Sergio Destefanis (University of Salerno)
Naqeeb Ur Rehman (Westminster International University in Tashkent)

The Employment Impact of Different Forms of Investment Expenditure across European NUTS2 Regions

Abstract

This study examines the effect of various forms of investment expenditure (gross fixed capital formation, R&D and European Structural and Investment Funds) on employment across NUTS2 European regions from 2000 to 2016. Developing upon Piva and Vivarelli (EABR, 2018), we estimate a conditional labour demand function through GMM. We find that gross fixed capital investment and European Structural and Investment Funds are generally labour friendly, while the effect of R&D is heavily conditional upon regional characteristics. Only in NUTS2 regions with medium to high levels of innovation, R&D is likely to generate employment. According to our results, the more European regions will shift closer to the world technology frontier, the more R&D expenditure, rather than investment in physical assets, will be capable to generate positive employment externalities.

Keywords: gross fixed capital formation, ESIF, R&D, employment, Cohesion policy.
JEL Codes: E24, O32, O33, O38.

1. Introduction

Investment is widely considered to be an engine of economic growth and prosperity. In today's economies, the role of investment in physical assets (gross fixed capital formation) is losing its key role with respect to investment in intangibles, among which expenditures in research and development (R&D). Hence, to fulfil the aim of the Lisbon Strategy, launched in March 2000 by the EU heads of state and government, that is to make Europe "the most competitive and dynamic knowledge-based economy in the world, capable of sustainable economic growth with more and better jobs and greater social cohesion". The main objective of EU 2020 policy was to transform EU28 economies into knowledge-based economies by increasing public and private R&D expenditure to 3% of GDP.[1] These policies were meant to accelerate innovation and uplift the socio-economic development of European regions (see, e. g., Blazek and Kadlec, 2018). Nonetheless, there are still today in the European Union profound cross-country and cross-region economic disparities, which led to the creation and strengthening of the European Structural and Investment Funds (henceforward the SFs). These funds are the European Union's primary tool to

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[1] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Europe_2020_indicators_-_research_and_development&oldid=290175#:~:text=Europe%202020%20strategy%20target%20on,%25%20of%20GDP'%20by%202020.

sustain regional development. For the new programming period (2021-2027), an amount of € 330.2 billion has been allocated in Europe for this policy, almost one third (30.7%) of the total budget of the European Union (€ 1,074.3 billion Euro net of Next Generation EU).[2] Under the label of SFs we consider in this paper: 1) the European Regional Development Fund (ERDF), created with the specific aim of reducing regional imbalances in the European Union; 2) the European Social Fund (ESF), whose aim is to promote active labour market policies; 3) the European Agricultural Fund for Rural Development (EAFRD), directed at facilitating the development of agricultural structures and rural areas; 4) the Cohesion Fund (CF), supporting transport and environment projects in countries where the gross national income per inhabitant is less than 90% of the EU average.

In principle, higher GDP per capita and faster growth should also foster job creation. Yet, the impact of gross fixed capital formation and R&D on employment is widely discussed in the empirical literature (stimulating accounts of this literature are provided in Goos et al., 2015; Piva and Vivarelli, 2018), although not much of this literature is devoted to regional analysis and data. Recently, this debate has also regarded the effects of SFs' expenditure (Becker et al., 2010; Mohl and Hagen, 2011; Crescenzi and Giua, 2020). Further discussion is provided in Section 2, but it should be immediately noted that, to the best of our knowledge, no study has simultaneously considered the impact on employment of gross fixed capital formation, R&D expenditure, and SFs. With a view to fill this gap in the literature, our study focuses on the employment impact of these three different forms of investment using panel data across NUTS2 European regions from 2000 to 2016. To get mileage from our dataset and acquire further knowledge of the effects of these investments on regional employment, we deployed interactive variables among these expenditures and various EU-based measures of regional competitiveness (Annoni and Kozovska, 2010). In the literature, the role of the economic context has often been highlighted when assessing the effects of SFs. Here we consider it for all the three forms of investment. As a result, we find a particularly strong conditioning role of the context for R&D expenditures.

The rest of the paper has the following structure. Section 2 reviews the relevant literature, while section 3 sets out the empirical strategy of the paper, also presenting the data. The results are presented in section 4. Lastly, section 5 concludes and provides some policy implications.

[2] https://www.consilium.europa.eu/it/policies/the-eu-budget/long-term-eu-budget-2021-2027/

2. The background

In this section we review the contributions about the employment impact of investment expenditures that provide the conceptual background of our estimates. We focus on contributions that highlight the interplay between direct and indirect effects (through various compensation mechanisms) and provide empirical assessments across European countries and, especially, regions.

2.1 Gross fixed capital formation and R&D

Ever since the classical age (see, e.g., Marx, 1969) economists have been aware that investment expenditures have both a direct displacement effect (due to the substitution of workers with new machines and technologies) and an indirect potential compensation mechanism through price and income effects. The higher productivity linked to investment and technological innovation reduces unit costs and is likely to lower prices, stimulating product demand and generating employment. Besides, lower prices boost real income, which may result in higher consumption and create more jobs (see, e.g., Bogliacino and Vivarelli, 2012; Harrison et al., 2014; Hou et al., 2018). However, these compensation mechanisms are conditioned upon certain factors, for example intensity of competition, price elasticity of demand, labour market flexibility, low entry barriers, policies targeted to increase market demand (Capello and Lenzi, 2012; Vivarelli, 2014, 2015; Ugur et al. 2018). Vivarelli (2015). Calvino and Virgillito (2017) also argue that, once a round of investment or technological innovation is carried out, delays in further investments due to cautious expectation of firms may result in structural unemployment.

Micro-level studies

This sub-section reviews some interesting micro level quantitative studies. Agovino et al. (2016) investigate the link between R&D and employment using data for 879 American, Japanese and European R&D-intensive manufacturing firms. They find a positive impact on employment for R&D expenditure and the ratio of patents to R&D. Piva and Vivarelli (2018), analysing European firms, find that R&D creates more jobs in high- and medium-tech firms than in low-tech firms. Likewise, Roy et al. (2018), using CIS panel data on European firms find that patent citations have a positive impact on job creation in manufacturing high-technology firms but not elsewhere. Bianchini and Pellegrino (2019) stress the importance of persistent R&D investment. Firms characterised by non-regular R&D investment are less likely to create jobs. Piva and Vivarelli (2018) also analyse the impact of gross fixed capital formation, finding that it is negatively related to employment. They argue that this labour-saving effect is related to the embodied technological change (akin to process innovation) incorporated in capital formation.

Macro-level studies

There is relatively little research at regional level regarding the effect of R&D on employment.[3] The studies analysing the effect of R&D on employment across EU regions provide heterogeneous findings. Fagerberg et al. (1997), analysing 64 EU regions, find that a higher share of R&D employment accelerates output growth, and, indirectly, growth in aggregate employment. However, they do not directly connect R&D indicators with employment growth. Similarly, Sterlacchini (2008), for 1995-2002 panel of 197 European NUTS2 regions using data, finds that EU regions below a certain threshold of economic development do not reap the same benefits of R&D on regional GDP growth as more developed regions.[4] Once more, no direct evidence is provided for the role of R&D on employment growth.

Bogliacino and Pianta (2010) examine eight EU countries from 1994 to 2004, finding that the effect of technological competitiveness (R&D expenditure per employee and share on turnover of new product sales) on employment is heterogeneous across Pavitt-taxonomy classes of industries. Technological competitiveness positively influences employment in the Science-based and Scale and Information Intensive industries. Also, Bogliacino and Vivarelli (2012), estimating a conditional labour demand function on data from 1996 to 2005 for fifteen European countries, single out a positive effect of R&D expenditure, as well as of gross fixed capital formation, on employment.

Capello and Lenzi (2012) analyse the NUTS2-level regions of 27 EU countries from 2005 to 2007. They find that product innovation accelerates employment growth, while process innovation displaces employment (innovation indicators are estimated by the authors on the basis of data from EUROSTAT's Community Innovation Survey). Furthermore, regions that have better managerial and production facilities reveal a stronger positive association between product innovation and

[3] In a meta-regression analysis, Ugur et al. (2018) find that 74% of the empirical studies regarding the effect of innovation on employment are at firm level.

[4] The developed regions are mainly from Belgium, Finland, Germany, Netherlands, Sweden and UK. More technologically backward regions from Greece, Portugal, Spain and Italy showed weak linkages across public and private R&D institutions and weak innovation policies.

employment, while the negative relation between process innovation and employment growth is amplified in regions with large cities.

Burger et al. (2012) take a 1999-2005 panel for 270 German labour market regions with information on four two-digit industries. Their results show that an increase in patents is associated with subsequent growth of employment in Medical and optical equipment industry and in Electrics and electronics, but not in Chemicals and Transport equipment. On the other hand, using NUTS2-level data from 2000 to 2011, Goos et al. (2015) find that high-technology jobs due to innovation also create jobs in the low-tech sectors. These jobs have multiplier effects across various sectors of the economy. More specifically, they argue that European peripheral regions (from Eastern and Southern Europe) have lower multipliers, which could be increased through higher public R&D investment, more spending in higher education and more effective connections with the core European regions. Finally, Mustra et al. (2020) study NUTS2 regions from on 28 European countries throughout 2007-2010. According to their results, regions with high innovation activities (as measured by the EU regional innovation index) have more resilient labour markets.

2.2 European Structural and Investment Funds

European Structural and Investment Funds (SFs) should in principle provide additional inputs to production, accelerate productivity of private capital and labour, and bring about higher growth and more favourable labour-market outcomes, especially for less developed areas. There is a vast literature on the effectiveness of European regional policy. As pointed out in Coppola et al. (2020), in most cases, this policy seems to have a positive impact on growth, but the significance of the results is far from uniform. A feature that emerges across various studies is that the policy impact depends on a series of conditioning factors (see Fratesi, 2016). These remarks seem also apt to describe the impact of structural funds upon employment.

Becker et al. (2010) find that SFs accelerate growth in GDP per capita across European regions at NUTS2 level but no effect on employment growth. Mohl and Hagen (2011) find that the impact of SFs on employment is higher in the European regions where the share of low-skilled population is low. In other words, SFs accelerate the growth of high-skilled, rather than total, employment.

Di Cataldo (2017) estimates the effect of SFs in two regions of the UK (Cornwall and South Yorkshire), finding that these funds have a positive impact on job creation and growth across these two regions. Consistently with these findings, the study of Crescenzi and Giua (2020) at NUTS3 level confirms that SFs positively influence growth and employment across German and UK regions. Yet, results are much more uneven across the Italian and Spanish regions.

Concerning a slightly different impact of SFs, the study of Gagliardi and Percoco (2016) shows that these funds significantly improve the economic growth of poor (rural) regions that are closely located to rich (urban) regions. Hence SFs are likely to enhance knowledge spillovers due to people-to-people and business-to-business contacts.[5]

3. The empirical set-up

There is a lack of studies on the impact of investment on employment on regional data. Besides, the examination of the literature reveals that gross fixed capital formation and expenditure on R&D have never been analysed alongside with SFs. Yet, jointly allowing for these three investment variables is likely to reduce the omitted variable bias in regression analysis. In this study, we consider gross fixed capital formation, gross expenditure on R&D and SFs in a conditional labour demand function that also includes output and real wages. Following Bogliacino and Vivarelli (2012) and Piva and Vivarelli (2018), we adopt this theoretically based setup, that easily accommodates various types of investment.

Several papers (Fagerberg et al., 1997; Sterlacchini, 2008; Capello and Lenzi, 2012; Fratesi, 2016) have also emphasised the role of the economic and industrial structure of the regions in determining the impact of investment on the economy. In this paper, we pursue these suggestions in a systematic manner, focusing on the interactions between our three types of investment and various indicators of regional competitiveness of EU source (Annoni and Kozovska, 2010; see also https://ec.europa.eu/regional_policy/en/information/maps/regional_competitiveness). More generally, we rely on EU based data throughout our empirical analysis. GDP, employment, gross fixed capital formation, R&D expenditure and wages are taken from EUROSTAT regional database. SFs are taken from the "Historic EU payments" provided by the EU Commission (see https://cohesiondata.ec.europa.eu/Other/Historic-EU-payments-regionalised-and-modelled/tc55-7ysv). In order to increase the size of the sample under scrutiny, we do not differentiate among types of R&D (public or private), and innovation (process or product, radical or incremental),

[5] The role of regional knowledge spillovers is also highlighted in Sanso-Navarro and Vera-Cabello (2017) with relationship to R&D expenditure.

leaving this kind of development to future studies. Indeed, to wield a larger dataset we also resort to a mild form of interpolation for R&D data, filling in through simple time series techniques blank values that are both preceded and followed by available data.

3.1 The empirical model

We adopt system GMM for estimation (Arellano and Bond, 1991; Arellano and Bover, 1995). This method was already implemented in some related studies (Bogliacino and Vivarelli, 2012; Piva and Vivarelli, 2018; Rehman and Hysa, 2020). With this method, the sizeable cross-section dimension of our dataset can be used to reduce the so-called Hurwicz bias on the lagged dependent variable. System GMM also alllows an effective treatment of the endogeneity bias that is likely to matter for some of our variables. In estimation we consider employment, output and gross fixed capital formation as endogenous (their instruments including lags from two to five periods), while wages, R&D and SFs are considered as weakly exogenous (their instruments including lags from one to two periods).

As customary in this literature, we provide a specification check on our estimates through the Hansen test of validity of instruments and the Arellano-Bond test for first- and second-order serial correlation of residuals. We used heteroskedasticity-robust standard errors across all estimates. Our baseline regression is:

$$(1)\ \ln(E_{it}) = a_1 \ln(E_{it-1}) + a_2 \ln(E_{it-2}) + b_1 \ln(W_{it}) + b_2 \ln(W_{it-1}) + b_3 \ln(Y_{it-1}) + \\ + b_4 \ln(GFCF_{it}) + b_5 \ln(R\&D_{it}) + b_6 \ln(SFs_{it-1}) + b_7(D_t) + \epsilon_{it}$$

In equation (1), subscripts, i and t represent respectively region and year. E stands for total employment, W for wage per employee, Y for GDP, GFCF for gross fixed capital formation, R&D for gross expenditure on R&D and SFs for the sum of European Structural and Investment funds. D is the set of year dummies. The dynamic structure of (1) comes from a general-to-specific search starting from a general specification with two lags on employment and current plus first-order lags on all other variables.

As already said, in our analysis we want to shed light on the role of the economic and industrial structure through the estimation of interaction terms between our three types of investment and a set of indicators of regional competitiveness. We do not explore interactions between these indicators and output or wages because for these regressors there is no a priori presumption of a consistent conditioning role for the economic and industrial context.[6] This gives rise to the following equation.

$$
\begin{aligned}
(2)\ \ln(E_{it}) &= \alpha_1 \ln(E_{it-1}) + \alpha_2 \ln(E_{it-2}) + \beta_1 \ln(W_{it}) + \beta_2 \ln(W_{it-1}) + \beta_3 \ln(Y_{it-1}) + \\
&+ \beta_4 \ln(GFCF_{it}) + \beta_5 \ln(GFCF_{it} * pillar_i) + \beta_6 \ln(R\&D_{it}) + \beta_7 \ln(R\&D_{it} * pillar_i) + \\
&+ \beta_8 \ln(SFs_{it-1}) + \beta_9 \ln(SFs_{it-1} * pillar_i) + \beta_{10}(D_t) + \epsilon_{it}
\end{aligned}
$$

In equation (2), GFCF, R&D, and SFs are interacted with a generic (time-invariant) variable $pillar_i$. These so-called pillars are, more in detail, a Basic pillar (score 1-100), which is a measure of institutions, macroeconomic stability, health, basic education; an Efficiency pillar (score 1-100) measuring higher education, labour market efficiency, market size; an Innovation pillar (score 1-100), a measure of technological readiness, business sophistication, innovation; and a Stage of development pillar (score 3=High; 2=Intermediate; 1=Medium) that sums up the performance of a given region in the three preceding dimensions. Different versions of equation (2) are estimated by taking the various pillars one at the time as well as in combination. Further details are provided in Section 4.

3.2 The data

Our empirical analysis is based on 264 NUTS2 level regions from 27 European countries (for details, see Table A1 in the Appendix) throughout the 2000-2016 period. Due to problems of data availability and the relatively small size of Croatia, Cyprus, Estonia, Latvia, Lithuania, Luxembourg, Malta and Slovenia, we treated these countries as NUTS2 level regions in our dataset. Table 1 sums up the information on the variables, their definitions and sources. All the monetary variables have been deflated using the GDP deflator index sourced from EUROSTAT (base year= 2010).

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[6] This presumption was borne out by some exploratory regressions that are available upon request.

Table 1: Variables, definitions and sources

Variable	Definition	Source
Employment	Ln (Total employment, 15 to 64 years)	Eurostat
Wage per employee	Ln (Wages/total employees)	“
GDP	Ln (GDP)	“
GFCF	Ln (Gross fixed capital formation)	
R&D	Ln (Gross expenditure in R&D)	“
SFs	Ln (European Structural and Investment Funds)	Historic EU payments
Basic pillar (score 1-100)	Measure of institutions, macroeconomic stability, health, basic education	Annoni and Kozovska (2010)
Efficiency pillar (score 1-100)	Measure of higher education, labour market efficiency, market size	“
Innovation pillar (score 1-100)	Measure of technological readiness, business sophistication, innovation	“
Stage of development pillar	1=Medium; 2=Intermediate; 3=High	“

The following remarks are in order. First, we consider the regional competitiveness indicators as time-invariant variables, taken in 2010, because this value is close to the middle of our sample period, and we thought that there would have been little gain in using also the values available for 2013 and 2016 (a further survey was carried out in 2019). Second, it is widely acknowledged that funds from the EU are paid out to the regions with a lag of approximately one year with respect to the regions' actual spending decisions. This time pattern between the payments to the member states and the dates on which expenditures take place on the ground is also noted in the "Historic EU payments" provided by the EU Commission. Accordingly, this dataset provides a measure of the 'expenditures taking place on the ground', the modelled expenditures, which are the SFs' indicators that we actually use in our empirical analysis.

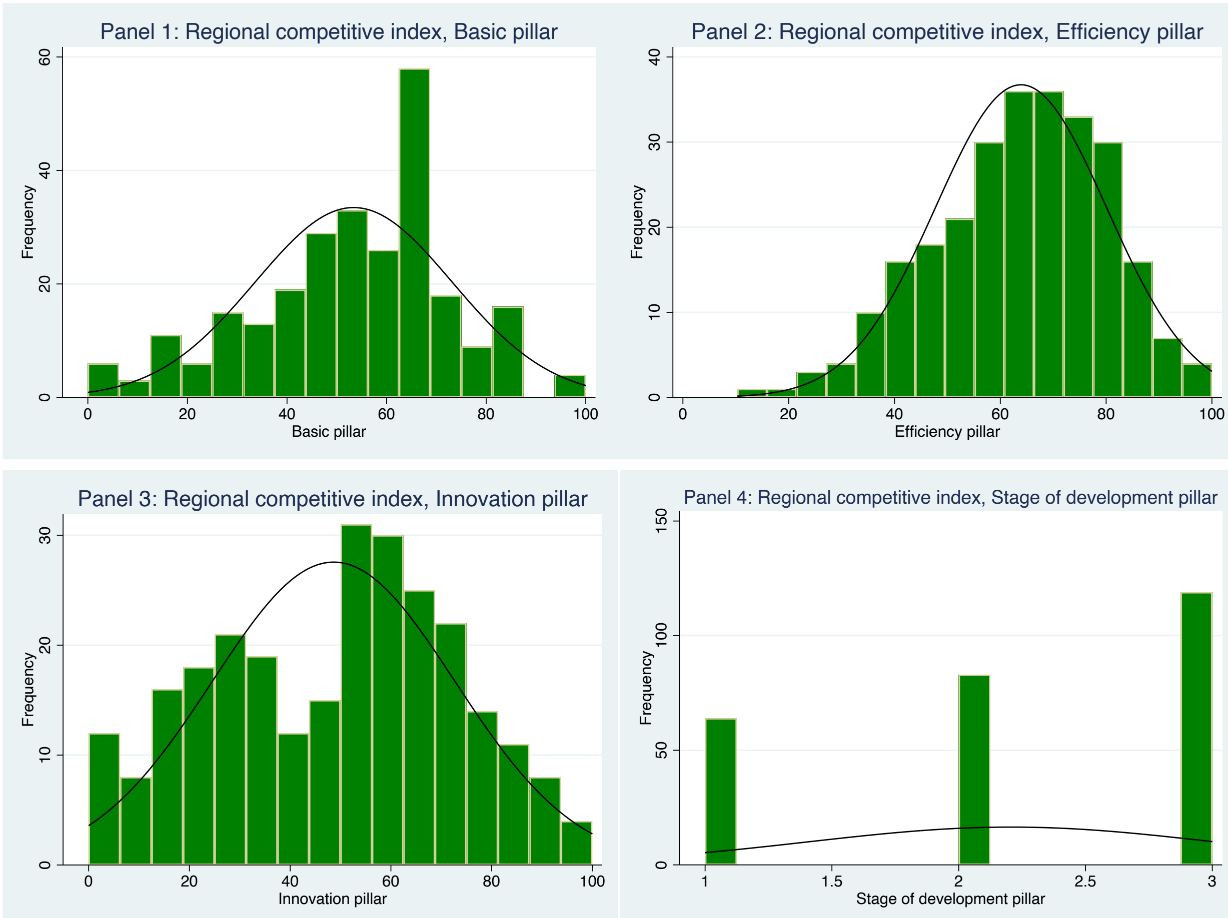
Table 2 provides some useful descriptive statistics (mean, standard deviations, 10^{th} percentile, 90^{th} percentile) for all variables.

Table 2: Summary statistics, N=3268					
Variables	$\overline{x}$	σ	10th percentile	median	90th percentile
Employment (000's)	838.472	662.275	216.003	663.882	1711.03
Wage per employee (000's €)	22.4149	28.2128	2.90100	15.0839	48.7772
GDP (Mio €)	47.6353	56.6641	7.84406	32.9657	103.132
GFCF (Mio €)	9.92730	11.4913	1.77993	6.79689	20.7380
R&D (Mio €)	0.88055	1.54087	0.02496	0.37402	2.28317
SFs (Mio €)	3.37559	2.28349	0.22213	3.30105	6.61528
Basic pillar	0.52	0.20	0.24	0.55	0.79
Efficiency pillar	0.63	0.16	0.40	0.65	0.83
Innovation pillar	0.47	0.24	0.15	0.51	0.79
Stage of development pillar	2.17	0.82	1.00	2.00	3.00
All the monetary variables are at 2010 constant prices.					

Clearly, employment, wages, GDP, GFCF and R&D have distributions that are skewed to the right. In all these cases, there are a few large values in the data that drive the mean upwards. On the other hand, the SFs and the scores for the four pillars of the regional competitiveness index apparently follow a much more symmetric distribution. Figure 1 shows the histograms for these scores, which play a very important role in our empirical strategy.

The distribution of the Basic pillar is indeed rather symmetric, while that for the Efficiency pillar is more negatively skewed. Both panels 1 and 2 present rather unimodal distributions, while in panel 3 there is some evidence of bimodality. The distribution for the Innovation pillar is also more spread out and thicker in the tails. Lastly, the distribution of the Stage of development pillar in panel 4 across the three stages is quite different from a bell-shaped distribution.

Figure 1: The regional competitiveness index across the regions under scrutiny.
The distribution of the scores for the four pillars.



Overall, these histograms suggest that the distributions of the four pillars across NUTS2 European regions are very different from each other, and that one cannot construct consistent groups of regions for all the pillars. Hence, generally speaking, it would not be appropriate to take into account the heterogeneity of European regions while estimating the effect of investment on employment by splitting the sample in different groups. Reliance on the interaction terms included in (2) seems to be a much sounder empirical strategy.

4. The results

We present out main results in Tables A2-A6 of the Appendix. Table A2 reports the results for equation (1) (the Baseline Model), and for GFCF interacted with the regional competitiveness pillars one by one (Models 1-4). In Tables A3 and A4 there are respectively the results for R&D and SFs interacted with the regional competitiveness pillars one by one (Models 5-8, and 9-12). In Table A5, all the three forms of investments are interacted at the same time with a regional competitiveness pillar (Models 13-16). Finally, Table A6 (Models 17-19) includes some selected specifications interacted with various regional competitiveness pillars at the same time. Obviously, Models 1-16 are all different versions of equation (2).

An immediate remark that applies across all estimation models is that our diagnostics do not highlight either serial correlation or over-identification problems. In other words, our models pass the customary specification checks. Going now to the economic content of our evidence, it is useful to start with the Baseline Model (in Table A2). The estimates for this model tell us that GFCF and SFs significantly generate employment, while the employment impact of R&D is positive but insignificant. The first two results will be validated by the remaining estimates. On the other hand, R&D will turn out to be relevant for employment only in given contexts that will be clarified in Tables A3, A5 and A6. Note that Model 3 shows a significant negative interaction of GFCF with the Innovation pillar, but this evidence is consistent with an overall positive impact of GFCF.

Table A3 is perhaps the key table of the Appendix. It reiterates the positive and significant impact of GFCF and SFs, but it also shows large and significant interactions (all with a positive sign) for R&D with all the regional competitiveness pillars. Given the relevance of this table, we provide in Figure A1 the marginal plots for these interaction effects. Their examination shows that, once allowance is made for the interaction effect with the Innovation pillar, R&D always has a positive effect. It also has a positive effect for the high and intermediate stages of development. In Table A4 we present the results from the interaction of SFs with the regional competitiveness pillars. There is here some sign of a positive, albeit not very significant, interaction with the Efficiency and the Innovation pillars.

Before going into the interpretation of these results, it could be asked whether the significance of the interaction terms (for instance with the Innovation pillar) may stem from a common latent factor. In order to shed light upon this issue, we carry out some estimates, presented in Table A5, where all investments are interacted at the same time with a given regional competitiveness pillar. This exercise leaves basically untouched the strong positive interactions of R&D with all pillars and the negative interaction of GFCF with the Innovation pillar. On the other hand, for SFs the interactions with the Efficiency and the Innovation pillars become insignificant and only the interaction with Stage of development is now (marginally) significant. These results vindicate our strategy of allowing for all three forms of investment simultaneously, as well as for a rich set of interactions, as a safeguard against spurious correlations.

In Table A6 we gather the threads of our empirical exercise. Model 17 includes all the interaction terms that were significant in the previous table. Remarkably, once we allow simultaneously for all the interaction terms involving R&D, the only one keeping significance is that related to the Innovation pillar. We acquire further knowledge on this matter by first excluding from the estimates the least significant interactions of Model 17, that is R&D*Efficiency pillar and SFs*Stage of development pillar, and then the least significant interaction of Model 18, R&D*Basic pillar. We end up with Model 19, where the only significant interactive terms relate both GFCF and R&D to the Innovation pillar. These interactions have the same sign and similar size to their analogues, respectively in Tables A2 and A3. We provide in Figure A2 their marginal plots. GFCF always has a positive coefficient, although not significantly so for the upper 10% of the observations. R&D, on the other hand, has a positive *and significant* impact on employment for more than a half of the observations.

We can now turn to commenting the economic content of our estimates. First of all, we can see that the values obtained for the output and wage coefficients are stable throughout all models and pretty much in line with those in the literature. The GFCF coefficient is very close to that in Bogliacino and Vivarelli (2012), especially if one takes into account the interaction with the Innovation pillar, but starkly differs from the negative value found in Piva and Vivarelli (2018). Our interpretation of these results is that the sectoral data used in Piva and Vivarelli (2018) do not make allowance for the existence of intersectoral spillovers (also noted in a slightly different context by Goos et al., 2015, 2018). It is reasonable to surmise that these spillovers, if internalised into the estimated model, may make for a positive impact of gross fixed capital formation on employment. As far as the negative interaction of the Innovation pillar is concerned, we believe its explanation lies in the fact that regions placed on the technology frontier may be more likely to trade off an increase in the capital stock with a reduction in employment. On the other hand, in regions below the technology frontier gross fixed capital formation and employment growth may actually be complementary. This story is broadly consistent with the results in Goos et al. (2018), according to which the high-tech job multiplier is larger in regions with an abundance of less-skilled workers and lower gross output per capita.

Both these explanations spring from the wide cross-sectional variation which is inherent to our regional sample. Yet, although regions differ from sectors, especially because of the above noted role for intersectoral spillovers, the evidence we find for R&D is very much in line with the results from Piva and Vivarelli (2018) and Roy et al. (2018). The labour-friendly nature of R&D expenditures comes out in regional contexts characterised by a relatively advanced technology. In regions with below-average values of the Innovation pillar the employment impact of R&D is first negative and then insignificant (it begins to be positive and significant when the value of the pillar overtakes the 0.5 mark). It is also noteworthy that, while there is a prima facie presumption of a conditioning effect on R&D for all the regional competitiveness indicators, the interaction with the Innovation pillar, which most makes sense from the a priori standpoint, is the one that stands up to our specification checks.

Finally, we invariably find a positive effect of SFs in employment, while this impact is much more ambiguous in the literature. We have two explanations for that. First, our specifications are richer than most of the specifications adopted in the literature, and hence less likely to be affected by an omitted variable bias. Second, we adopt a new empirical indicator for the SFs, the modelled expenditures from the "Historic EU payments" provided by the EU Commission, that are likely to give a better representation of the actual impact of the SFs in the EU regions.

5. Concluding remarks

In this study we explored the employment impact of gross fixed capital formation, R&D and European structural and investment funds using panel data from 2000 to 2016 across NUTS2 level European regions. We estimate a conditional labour demand function through system GMM and find that gross fixed capital investment and European Structural and Investment Funds are generally labour friendly, while the effect of R&D is conditional based upon regional characteristics. Only in NUTS2 regions characterised by a medium to high level of the Innovation pillar of competitiveness, R&D is likely to generate employment. This result is well in accord with some previous evidence in the literature. On the other hand, the negative association of the employment impact of gross fixed capital formation with the Innovation pillar, and the generally significant and positive impact of European Structural and Investment Funds highlight the novelty content of our dataset and out results.

Kastronos (2015), in a report to the European Commission, maintains that technological investment is a primary driver of economic growth and employment across European regions. Accordingly, the political agreement of the European Council with the European Parliament about the EU's 2021-2027 long-term budget includes a targeted reinforcement of EU programmes, including Horizon Europe, which has a strong emphasis on research infrastructures and an innovative Europe (https://www.consilium.europa.eu/en/policies/the-eu-budget/long-term-eu-budget-2021-2027/). Our results support this focus in the sense that the more regions will shift closer to the world technology frontier, the more R&D expenditure, rather than investment in physical assets, will be needed to create job opportunities. Encouraging an innovation-friendly environment in terms of technological readiness and business sophistication is also likely to increase the positive employment externalities of R&D. Our findings suggest too that European Structural and Investment Funds are capable to affect employment positively and, hence, caeteris paribus, to reduce income disparities across developed and peripheral European regions.

In future work we aim to sharpen the policy prescription content of our analysis by distinguishing between private and public R&D and by including output indicators of innovation in our framework. Both developments are going to require further work on the dataset, possibly integrating with other sources (such as for instance the Community Innovation Survey). Other interesting future developments may involve the sectoral disaggregation of the analysis and the assessment of the role of single European Structural and Investment Funds.

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Appendix

Table A1: The (EU28) NUTS2 level regions included in the sample of analysis

Country	*Number of regions*
UK	37
Germany	36
France	22
Italy	21
Spain	19
Poland	16
Greece	13
Netherlands	12
Belgium	11
Austria	9
Czech Republic	8
Romania	8
Sweden	8
Hungary	7
Portugal	7
Bulgaria	6
Finland	5
Denmark	5
Slovakia	4
Republic of Ireland	2
Croatia	1
Cyprus	1
Estonia	1
Latvia	1
Lithuania	1
Luxembourg	1
Malta	1
Slovenia	1
Total	**264**

Table A2: System GMM analysis across European regions: Baseline model and GFCF interacted with regional competitiveness pillars, one by one

Dep. var.: Ln employment	Baseline Model	Model (1)	Model (2)	Model (3)	Model (4)
Regressors	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$
Ln Employment *(t-1)*	0.803*** (0.037)	0.797*** (0.036)	0.794*** (0.034)	0.780*** (0.034)	0.793*** (0.037)
Ln Employment *(t-2)*	-0.102*** (0.029)	-0.101*** (0.029)	-0.101*** (0.034)	-0.098*** (0.020)	-0.097*** (0.020)
Ln Wage per employee	-0.236*** (0.026)	-0.235*** (0.026)	-0.237*** (0.027)	-0.239*** (0.020)	-0.233*** (0.020)
Ln Wage per employee *(t-1)*	0.124*** (0.021)	0.122*** (0.021)	0.123*** (0.021)	0.120*** (0.210)	0.121*** (0.021)
Ln GDP *(t-1)*	0.047*** (0.011)	0.049*** (0.021)	0.049*** (0.011)	0.047*** (0.012)	0.050*** (0.011)
Ln GFCF	0.076*** (0.008)	0.086*** (0.013)	0.099*** (0.016)	0.096*** (0.010)	0.072*** (0.015)
Ln (GFCF*Basic pillar)	-	-0.024 (0.030)	-	-	-
Ln (GFCF*Efficiency pillar)	-	-	-0.044 (0.033)	-	-
Ln (GFCF*Innovation pillar)	-	-	-	-0.065** (0.028)	-
Ln (GFCF*Stage of dev. pillar)	-	-	-	-	0.003 (0.008)
Ln R&D	0.004 (0.006)	0.003 (0.005)	0.002 (0.005)	0.004 (0.005)	0.002 (0.005)
Ln SFs *(t-1)*	0.011*** (0.003)	0.011*** (0.002)	0.011*** (0.002)	0.011*** (0.002)	0.118*** (0.003)
Year dummies	Yes	Yes	Yes	Yes	Yes
AR (1) P-value	0.000	0.000	0.000	0.000	0.000
AR (2) P-value	0.764	0.825	0.835	0.996	0.803
Hansen test P-value	0.560	0.646	0.656	0.674	0.609
No. of observations	3268	3268	3268	3268	3268

***/**/* 1%, 5%, 10% significance level. Robust standard errors reported in the parentheses.

Table A3: System GMM analysis across European regions: Expenditure on R&D interacted with regional competitiveness pillars, one by one

Dep. var.: Ln employment	Model (5)	Model (6)	Model (7)	Model (8)
Regressors	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$
Ln Employment *(t-1)*	0.7976*** (0.037)	0.7926*** (0.0357)	0.7870*** (0.0366)	0.7893*** (0.0388)
Ln Employment *(t-2)*	-0.1114*** (0.023)	-0.1051*** (0.0289)	-0.1096*** (0.0290)	-0.1145*** (0.0296)
Ln Wage per employee	-0.2245*** (0.029)	-0.2271*** (0.0292)	-0.2193*** (0.0290)	-0.2194*** (0.0279)
Ln Wage per employee *(t-1)*	0.1261*** (0.022)	0.1226*** (0.0221)	0.1242*** (0.0223)	0.1305*** (0.0224)
Ln GDP *(t-1)*	0.0465*** (0.012)	0.0493*** (0.0117)	0.0481*** (0.0118)	0.0473*** (0.0125)
Ln GFCF	0.0766*** (0.008)	0.0759*** (0.0080)	0.0757*** (0.0081)	0.0790*** (0.0084)
Ln R&D	-0.0124 (0.010)	-0.0236* (0.0137)	-0.0117 (0.0081)	-0.0187* (0.0105)
Ln (R&D*Basic pillar)	0.0394** (0.018)	-	-	-
Ln (R&D*Efficiency pillar)	-	0.0479** (0.0221)	-	-
Ln (R&D*Innovation pillar)	-	-	0.0509*** (0.0171)	-
Ln (R&D*Stage of dev. pillar)	-	-	-	0.0149*** (0.0050)
Ln SFs *(t-1)*	0.0072** (0.0035)	0.0098*** (0.0031)	0.0104*** (0.0031)	0.0077* (0.0043)
Year dummies	Yes	Yes	Yes	Yes
AR (1) P-value	0.000	0.000	0.000	0.000
AR (2) P-value	0.656	0.723	0.693	0.724
Hansen test P-value	0.654	0.668	0.667	0.672
No. of observations	3268	3268	3268	3268

***/**/* 1%, 5%, 10% significance level. Robust standard errors reported in the parentheses.

Table A4: System GMM analysis across European regions: SFs interacted with regional competitiveness pillars, one by one				
Dep. var.: Ln employment	Model (9)	Model (10)	Model (11)	Model (12)
Regressors	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$
Ln Employment *(t-1)*	0.7919*** (0.0392)	0.7926*** (0.0379)	0.7802*** (0.0381)	0.8010*** (0.0386)
Ln Employment *(t-2)*	-0.0974*** (0.0300)	-0.1021*** (0.0301)	-0.0993*** (0.0298)	-0.1017*** (0.0300)
Ln Wage per employee	-0.2341*** (0.0293)	-0.2265*** (0.0292)	-0.2255*** (0.0289)	-0.2298*** (0.0271)
Ln Wage per employee *(t-1)*	0.1209*** (0.0214)	0.1225*** (0.0219)	0.1217*** (0.0218)	0.1229*** (0.0217)
Ln GDP *(t-1)*	0.0542*** (0.0117)	0.0484*** (0.0118)	0.0503*** (0.0118)	0.0479*** (0.0118)
Ln GFCF	0.0833*** (0.0057)	0.0766*** (0.0075)	0.0790*** (0.0077)	0.0765*** (0.0076)
Ln R&D	0.0012 (0.0057)	0.0040 (0.0057)	0.0037 (0.0059)	0.0041 (0.0059)
Ln SFs *(t-1)*	0.0825 (0.2069)	-0.3567* (0.1953)	-0.1776** (0.0751)	0.0093 (0.0242)
Ln (SFs*Basic pillar)	-0.1038 (0.3101)	-	-	-
Ln (SFs*Efficiency pillar)	-	0.5567* (0.2980)	-	-
Ln (SFs*Innovation pillar)	-	-	0.4447** (0.1780)	-
Ln (SFs*Stage of dev. pillar)	-	-	-	0.0012 (0.0114)
Year dummies	Yes	Yes	Yes	Yes
AR (1) P-value	0.000	0.000	0.000	0.000
AR (2) P-value	0.879	0.742	0.792	0.761
Hansen test P-value	0.656	0.654	0.656	0.683
No. of observations	3268	3268	3268	3268
***/**/* 1%, 5%, 10% significance level. Robust standard errors reported in the parentheses.				

Table A5: System GMM analysis across European regions: All investments interacted at the same time with the regional competitiveness pillars

Dep. var.: Ln employment	Model (13)	Model (14)	Model (15)	Model (16)
Regressors	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$	$\hat{\beta}$ $(s.e.)$
Ln Employment *(t-1)*	0.7826*** (0.0406)	0.7911*** (0.0380)	0.7734*** (0.0391)	0.7960*** (0.0414)
Ln Employment *(t-2)*	-0.1084*** (0.0302)	-0.1049*** (0.0301)	-0.1063*** (0.0300)	-0.1160*** (0.0300)
Ln Wage per employee	-0.2226*** (0.0306)	-0.2214*** (0.0300)	-0.2152*** (0.0300)	-0.2046*** (0.0282)
Ln Wage per employee *(t-1)*	0.1240*** (0.0218)	0.1218*** (0.0222)	0.1217*** (0.0225)	0.1309*** (0.0233)
Ln GDP *(t-1)*	0.0467*** (0.0126)	0.0453*** (0.0118)	0.0407*** (0.0120)	0.0438*** (0.0126)
Ln GFCF	0.0887*** (0.0135)	0.0935*** (0.0158)	0.0929*** (0.0109)	0.0707*** (0.0138)
Ln R&D	-0.0258*** (0.0096)	-0.0233* (0.0143)	-0.0107 (0.0089)	-0.0255** (0.0106)
Ln SFs *(t-1)*	0.2407 (0.2097)	-0.1361 (0.1895)	-0.0417 (0.0962)	0.0681* (0.0359)
Ln (GFCF*Basic pillar)	-0.0075 (0.0330)	-	-	-
Ln (R&D* Basic pillar)	0.0643*** (0.0186)	-	-	-
Ln (SFs*Basic pillar)	-0.3529 (0.3147)	-	-	-
Ln (GFCF*Efficiency pillar)	-	-0.0354 (0.0314)	-	-
Ln (R&D*Efficiency pillar)	-	0.0488** (0.0236)	-	-
Ln (SFs*Efficiency pillar)	-	0.2217 (0.2876)	-	-
Ln (GFCF* Innovation pillar)	-	-	-0.0555** (0.0277)	-
Ln (R&D*Innovation pillar)	-	-	0.0505** (0.0204)	-
Ln (SFs*Innovation pillar)	-	-	0.1236 (0.2030)	-
Ln (GFCF*Stage of dev. pillar)	-	-	-	0.0057 (0.0077)
Ln (R&D*Stage of dev. pillar)	-	-	-	0.0185*** (0.0053)
Ln (SFs*Stage of dev. pillar)	-	-	-	-0.0278* (0.0169)
Year dummies	Yes	Yes	Yes	Yes
AR (1) P-value	0.000	0.000	0.000	0.000
AR (2) P-value	0.793	0.774	0.880	0.722
Hansen test P-value	0.346	0.340	0.332	0.310
No. of observations	3268	3268	3268	3268

***/**/* 1%, 5%, 10% significance level. Robust standard errors reported in the parentheses.

A6: System GMM analysis across European regions: Selected specifications interacted with various regional competitiveness pillars at the same time			
Dep. var.: Ln employment	Model (17)	Model (18)	Model (19)
Regressors	$\hat{\beta}\ (s.e.)$	$\hat{\beta}\ (s.e.)$	$\hat{\beta}\ (s.e.)$
Ln Employment *(t-1)*	0.8223*** (0.0393)	0.7950*** (0.0385)	0.7786*** (0.0353)
Ln Employment *(t-2)*	-0.1112*** (0.0286)	-0.1104*** (0.0298)	-0.1079*** (0.0290)
Ln Wage per employee	-0.2329*** (0.0280)	-0.2335*** (0.0301)	-0.2237*** (0.0292)
Ln Wage per employee *(t-1)*	0.1250*** (0.0223)	0.1245*** (0.0218)	0.1219*** (0.0221)
Ln GDP *(t-1)*	0.0557*** (0.0115)	0.0605*** (0.0118)	0.0436*** (0.0119)
Ln GFCF	0.0749*** (0.0102)	0.0819*** (0.0112)	0.0921*** (0.0107)
Ln R&D	0.0036 (0.0166)	-0.0051 (0.0107)	-0.0091 (0.0084)
Ln SFs *(t-1)*	0.0393 (0.0338)	0.0120*** (0.0041)	0.0097*** (0.0031)
Ln (GFCF*Basic pillar)	-	-	-
Ln (R&D*Basic pillar)	-0.0474 (0.0345)	-0.0428 (0.0375)	-
Ln (SFs*Basic pillar)	-	-	-
Ln (GFCF*Efficiency pillar)	-	-	-
Ln (R&D*Efficiency pillar)	0.0010 (0.0321)	-	-
Ln (SFs*Efficiency pillar)	-		-
Ln (GFCF*Innovation pillar)	-0.0130 (0.0281)	-0.0341 (0.0278)	-0.0604** (0.0282)
Ln (R&D*Innovation pillar)	0.1036** (0.0535)	0.0967*** (0.3390)	0.0468*** (0.0177)
Ln (SFs*Innovation pillar)	-	-	-
Ln (GFCF*Stage of dev. pillar)	-	-	-
Ln (R&D Stage of dev. pillar)	-0.0067 (0.0081)	-	-
Ln (SFs*Stage of dev. pillar)	-0.0111 (0.0160)	-	-
Year dummies	Yes	Yes	Yes
AR (1) P-value	0.000	0.000	0.000
AR (2) P-value	0.702	0.791	0.852
Hansen test P-value	0.869	0.441	0.668
No. of observations	3268	3268	3268

***/**/* 1%, 5%, 10% significance level. Robust standard errors reported in the parentheses.

Figure A1: Marginal plots of R&D, interaction with regional competitiveness index pillars, from Table A3

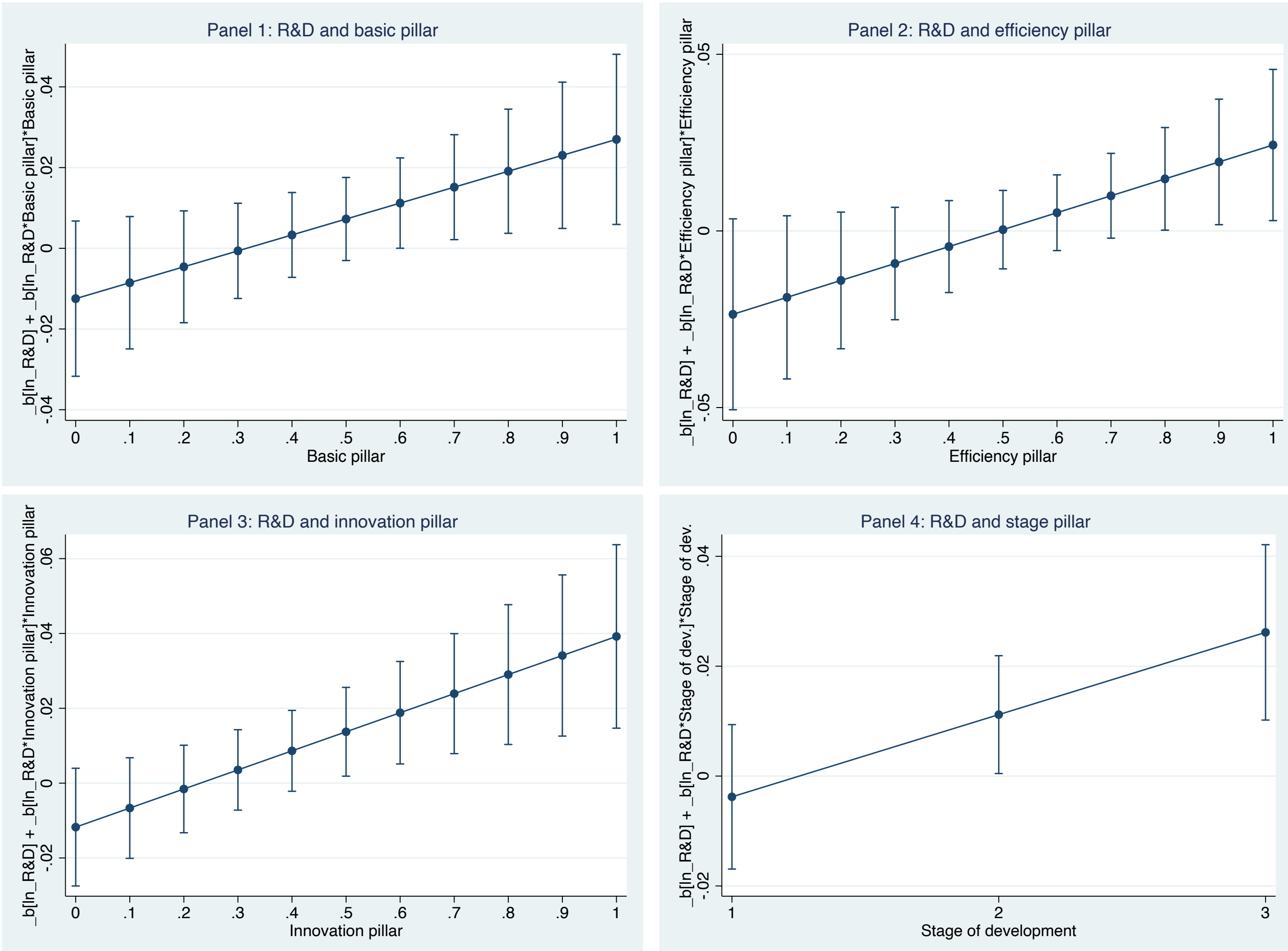

Figure A2: Marginal plots of GFCC and R&D, interaction with Innovation pillar, from Model 19, Table A6