Social Investment and youth labour market participation

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November 28, 2018

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). This 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).

Importantly, there is still considerable cross-country variation when it comes to youth labor market participation. For instance, Central European countries (especially Germany and Austria) have a lower youth unemployment and inactivity rates, along with higher employment rates, than the rest of the EU—especially Southern and Eastern Europe (Pastore 2018, Tomić 2018). The recent financial crisis has further deepened regional disparities having a profound impact on the employability of the young (Bruno et al. 2014, 2015). In this regard, the worst changes have been recorded in Southern regions, where the youth unemployment rate has doubled or tripled since the onset of the recession (Mascherini et al. 2012; Bruno et al. 2014). Chen et al. (2018) also show that the risk of poverty for the young (and the working-age population) has increased significantly since the financial crisis in 2008, while it has declined sharply for the elderly.

The main contribution of this paper is thus to empirically investigate – at a regional level – the role that different policies adopted in the recent years had on youth employability. Except from few studies (see e.g. Bruno et al. 2015), there are limited regional studies on that topic. Traditional indicators of labour market participation, however, 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, in addition to traditional indicators of young employment and unemployment rate, in this paper we also focus our attention on the share of young people that 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, in line with the recent literature on social investments (see e.g. Nikolai 2012; Hemerijck 2013), our aim is to differentiate between two broad types of policies: *social-investment* and *compensatory* policies. 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. Social investment 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 (see, for example, Nikolai 2012). 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. Indeed, several studies have documented a transition from the traditional welfare state to a new investment state in many European countries (e.g. Bonoli 2007; Ferragina et al. 2015; Obinger and Starke 2014). 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, it is quite impossible to properly assess the impact of the two types of policies without having expenditure data disaggregated at a regional level. 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 (Commission, 2010; Verma et al. 2013). Therefore, the second 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 particular, we are able to compute – for a subset of European countries – the average amount of cash transfers that a household received for each category of compensatory and social-investment spending in a year. In doing so, we are thus able to derive for each category of spending a regional indicator which is comparable across time and across countries, and tends to be - compared to national measures - more precise for monitoring and assessing the effectiveness of each policy. Indeed, the recent "Youth Guarantee" program

targeting all the young people under 25 years in Europe is implemented at a regional level. More-over, these regional indicators will allow us to (indirectly) take into account the important role of intra-family transfers as suggested by recent studies (see, for example, Gál et al. 2018, Francesconi and Heckman 2016).

We then 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 ap-proach, recently introduced in the literature by Moneta et al. (2013), which rely on Independent Component Analysis to identify structural parameters in SVAR (Gouriéroux et al. 2017; Lanne et al. 2017,Shimizu et al. 2006). Specifically, we adopt an identification scheme, called *LiNGAM*, i.e. Linear Non-Gaussian Acyclic Model (Shimizu et al. 2006), to identify contemporaneous pa-rameters in order to describe the causal relationships among variables. Differently from standard methods (such as Cholesky decompositon), which necessarily requires either a theoretical justifi-cation or an institutional knowledge, this method has the great advantage to achieve identification of structural parameters directly from the data and statistical analysis alone. More specifically, this method allows us to identify the exogenous shocks affecting - at each time and in an independent way – our policy variables, i.e. the level of compensatory and social-investment spending. In so doing, we are thus able to identify - through the impulse response function (IRFs) - both the direct and indirect effects that a shock in our policy variables has on youth employment outcomes. For example, we will be able to assess how a shock in the level of (household) compensatory spend-ing directly impacts on the level of youth unemployment, as well as how it will indirectly affect (either through family links or an increase in the level of GDP per capita) the level of NEETs.

Our analysis of regional spending suggests that, even though the evidence is consistent with previ-ous 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 effective to reduce the level of NEETs and increase the level of youth employment.

In the following, we first give a brief overview of the literature on youth labour market partici-pation. We then describe how we derive our dataset. In particular, in section 3 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 regional data on expenditure. In section 4 we describe the cumulation methodology, and we apply it to EU-SILC in order to develop indicators of compensatory and social-investment spending at regional level, while in section 5 we rely on a recently econometric methodology developed by Moneta et al. 2013 to investigate the effects of these types of policies on labour market outcomes. Section 6 concludes our argument.

2   Literature review

The number of regional studies about the impact of recent policies on youth labour market participation is still rather limited. Moreover, very few of them address the issue of NEETs specifically. Indeed, 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 – as defined by the European Commission (DG EMPL) – 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.[1]

In particular, a number of recent papers confirm a larger impact of the recent financial crisis

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[1]More precisely, we have

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

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

An alternative measure is to look at the ratio of youth to adult unemployment rates, which more closely reflects a country's institutional characteristics and the functionality of its school-to-work transition system (Pastore 2018, Corsini and Brunetti 2018).

on youth employment rates when compared to adult rates, as well as a greater responsiveness of young employment to the business cycle (Bruno et al. 2015; Coppola and O'Higgins 2015; OH́iggins 2012). More precisely, when an economy is expanding, its youth unemployment rate decreases more than the average, while it increases more than average when an economy is contracting (Pastore 2018). The main reason have been identified in the lower qualifications of the young, their experience "gap" along with weaker work contracts (Tomić 2018). Another important factor is the role of educational policy and differences in school-to-work transition regimes (e.g. Corsini and Brunetti 2018). OH́iggins (2012) also highlights that the negative effects of a recession are likely to last longer for the young.

Very few papers, though, analyze the effect of various policies on NEETs by comparing different European countries. Bruno et al. (2015) show that NEET rates, both for male and female, are persistent over time to a degree comparable to youth unemployment rate, and this persistence further increases over the crisis years. Moreover, the sensitivity of NEETs to GDP substantially decreases: an increase in GDP after many years of stagnation would thus only have a limited impact on the situation of young people. Thus, the policy implications of this analysis is that both structural and counter-cyclical policies are required. However, no direct indicators for the policies at regional/national level is available. Finally, Caliendo and Schmidl (2016) provide a comprehensive survey of the recent evidence on the effectiveness of active labour market programmes (ALMP) for youth in Europe. Overall, the aggregate evidence is somewhat discouraging: while job search assistance results in positive effects for young employability, there are clearly negative effects for public programs and mixed evidence for training and wage subsidies.

Overall, recent studies on labour market participation of the young in Europe suggest that young employability has significantly worsen in recent years, especially in Eastern and Souther counties. Importantly, (un)employment and NEETs rates do not quickly respond to an increase in GDP. However, there is no studies which specifically dress – at a regional level – the role of compensatory and investment policies in tackling this issue. That will be the objective of the following empirical analysis.

3 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).

3.1 Regional Data on young people's labour market participation

We report measures for unemployment, employment and NEETs rate for the 15-24 age group in Table (1), Table (2) and Table (3) as computed at NUTS1 level.

<center>INSERT TABLE (1) HERE</center>

<center>INSERT TABLE (2) HERE</center>

<center>INSERT TABLE (3) HERE</center>

In particular, these tables report 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]

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

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[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 $\sigma - convergence$.

Slovakia (SK), Bulgaria (BG), Lithuania (LT), Italy (IT), Hungary (HU) and Greece (GR). Moreover, although there is a moderate variation in youth employment rate across European countries, there is a greater variation in youth unemployment rate (with the CV being as high as 50%, see Table 2). The level of NEETs is also very different among EU countries, although slightly lower than unemployment rates (see Table 3). However, once again Southern and Eastern Europe counties tend to have the higher NEET rates.

In these tables, we also focus our attention on the time variation that occurred in our outcome variables between years 2009-2007 and 2013-2011. These measures will be specifically used in our empirical analysis (see the next section), and highlight a huge impact of the financial crisis on youth employability. In line with Bruno et al. (2015), it is possible to notice the dramatic variation in unemployment rates that occurred in Eastern and Southern countries, being around around +20% in 2009-2007. The variations in NEETs rates have been smaller (at most about 6%). In that case, though, it is possible to notice that Anglo-saxon countries performed worse compared to new Member States. In addition, these tables highlight a significant variation in country responsiveness to the financial crisis. While in some countries, the situation of the young experienced a recover in 2013-2011, in other countries, especially the Southern European ones, experienced a further worsening.

Finally, 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

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 within 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%.

3.2 Regional data on expenditure

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

1. maintenance or restoration of the capacity of labour market participants (e.g. old age pensions);

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

3. investment 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 - in particular on cumulation technique - to derive regional indicators of investment and compensatory policies from EU-SILC survey (Betti et al. 2012; Verma et al. 2013). Specifically, for each category of spending (social-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., 2016 on this issue).

4 Cumulation Methodology & EU-SILC variable selection

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, we rely on (average) measures, which are obtained by cumulating and consolidating the information over waves of national sample surveys in order to obtain indicators that permit greater spatial disaggregation (see 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, in our sample 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 are able to derive 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 can only derive country-level indicators from EU-SILC.

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 $\bar{y}_t^c$ as the one-year moving average over 3 consecutive years of the annual average $\bar{y}_t$, that is

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

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 $\bar{y}_{2007}^c, \bar{y}_{2009}^c, \bar{y}_{2011}^c, \bar{y}_{2013}^c$.

In particular, we rely on the following EU-SILC variables to derive the level of compensatory spending (we report the EU-SILC number and a detailed description for each variable in the online Appendix):

1. unemployment benefits;

2. old-age & survivors benefits;

3. sickness benefits;

4. disability benefits;

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

1. education-related allowances;

2. family/children allowances;

3. housing allowance;

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.

4.1 Regional compensatory and social-investment spending

We now apply the cumulation methodology to obtain – for each one of the selected variable described in the previous section – the NUTS1 level average average of the amount of Euro an household received in a year. We then categorized all these variables into the two groups of compensatory and social-investment variables. The national average over 4 years is reported in Table (4),

while in Figure (2) we report the CV indicators computed at European level (EU28) for both total social-investment and total compensatory variables.

INSERT TABLE (4) HERE

INSERT FIGURE (2) HERE

First of all, we observe that there is a remarkable difference in the CV for total social-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 social-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 social-investment spending in Europe, while we observe a more stable pattern for total spending for compensatory policy.

5   SVAR Analysis

In this section we use the dataset described in the previous sections to estimate a structural vector autoregressions (SVAR) model to identify causal relationships among our variables of interests. SVAR models are among the most prevalent tools in empirical economics to analyze causal 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).

5.1   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 $E(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t') = \sum_\epsilon$. 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*

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

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

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 $\mathbf{\Gamma}_0 \mathbf{u}_t = \boldsymbol{\epsilon}_t$. 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, $\mathbf{\Gamma}_0$ and $\boldsymbol{\epsilon}_t$ 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 ϵ_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 ϵ_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, $\mathbf{\Gamma}_0^{-1}$ 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 $\mathbf{\Gamma}_0^{-1}$ so that all the shocks have unit variance, to solve indeterminacy of the order of the column of $\mathbf{\Gamma}_0^{-1}$ 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 *recursiveness*. This assumption means that, given a particular contemporaneous causal order of the variables, the $\mathbf{\Gamma_0}$ 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).[3]

It is important to notice that with *LiNGAM* the specific ordering of the variables that produces a lower triangular matrix ($\mathbf{\Gamma_0}$) 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 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.

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[3]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).

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.

5.2 Results

Relying on NUTS1 level data, we apply the ICA method to explore relationship between the level of compensatory and social-investment spending on the level of NEETs, unemployment and employment of the young. The results from this SVAR analysis are reported in Table (5) and can be interpreted in a causal way. The column variables are the cause, while the row 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 (5). 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.[4] For our purpose, this matrix is not very informative as it implies zero contemporaneous impact of social-investment spending (i.e. *Log Inv*) 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 (3) we report the IRFs which are related to our policy variables, i.e. the total amount spent in compensatory and social-investment policies per household. However, it is important to remark that although we focus our attention on a single shock hitting only one policy variable at time, the shock in the policy variable will consequently affects all our variables in the system. Through the IRF analysis, we thus take into account both the direct and indirect effects (e.g. through a variation in GDP) of a shock in one of our policy variables.

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 social-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 (3) HERE

We then observe that the same shock in compensatory spending has no significant effect on employment, while the shock in social-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 to

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

0.6%), while the shock in investment spending has a significant, although smaller, negative effect on it (up to -1%). We check the robustness of these results by replacing youth unemployment rates with the ratio of youth to adult unemployment rates. Indeed, it has been shown (see for example Pastore, 2018) that this indicator is less affected by the fluctuations of the economic cycle and more closely reflect a country's institutional characteristics. While no significant effects emerge for the relative unemployment rates, results (available upon request) confirm that investment spending has a positive effect on NEETs and employment rates.

Overall, these results suggest that shocks in the level of total investment spending lead to positive economic outcomes. Two remarks, however, are in order. First of all, as highlighted above, through the IRFs we are observing both the direct and indirect effects of a shock in a policy variable. That is, our results suggest that a shock in the level of compensatory spending does not ultimately lead (e.g. through an increase in GDP) to a significant reduction in the level of NEETs and unemployment. This result is in line with the analysis of Bruno et al. (2015) who found that both NEETs and unemployment rates respond slowly to an increase in GDP, with many years elapsing before the situation of the young improves. In addition, as recent studies on intra-familial transfers suggest (see, for example, Gál et al., 2018, Francesconi and Heckman, 2016), there is a danger in looking at data on public transfer alone without considering intergenerational transfers (cash) and the household economy (time), as social investments may have a differential impact across childhood and early youth through family investments.

6 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 construct new indicators of regional spending and we 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 social-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 causal 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 effective to enhance labour market outcomes of the young. Indeed, it is possible to observe an improvement in both NEETs and employment rates after a shock in social-investment. Moreover, in line with the analysis of Bruno et al. (2015), our results suggest that youth labour market indicators are less responsive to variation in compensatory spending as the total effects of a shock in these policy variables do not ultimately lead to an increased participation of the youth in the labor market. These results also highlight the importance of explicitly considering the role of intra-familial transfers in future analysis as social investments may have a differential impact across childhood and early youth through family investments (see, for example, Gál et al., 2018, Francesconi and Heckman, 2016). At the same time, we need to be cautious as we did not consider any redistributive/differential effect that such policies can have at the individual levels (Bonoli and Liechti 2018, Pavolini and Van Lancker 2018), nor any regional spillover effects that policies can have among regions. Future research thus need to further investigate possible complementaries between the two types of policies as well as the explicit role of family investments (both in cash and in time), as youth employment remains the crucial node to sustainable economic and social development.

References

Betti, G., Gagliardi, F., Lemmi, A., Verma, V., 2012. Subnational indicators of poverty and deprivation in europe: methodology and applications. Cambridge Journal of Regions, Economy and Society 5 (1), 129–147.

Bonoli, G., 2007. New social risks and the politics of post-industrial social policies. In: The politics of post-industrial welfare states. Routledge, pp. 21–44.

Bonoli, G., Liechti, F., 2018. Good intentions and matthew effects: access biases in participation in active labour market policies. Journal of European Public Policy 25 (6), 894–911.

Brenner, T., Capasso, M., Duschl, M., Frenken, K., Treibich, T., 2017. Causal relations between knowledge-intensive business services and regional employment growth. Regional Studies, 1–12.

Bruno, G. S., Marelli, E., Signorelli, M., 2014. The rise of neet and youth unemployment in eu regions after the crisis. Comparative Economic Studies 56 (4), 592–615.

Bruno, G. S., Marelli, E., Signorelli, M., 2015. The regional impact of the crisis on young people in different eu countries. Youth and the Crisis, edited by G. Coppola and O âHiggins N., 249.

Caliendo, M., Schmidl, R., 2016. Youth unemployment and active labor market policies in europe. IZA Journal of Labor Policy 5 (1), 1.

Chen, T., Hallaert, M. J.-J., Pitt, M. A., Qu, M. H., Queyranne, M. M., Rhee, A., Shabunina, M. A., Vandenbussche, J., Yackovlev, I., 2018. Inequality and Poverty across Generations in the European Union. International Monetary Fund.

Ciarli, T., Coad, A., Moneta, A., 2018. Exporting and productivity as part of the growth process: Results from a structural var.

Commission, E., 2010. Europe 2020: A strategy for smart, sustainable and inclusive growth. Working paper European Commission.

Coppola, G., O'Higgins, N., 2015. Youth and the crisis: Unemployment, education and health in Europe. Routledge.

Corsini, I. B.-L., Brunetti, I., 2018. School-to-work transition and vocational education: a comparison across europe. Dipartimento di Economia e Management (DEM), University of Pisa, Pisa.[Google Scholar].

De Deken, J., et al., 2014. Identifying the skeleton of the social investment state: defining and measuring patterns of social policy change on the basis of expenditure data. Reconciling work and poverty reduction. How successful are European welfare states, 260–285.

Eurofond, 2012. Neets: Young people not in employment, education or training: Characteristics, costs and policy responses in europe. Publications Office of the European Union, Luxembourg.

Ferragina, E., Seeleib-Kaiser, M., Spreckelsen, T., 2015. The four worlds of welfare reality: social risks and outcomes in europe. Social Policy and Society 14 (2), 287–307.

Francesconi, M., Heckman, J. J., 2016. Child development and parental investment: Introduction. The Economic Journal 126 (596), F1–F27.

Gál, R. I., Vanhuysse, P., Vargha, L., 2018. Pro-elderly welfare states within child-oriented societies. Journal of European Public Policy 25 (6), 944–958.

Gouriéroux, C., Monfort, A., Renne, J.-P., 2017. Statistical inference for independent component analysis: Application to structural var models. Journal of Econometrics 196 (1), 111–126.

Guerini, M., Moneta, A., 2017. A method for agent-based models validation. Journal of Economic Dynamics and Control.

Heitzmann, K., Wukovitsch, F., et al., 2015. Towards social investment and social innovation in eu member states? first observations of recent developments in austria. Tech. rep., Herman Deleeck Centre for Social Policy, University of Antwerp.

Hemerijck, A., 2013. Changing welfare states. Oxford University Press.

Hemerijck, A., 2017. The uses of social investment. Oxford University Press.

Herwartz, H., 2018. Hodges–lehmann detection of structural shocks–an analysis of macroeconomic dynamics in the euro area. Oxford Bulletin of Economics and Statistics.

Hyvärinen, A., Karhunen, J., Oja, E., 2001. Independent component analysis. john willey & sons. Inc. New York.

Iammarino, S., Rodríguez-Pose, A., Storper, M., 2018. Regional inequality in europe: evidence, theory and policy implications. Journal of Economic Geography.

Kilian, L., Lütkepohl, H., 2017. Structural vector autoregressive analysis. Cambridge University Press.

Lanne, M., Meitz, M., Saikkonen, P., 2017. Identification and estimation of non-gaussian structural vector autoregressions. Journal of Econometrics 196 (2), 288–304.

Marchetti, S., Giusti, C., Pratesi, M., Salvati, N., Giannotti, F., Pedreschi, D., Rinzivillo, S., Pappalardo, L., Gabrielli, L., et al., 2015. Small area model-based estimators using big data sources. J. Off. Stat 31 (2), 263–281.

Mascherini, M., Salvatore, L., Meierkord, A., Jungblut, J.-M., 2012. NEETs: Young people not in employment, education or training: Characteristics, costs and policy responses in Europe. Publications Office of the European Union Luxembourg.

Moneta, A., Entner, D., Hoyer, P. O., Coad, A., 2013. Causal inference by independent component analysis: Theory and applications*. Oxford Bulletin of Economics and Statistics 75 (5), 705–730.
URL http://dx.doi.org/10.1111/j.1468-0084.2012.00710.x

Monfort, P., 2008. Convergence of EU regions: Measures and evolution. Citeseer.

Nikolai, R., 2012. Towards social investment? patterns of public policy in the oecd world. Towards a social investment welfare state, 91–116.

Obinger, H., Starke, P., 2014. Welfare state transformation: Convergence and the rise of the supply side model. TranState Working Papers 180, University of Bremen, Collaborative Research Center 597: Transformations of the State.
URL https://ideas.repec.org/p/zbw/sfb597/180.html

OH́iggins, N., 2012. This time it's different? youth labour markets during âthe great recessionâ. Comparative Economic Studies 54 (2), 395–412.

Pastore, F., 2018. Why is youth unemployment so high and different across countries? IZA World of Labor.

Pavolini, E., Van Lancker, W., 2018. The matthew effect in childcare use: a matter of policies or preferences? Journal of European Public Policy 25 (6), 878–893.

Prandini, R., Orlandini, M., Guerra, A., 2016. Social Investment in Times of Crisis: A Quiet Revolution or a Shaken Welfare Capitalism? European Commission, Belgium.

Shimizu, S., Hoyer, P. O., Hyvärinen, A., Kerminen, A., 2006. A linear non-gaussian acyclic model for causal discovery. Journal of Machine Learning Research 7 (Oct), 2003–2030.

Stock, J. H., Watson, M. W., 2007. Introduction to econometrics.

Tomić, I., 2018. What drives youth unemployment in europe? economic vs non-economic determinants. International Labour Review 157 (3), 379–408.

Verma, V., Betti, G., Gagliardi, F., 2010. Robustness of some eu-silc based indicators at regional level. Eurostat Methodologies and Working papers, Luxembourg: Publications Office of the European Union.

Verma, V., Gagliardi, F., Ferretti, C., 2013. Cumulation of poverty measures to meet new policy needs. In: Advances in Theoretical and Applied Statistics. Springer, pp. 511–522.

Wunsch, P., 2013. Is the european integration machine broken. Intereconomics 2 (2013), 78–83.

Figure 1: European CV - Neets, young employment and young unemployment
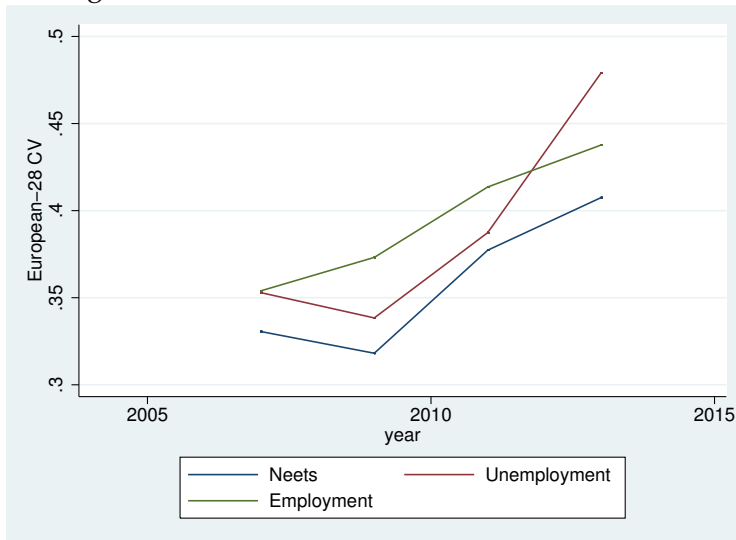
This figures reports the coefficient of variation (i.e. cv) for the European countries in Table (1)

Figure 2: EUROPEAN CV - TOTAL COMPENSATORY & TOTAL SOCIAL INVESTMENT SPENDING
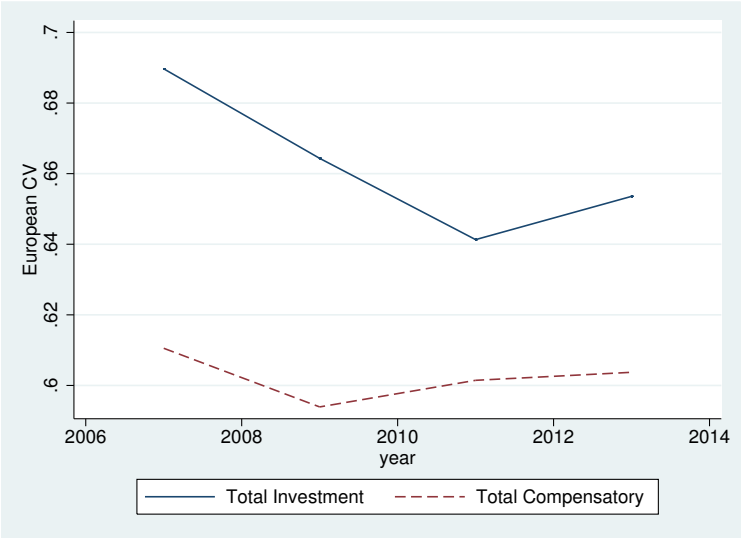
This figures reports the coefficient of variation (i.e. cv) for the European countries for Total Compensatory and Investment spending as derived in Table (5).

Figure 3: IMPULSE RESPONSE FUNCTION

Table 1: EMPLOYMENT RATE YOUNG (15-24)

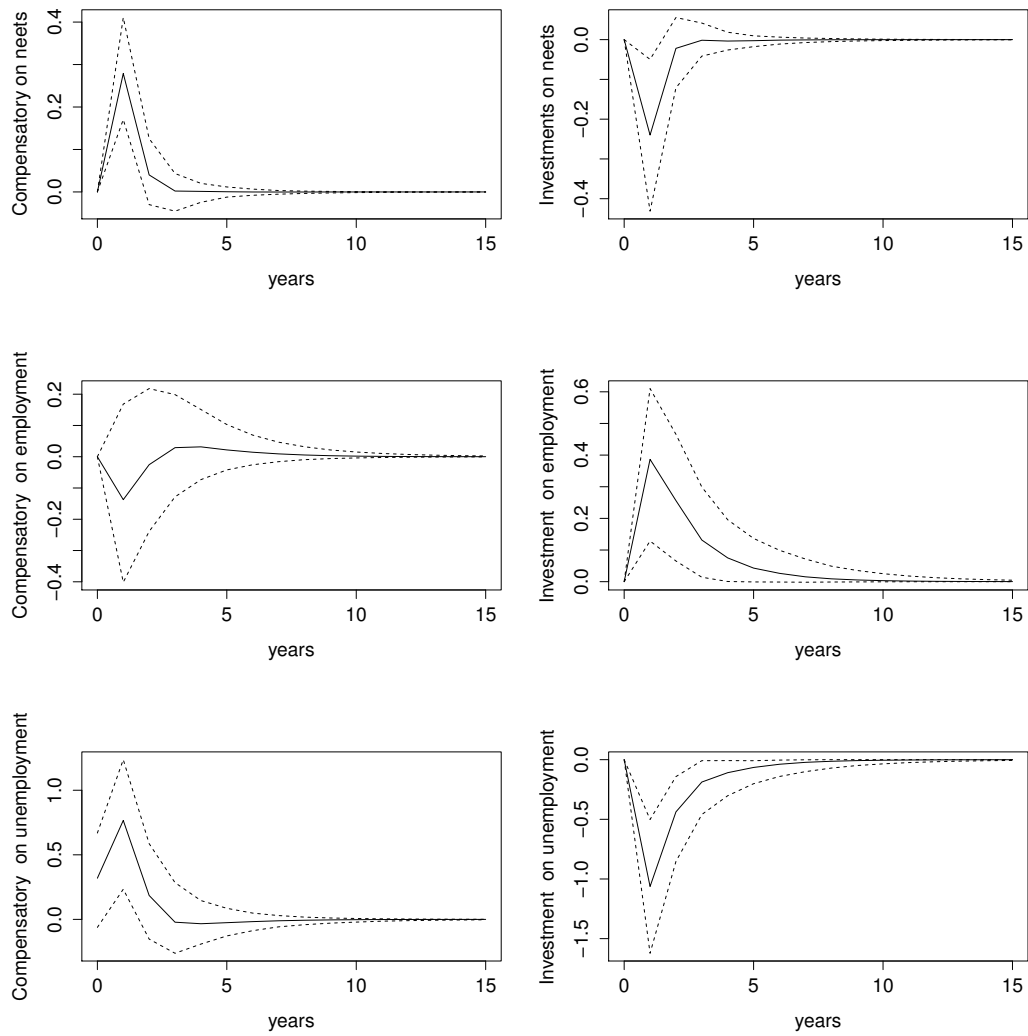The employment rate is computed as the share of employed young over the working population (15-24 years old). Statistics are computed relying on data available at Eurostat for years 2007-2013. The coefficient of variation (CV) is computed by dividing the country mean over the standard deviation. The regional coefficient of variation (Reg. CV) is computed by dividing the regional mean over the regional standard deviation (where NUTS1 data are available).

Employment rate young						
Country	**Mean**	**Std**	**CV**	**Reg. CV**	$\Delta_{2009-2007}$	$\Delta_{2013-2011}$
AT	53.00	4.96	0.09	0.11	-0.57	-1.23
BE	23.41	5.25	0.22	0.26	-1.57	-2.50
BG	23.01	2.50	0.11	0.10	0.35	0.00
CY	32.99	5.24	0.16	.	-2.60	-6.60
CZ	26.69	1.36	0.05	.	-2.00	1.10
DE	45.01	4.80	0.11	0.09	1.34	-2.69
DK	60.04	4.67	0.08	.	-2.80	-3.80
EE	31.31	2.89	0.09	.	-5.80	1.30
EL	19.99	6.65	0.33	0.15	-0.50	-4.03
ES	27.82	9.01	0.32	0.11	-10.54	-5.54
EU15	39.12	13.79	0.35		-3.00	-1.60
EU27	35.83	13.34	0.37		-2.40	-1.10
EU28	35.73	13.35	0.37		-2.40	-1.20
FI	41.67	1.92	0.05	.	-5.00	1.20
FR	29.08	4.82	0.17	0.15	-0.79	-1.10
HR	23.28	4.65	0.20	.	-0.30	-5.70
HU	20.72	2.90	0.14	0.12	-2.93	2.07
IE	38.59	9.64	0.25	.	-14.10	-0.50
IT	21.96	7.58	0.35	0.31	-3.18	-3.22
LT	22.54	2.99	0.13	.	-4.20	5.60
LU	22.76	1.90	0.08	.	4.20	1.20
LV	31.06	4.35	0.14	.	-10.60	4.40
MT	45.25	1.03	0.02	.	-2.70	1.00
NL	64.21	4.22	0.07	0.04	-0.43	-1.25
PL	24.84	2.80	0.11	0.09	1.17	-0.87
PT	29.68	7.49	0.25	0.12	-3.00	-5.83
RO	24.11	2.38	0.10	0.09	0.10	-0.55
SE	40.29	1.96	0.05	0.03	-4.33	0.57
SI	32.76	4.21	0.13	.	-2.30	-5.00
SK	23.39	2.95	0.13	.	-4.80	0.40
UK	49.70	5.93	0.12	0.10	-4.99	0.19

Table 2: UNEMPLOYMENT RATE YOUNG (15-24)

The unemployment rate is computed as the share of unemployed young over the labour force (15-24 years old). Statistics are computed relying on data available at Eurostat for years 2007-2013. The coefficient of variation (CV) is computed by dividing the country mean over the standard deviation. The regional coefficient of variation (Reg. CV) is computed by dividing the regional mean over the regional standard deviation (where NUTS1 data are available).

	Unemployment rate young					
Country	**Mean**	**Std**	**CV**	**Reg. CV**	$\Delta_{2009-2007}$	$\Delta_{2013-2011}$
AT	9.83	2.95	0.30	0.34	1.33	1.03
BE	26.07	9.71	0.37	0.43	1.33	5.37
BG	21.69	6.37	0.29	0.27	1.20	3.20
CY	20.00	11.18	0.56	.	3.60	16.50
CZ	16.43	3.49	0.21	.	5.90	0.90
DE	12.11	4.41	0.36	0.29	1.33	-0.43
DK	10.85	2.77	0.26	.	1.33	-1.10
EE	18.78	7.17	0.38	.	1.20	-3.70
EL	38.52	15.42	0.40	0.11	3.60	11.93
ES	36.17	15.01	0.42	0.16	5.90	10.60
EU15	20.48	11.94	0.58	.	-1.39	2.20
EU27	20.90	10.85	0.51	.	4.30	1.90
EU28	21.01	10.91	0.52	.	17.30	2.00
FI	20.37	2.93	0.14	.	3.80	-0.20
FR	24.21	8.76	0.36	0.31	19.21	2.22
HR	34.82	8.68	0.25	.	4.70	13.30
HU	20.87	6.61	0.32	0.29	4.40	1.13
IE	19.22	8.94	0.46	.	4.40	-2.30
IT	30.59	13.02	0.43	0.40	5.00	10.62
LT	20.83	8.79	0.42	.	4.51	-10.70
LU	16.86	2.34	0.14	.	0.00	-1.30
LV	21.90	8.59	0.39	.	8.60	-7.80
MT	13.89	1.98	0.14	.	14.90	-0.30
NL	9.18	2.79	0.30	0.11	5.08	3.20
PL	26.37	7.40	0.28	0.14	21.20	1.85
PT	31.99	12.54	0.39	0.18	2.00	10.00
RO	21.93	3.58	0.16	0.15	22.70	0.02
SE	22.34	2.35	0.11	0.05	1.00	0.33
SI	15.58	3.70	0.24	.	0.68	5.90
SK	28.92	5.17	0.18	.	-0.87	0.30
UK	16.81	4.56	0.27	0.18	3.60	-0.40

Table 3: Neets rate (15-24)

The NEET rate is computed as the share of young not education, employment and training over the working population (15-24 years old). Statistics are computed relying on data available at Eurostat for years 2007-2013. The coefficient of variation (CV) is computed by dividing the country mean over the standard deviation. The regional coefficient of variation (Reg. CV) is computed by dividing the regional mean over the regional standard deviation (where NUTS1 data are available).

				Neets		
Country	**Mean**	**Std**	**CV**	**Reg. CV**	$\Delta_{2009-2007}$	$\Delta_{2013-2011}$
AT	9.25	1.69	0.18	0.20	1.07	0.27
BE	17.67	5.18	0.29	0.34	-0.83	0.40
BG	26.48	7.29	0.28	0.34	0.25	-0.30
CY	18.74	5.00	0.27	.	0.90	4.10
CZ	11.73	2.60	0.22	.	1.60	0.80
DE	12.66	3.22	0.25	0.195	-0.02	-1.08
DK	7.56	1.22	0.16	.	1.10	-0.30
EE	14.58	2.68	0.18	.	5.60	-0.30
EL	22.86	6.27	0.27	0.21	1.50	2.45
ES	18.52	5.36	0.29	0.21	5.87	0.71
EU15	15.10	6.32	0.42		1.70	-0.10
EU27	15.61	6.05	0.42		1.40	0.00
EU28	15.65	6.06	0.39		1.40	0.10
FI	11.87	1.50	0.17	.	2.80	0.80
FR	16.15	4.22	0.26	0.23	2.25	-1.04
HR	21.14	4.14	0.20	.	0.50	3.40
HU	16.30	4.13	0.25	0.28	2.20	2.20
IE	18.42	4.88	0.27	.	7.80	-2.70
IT	23.77	9.29	0.39	0.41	1.60	2.62
LT	13.97	2.41	0.17	.	5.00	-0.70
LU	7.58	0.71	0.09	.	0.10	0.30
LV	16.73	3.19	0.19	.	5.60	-3.00
MT	10.93	1.56	0.14	.	-1.60	-0.30
NL	6.12	1.00	0.16	0.08	0.58	1.48
PL	16.08	2.89	0.18	0.13	-0.35	0.77
PT	19.98	6.19	0.31	0.23	-0.07	2.13
RO	19.78	3.48	0.18	0.09	0.73	-0.38
SE	11.03	1.65	0.15	0.10	2.13	-0.03
SI	10.08	1.60	0.16	.	0.80	2.10
SK	18.08	2.42	0.13	.	0.00	-0.10
UK	15.31	3.89	0.25	0.16	1.54	-0.91

Table 4: 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 Social 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 5: 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

A   EU-SILC Variable Selection

Variable included in compensatory spending:

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);

Variable included in **social-investment policies**:

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).[5]

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