutionary Economic Geography and its Implication for Regional Innovation Policy.* Paris: OECD.

Boschma, R. A., and Frenken, K. 2009a. Some Notes on Institution in Evolutionary Economic Geography. *Economic Geography, 85*(2), pp.151-158.

Boschma, R. A., and Frenken, K. 2009b. Technological Relatedness and Regional Branching. *Paper in Evolutionary economic Geography*.

Boschma, R. A., and Martin, R. 2007. Constructing an Evolutionary Economic Geography. *Journal of Economic Geography, 7*(5),pp.537-548.

Boschma, R., and Frenken, K. 2011. The Emerging Empirics of Evolutionary Economic Geography. *Journal of economic Geography, 11*, pp.295-307.

Boschma, R., and Gainnelle, C. 2014. *Regional Brances and Smart Specialization Policy.* JRC Technical Report.

Brashears, M. E. 2008. Gender and Homophily: Differences in male and Female Association in Blue Space. *Social Science Research*, pp.400-415.

Caragliu, A., de Dominicis, L., and de Groot, H. L. 2016. Both Marshall and Jacobs were right! *Economic Geography, 92*(1), pp.87-111. doi:10.1080/00130095.2015.1094371

Collishon, M., and Eberl, A. 2021. Social Capital as a Partial Explanation for Gender wage Gaps. *The British Journal of Sociology, 0*, pp.1-17.

Combes, P. 2000. Economic Structure and Local Growth: France, 1984-1993. *Journal of Urban Economics, 47*(3), pp.329-355. doi:10.1006/juec.1999.2143

Content, J., and Frenken, K. 2016. Related variety and economic development: a literature review. *European Planning Studies, 24*(12), pp.2097-2112. doi:10.1080/09654313.2016.1246517

Cortinovis, N., and van Oort, F. 2015. Variety, Economic growth and knoledge intensity of European regions: a spatial panel analysis. *The Annals of Regional Science, 55*, pp.7-32.

Eagly, A. H. 1987. *Sex Differences in Social Behaviour. A Social Role Interpretation.* Hillsade NJ: Lawrence Erlbaum Associates Publisher.

Eagly, A. H., and Wood, W. 2012. Social Role Theory. In P. A. Van Lange, A. W. Kruglansky, and E. T. Higgins, *Handbook of Theory and Social Psycology* (pp. 458-476). Sage Publication LTd.

Eagly, A. H., Wood, W., and Diekman, A. B. 2000. Social Role Theory of Sex Differences and Similarities: a Current Appraisal. In T. Eckes, and H. M. Trautner, *The Developmental Social Psycology of Gender* (pp. 123-174). Mahwan NJ: Lawrence Erlbaum Associates Publisher.

Eberl, M. 2018. *Organizational Routines Meet Experimental Psycology. The Role of Implicit Learning in the Modification of Organizational Routines.* Spinger.

Frenken, K., and Boschma, R. A. 2007. A Theoretical Framework for Evolutionary Economic Geography: Industrial Dynamics and Urban Growth as a Branching Process. *Journal of Economic Geography, 7*(5), pp.635-649.

Frenken, K., Van Oort, F., and Verburg, T. 2007. Related Variety, Unrelated Variety and Regional Economic Growth. *Regional Studies, 41*(5), pp.685-697.

Golgher, A. B., and Voss, P. R. 201). How to interpret the coefficient of Spatial Models: spillovers, direct and indirect effects. *Spatial Demography, 43*(3), pp.175-203. doi:10.1007/s40980-015-0016-y

Hakim, C. 2000. *Work-Lifestyle Choices in the 21st Century.* Oxford: Oxford University Press.

Hall, D., Gains, F., Lupton, R., Sanders, A., and et al.,. 2019. *On Gender: Analysis and Ideas on taking Gender Lens to Policy.* Mancester: Mancester Universtity.

Hartoog, M., Boschma, R., and Sotarauta, M. 2012. The Impact of Related Variety on Regional Employment Growth in Finland 1993-2006: Hightech versus Medium/Low Tech. *Industry Innovation, 16*(6), pp.459-476. doi:10.1080/13662716.2012.718874

Hirscher, P. 2010. Gender and Regional Studies. *Regional Studies Insights, 1*,pp. 1-3.

Iammarino , S. 2011. Regional Innovation Diversity. In P. Cooke, A. Bjorn, R. Boschma, R. Martin, D. Schwartz, and F. Todtling, *Handbook of Regional Innovation and Growth* (pp. 143-151). Cheltenham UK: Edward Elgar.

Jacobs, J. 1969. *The Economy of Cities* . New York: Random House.

Jaya, G. N., and Ruchjana, B. N. 2016. The Comparison of Spatial Econometric Models to Estimate Spillover Effect by Means of Monte Carlo Simulation. *ARPN Journal of Engeneering and Applied Science, 24*, pp.14178-14175.

Lacomb, D., and LeSage, P. 2018. Use and interpretation of spatial autoregressive probit models. *The annals of Regional Science, 60*, pp.1-24.

LeSage, J. P. 2014. What Regional Scientists Need to Know about Spatial. *The Review of Regional Studies, 44*, pp.13-32. doi:http://dx.doi.org/10.2139/ssrn.2420725

LeSage, J., and Pace, R. K. 2009. *Introduction to Spatial Econometrics.* NW: Taylor and Francis.

Mameli, F., Iammarino, S., and Boschma , R. 2012. Regional Variety and Employment Growth in Italaian Labour Market Areas: Services versus Manufacturing Industries. *Papers in Evolutionary Economic Geography (PEEG)*(1203).

Martin, R., and Sunley, P. J. 2001. Rethinking the 'Economic' in Economic Geography: Broadering Our Vision or Loosing Our Focus. *Antipode, 33*(2), pp.148-161.

Nelson, R., and Winter, R. 1982. *An Evolutionary Theory of Economic Change.* Cambridge US: Belknap Press of Harvard University.

Ngai, R., and Petrolongo, B. 2017. Gender gaps and the raise of the service economy. *American Economic Journal: Macroeconomics, 9*(4), pp.1-44.

Noback, I., Broersma, L., and Van DijK, J. 2013. Gender-Specific Spatial Interractions on Dutch Regional Labor Markets and the Gender Employment Gap. *Regional Studies, 47*(8), pp.1299-1312.

Noteboom, B. 2000. Learning by Interrection: Absorptive Capacity, Cognitive Distanca and Governance. *Journal of Managment and Governance, 4*, pp.69-92.

Olivetti, C., and Petrongolo, B. 2016. The Evolution of Gender Gaps in Industrialized Countries. *Annual Review of Economics, 8*, pp.405-434.

Paci, R., and Usai, S. 2008. Agglomaration Economies, Spatial Dependence, and Local Industry Growth. *Revue d'Economie Industrielle, 123*(3), pp.87-109. doi:10.4000/rei.3917

Pavlyuk, D. 2011. Spatial Analysis of Regional Employment Rates in Latvia. *Journal of Riga Technical University Sustainable Spatial Development*(2), pp.56-62.

Pesaran, M. H. 2004. General Diagnostic Test for Cross Section Dependence in Panels. *IZA DP*(1240).

Petrongolo, B., and Ronchi, M. 2020. Gender Gap and the Structure of Local Labour Market. *Labour Economics, 64*.

Piras, G., and Prucha, I. R. 2014. On the Finite Sample Properties of Pre-Test Estimators of the Spatial Models. *Regional Science and Urban Economics, 46*, pp.103-115.

Quatraro, F. 2010. Knowledge Coherence, Variety and Economic Growth: Manufacturing Evidence from Italian regions. *Research Policy, 39*(10), pp.1289-1302. doi:10.1016/j.respol.2010.09.005

Sammie, J. 2005. Innovation and Space: a critical review of the literature. *Regional Studies, 36*(9), pp.789-804.

Shannon, C. E. 1948. A Mathematical Theory of Cummunication. *The Bell System Technical Journal*, *27*(3), pp.379-423.

ter Wal , A. L., and Boschma, R. 2007. Co-evolution of Firms, Industries and Networks in Space. *Papers in Evolutionary Economic Geograpry*(07).

Theil, H. (1972). *Statistical Decomposition Analysis.* Amsterdam: North-Holland Publishing Company.

Van Emmeik, I. J. 2006. Gender Differences in the Creation of Different Type of social Capital: a Multilevel Study. *Social Network, 28*, pp.24-37.

Appendix 1

Table 1.A NACE2_Rev definition	
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific, and technical activities
N	Administrative and support service activities
P	Education
Q	Human health and social work activities
R	Arts, entertainment, and recreation
S	Other service activities

Table 2 A: Aggregation of manufacturing and services -European Union classification, NACE Rev.2-

Manufacturing			Services					
Group 2	Division	EU classification	Group 2	Division	EU classification	Group 2	Division	EU classification
10	C	LMAN	45	G	LKIS	69	M	KSI
11	C	LMAN	46	G	LKIS	70	M	KSI
12	C	LMAN	47	G	LKIS	71	M	KSI
13	C	LMAN				72	M	KSI

14	C	LMAN	49	H	LKIS			
15	C	LMAN	50	H	KSI	77	N	LKIS
16	C	LMAN	51	H	KSI	78	N	KSI
17	C	LMAN	52	H	LKIS	79	N	LKIS
18	C	LMAN	53	H	LKIS	80	N	KSI
19	C	LMAN				81	N	LKIS
20	C	HT	55	I	LKIS	82	N	LKIS
21	C	HT	56	I	LKIS			
22	C	LMAN				85	P	KSI
23	C	LMAN	58	J	KSI			
24	C	LMAN	59	J	KSI	86	Q	KSI
25	C	LMAN	60	J	KSI	87	Q	KSI
26	C	HT	61	J	KSI	88	Q	KSI
27	C	HT	62	J	KSI			
28	C	HT	63	J	KSI	90	R	KSI
29	C	HT				91	R	KSI
30	C	HT	64	K	KSI	92	R	KSI
31	C	LMAN	65	K	KSI	93	R	KSI
32	C	LMAN	66	K	KSI			
33	C	LMAN				94	S	LKIS
			68	L	LKIS	95	S	LKIS
						96	S	LKIS
			73	M	KSI			
			74	M	KSI			
			75	M	KSI			

Table 3.1A Related Variety by sub-groups and gender

	RVF average	RVM average		RVF average	RVM average
	KIS			**HTM**	
Mean	1.764	1.712	Mean	1.966	2.129
Std. Dev.	0.135	0.146	Std. Dev.	0.696	0.74
Min	1.362	1.362	Min	0.238	0.495
Max	2.001	2.035	Max	3.339	3.62
	LKIS			**LTM**	
Mean	3.241	3.005	Mean	2.352	2.475
Std. Dev.	0.247	0.205	Std. Dev.	0.357	0.343
Min	2.552	2.385	Min	0.764	1.099
Max	3.806	3.436	Max	3.006	3.155

Table 3.2A Unrelated Variety by sub-groups and gender

	UVF average	UVM average		UVF average	UVM average
	KIS			**HTM**	
Mean	3.407	3.68	Mean	2.093	1.947
Std. Dev.	0.169	0.11	Std. Dev.	0.295	0.327
Min	2.782	3.168	Min	0.823	0.796
Max	3.788	3.903	Max	2.586	2.609

	LKIS			LTM	
Mean	3.042	3.4	Mean	2.908	3.15
Std. Dev.	0.199	0.139	Std. Dev.	0.437	0.285
Min	2.604	3.031	Min	1.505	2.154
Max	3.681	3.89	Max	3.62	3.65

Table 4.A panel data estimation results

Panel FE estimation results
dep var labour growth

	KIS			**LKIS**			**HTM**			**LTM**		
	all	Females	Males	all	Females	Males	all	Females	Males	all	Females	Males
UV	-0.0328238	0.0206127	-0.0392448	-0.12723	-0.1874812	-0.0317902	-0.1471929**	-0.18748	-0.03179	-0.3726383***	-0.2459213***	-0.2704405**
	0.562	0.695	0.444	0.212	0.08	0.732	0.004	0.08	0.732	0.000	0.000	0.001
RV	-0.3476548***	-0.3227481***	-0.3263799***	-0.4371307***	-0.4526257***	-0.3781092	-0.0697684	-0.4526257***	-0.3781092***	0.043057	0.1359834**	-0.0428
	0.000	0.000	0.000	0.000	0.000	0.000	0.123	0.000	0.000	0.403	0.001	0.441
Lpopden	0.0004198	0.0000871	0.0009295*	0.000214	0.0001528	0.0005241	0.0007689	0.000153	0.000524	0.000652	0.000664	0.00075
	0.324	0.834	0.068	0.55	0.673	0.168	0.309	0.673	0.168	0.88798	0.151	0.104
cons	0.64738	0.4947629	0.4909927	1.744814***	1.995085	1.111578	0.2288771	1.995085	1.111578	0.142**	0.198676	0.745062
	0.005	0.026	0.023	0.000	0.000	0.004	0.378	0.000	0.004	0.006	0.335	0.023
CD test	26.904	27.213	23.645	82.325,	77.575	80.321	24.033,	77.575	80.321	54.013	57.098	55.295
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 5.1A SDM estimation results HTM

SDM model Fixed Effects- HTM
Dependent variable Labour growth/ Femal labour growth/ Male labour growth

	All	Female	Male
ρ	0.2709006***	-0.0429536	0.1365041*
	0.000	0.475	0.014
UV	-0.1819334***	-0.8265104***	-0.8084016***
	0.000	0.000	0.000
RV	-0.0654709	-0.4818988***	-0.6746581***
	0.09	0.000	0.000
lpop	-0.6711585	-0.2813793	1.508819
	0.247	0.81	0.089
Wx			
UV	0.3054332***	0.5018121***	0.2186543*
	0.000	0.000	0.025
RV	0.0007062	-0.1241848	-0.1797816
	0.992	0.218	0.082
lpop	0.5103534	0.92517	-1.618391
	0.498	0.546	0.162
Direct			
UV	-0.1617846***	-0.8296747***	-0.8031042***
	0.000	0.000	0.000
RV	-0.067593	-0.4836472***	-0.6859289***
	0.08	0.000	0.000
lpop	-0.5899161	-0.1694662	1.551583

	0.274	0.881	0.062
Indirect			
UV	0.3330255***	0.518871***	0.1201644
	0.000	0.000	0.254
RV	-0.020867	-0.0980055	-0.3047019**
	0.811	0.275	0.006
lpop	0.4274784	0.8679621	-1.605553
	0.611	0.548	0.172
Total			
UV	0.1712409	-0.3108037*	-0.6829398***
	0.124	0.027	0.000
RV	-0.0884599	-0.5816527***	-0.9906308***
	0.41	0.000	0.000
lpop	-0.1624376	0.6984959	-0.0539706
	0.842	0.551	0.959
legend: * p<.05; ** p<.01; *** p<.001			

Table 5.2 A SDM estimation results LTM

SDM model Fixed Effects- LTM

dependent variable Labour growth/ Femal labour growth/ Male labour growth

	Model 1	Model 1.a female	Model 1.b male
ρ	0.3470089***	0.2574817***	0.3853311***
	0.000	0.000	0.000
UV	-0.2279429***	-0.157674***	-0.2205826***
	0.001	0.001	0.001
RV	0.0347416	0.092505**	-0.0521916
	0.409	0.009	0.253
lpop	0.2832035	0.089697	0.3360564
	0.374	0.797	0.31
Wx			
UV	-0.4017192***	-0.1990002*	-0.1649487
	0.000	0.015	0.136
RV	0.0947343	0.1666689*	0.1098818
	0.225	0.01	0.151
lpop	-0.0096241	0.5610271	-0.0017773
	0.982	0.219	0.997
Direct			
UV	-0.2728649***	-0.1724365***	-0.2464119***
	0.000	0.000	0.000
RV	0.0436986	0.1038296**	-0.0436805
	0.313	0.004	0.352
lpop	0.3244949	0.1649463	0.3844782
	0.272	0.612	0.211
Indirect			
UV	-0.6916676***	-0.3077598**	-0.3801816*
	0.000	0.002	0.017

RV	0.1542415	0.244574**	0.1371845
	0.177	0.003	0.243
lpop	0.1287444	0.7460808	0.1972387
	0.799	0.131	0.722
Total			
UV	-0.9645324	-0.4801963***	-0.6265934***
	0	0.000	0.001
RV	0.19794	0.3484037***	0.093504
	0.151	0.000	0.515
lpop	0.4532393	0.911027	0.581717
	0.395	0.071	0.324
legend: * p<.05; ** p<.01; *** p<.001			

Table 5.3A SDM estimation results KIS

SDM model Fixed Effects- KIS

dependent variable Labour growth/ Femal labour growth/ Male labour growth

	Model 1	Model 1.a female	Model 1.b male
ρ	0.2866109***	0.2875429***	0.2875731***
	0.000	0.000	0.000
UV	-0.1189656*	-0.0852485	-0.1026436*
	0.017	0.082	0.021
RV	-0.2941984***	-0.3175369***	-0.2636271***
	0.000	0.000	0.000
Lpop	-0.0440937	-0.0210115	-0.301978
	0.89	0.947	0.425
Wx			
UV	0.3706334***	0.3122475***	0.2699549***
	0.000	0.000	0.000
RV	0.0256973	0.1774777*	-0.0929681
	0.684	0.011	0.098
Lpop	0.1674149	0.0172183	0.8878483
	0.688	0.967	0.073
Direct			
UV	-0.0909532	-0.0609787	-0.0823073
	0.077	0.22	0.071
RV	-0.3005293***	-0.3123741***	-0.2786238***
	0.000	0.000	0.000
Lpop	-0.001374	0.0103933	-0.2027794
	0.996	0.972	0.564
Indirect			
UV	0.4462372***	0.3816913***	0.3189481***
	0.000	0.000	0.000
RV	-0.0759033	0.1164919	-0.2228856***
	0.287	0.166	0.000
Lpop	0.2075374	0.0183873	1.063463
	0.659	0.969	0.057
Total			

UV	0.3552839**	0.3207126**	0.2366408*
	0.002	0.001	0.012
RV	-0.3764326***	-0.1958822*	-0.5015094***
	0.000	0.039	0.000
Lpop	0.2061634	0.0287806	0.8606833
	0.66	0.952	0.12
legend: * p<.05; ** p<.01; *** p<.001			

Table 5.4A SDM estimation results LKIS SDM model Fixed Effects- LKIS dependent variable Labour growth/ Femal labour growth/ Male labour growth			
	Model 1	Model 1.a female	Model 1.b male
ρ	0.5007727***	0.5344403***	0.5114209***
	0.000	0.000	0.000
UV	0.0112517	-0.1350075	0.070176
	0.893	0.128	0.361
RV	-0.2512042***	-0.2705596***	-0.2566965***
	0.000	0.000	0.000
lpop	0.0998893	0.1301443	0.0456917
	0.681	0.588	0.858
Wx			
UV	-0.0843342	0.0846414	-0.174573
	0.542	0.5	0.172
RV	-0.0803186	0.0039617	-0.0541192
	0.289	0.961	0.502
lpop	-0.4492633	-0.5563028	-0.1462497
	0.174	0.08	0.682
Direct			
UV	0.0012802	-0.1297176	0.0493179
	0.988	0.155	0.533
RV	-0.2861313***	-0.2966608***	-0.2894549***
	0.000	0.000	0.000
lpop	0.061038	0.0687775	0.0516521
	0.788	0.759	0.83
Indirect			
UV	-0.1475631	0.022233	-0.2645345
	0.533	0.919	0.229
RV	-0.3777514***	-0.2756186*	-0.3459372**
	0.001	0.023	0.009
lpop	-0.7247369	-0.9464866	-0.2162312
	0.145	0.059	0.699
Total			
UV	-0.1462829	-0.1074846	-0.2152166
	0.585	0.664	0.378
RV	-0.6638828***	-0.5722794***	-0.6353921***
	0.000	0.000	0.000
lpop	-0.6636989	-0.8777091	-0.1645791

	0.221	0.11	0.789
legend: * p<.05; ** p<.01; *** p<.001			

Appendix 2: Entropy decomposition properties

Following Attran (2006), the diversity measure D will compare the regional (provincial) employment distribution against a uniform employment distribution where the employment is equi-proportional in all the sectors. Using the Shannon index (1948), the measure of industrial diversity in each region (province) is defined as:

$$D(P_1, P_2, \ldots\ldots P_n) = -\sum_{i=1}^{N} P_i \, log_2(P_i) \qquad \text{(1-A)}$$

where $P_i = \frac{E_{ij}}{E_j}$, E_{ij} represents the number of employed in sector *i* at 5 digits in region (province) j, E_j is the total employment in region (province) *j*, and *N* is the number of economic sectors in region (province) j. Shannon builds its index taking into consideration 2, 10 and *e* as logarithm bases. The equation (1) can be rewritten as:

$$D(P_1, P_2, \ldots\ldots P_n) = -\sum_{i=1}^{N} P_i \, ln(P_i) \qquad \text{(2.A)}$$

Equation (2.A) represents the Variety in accordance with Frenken et al., 2007. Moreover, 0 $\leq D \leq ln(N)$ where D=0 corresponds to the highest concentration and it occurs when $E_{ij} = 1$ i.e when all the employment is concentrated in only one sector while $D = ln(N)$ represents the greatest level of dispersion end corresponds to and equi-proportional distribution in all the sectors. D depends only on N, $P_1, P_2, \ldots\ldots P_n$, and is a symmetric continuous function of the p's depending only on their relative magnitude and not on their order. If one sector, n^{th}, were subdivided into two sectors with relative share q_1 and q_2, then the new measure of diversity is the original measures plus the conditional diversity within the sectors (Hackbart and Anderson 1975).

Equation (2.A) can be normalized as follows:

$$D_{norm} = \frac{D}{D_{max}} \quad \text{with } 0 \leq D_{norm} \leq 1 \qquad \text{(3.A)}$$

where $D_{norm} = 1$ there is the greatest level of dispersion and when $D_{norm} = 0$ there is the highest concentration level. Normalization allows us to compare results obtained for different observation units. Nevertheless, D does not highlight which is the optimal combination i.e. different combinations can have the same distance measure.

Following Frenken et al., (2007) a pre-given hierarchical classification, as provided by the Nace_2 Rev classification, will be used. The *i*-five-digit industry can fall exclusively under two-digit industry g, P_g can be defined as:

$$P_g = \sum_{i \in g} P_i \qquad \text{(4.A)}$$

where $P_g = \frac{E_{gj}}{E_j}$ represents the share of employment at two-digit level (g) in province *j* on the total employment in province *j*. Using equation (4.A) the equation (2.A) can be rewritten as:

$$D = \sum_{g=1}^{G} \sum_{i \in g} P_i \ln\left(\frac{1}{P_i}\right) \qquad \text{(5.A)}$$

Multiplying for $\frac{Pg}{P_g}$ equation (5.A) can be rewrite as:

$$D = \sum_{g=1}^{G}\left[\sum_{i\in g}\frac{P_g}{P_g} * P_i\left(ln\frac{P_g}{P_g}\frac{1}{P_i}\right)\right]$$

Applying the log properties, we obtain:

$$D = \sum_{g=1}^{G}\left[\sum_{i\in g}\frac{P_g}{P_g} * P_i\left(ln\frac{P_g}{P_i} + ln\frac{1}{P_g}\right)\right]$$

and rearranging:

$$D = \sum_{g=1}^{G}\left[\sum_{i\in g}\frac{P_g}{P_g} * P_i ln\frac{P_g}{P_i} + \sum_{i\in S}\frac{P_g}{P_g} * P_i ln\frac{1}{P_g}\right] \quad (6.A)$$

Using equation (4.A), equation (6.A) can be re-written as:

$$D = \sum_{g=1}^{G}\left[\sum_{i\in g}\frac{P_i}{P_g} * P_i ln\frac{P_g}{P_i} + P_g ln\frac{1}{P_g}\right]$$

and:

$$D = \sum_{g=1}^{G} P_g\left[\sum_{i\in S}\frac{P_i}{P_g} ln\frac{P_g}{P_i}\right] + \left[\sum_{g=1}^{G} P_g ln\frac{1}{P_g}\right] \quad (7.A)$$

The diversity measures can be decomposed in two different terms, the first one,

$$\text{DB}=\left[\sum_{g=1}^{G} P_g ln\frac{1}{P_g}\right] \quad (8.A)$$

represents the entropy between sectors, while the second one,

$$\text{DW}=\left[\sum_{i\in S}\frac{P_i}{P_g} ln\frac{P_g}{P_i}\right] \quad (9.A)$$

represent the diversity within the sectors. So, equation (2) can be rewritten as

$$D = \sum_{g=1}^{G} P_g DW + DB \quad (10.A)$$

where $\sum_{g=1}^{G} P_g DW$ is the weighted within entropy.

The diversification index in equation (10.A) is the Variety and it can be decomposed in the sum of within and between diversification i.e. related and unrelated Variety:

$$VAR = RV + UV \text{ (11.A)}$$

where RV represents the entropy within the sectors (Equation 9.A) and UV represents the entropy between the sectors (Equation 8.A). The UV values can vary from 0, all employment is concentrated in only one two-digit industry, to $ln(G)$, when all the industries employ and equal numbers of employees. The RV value can range from 0 (employment in each two-digit industry is concentrated in only one of its five-digit industries) to $ln(I) - ln(G)$ when all five-digit industries within a two-digit industry have an equal employment share (Castaldi et al., 2015, Fritsch and Kublina 2016).

Our aim is to investigate the unrelated, related and the Variety for females and males. To do so, the equation previously discussed will be modified as follows: $P_{Fi} = \frac{E_{Fij}}{E_{Fj}}$, E_{Fij} represents the number of females employed in sector i at 5 digits in province j and E_{Fj} is the total female employment in province j, $P_{Fg} = \frac{E_{Fgj}}{E_{Fj}}$ represents the share of female employment at two-digit level in province *j* on the total female employment in province *j*. The same holds for male.

Appendix 3: Direct and indirect effects

To explore the direct and indirect effects for an SDM model, in accordance with LeSage and Pace (2009) pp.34, we express equation:

$$y = \rho Wy + X\beta + \theta WX + u$$

$$u = \lambda Wu + \epsilon$$

in the reduced form, putting λ=0 and obtaining:

$$(I_n - \rho W)y = X\beta + \theta WX + \iota_n \alpha + \epsilon$$

$$y = \sum_{r=1}^{k} S_s(W)x_r + V(W)\iota_n \alpha + V(W)\epsilon \quad \text{(A1)}$$

where:

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

$$V(W) = (I_n - \rho W)^{-1} = I_n + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots ...$$

Where $(I_n - \rho W)^{-1}$ is a nxn inverse matrix. Through the higher order terms $\rho^n W^n$ with n>1 location farther away are reached any way even if they are not directly connected. Equation (A1) can be rewritten as:

$$\begin{pmatrix} y_1 \\ \\ y_n \end{pmatrix} = \sum_{i=1}^{k} \begin{pmatrix} S_r(W)_{11} & & S_r(W)_{1n} \\ & & \\ S_r(W)_{n1} & & S_r(W)_{nn} \end{pmatrix} \begin{pmatrix} x_1 \\ \\ x_n \end{pmatrix} + V(W)\iota_n \alpha + V(W)\epsilon$$

Looking only at the $S_r(W)_{ij}$ observation, where i,jth elements of the matrix $S_r(W)$,

$$y_i = \sum_{r=1}^{k} [S_s(W)x_{i1} + \cdots S_s(W)x_{i1}] + V(W)_i \iota_n \alpha + VV(W)_i \epsilon \quad \text{(A2)}$$

The derivative of y_i with respect to x_{jr} is:

$$\frac{\partial y_i}{\partial x_i} = S_r(W)_{ij}$$

Consequently, the change in the explanatory variable for a single province can affects the dependent variable in other provinces. Finally, $S_r(W)_{ii}$ measurers the impact on dependent variable observation I from a change in x_{ir}, the impact includes the effect of feedback loops where observation i affects observation j and observation j affects observation i as well as longer paths which might go from observation i to j to k and back to i. These results can be summarized as follows: the average total impact is the average of all derivatives of y_i with respect to x_{ij} for each i,j. The average direct impact is the average of all own derivatives. The average al all derivatives (average total impacts) less the average own derivative (average direct impact) equals the average cross derivative (average indirect impacts).