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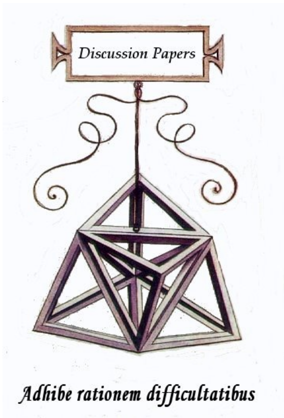

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Social Investment and youth labour market participation: a EU regional analysis

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Abstract

In this paper, we first rely on small area techniques to derive from EU-SILC survey new indicators of compensatory and investment policies at regional level. While compensatory policies have mainly the goal of protecting individuals from "old" risks (e.g. old-age), investment-related social policies tend to focus more on "new social risks" (i.e. skill deficits). We rely on these new indicators to perform a data-driven SVAR analysis to investigate the casual relationships between youth labour market outcomes and these two types of spending. Our results support the view that investment policies are more effective for tackling new social challenges.

Keywords: small area techniques, investment policies, compensatory policies, SVAR analysis; ICA

JEL: C18, C54, E02

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1 Introduction

Since its inception, the EU has experienced robust convergence in terms of GDP per capita. However, even though there was a convergence process at the country level, the convergence at the regional level has been much weaker. In particular, there are still some countries exhibiting regional divergence or sustained North-South (or West-East) divides (Monfort [2008], Wunsch [2013]). That means, for example, that there tends to be much higher negative correlation between GDP and unemployment within countries than across countries. However, both mainstream and heterodox theories cannot explain the existence of these different regional trajectories and the weakness of the convergence processes among them (Iammarino et al. [2018]).

From an empirical perspective, this obviously raises the question about the role of the different policies adopted in the last years, both at European and country level (Wunsch [2013]). In this regard, in many European countries, several studies has documented a transition from the traditional welfare states to a new investment state (e.g. Bonoli [2007], Ferragina et al. [2015], Obinger and Starke [2014]). In particular, it is possible to differentiate between two broad types of policies: *investment-related* and *compensatory* policies (see, for example, Nikolai [2012]). Compensatory policies are mainly based on a contribution-financed social security with the goal of protecting individuals from "old" risks, such as unemployment and old-age. Investment-related social policies tend to focus more on "new social risks" to overcome, through education and training, skill deficits that may emerge in post-industrial labour markets. Furthermore, these policies tend to reconcile work and family life. Thus, the focus is on investment in human capital as well as the provisions for the needs and the future of the younger generations. For example, Nikolai [2012] finds mixed evidence in support of a shift toward more social investment, with Continental and Southern European Countries being characterized by more spending for compensatory and less spending for investment-related policy (especially education).

However, without having expenditure data disaggregated at a regional level, it is quite impossible to properly assess the impact of the two types of policies. As it has also been highlighted by the DG Regional Policy of the European Commission, in order to better target policy measures, there is an increasing need of social policy indicators developed at regional regional level (Verma et al. [2013]). Therefore, the first contribution of our paper is to present new indicators of regional spending (which are comparable across regions and countries) which are derived through the cumulation methodology applied to the EU Statistics on Income and Living Conditions (EU-SILC) dataset (see Betti et al. [2012]). In so doing, we will be able to derive for a subset of European countries, two regional indicators of compensatory and investment spending which are comparable across time and across countries.

The second contribution of our paper is to investigate the impact of these indicators on youth labour market participation within a Structural Vector Autoregressive (SVAR) framework. In particular, we rely on a data-driven approach, recently introduced in the literature by Moneta et al. [2013], which rely on Indipendent Component Analysis to identify structural parameters in SVAR (Gouriéroux et al. [2017], Lanne et al. [2017],Shimizu et al. [2006]). In particular, we adopt a more general identification scheme, called *LiNGAM, i.e.* Linear Non-Gaussian Acyclic Model (Shimizu et al. [2006]), to identify contemporaneous paramaters in order to identify the causal relationships among variables. Differently from standard methods (such as Cholesky decompositon), which necessarily requires either theoretical justification, this method has the great advantage to achieve *identification* directly from the data and statistical analysis alone.

While the low level of market participation of young people is not a new problem, the scale that has reached in the current economic crises is astonishing. For example, in some countries the youth unemployment rate has doubled or tripled since the onset of the recession (Mascherini et al. [2012]). Therefore, traditional indicators of labour market participation, such as unemployment and youth employment rates do not adequately capture new "grey" area that represent market attachment in contemporary societies (Mascherini et al. [2012]). For this reason, we also investigate the effects of investment and compensatory policies on the share of young people who are disengaged from both work and education, usually indicated with the term NEETs (*not* in *employment*, *education* and *training*). The needs to focus more on NEETs is now central in the European policy debate, and the term is explicitly mentioned in the Europe 2020 agenda as well as in the 2012 Employment Package "*Towards a job-rich recovery*" (Eurofond [2012]). In particular, at the European level, the term NEETs has caught the attention of policy markers as a useful indicators for monitoring the labour market participation and social situation of the young.

Our analysis of regional spending suggests that, even though the evidence is consistent with previous analyses using national data to what concern the compensatory component (see, for example, Hemerijck [2013], Heitzmann et al. [2015], Hemerijck [2017]), there is higher regional variation in the investment component, even within the same country. The results from our SVAR analysis also suggest that investment policies are more effective to reduce the level of NEETs and increase the level of youth employment.

In the following, we first describe how we derive our dataset. In particular, in section 2 we briefly review the main statistics on labour market participation of the young, which are currently available at Eurostat, and the main issues related to data on regional expenditure. In section 3 we describe the cumulation methodology, and we apply it to EU-SILC in order to develop indicators of compensatory and investment spending at regional level, while in section 4 we rely on a recently developed econometric methodology (Moneta et al. [2013]) to investigate the effects of these types of policies on labour market outcomes. Section 5 concludes our argument.

2 Issues with regional data

In this section we describe the economic indicators of youth labour market participation we will use in our analysis (i.e. our outcome variables), and we discuss the main issues related to the collection of regional data on expenditure (i.e. our policy variables).

2.1 Regional Data on young people's labour market participation

While NEETs and youth (un)employment are related concepts, there are important differences. In particular, unemployment rate measures the share of the labour population who are not able to find a job. More precisely, it is a measure of those who are out of work, but have actively looked for work in the recent past and is available for work in the near future. However, this measure does not take into account the "new risks", that is it does not capture those who became discouraged and decided to stop looking for a job (Mascherini et al. [2012], Eurofond [2012]). This implies that the unemployment rate may stop falling even when a relevant number of individuals are at high risk of labour market and social exclusion. A similar remark can be made for youth employment rate, which measure the share of the working age population (i.e. people aged 15 to 24) who is currently employed. In contrast, the NEETs captures the share of the young population currently disengaged from the labour market and education, namely unemployed and inactive young people not in education or training. More precisely, we have

$$Youth\ unemployment\ rate = \frac{Total\ young\ unemployed}{Young\ Labour\ Force} \tag{1}$$

$$NEET\ rate = \frac{Total\ NEET}{Young\ Population} \tag{2}$$

For this reason, to have an additional indicator for monitoring the situation of young people in the framework of the Europe 2020 strategy the European Commission (DG EMPL) agreed on a definition and methodology for a standardized indicator to quantify the size of the NEETs population among Member States. This indicator has been built by Eurostat using equation (2), and is available at Eurostat.[1] We report it in Table (1) as computed at NUTS1 level, along with measures for unemployment and employment of the young for the 15-24 age group.

INSERT TABLE (1) HERE

In particular, this table reports for each variable, in addition to the mean (μ) and the standard deviation (σ) computed at country-level, the coefficient of variation (CV). This latter indicator is a normalized measure of dispersion defined as the ratio between the standard deviation and the mean (i.e. $\frac{\sigma}{|\mu|}$). For a given standard deviation value, it thus indicates a high or low degree of variability only in relation to the mean value. Since the coefficient of variation is a measure of relative variability which is unit-free (i.e. does not depend on the unit of measurement), it is often preferred to the standard deviation which has no interpretable meaning on its own. In particular, the CV indicators is among those indicators of $\sigma - convergence$, which is a term used to refer to a reduction of disparities among regions over time (see Monfort [2008]).[2]

[1] More precisely, the numerator of the indicator refers to persons who meet the following two definitions: a) they are not employed and b) they have not received any training or education in the four weeks preceding the survey.

[2] The concept of $\sigma - convergence$ is strictly related to the concept of $\beta - convergence$, which implies a catching up process. Formally, $\beta - convergence$ is necessary but not sufficient for $\sigma - convergence$.

For example, from Table (1) we can observe that high level of youth employment rates can be observed in Austria (AT), Denmark (DK), Finland (FI), the Netherlands (NL), and United Kingdom (UK). Conversely, young people seem particularly disengaged from the labour market in Slovakia (SK), Bulgaria (BG), Lithuania (LT), Italy (IT), Hungary (HU) and Greece (GR). Moreover, although there is not high variation in youth employment rate across European countries, there is a large variation in youth unemployment rate (with the CV being between 13-15%). The level of NEETs is also very different among EU countries.

However, as Figure (1) suggests, the EU-28 CV computed at NUTS1 level is increasing over time for all these measures. This suggests a divergence among EU countries in the level of unemployment, employment and NEETs.

INSERT Figure (1) HERE

Finally, it is important to notice, that the increase in Regional disparities within EU as a whole does not prevent disparities from decreasing within each Member states (Monfort [2008]). For this reason, we also compute CV indicators for each Member State at regional level (where NUTS1 level data are available). However, even when we look at the regional variation between countries for the same variable, we can notice that for some countries, the regional variation can be very large: for example, in Italy and Portugal the CV is about 40%. The aim of the next sections will be to investigate how tcompensatory or investment-related policies affect these outcome variables.

2.2 Regional data on expenditure

Social policies that are defined as social investment policies are usually categorized according to three aspects (Heitzmann et al. [2015]):

1. Policies that help maintain or restore the capacity of labour market participants (e.g. old age pensions);

2. Policies that facilitate the entrance of new labour market participants (short-term unemployment insurance; short-term maternity leave)

3. Policies that invest in the capacity of new labour market participants (elderly care, child care);

Unfortunately data on these dimensions are often not available at regional level and for several years. For these reasons, any attempt to examine the development of social investment across regions and countries often fails. Even if alternative approaches are available (e.g. De Deken et al. [2014]), because of data limitation, researchers largely end up with two categories, one for compensatory (i.e. the old risk categories) and another for social investment policies (i.e. the new risk categories).

In this analysis, we similarly distinguish between these two broad categories, but in addition to previous research we rely on data from EU-SILC survey to derive indicators at country regional level. The EU-SILC is a very rich survey on income and social condition collected at household (and individual) level under a standard integrated design by nearly all EU countries. As explained below, we rely on small area estimation (SAE) techniques to derive regional indicators of investment and compensatory policies from EU-SILC survey (Betti et al. [2012]). More precisely, for each category of spending (investment and compensatory), we derive a series of indicators by computing the average amount received per household at NUTS1 level. This an important contribution to previous studies, in which indicators of total spending where usually derived – at a country level – as a share of the GDP (see also Prandini et al (2015) on this issue). In particular, as described in the next section, we rely on cumulation technique (Betti et al. [2012], Verma et al. [2013]).

3 Cumulation Methodology

In order to better target policy measures, there is an increasing need of social policy indicators developed at regional regional level. For example, the DG Regional Policy of the European Commission is aiming to use regional level data to correctly identify regions with the highest proportion of people being poor or socially excluded Commission [2010]. However, regional level data, which is homogeneously gathered across countries, is often lacking.

For these reasons, EU-wide comparative datasets such as EU-SILC, even though primarily developed to construct indicators at the national level, can serve as a unique source for generating comparative indicators at regional levels through SAE techniques. Such methodologies have already been proved to be successful to derive regional measures of poverty (Betti et al. [2012]Verma et al. [2013, 2010], Marchetti et al. [2015], Betti et al. [2012]).

In particular, two types of measures can be constructed from national survey by aggregating information on individual elementary units at the regional level:

1. **average measures** such as totals, means, rates and proportions constructed by aggregating or averaging individual values; and

2. **distributional measures**, such as measures of variation or dispersion among households and persons in the region.

In particular, we rely on the first type of measures, which are obtained by cumulating and consolidating the information over waves of national sample surveys in order to obtain measures which permit greater spatial disaggregation. However, many measures of averages can also serve as indicators of disparity and deprivation when seen in the regional context: the dispersion of regional means is of direct relevance in the identification of geographical disparity (Verma et al. [2013]).

To be able to compute spatial statistics through cumulation, the only information required is the strata identifiers from which individuals are sampled from. More specifically in our case, to cumulate over waves we need to know from which NUTS1 region the individuals were sampled. Unfortunately, this information is only available for a limited numbers of countries, namely: Austria, Belgium, Bulgaria, Czech Republic, France, Greece, Hungary, Italy, Poland, Spain, Sweden, United Kingdom. Therefore, only for this group of countries, we were able to derive a an indicator of regional spending at NUTS1 level along with a measure of dispersion (i.e. the regional CV). For the remain group of countries, we were only able to derive country-level indicators from EU-SILC.

Specifically, we proceed as follows. Given that we have the cross-sectional dataset of the EU-SILC survey for 9 consecutive years (from 2006 to 2014), the objective is to compute the cumulative average of a given measure y over 3 years, i.e. $\bar{y}_t^c$.

We first construct for each year (i.e. for each EU-SILC wave) the yearly average relying on N individual observations (i.e. $\bar{y}_t = \frac{1}{N}\sum_{i=1}^{N} y_i$). Then for each year t, we estimate the required statistic $\bar{y}^c_t$ as the one-year moving average over 3 consecutive years of the annual average $\bar{y}_t$, that is

$$\bar{y}^c_t = \frac{\bar{y}_{t-1} + \bar{y}_t + \bar{y}_{t+1}}{3} = \frac{1}{t}\sum_{j=1}^{t} \bar{y}_j$$

However, to allow for more variability in our dataset, we only allow for one overlapping year across observations, relying therefore on 4 central years, i.e. we select $\bar{y}^c_{2007}$, $\bar{y}^c_{2009}$, $\bar{y}^c_{2011}$, $\bar{y}^c_{2013}$.

3.1 EU-SILC Variable Selection.

As explained above our reference data is the EU-SILC survey, which provide us the necessary variables to compute indicators of compensatory and investment policies as in the current literature. In particular, we rely on the following variables from EU-SILC data available from questions related to household gross income to derive the level of **compensatory spending** (in parentheses we report the EU-SILC number of each variable):[3]

1. unemployment benefits (PY090G): refers to (full o partial) benefits for benefits compensating for loss of earnings. It also includes early retirement, *vocational training*, redundancy compensation, severance and termination payments;
2. old-age & survivors benefits (PY100G): refers to the provision of social protection against the risk linked to old age (e.g. old age pensions, care allowance) or to the loss of the spouse (survivor's pension, death grant);
3. sickness benefits (PY120G): refers to benefits that replace in whole or in part loss of earnings during temporary inability to work due to sickness or injury (e.g.. paid sick leave);
4. disability benefits (PY130G): refers to benefits that provide an income to persons impaired by a physical or mental disability (e.g. disability pensions, care allowance);

Similarly to derive the level of **investment policies**, we select the following variables:

[3]See http://ec.europa.eu/eurostat/web/income-and-living-conditions/methodology/list-variables to have a complete lists of the variables available from EU-SILC.

1. education-related allowances (PY140G): refers to grants, scholarships and other education help received by students;

2. family/children allowances (HY050G): refers to benefits that provide financial support to bringing up children and relatives other than children (e.g. Birth grant, Parental leave benefits, earning-related payments to compensate loss of earnings);

3. housing allowance (HY070G/HY070Y)): interventions that help households meet the costs of housing (e.g. rent benefits granted to tenants);

More generally, both groups of variables are defined as current transfers received by the household during the reference period, through collectively organized schemes, or outside such schemes by government units and Non-Profits Institutions Serving Households (NPISHs). Therefore, this definition includes the value of any social contributions and income tax payable on the benefits by the beneficiary to social insurance scheme or tax authorities. To be included in these groups of variables, the transfer must meet two criteria: i) the coverage is compulsory; ii) it is based on the principle of social solidarity. Importantly, the social benefits included in EU-SILC, with the exception of housing benefits, are restricted to cash benefits.

3.2 Regional Spending Results

We now apply the cumulation methodology to obtain – for each one of the selected variable described in the previous section – the NUTS1 level average. We then categorized all these variables into the two groups of compensatory and investment variables. The national average over 4 years is reported in Table (2), while in Figure (2) we report the CV indicators computed at European level (EU28) for both total investment and total compensatory variables.

INSERT TABLE (2) HERE

INSERT FIGURE (2) HERE

First of all, we observe that there is a remarkable difference in the CV for total investment across Europe, being the CV almost 0.70 in 2007 and much larger in comparison to the CV for total compensatory. However, we also observe that even though the difference for total investment remains higher than for total compensatory, there is a tendency for a reduction in the period 2007-2013. In line with Nikolai (2012) and Obinger and Starke [2014], but relying on a very different dataset, we therefore find evidence for a $\sigma - convergence$ in investment spending in Europe, while we observe a more stable pattern for total spending for compensatory policy.

In addition, we are able to compute indicators of regional variation in total spending within a group of European countries. As highlighted above, even if regional disparities decrease (or increase) when considering the EU as whole, it does not prevent disparities from increasing (or decreasing) with each Member states. The CV for total compensatory and total investment are respectively reported in Figure (3). While the regional CVs are much smaller than European CVs, we can similarly observe a similar pattern. That is, we also observe within countries a much smaller level of the CVs for compensatory policy (being always smaller than 0.15), while we observe a larger level of CVs for total investment (being in some cases around 0.40). However, even in this case, we observe a tendency for a $\sigma - convergence$, with the only exception being Bulgaria and Greece for total investment.

INSERT FIGURE (3) HERE

4 SVAR Analysis

In this section we use the dataset described in the previous sections to estimate a structural vector autoregressions (SVAR) model to identify casual relationships among our variables of interests. SVAR models are among the most prevalent tools in empirical economics to analyze casual effects (see Stock and Watson [2007]). The underlying set-up is the reduced-form Vector Autoregressive (VAR) model, which is a system of equations for a vector of k variables, in which each variable is made dependent on its own past values, the lagged values of the other variables, and a specific white-noise error term. This model can be easily estimated through standard regression methods (e.g. OLS), since all the regressors are pre-determined variables. The reduced-form VAR model, however, does not provide enough information to study the causal relationships among the variables and is typically used for the sake of descriptive statistics and forecasting only. It does not provide the structural information because it typically omits the possible influence of contemporaneous values and it delivers error terms that are usually correlated (across variables), so that they cannot be interpreted as genuine shocks affecting the system or as exogenous interventions. Thus, the estimated parameters cannot be used to predict the effect of an intervention. Structural analysis is instead the objective of SVAR models, which add structural information to the VAR (i.e. they solve the *identification problem*) so that one can recover the causal relationships existing among the variables under investigation. The common approach is to derive this structural information from economic theory or from institutional knowledge related to the data generating mechanism (Stock and Watson [2007]).

In the following, we instead rely on a more data-driven approach recently developed in the literature by Moneta et al. [2013] to fully identify the SVAR model. In particular, Moneta et al. [2013] have shown that if the estimated (reduced-form) VAR residuals are non-Guassian, one can exploit higher-order statistics of the data and apply *ICA*, i.e. *Independent Component Analysis* (*Hyvärinen et al. [2001]*). This method has therefore the great advantage of avoiding subjective choices and theory-driven considerations to estimate SVAR model. ICA methods for the statistical identification of SVAR models have also been proposed by Gouriéroux et al. [2017] and Lanne et al. [2017]. In the following we briefly review this methodology. For interesting applications of this method see Brenner et al. [2017], Guerini and Moneta [2017], Ciarli et al. [2018], Herwartz [2018].

4.1 Independent component analysis and SVAR identification

We can denote by $\mathbf{Y}_t = (Y_{1t}, .., Y_{kt})'$ the values at a particular time t of a multiple time series dataset composed of k variables collected for T periods. A simple - but useful - way of representing the data generating process is to model the value of each variable Y_{kt} as a linear combination of the previous values of all the variables as well as their contemporaneous values:

$$\mathbf{Y}_t = \mathbf{B}\mathbf{Y}_t + \mathbf{\Gamma}_1\mathbf{Y}_{t-1} + ... + \mathbf{\Gamma}_p\mathbf{Y}_{t-p} + \boldsymbol{\epsilon}_t \tag{3}$$

where the diagonal elements of the matrix $\mathbf{B}$ are set equal to zero by definition and where $\boldsymbol{\epsilon}_t$ represents a vector of error terms with covariance matrix $E(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') = \sum_{\boldsymbol{\epsilon}}$. Since these terms represent the structural shocks affecting the system, we can assume that they are uncorrelated, so that $\sum_{\epsilon}$ is a diagonal matrix and that $\epsilon_{1t}, \ldots, \epsilon_{kt}$ are mutually independent. Uncorrelatedness of the shocks is a standard assumption in the SVAR literature, while independence is usually not explicitly assumed (also because in a Gaussian setting it is equivalent to uncorrelatedness), but is implicit in many discussions about the economic interpretations of the shocks (Kilian and Lütkepohl [2017]).

The model in the standard SVAR form c an be equivalently written as

$$\mathbf{\Gamma}_0 \mathbf{Y}_t = \mathbf{\Gamma}_1 \mathbf{Y}_{t-1} + ... + \mathbf{\Gamma}_p \mathbf{Y}_{t-p} + \boldsymbol{\epsilon}_t \tag{4}$$

where $\mathbf{\Gamma}_0 = \mathbf{I} - \mathbf{B}$. Since variables are endogenous in (3) and (4) this model cannot be directly estimated without biases. It is typical therefore to derive and estimate the *VAR reduced form*

$$\mathbf{Y}_t = \mathbf{\Gamma}_0^{-1} \mathbf{\Gamma}_1 \mathbf{Y}_{t-1} + ... + \mathbf{\Gamma}_0^{-1} \mathbf{\Gamma}_p \mathbf{Y}_{t-p} + \mathbf{\Gamma}_0^{-1} \boldsymbol{\epsilon}_t$$

$$\mathbf{Y}_t = \mathbf{A}_1 \mathbf{Y}_{t-1} + \ldots + \mathbf{A}_p \mathbf{Y}_{t-p} + \mathbf{u}_t \tag{5}$$

which can be straightforwardly estimated through standard regression methods (e.g. OLS regressions).

The problem of *identification* is therefore the problem of finding the appropriate $\mathbf{\Gamma}_0$. Traditionally, this problem is solved by choosing $\mathbf{\Gamma}_0$ on the basis of a Cholesky factorization of the estimated matrix Σ_u of covariance among the reduced-form residuals $\mathbf{u}_t$. This imposes a recursive structure among the variables ($\mathbf{\Gamma}_0$ results lower triangular) and yields orthogonal structural shocks. A problem with this method, however, is the Cholesky factorization is dependent on the chosen order of the variables $(Y_{1t}, \ldots, Y_{kt})'$ in $\mathbf{Y}_t$. A re-ordering of the variable will produce a different Cholesky factorization and a different recursive causal chain among the variables. Thus, this way of proceeding can only be used when the recursive ordering implied by the identification scheme is supported by theoretical or institutional knowledge.

The method proposed by Moneta et al. [2013] instead, applies a search procedure based on ICA, which is able to find, on the basis of data and statistical analysis alone, the appropriate matrix $\mathbf{\Gamma}_0$

that relates the vector of the structural shocks $\boldsymbol{\epsilon}_t$ such that $\boldsymbol{\Gamma_0 u_t} = \epsilon_t$. ICA starts from the consideration that $\mathbf{u_t}$ are mixtures, i.e. linear combinations, of latent sources, or *independent components*, $\boldsymbol{\epsilon}_t$. It is crucial for ICA, that $\boldsymbol{\epsilon}_t$ are independent and non-Gaussian. Hence, $\boldsymbol{\Gamma_0}$ and ϵ_t are recovered by searching the linear combinations of $\mathbf{u_t}$ that are least statistically dependent in the style of unsupervised statistical learning typical of the machine learning research (Hyvärinen et al. [2001]), where the measure of statistical dependence used in this context is mutual information. Non-Gaussianity here goes hand in hand with independence: if $\boldsymbol{\epsilon}_t$ are non-Gaussian and independent, any linear combination of them will be closer to a Gaussian distribution (see central limit theorem). Then ICA can also be seen as method which searches for linear combinations of the data that maximizes non-Gaussianity. Hyvärinen et al. [2001] show that searching for linear combinations of $\mathbf{u_t}$ that are maximally independent (or least dependent) is equivalent to searching for $\boldsymbol{\epsilon}_t$ that are maximally non-Gaussian (using the notion of negentropy).

ICA alone, however, leaves undetermined the scale, the sign and order of the latent sources or structural shocks. In other words, $\boldsymbol{\Gamma}_0^{-1}$ is identifiable up to a column permutation and the multiplication of each of its diagonal elements by an arbitrary non-zero scalar (see Gouriéroux et al. [2017]). While the scale indeterminacy can easily solved by rescaling the column of $\boldsymbol{\Gamma}_0^{-1}$ so that all the shocks have unit variance, to solve indeterminacy of the order of the column of $\boldsymbol{\Gamma}_0^{-1}$ we need to make further steps, hinging on a further assumption.

Hence, in the following we rely on a more general identification scheme, called *LiNGAM, i.e.* Linear Non-Gaussian Acyclic Model (Shimizu et al. [2006], Moneta et al. [2013]), which incorporates ICA (more specifically, the FastICA algorithm by Hyvärinen et al. [2001]) in the first step, and then solves its indeterminacy problems by making the further assumption of *recursivenes*. This assumption means that, given a particular contemporaneous causal order of the variables, the $\boldsymbol{\Gamma_0}$ matrix can be transformed in a lower-triangular matrix and the contemporaneous causal order of the variables can be represented as a directed acyclic graph (Moneta et al. [2013]).[4]

It is important to notice that with *LiNGAM* the specific ordering of the variables that produces a lower triangular matrix ($\boldsymbol{\Gamma_0}$) is found out directly from the data, while in the Choleski scheme is given *a priori*. LiNGAM recovers the specific ordering of the variables that produces a lower

[4]For other methods based on a-theoretical search procedures based on normality see e.g. Swanson and Granger (1997), Bessler and Lee (2002), Demiralp and Hoover (2003).

triangular matrix ($\mathbf{\Gamma_0}$) from the output of ICA. Since, under recursiveness, both $\mathbf{\Gamma}_0$ and $\mathbf{\Gamma}_0^{-1}$ contain $k(k-1)/2$ zero entries, LiNGAM search for the unique permutation of $\mathbf{\Gamma}_0^{-1}$ which has non-zeros on the main diagonal. Since ICA estimates $\mathbf{\Gamma}_0^{-1}$ with measurement errors, LiNGAM actually searches the permutation which makes $\mathbf{\Gamma}_0^{-1}$ the closest as possible to lower triangular.

To summarise, our procedure is based on the following assumption:

1. the shocks $(\epsilon_{1t}, .., \epsilon_{kt})$ are non-normally distributed;
2. the shocks $(\epsilon_{1t}, .., \epsilon_{kt})$ are statistically independent;
3. the contemporaneous causal structure among $(Y_{1t}, .., Y_{kt})$ is *recursive*, that is there exists a re-ordering of the variables such that Γ_0 is lower triangular; the appropriate ordering of the variables, however, is not known to the researcher a priori.

The first assumption can be easily tested in the data. The second assumption is consistent with the interpretation of the elements of ϵ_t as structural shocks, i.e. exogenous processes that affect each variable of the system at each time in an independent way. In other words, this assumption means that any shock affecting, for example, the level of compensatory spending will not simultaneously affect the *shock* affecting the level of investment spending (although it can of course also affect the *variable* level of investment spending). This assumption, however, cannot be directly tested. Finally, the third assumption is necessary to perform the LiNGAM method. While it has the disadvantage of relying on a lower-triangular scheme, LiNGAM has the clear advantage compared to other algorithms of providing a complete identification of Γ_0 (with the entire causal graph of the contemporaneous structure) directly from the data.

4.2 Results

Relying on NUTS1 level data, we apply the ICA method to explore relationship between the level of compensatory and investment spending on the level of NEETs, unemployment and employment of the young. The results from this SVAR analysis are reported in Table (3) and can be interpreted in a causal way. The column variables are the cause, while the raw variables are the effects. The model is estimated in differences as variables are highly persistent. To validate the use of this methodology, we conducted checks on the empirical distributions of the VAR residuals (u) – as well as the results of the Shapiro-Wilk and the Jarque-Bera tests for normality; for all the variables, the tests rejects the null hypothesis of normality for the residuals (results are available upon request).

We start by observing the contemporaneous effects from Table (3). It must be noted that the structure of this table reflects the recursive structure implied by the ICA method. After re-ordering the variables (i.e. *NEETs, Employment Young, Log Compensatory, Unemployment Young, Log GDP* and *Log Inv)*, a lower triangular structure emerges.[5] For our purpose, this matrix is not very informative as it implies zero contemporaneous impact of investment spending on any of our variables of interests, i.e. (un-)employment and NEETs, and a significant impact of compensatory spending on GDP.

We therefore resort to an impulse-response function (IRF), which describes over a specified time horizon the evolution of the variable of interest after a (one-standard deviation) shock to another variable in the system. In Figure (4) we report the IRFs which are related to our policy variables, i.e. the total amount spent in compensatory and investments policies per household. The first thing to notice is that a one shock deviation in the level of compensatory spending per household (about 1000 Euro) will slightly and significantly increase up to 0.2% the level of NEETs, although this effect tends to become zero and statistically insignificant within three years. On the contrary, a shock in the level of investment spending per household (about 1350 Euro) will slighlty reduce the level of NEETS (about -0.2%) although this effect tends to become zero and statistically insignificant over time.

INSERT FIGURE (4) HERE

We then observe that the same shock in compensatory spending has no significant effect on employment, while the shock in investment spending has a small positive and significant effect on it (up to 0.4%). This latter effect tends to disappear after few years. Finally, we observe that the shock in compensatory spending has also a significant and positive effect on unemployment (up

[5]In other words, it contains $k \cdot (k-1)/2$ non-zero elements.

to 0.6%), while the shock in investment spending has a significant, although smaller, negative effect on it (up to -1%).

Overall, these results suggest that shocks in the level of total investment spending lead to more positive economic outcomes, while the opposite is true for total compensatory.

5 Conclusions

As it has been already highlighted, both in the literature and at the institutional level, the regional dimension does matter. There are strong differences across regions in EU, but also inside individual countries. Therefore, in order to better target policy measures, there is an increasing need of social policy indicators developed at regional level. Moreover, since young people paid the highest price during the global economic crises, there is also a renewed sense of urgency to integrate them into the labour market and into the education system. Our paper offers contributions in both respects: we first construct new indicators of regional spending to then investigate their impact on new indicators - such as NEETs - of youth labour market participation.

In particular, we relied on Small Area Estimation techniques, as applied to the EU-SILC survey, to develop new indicators of compensatory and investment spending at NUTS1 level. These methodologies have already been proved to be successful to derive regional measures of poverty (Verma et al. [2013], Betti et al. [2012]). Interestingly, by looking at these measures, we can observe across EU Member States regional convergence of compensating expenditure, and a milder of social investment.

We then used these new regional indicators of spending in combination with a recently developed SVAR approach (Moneta et al. [2013], Shimizu et al. [2006]) to investigate the casual relationships between labour market outcomes and different types of spending. While relying on Independent Component Analysis, this method has the great advantage of avoiding subjective choices and theory driven considerations to estimate SVAR model (Gouriéroux et al. [2017], Lanne et al. [2017]) Our main result suggests that social investment policies strongly differ across EU regions but can be more effective to enhance labour market outcomes of the young. This has an important policy implication as youth employment remains the crucial node to sustainable economic and social development.

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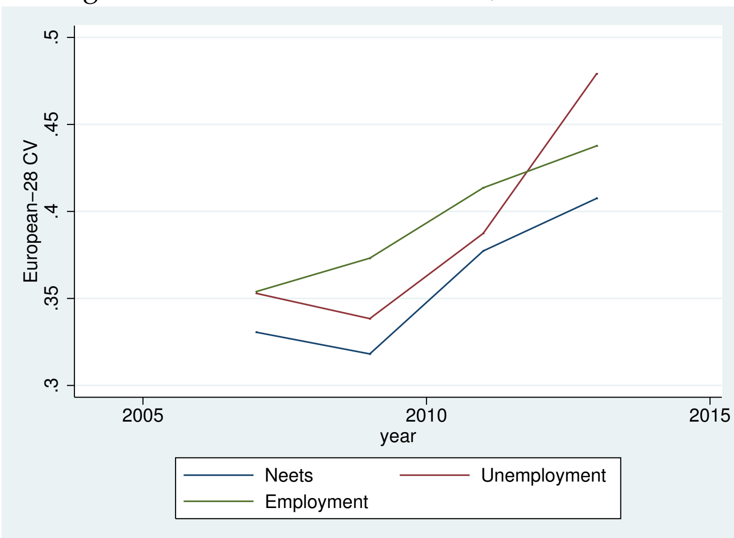
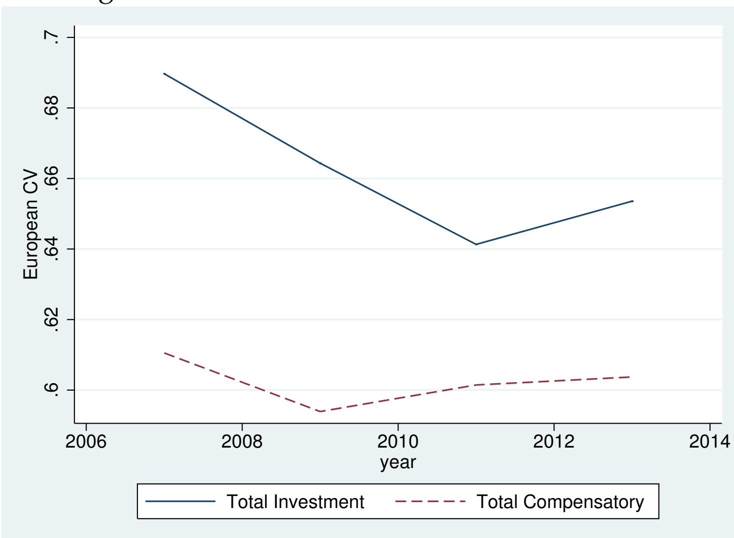
Figure 1: EUROPEAN CV - NEETS, YOUNG EMPLOYMENT AND YOUNG UNEMPLOYMENT



This figures reports the coefficient of variation (i.e. cv) for the European countries in Table (1)

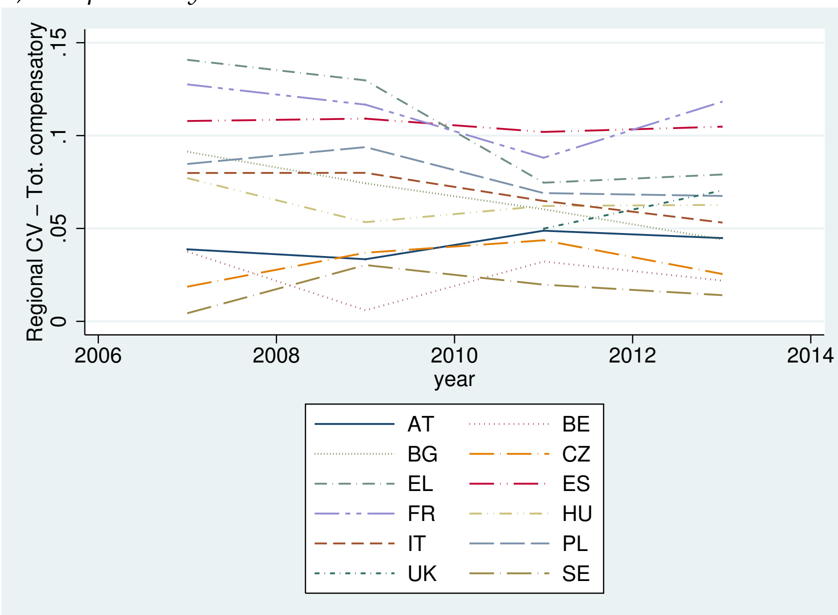
Figure 2: EUROPEAN CV - TOTAL COMPENSATORY & TOTAL INVESTMENT SPENDING



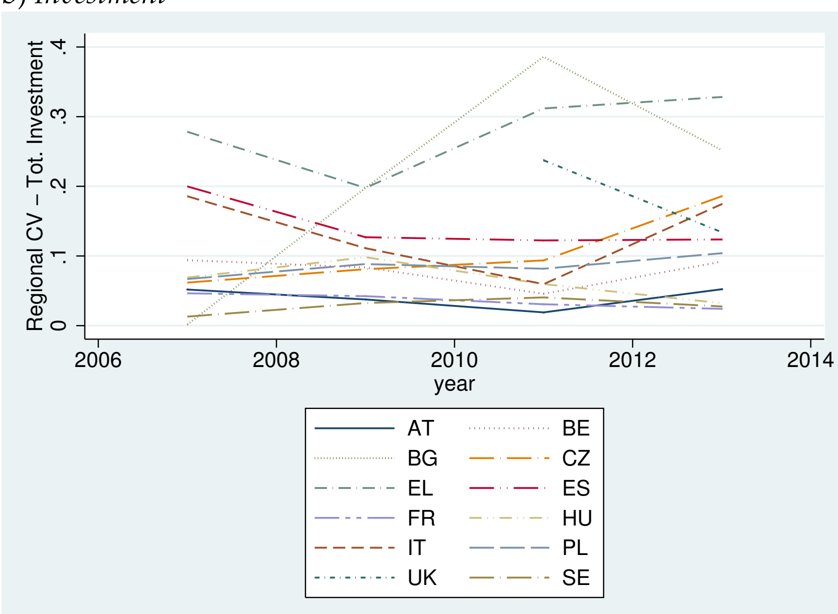
This figures reports the coefficient of variation (i.e. cv) for the European countries for Total Compensatory and Investment spending as derived in Table (3).

Figure 3: REGIONAL CV - TOTAL COMPENSATORY AND IVESTMENT SPENDING

a) *Compensatory*



b) *Investment*



These figures reports the regional coefficient of variation (i.e. cv) for the European countries for Total Compensatory and Investment spending as derived in Table (3)

Figure 4: IMPULSE RESPONSE FUNCTION

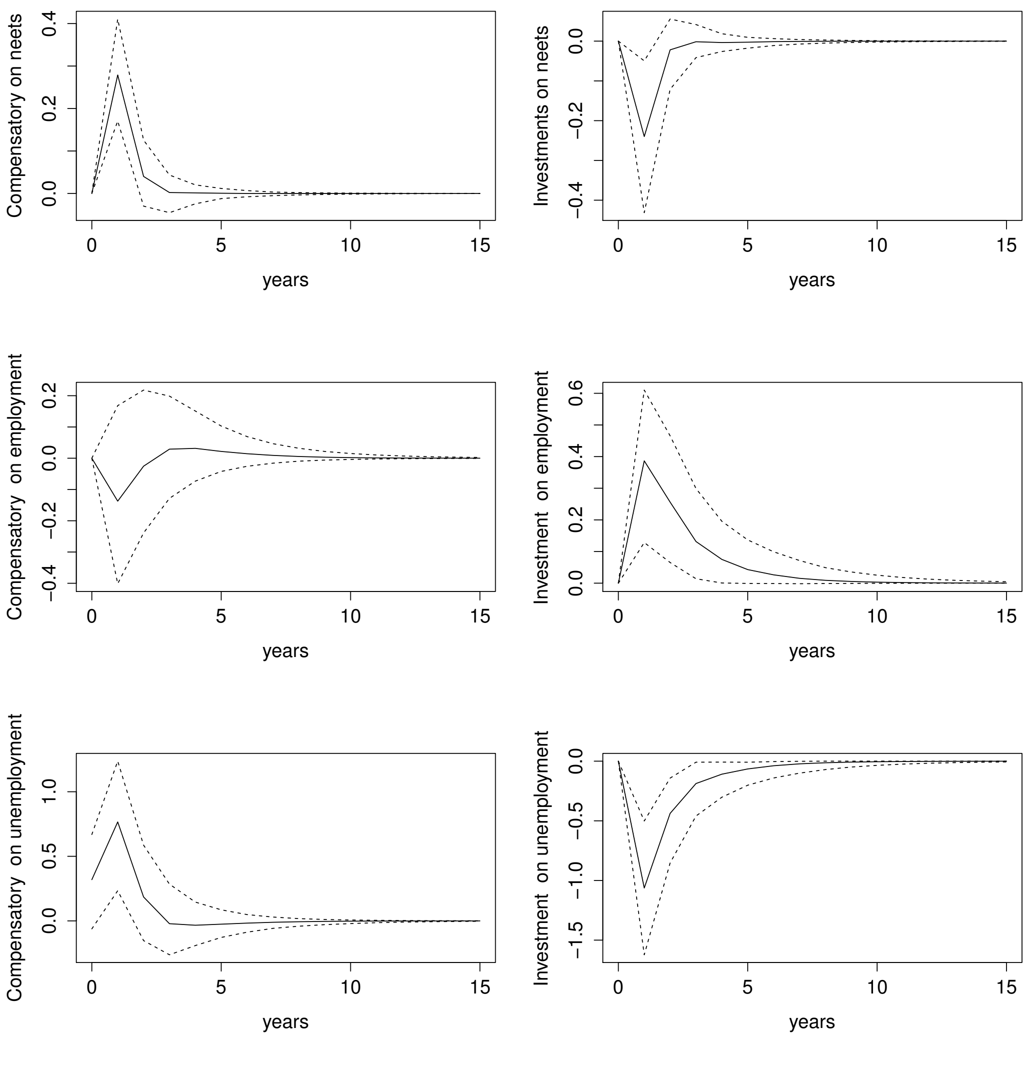


Table 1: (UN)EMPLOYMENT RATE YOUNG (15-24) AND NEETS

	Employment rate young				*Unemployment rate young*				*Neets*			
Country	**Mean**	**Std**	**CV**	**Reg. CV**	**Mean**	**Std**	**CV**	**Reg. CV**	**Mean**	**Std**	**CV**	**Reg. CV**
AT	53.003	4.956	0.094	0.105	9.828	2.954	0.301	0.342	9.247	1.694	0.183	0.195
BE	23.406	5.251	0.224	0.258	26.072	9.712	0.372	0.432	17.672	5.181	0.293	0.344
BG	23.005	2.503	0.109	0.103	21.688	6.374	0.294	0.269	26.475	7.291	0.275	0.343
CY	32.991	5.237	0.159	.	20.000	11.176	0.559	.	18.742	5.002	0.267	.
CZ	26.691	1.363	0.051	.	16.433	3.485	0.212	.	11.733	2.603	0.222	.
DE	45.011	4.797	0.107	0.093	12.113	4.408	0.364	0.286	12.656	3.217	0.254	0.195
DK	60.036	4.665	0.078	.	10.850	2.769	0.255	.	7.556	1.218	0.161	.
EE	31.309	2.890	0.092	.	18.783	7.168	0.382	.	14.575	2.683	0.184	.
EL	19.994	6.648	0.332	0.145	38.517	15.420	0.400	0.107	22.858	6.267	0.274	0.214
ES	27.819	9.013	0.324	0.113	36.169	15.010	0.415	0.160	18.506	5.365	0.290	0.212
EU15	39.115	13.790	0.353		20.483	11.937	0.583	.	15.098	6.317	0.418	
EU27	35.829	13.343	0.372		20.901	10.852	0.506	.	15.611	6.053	0.416	
EU28	**35.725**	13.351	0.374		21.009	10.912	0.520	.	15.650	6.058	0.389	
FI	41.673	1.918	0.046	.	20.367	2.926	0.144	.	11.875	1.502	0.126	.
FR	29.078	4.821	0.166	0.155	24.206	8.759	0.362	0.307	16.146	4.216	0.261	0.234
HR	23.282	4.646	0.200	.	34.817	8.676	0.249	.	21.144	4.140	0.196	.
HU	20.718	2.898	0.140	0.119	20.872	6.614	0.317	0.288	16.300	4.133	0.254	0.282
IE	38.591	9.640	0.250	.	19.217	8.945	0.465	.	18.417	4.876	0.265	.
IT	21.956	7.577	0.345	0.312	30.587	13.024	0.426	0.401	23.767	9.285	0.391	0.409
LT	22.536	2.986	0.133	.	20.825	8.786	0.422	.	13.967	2.407	0.172	.
LU	22.764	1.896	0.083	.	16.858	2.340	0.139	.	7.583	0.713	0.094	.
LV	31.055	4.354	0.140	.	21.900	8.586	0.392	.	16.725	3.186	0.191	.
MT	45.245	1.027	0.023	.	13.892	1.979	0.142	.	10.933	1.558	0.143	.
NL	64.211	4.219	0.066	0.035	9.185	2.790	0.304	0.113	6.117	1.008	0.165	0.084
PL	24.842	2.800	0.113	0.089	26.369	7.403	0.281	0.136	16.079	2.894	0.180	0.134
PT	29.682	7.492	0.252	0.120	31.995	12.542	0.392	0.183	19.981	6.192	0.310	0.234
RO	24.114	2.375	0.098	0.088	21.933	3.579	0.163	0.150	19.779	3.484	0.176	0.091
SE	40.285	1.957	0.049	0.032	22.342	2.350	0.105	0.052	11.031	1.647	0.149	0.099
SI	32.764	4.213	0.129	.	15.583	3.696	0.237	.	10.075	1.600	0.159	.
SK	23.391	2.953	0.126	.	28.917	5.172	0.179	.	18.083	2.423	0.134	.
UK	49.699	5.931	0.119	0.098	16.813	4.563	0.271	0.179	15.314	3.890	0.254	0.147

Table 2: DATA EU-SILC

This table reports the average (computed over 4 years: 2007, 2009, 2011, 2013) of the amount of euro an **household** received for each spending category. Data are derived from EU-SILC data through the cumulation methodology (see Section 3).

	Old age & Survivors	*Sickness*	*Unemployment*	*Disability*	**Total Compensatory**	*Education*	*Family*	*Housing Allowances*	**Total Investment**
AT	28963.660	2,133.389	3,983.593	12269.675	47350.318	2,395.584	5,024.067	1,540.396	8,960.046
BE	29985.481	6,882.746	8,393.498	9,745.557	55007.282	917.002	3,834.507	1,779.114	6,530.623
BG	2,050.337	295.416	506.534	889.021	3,741.309	282.490	487.128	157.721	927.339
CY	21591.830	1,997.840	6,341.432	8,135.511	38066.613	2,846.973	1,849.577	6,508.598	11205.148
CZ	5,481.341	966.027	955.940	3,276.192	10679.499	398.300	1,740.774	758.679	2,897.753
DE	21923.336	4,218.311	5,349.471	8,453.336	39944.454	3,580.148	3,757.179	2,303.338	9,640.665
DK	30574.877	4,678.608	8,326.608	19573.360	63153.454	5,292.157	3,032.879	2,398.943	10723.979
EE	4,559.260	321.178	1,244.568	1,769.974	7,894.980	708.651	1,492.453	558.574	2,759.678
EL	18139.462	2,019.569	2,904.287	6,043.221	29106.540	2,530.247	1,435.487	1,681.500	5,647.234
ES	19903.970	4,480.739	4,434.187	9,246.095	38064.990	1,497.090	2,735.697	2,222.783	6,455.570
FR	26178.656	3,014.565	6,113.630	6,409.401	41716.253	1,415.041	3,665.754	2,049.838	7,130.633
HU	5,480.686	385.845	958.555	2,322.598	9,147.684	614.371	1,536.951	207.887	2,359.209
IE	29213.996	2,549.636	8,027.722	7,420.527	47211.879	3,712.418	6,488.660	1,626.399	11827.477
IS	22798.902	8,001.309	4,240.782	14165.254	49206.247	2,463.721	3,163.754	1,791.669	7,419.144
IT	24419.023	.	3,870.974	6,591.035	34881.032	4,880.047	1,068.580	1,239.233	7,187.860
LT	3,186.222	412.592	845.385	1,774.985	6,219.184	430.034	1,422.239	142.519	1,994.792
LU	42241.571	13005.274	17458.672	19277.024	91982.543	4,268.158	8,058.280	1,853.503	14179.940
LV	3,977.220	536.278	855.717	1,574.061	6,943.276	507.077	802.829	215.703	1,525.609
NL	27844.778	4,981.020	8,273.349	14245.024	55344.171	2,818.128	1,967.597	1,810.706	6,596.431
NO	31123.304	5,802.989	6,474.943	17951.443	61352.680	2,447.223	5,948.912	2,287.293	10683.427
PL	7,615.036	828.574	1,472.368	2,364.762	12280.740	702.988	953.252	397.547	2,053.786
PT	11264.240	2,837.172	4,185.207	4,530.107	22816.727	2,339.191	770.973	436.278	3,546.441
SE	22602.767	2,388.459	6,088.357	10902.041	41981.625	2,996.206	4,810.426	2,421.003	10227.635
SI	14169.719	1,454.165	2,616.632	5,681.010	23921.527	1,625.774	2,203.959	699.723	4,529.455
SK	5,124.139	678.925	1,253.619	2,298.632	9,355.316	1,173.672	749.115	631.964	2,554.751
UK	19071.733	5,740.334	5,234.869	5,789.690	35836.626	4,764.372	4,074.775	4,947.629	13786.776

Table 3: VAR ESTIMATION: VARIABLES IN DIFFERENCE (235 OBS - 4 YEARS)

The column-variables are the causes, while the row-variables are the effects. The B0-coefficients give us the contemporaneous effects The B1-coefficients provides the effect of lagged variables (at time *t-1*) on current variable (at time *t*)

Contemporaneous Effect (t): B_0						
	Neets	*Employment Young*	*Unemployment Young*	*Log_GDP*	*Log Compens.*	*Log Inv*
Neets	0.000	0.000	0.000	0.000	0.000	0.000
Employment Young	-0.547***	0.000	0.000	0.000	0.000	0.000
Unemployment Young	1.469 ***	-0.862 ***	0.000	0.000	0.055	0.000
Log_GDP	-0.725 *	0.349	-0.324	0.000	0.334 **	0.000
Log Compens.	0.705**	-0.201	0.000	0.000	0.000	0.000
Log Inv	-2.607	0.131	1.270 **	1.258 ***	0.350	0.000

Lagged Effect (t-1): Γ_1						
	Neets	*Employment Young*	*Unemployment Young*	*Log GDP*	*Log Compens.*	*Log Inv*
Neets	-0.165	-0.113	-0.071	0.003	0.071 ***	-0.021
Employment Young	0.063	0.100	-0.087	0.087	-0.091	0.056
Unemployment Young	0.355	-0.018	-0.198	-0.019	0.057	-0.031
Log_GDP	0.123	0.279	-0.205	-0.193 *	0.178	0.049
Log Compens.	0.083	0.189	0.231	0.310 **	0.211 **	0.028
Log Inv	2.269 **	0.773	0.052	0.649 ***	-0.044	-0.047