The suggested structure of final demand shock for sectoral labour digital skills

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ABSTRACT
International data seem to confirm that countries with a relative abundancy of highly-skilled labour with digital competences grow faster than others. For this reason, digital competences and skills in general are progressively assuming a central role in labour market policies. In this article, we show the potential of the disaggregated multisectoral analysis with the macro multipliers approach as a tool of economic policy. Such analyses allow identifying a set of endogenous policies in which specific objectives do not clash with growth objectives. The identification and the quantification of the macro multipliers is based on an extended multi-industry, multi-factor and multi-sector model, which accounts for the representation of the income circular flow as in the social accounting matrix (SAM). The SAM constructed for this exercise allows for a proper disaggregation of the labour factor by formal educational attainment, digital competences and gender for the case of Italy.

KEYWORDS
Digital skills; social accounting matrix; multisectoral extended model; MM approach

JEL CODES
C67; D57; E16; J23; J24

1. Introduction

The 2008 economic crisis struck just after the world had become strongly integrated economically. That is, the crisis occurred just after global value chains had adjusted and production had redistributed globally. From 2008 to 2014, it caused reduced output and increased employment worldwide. In the meantime, income levels rose for professionals, elementary occupations and sales jobs, and worsened for blue-collar and basic service labour. Moreover, the composition of output and employment changed with a shift towards (both high-skill-intensive and low-skill-intensive) services and away from (especially low-technology) manufacturing (e.g. construction).

The current economic recovery seems to confirm these trends, which actually reflect the complementarity between technology and skills in productivity performance (e.g. Bresnahan et al., 2002; OECD, 2003). Indeed, the OECD (2016c) recognises the process of

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integration had strongly benefitted from the improvements in ICT, both in goods and service production. The digital economy has become ‘a powerful catalyst for innovation, growth and social prosperity’ (OECD, 2016b, p. 1). In view of the critical role of digital technologies, the skills required to efficiently engage them still require a reasonable amount of formal educational attainment. Such digital competence, in turn, has a significant impact on the long-run employability and labour compensation of workers (OECD, 2016c); it also includes so-called digital competences. In this (updated) perspective, the notion of highly-skilled labour is extended to mean high educational attainment with good digital competences. The European Commission (EC, 2006) defines ‘digital competencies’ as a combination of knowledge, specific skills and attitudes appropriate to a digital context.

According to the EC definition, around 31% of the EU population has insufficient digital competences, and 9% of it has none at all. At the same time, national education systems are still incapable of unlocking the potential of digital technologies (OECD, 2016a; Van Deursen and Van Dijk, 2014). According to the EU (2016), this situation poses a real skills challenge that calls for a multi-layered policy effort, which involves reforms in the education and training systems as well as investments in human capital. In this respect, the EU *Digital Agenda for Europe* (EC, 2010) devotes a whole pillar to the improvement of digital skills with the final aim of reducing the digital divide (Matzat and Sadowski, 2012). More specifically, the *Digital Agenda for Europe* implements several investment packages to help EU workers to identify their digital gap, and to undertake life-long transition programmes (Leahy and Wilson, 2014).

Samans et al. (2017) have developed the Global Human Capital Index with the aim of measuring the stock and the quality of human capital in 130 countries around the world. The index accounts for initial formal education attainment as well as all further educational achievements, including life-long improvements obtained either through the formal education system, or the vocational employment training (VET) or life-long-learning (LLL) programmes. According to that 2017 release, Europe’s best performers were Switzerland and the northern European countries; at the global level, the United States performed well. The main characteristics of these countries are a low unemployment rate, a high quality of primary schools and overall education system, as well as a high and diversified vocational and tertiary education offer.

International data seem to confirm that countries with a relative abundancy of high digitally-skilled labour (i.e. workers with high educational attainment and good digital competences) grow faster. More specifically, higher digital competences imply higher labour productivity (OECD, 2017). In terms of policy, this indicates the need of enhancing the level of both formal education and digital competences. Since skills and digital competences are unevenly distributed across industries, it is crucial to identify the ones, in which this type of labour is used more intensively, and to foster them with the appropriate policy measures. At the same time, it is important to select adequate policies.

Considering the strong interdependency among industries, this paper adopts a multisectoral approach. It does not resort to the standard multiplier analysis, but it applies the macro multiplier (MM) approach (Ciaschini and Socci, 2007). MMs have the role of modifying the sum of the policy control vector in order to achieve the wanted effect on the policy target vector using a realistic structure for the policy variable control (Ciaschini and Socci, 2006). In the case of the present paper, because of the strong interdependencies among the economy’s industries, it is crucial to undertake a multisectoral analysis on the basis of a social accounting matrix (SAM). The contribution of this paper lies in the type of approach used for this analysis – Ciaschini and Socci's (2007) MM approach. This approach is based on the singular value decomposition (SVD) and enables analysts to identify and compute a set of aggregate MMs that describe the most convenient composition of the policy variable, namely final demand, while the value added vector is the policy target vector, i.e. the policy commodity. This enables one to capture a particular effect on the objective which as not only an increase in total value added, but it also involves a differentiated change in selected value-added components (i.e. highly-skilled labour with digital competences). The identification and the computation of the MM follow as a result from SVD of the inverse matrix resulting from the reduced form of the multisectoral model of value added related to labour by gender and skill. This approach is useful for quantifying the effects of policies on labour demand in the context of deep relations among industries and institutional sectors (Socci, 2004).

Considering its poor economic performance over the last two decades, we focus on Italy. Italy's economy is lagging and also is underperforming in terms of both digital competences and productivity. In fact, along other European Mediterranean countries, Italy is facing difficulties positioning itself in the new international labour division. Furthermore, the well-known coexistence of both traditional and innovative activities in Italy avails many interesting avenues for investigations.

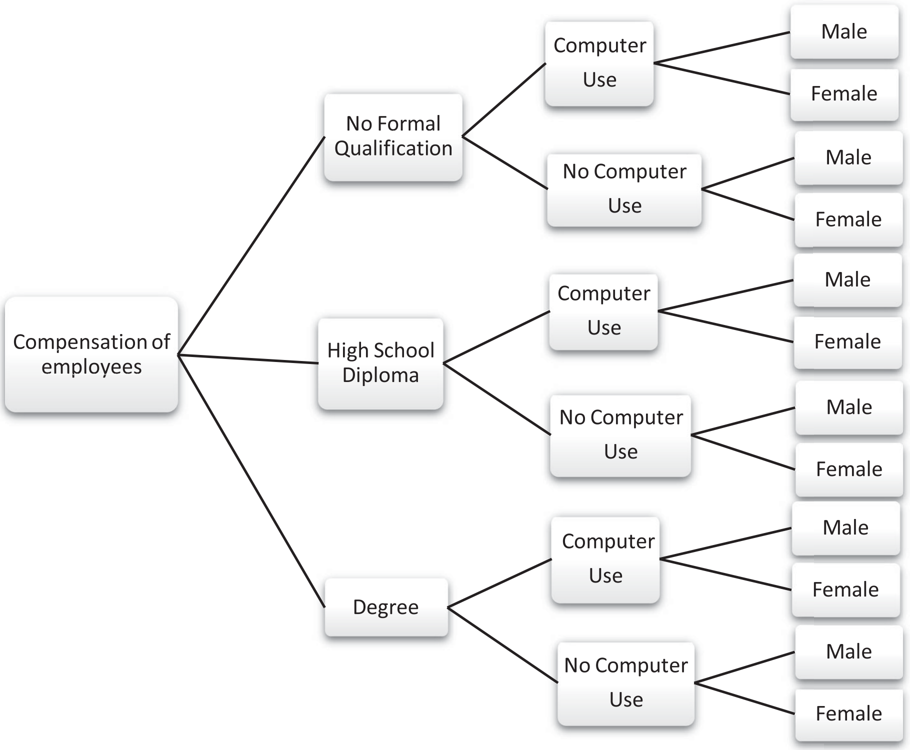
Our analysis is based on the data contained in the SAM for the year 2013, i.e. the year of the latest year of a national accounts (NA) release by Istituto Nazionale di Statistica (ISTAT). The Italian economy languishes in recession according to ISTAT as we write this paper. So using a SAM for 2013 should be no issue for our exercise. This type of analysis could prove problematic if it is based on data tainted by the period's economic crisis. Still, structural parameters, which describe interindustry and intersectoral interdependencies, should hold throughout the cycle. And while intersectoral relations are unlikely to be subject to major changes, value-added structures could be. In fact, such bias could strengthen our conclusions in terms of ICT: that is, the restructuring of firms and of the economic activities during the crisis should exacerbate innovation processes and the consequent changes in the composition in labour demand as evident through ISTAT data on employment by occupation.

2. A SAM with labour flows: digital competences analysis

A SAM represents a real picture of the economy because it records all transactions between economic agents in a specific economy for a specific period of time (Stone, 1960). It describes all phases of the circular flow of income, going from its generation (by means of production) to its distribution and, finally, to its use for final consumption (Stone, 1985). SAMs are the database for multisectoral models that quantify the effects of exogenous shocks on the different macroeconomic variables and the distributional implications on institutional sectors (Pyatt and Round, 1977).

Standard SAMs record the compensation of employees as a single flow that runs from industries to households. For the purposes of this study, we modify this standard structure and disaggregate the compensation of employees into twelve different categories (see Figure 1) that derive from the combination of the levels of three attributes: formal

Figure 1. The disaggregation of the compensation of employees.



educational attainment (three levels), digital competences (two levels) and gender (two identities).

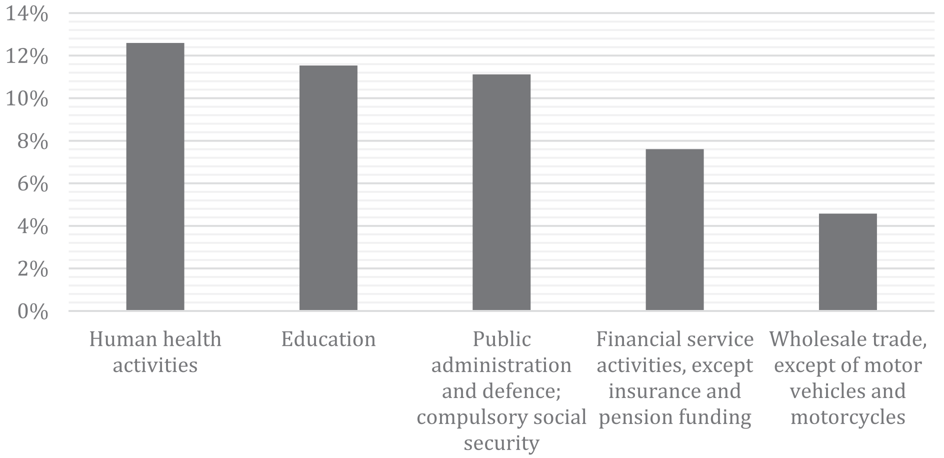
2.1. Data description

The SAM used in this paper is the result of the authors' own calculations, and it is based on the data contained in the NA and in the Use (commodity by industry) and Make (industry by commodity) tables (ISTAT, 2016). In the NAM classification for Italy, there are 63 commodities, 63 industries[1] and 4 value added components (compensation of employees, mixed income, gross operating surplus and taxes net of production subsidies). The Institutional Sectors (Households, financial and non-financial Corporates and Government) are decomposed in six sub-sectors according to the classification contained in the Italian NA. Moreover, the SAM also includes the capital formation account.

The detailed labour flows that we use to disaggregate the compensation of employees are from country's NAs (ISTAT, 2016) as well as from other, more specific sources, that collect data on employment by industry and by level of formal educational attainment. The main data source for the disaggregation by education (and also by gender) is the EU KLEMS Growth and Productivity Accounts (Jäger, 2018). In this dataset, there are three levels of formal education (*Primary school diploma or lower qualification*, *High school diploma* and

[1] The list of industries is given in Appendix Table A1.

Figure 2. Highly educated male workers with digital competences (share of total male employee compensation).

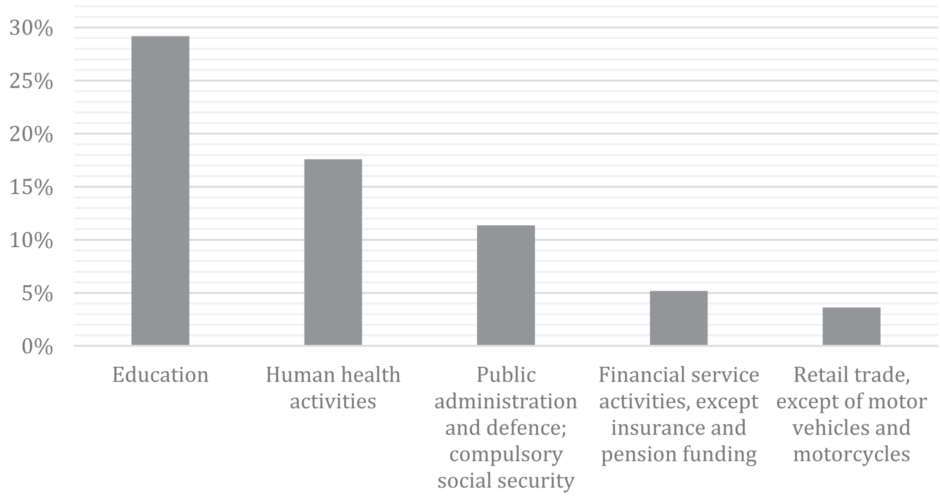


University degree). The EU KLEMS data are overly aggregated by activity (e.g. it reports manufacturing as a single activity) and beg to be converted to greater detail,[2] so we use the classification by digital competence in ISTAT (2016). This dataset describes the distribution of employees by formal education attainment and by (informal) digital competence level, which is proxied by the relative ability to use a computer with or without internet access at the workplace. Data from the OECD *Programme for the International Assessment of Adult Competencies* (PIAAC) are also used, since they are compatible with and complementary to the ISTAT data on digital competences. The adopted disaggregation finally accounts for two levels of digital competences: workers with digital skills ('computer use') and workers with no digital skills ('no computer use').

The disaggregation of employee compensation allows us to compute allocative shares of compensation to each of twelve labour categories. On this basis, one can rank industries on various criteria. Figure 2 (for males) and Figure 3 (for females) for example, rank industries by the share of compensation of employees paid to highly-skilled workers (i.e. workers with the highest educational attainment level *and* with digital competences). Besides providing a very informative picture of the Italian economy, this ranking is the necessary background for designing the structure of the policy aimed at stimulating highly-skilled labour demand by industry. As shown in both figures, industries with the highest level of highly-skilled employment are (both for male and for female workers) Human health activities (56), Education (55), Public administration (54), Financial service activities (41) and Wholesale trade (29)/Retail Trade (30). Industries with male prevalence are Security and investigation activities (53) and Wholesale trade (29). By contrast, Education (55) and Activities of households (63) show a higher female prevalence. Barring these differences, Figures 2 and 3 reveal a similar profile in four out of the five industries, with the exceptions of Wholesale Trade (29) for males and Retail Trade (30) for women.

[2] This result was achieved by taking into account the intensity of investment in ICT and R&D in terms of value added, under the assumption that greater innovation intensity is highly correlated with the use of workers with higher levels of digital skills.

Figure 3. Highly educated female workers with digital competences (share of female employee compensation).



Male workers with medium and low education (i.e. 'Primary school diploma or lower qualification' and 'High School Diploma') and with no digital competences (i.e. 'No Computer Use') are concentrated in Construction (27), Public administration (54) and Wholesale trade (29); while their female counterparts are mostly employed in Accommodation and food services activities (36), Education (55) and Activities of households (63). Male workers with the same educational attainment but ***with*** digital competence are mostly concentrated in Construction (27), Manufacture of machinery and equipment (19), Electricity, gas, steam and air conditioning supply (24) and Wholesale trade (29). Women with the same education and skills are mostly employed in Human health activities (56), Accommodation and food services activities(36), Manufacture of textiles (6) and Education (55).

Regardless of gender highly educated workers (education attainment is 'Degree') with digital competence tend to concentrate employment in Human health activities, Education, Public administration and defence, Financial service activities and Wholesale trade/retail trade. Highly educated and skilled working men (only) also concentrate in Security and investigation activities and Wholesale trade. Highly educated and skilled working women concentrate in Education and Households' activities. Figures 2 and 3 show a similar profile in four out of five industries with exceptions of Wholesale trade (men) and Retail trade (women).

3. The extended multisectoral model

Our model extends Miyazawa's (1976) multi-industry, multifactor, multisector setting using the work of Ciaschini and Socci (2007). It provides a coherent framework for the full representation of the circular flows of income. Since the production function is of a Leontief-type, input coefficients are fixed and any substitution between intermediate consumption and primary factors is disabled. Prices are constant.

Using the model, one can quantify the effects of a given policy shock on the model's n commodities, m industries, c primary factors and h institutional sectors it accounts. The computation of the model solution starts with First, we obtain the commodity-by-industry coefficients matrix:

$$\mathbf{B} = \mathbf{U}\hat{\mathbf{x}}^{-1} \tag{1}$$

as the matrix of intermediate commodity input requirements per industry output. Here $\mathbf{U}$ is the $(n \times m)$ Use matrix that identifies the demand of intermediate goods by industry, $\mathbf{x}$ is the total industry output vector, the hat or circumflex ˆ denotes a diagonal matrix – here a matrix with the inverse of the vector values of $\mathbf{x}$ on its diagonal.[3]

An $(n \times n)$ commodity technology coefficient matrix is obtained by:

$$\mathbf{A} = \mathbf{BM} \tag{2}$$

where $\mathbf{M} = \mathbf{W}\hat{\mathbf{q}}^{-1}$ is the product between the (industry-by-commodity) Make table, $\mathbf{W}$ and $\mathbf{q}$ is the vector of commodity output. The output-by-industry vector $\mathbf{x}$ is distributed to intermediate use and to final demand $\mathbf{f}$ via $\mathbf{x} = \mathbf{Mq}$, so that

$$\mathbf{q} = \mathbf{BMq} + \mathbf{f} \tag{3}$$

the general formulation for the demand-driven model, in which final demand is a function of disposable income $\mathbf{y}$.

Given $\mathbf{A}$ in Equation (2), we can calculate value added coefficients, i.e. the shares of value added on gross industry output. For each commodity j ($j = 1, \ldots$ n), these coefficients are the difference between 1 and the sum of the coefficients of the n intermediate inputs:

$$v_j = 1 - \sum_{i=0}^{n} a_{ij} \tag{4}$$

where $\boldsymbol{\nu}$ is vector of commodity value-added shares. A vector of total value added by commodity can then be obtained as the product of matrix $\hat{\boldsymbol{\nu}}$ with vector $\mathbf{q}$ of gross output by commodity:

$$\mathbf{v} = \hat{\mathbf{v}}\mathbf{q} \tag{5}$$

A vector of the components of value added can be estimated as:

$$\mathbf{v}^{\mathrm{c}} = \mathbf{Nv} \tag{6}$$

where the $(c \times n)$ matrix $\mathbf{N}$ (uppercase Greek 'nu') contains the share of value added for each of the c components for each of n commodities.

Value added by component can be allocated to institutional sectors as:

$$\mathbf{v}^{\mathrm{h}} = \mathbf{P}\mathbf{v}^{\mathrm{c}} \tag{7}$$

where $\mathbf{P}$ is the $(h \times c)$ structural matrix for the distribution of the shares of institutional value added by component. Arbitrary element $p_{i,j}$ is given by the i^{th} component's share of value added within the j^{th} institutional sector.

[3] Note throughout this manuscript matrices are denoted in uppercase bold font, vectors in lowercase bold font, and scalars in italics.

Disposable income $\mathbf{y}$ is obtained by adjusting the primary income assigned to institutional sectors through a $(h \times h)$ matrix of transfers $\mathbf{T}$ in the secondary income distribution among institutional sectors:

$$\mathbf{y} = (\mathbf{I} + \mathbf{T})\mathbf{v}^{\mathrm{h}} \tag{8}$$

In Equation (8), an element $\mathbf{T}$ reveals the net transfers between two given institutional sectors. Arbitrary element t_{ij} is the share of all net transfers of primary income from institutional sector i assigned to institutional sector j. Disposable income includes overseas net transfers. Disposable income is used for consumption ($\mathbf{Fy}$) and savings, which in turn drives investment decisions($\mathbf{Ky}$). A part of final demand is considered exogenous $\mathbf{f}^0$.

Final consumption demand depends on the $(n \times h)$ structure of the expenditures by each institutional sector for each commodity, $\mathbf{F}^1$, and by the level of its consumption propensity represented by the $(h \times h)$ matrix $\mathbf{C}$:

$$\mathbf{F} = \mathbf{F}^1\mathbf{C} \tag{9}$$

Investment demand is obtained as:

$$\mathbf{K} = \mathbf{K}^1\hat{\mathbf{s}}(\mathbf{I} \text{ - } \mathbf{C}) \tag{10}$$

where $\mathbf{K}^1$ shows the structure of the institutional sectors' demand for investment by commodity and $\mathbf{s}$ is the vector of active savings, i.e. the share total savings generated by each institutional sector.

Final demand is summarised as:

$$\mathbf{f} = \mathbf{Fy} + \mathbf{Ky} + \mathbf{f}^0 = (\mathbf{F} + \mathbf{K})\mathbf{y} + \mathbf{f}^0. \tag{11}$$

The sum of consumption and investment is total endogenous demand:

$$\mathbf{D} = \mathbf{F} + \mathbf{K}. \tag{12}$$

Therefore, using Equation (12), Equation (11) can be re-written as:

$$\mathbf{f} = \mathbf{Dy} + \mathbf{f}^0 \tag{13}$$

and the solution to the model is given by:

$$\mathbf{R} = [\mathbf{I} - \mathbf{A} - \mathbf{D}(\mathbf{I} + \mathbf{T})\mathbf{PV}]^{-1} \tag{14}$$

where $\mathbf{R}$ is the inverse matrix of the model and the vector $\mathbf{f}$ is:

$$\mathbf{f} = \mathbf{D}(\mathbf{I} + \mathbf{T})\mathbf{PVq}. \tag{15}$$

Substituting (14) into (3) yields:

$$\mathbf{q} = [\mathbf{I} - \mathbf{A} - \mathbf{D}(\mathbf{I} + \mathbf{T})\mathbf{PV}]^{-1}\mathbf{f}^0 = \mathbf{Rf}^0 \tag{16}$$

where $\mathbf{D}(\mathbf{I} + \mathbf{T})\mathbf{V}$ is the matrix of final uses (consumption and investment) per unit of output. Equation (16) can also be expressed in terms of value added by component $\mathbf{v}^{\mathrm{c}}$ by multiplying both sides by $\mathbf{V}$.

$$\mathbf{v}^{\mathrm{c}} = \mathbf{Vq} = \mathbf{VRf}^0 \tag{17}$$

where $\mathbf{V}$is the matrix of the coefficients of value-added component normalised by output.

4. The macro multiplier (MM) approach

The extended multisectoral model of Section 3 computes production volumes of each industry given final demand. Matrix $\mathbf{R}$ in Equation (14) combines the direct, the indirect and the induced effects associated with the generation of value added, with its (primary and secondary) distribution, as well as with its use for final consumption when final demand is given an exogenous shock. Indeed, the elements of matrix $\mathbf{R}$ are disaggregated multipliers that show both the direct and the indirect requirement of intermediate consumption i to produce one unit of commodity j.

The disaggregated multipliers, however, are affected by the unitary composition of final demand (Ciaschini and Socci, 2006). Their value can significantly change in the presence of different composition effects. The MM approach, which is based on SVD, overcomes these problems (Ciaschini and Socci, 2007; Lancaster and Tiesmenetsky, 1985; Meyer, 2000; Ciaschini et al., 2009). The SVD brings out the set of endogenous final demand structures that are latent in the inverse matrix of the reduced-form model and, thus, it enables the achievement of desired policy targets.

Using the MM approach to decompose matrix $\mathbf{R}$ yields:

$$\mathbf{R} = \mathbf{U}\hat{\mathbf{z}}\mathbf{W}' = \sum\nolimits_{\mathrm{i}=1}^{n} \mathbf{u}_i\mathbf{z}_i\mathbf{w}_i \tag{18}$$

where $\mathbf{U}$ and $\mathbf{W}$ are two unitary matrices, $\hat{\mathbf{z}}$ has positive elements (the MM) and $'$ denotes array transposition. On the right-hand side of (18), $\mathbf{u}_i$ is the ith column of matrix $\mathbf{U}$; z_i is the ith element of the vector of MMs, denoted by $\mathbf{z}$; and $\mathbf{w}_i$ is the ith row of matrix $\mathbf{W}$. Since the rows of matrix $\mathbf{W}$ are orthonormal, in $\mathbf{u}_i\mathbf{z}_i\mathbf{w}_i$ only the stimulus from the control vector $\mathbf{w}_i$ transmits, after being multiplied by the vector $\mathbf{z}_i$ and transformed into the target vector $\mathbf{u}_i$. This can also be shown by substituting (18) in (16), rearranging terms and letting $\mathbf{U}'\mathbf{q} = \bar{\mathbf{q}}$ and $\mathbf{W}'\mathbf{f}^0 = \bar{\mathbf{f}}^0$: $\bar{\mathbf{q}} = \mathbf{Z}\bar{\mathbf{f}}^0 = \bar{\mathbf{f}}^0$ (19).

By using $\mathbf{VR}$, as in Equation (18), we obtain $\mathbf{R}^1$ that is an $m \times n$ matrix with m value added components and n commodities, i.e. m policy targets and n policy controls:

$$\mathbf{R}^1 = \mathrm{V}\mathbf{NR} = \mathbf{U}^1\hat{\mathbf{z}}^1\mathbf{W}^{1\prime} = \sum_{i=1}^{v} \mathbf{u}_i^1\mathbf{z}_i^1\mathbf{w}_i^1 \tag{20}$$

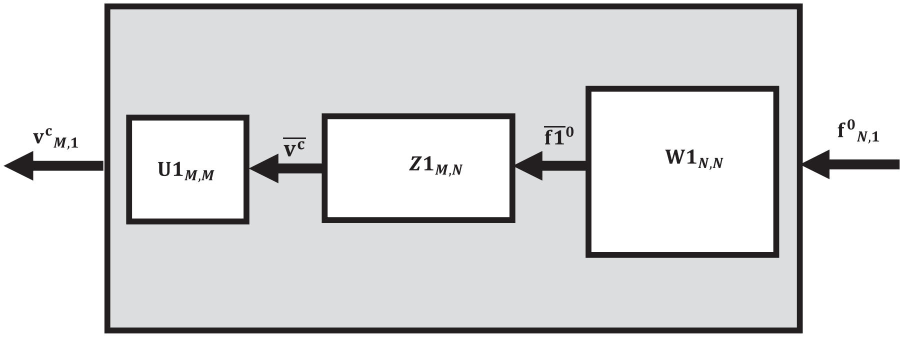
where $\mathbf{U}^1$and matrix $\mathbf{W}^1$are orthonormal, and $\hat{\mathbf{z}}^1$ has only positive elements (again, the MM). On the right-hand side of (20), $\mathbf{u}_i^1$ is the i^{th} column of matrix $\mathbf{U}^1$and $\mathbf{z}_i^1$ is the i^{th} element of the vector of MMs and $\mathbf{w}_i^1$ is the i^{th} row of $\mathbf{W}^1$. Observe now that $\mathbf{R}^{\mathbf{1}}$ is an $m \times n$ matrix with m value added components and n commodities, i.e. m policy targets and n policy controls.

By substituting (20) into (17), rearranging terms and assuming $\mathbf{U}^{1\prime}\mathbf{v}^c(\mathbf{q}) = \bar{\mathbf{v}}^c$ and $\mathbf{W}^{1\prime}\mathbf{f}^0 = \bar{\mathbf{f}}^1$ one obtains:

$$\bar{\mathbf{v}}^c = \hat{\mathbf{z}}^1\bar{\mathbf{f}}^{10} \tag{21}$$

where the target vector $\mathbf{v}^c$ is represented by vector $\bar{\mathbf{v}}^c$ in the orthonormal basis as defined by $\mathbf{U}^1$ while the control vector $\mathbf{f}^0$ is represented by $\bar{\mathbf{f}}^{10}$ in the orthonormal basis as defined by $\mathbf{W}^1$. The equations of each sum in (21) are completely independent of each other. This implies that a specific structure defined by a column of $\mathbf{W}^1$ activates a single MM $\mathbf{z}_i^1$ when

Figure 4. Representation of SVD on the VLR matrix.



obtaining the output via a specific column of $\mathbf{U}^1$ (Ciaschini and Socci, 2007). The process is represented in Figure 4. In this context, the modulus of the dominant structure $\mathbf{W}_1^1$ associated with the MM $\mathbf{z}_i^1$ enables one to obtain the highest modulus of the target variable $\mathbf{U}_1^1$.

In other words, a policy structure given by a row of matrix $\mathbf{W}^{1\prime}$ transforms the exogenous final demand vector into the control variable. This determines the level of the target variable through the convenient MM. The new value added vector is given by multiplying $\mathbf{W}^1$ by the target variable. Each $\mathbf{R}^1$ yields a set of different demand structures of different magnitude. The magnitude is given by the MMs: choosing the demand structure associated with the highest MM $(\mathbf{u}_i^1, \mathbf{z}_i^1)$ means generating the largest effects on the economy (dominant structure). Conversely, a policy can pursue a more specific objective, for example an increase in highly-skilled employment with digital competences (see Section 5). In this case, a different structure (i.e. the second) may be effective. In general, if several structures are contemporaneously relevant, they can be linearly combined. In our case with two structures, a linear combination can help achieve both effects. For instance, the combination of the first two structures reads.

$$\mathbf{f}^0 = \alpha_1 \mathbf{w}_1^1 \alpha_1 \mathbf{w}_1^1 + (1 - \alpha_1)\mathbf{w}_2^1 (1 - \alpha_1)\mathbf{w}_2^1 \tag{22}$$

$$\mathbf{v}^c = \alpha_1 \mathbf{u}_1^1 \mathbf{z}_1^1 \alpha_1 \mathbf{u}_1^1 \mathbf{z}_1^1 + (1 - \alpha_1)\mathbf{u}_2^1 \mathbf{z}_2^1 (1 - \alpha_1)\mathbf{u}_2^1 \mathbf{z}_2^1 \tag{23}$$

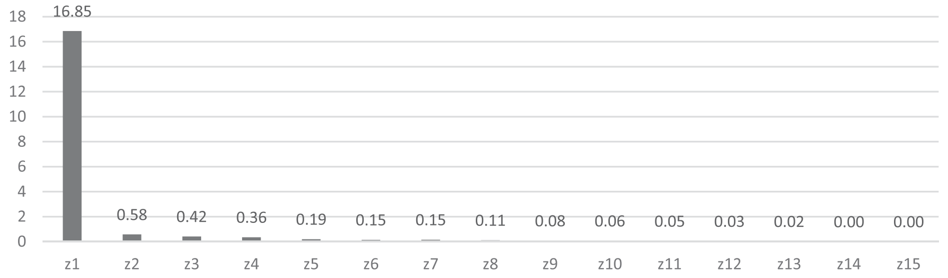
where α_1 and $(1 - \alpha_1)$ are the weights. Here, Equation (22) represents the combined input structure while Equation (23) gives the combined effect on the value added components.

5. Macro multiplier analysis and relationship between final demand and value added

Since there are 15 value-added components in the economy, solving the model for the value added though the SVD technique yields 15 MM. Each MM is associated with a specific final demand structure and is connected to the structure of total production. Hence, for any demand structure, the associated MM quantifies the aggregate effect on the economy and it generates a distinct value added (and output) structure.[4] The 15 MM are represented

[4] Appendix Figure A11 shows the 15 output structures of value added, which correspond to the 15 MMs.

Figure 5. Macro Multipliers (MM) in R[1].



in Figure 5, which shows that only one MM (the first) is greater than one, exerting an expansive effect on the target variable.

The aim of this study is to identify that specific final demand structure, which is most effective in stimulating highly-skilled employment with digital competences. This demand structure is the one which is associated with the highest MM (i.e. $z_1 = 16.85$), as it has the highest impact on all value added components. The third demand structure (i.e. the one associated with the third highest MM) is particularly effective on highly-skilled employment with digital competences. The other structures are less relevant.

In order to appraise these results, we perform three exercises. In the first, we compute the effects of a one percent shock on final demand using the demand structure associated with the highest MM. In the second exercise, we maintain the same shock, but we assume the third demand structure. And in the last exercise we assume a linear combination of the two structures used in the first two exercises.

Figures 6 and 7 refer to the first exercise. Figure 6 shows the effects on the twelve labour categories. The largest effects (around 3.5 percent) are those on female workers with low education and no digital competences and on male workers with the same education level but with digital competences. The overall effect on the six labour categories with digital competences is slightly lower than the one on their counterparts without digital competences. It adds up to 3.0 percent for males and it ranges between 2.0 and 2.5 percent for females.[5]

Figure 7 illustrates the effects at industry level. This decomposition allows highlighting that there are some industries [Public administration and defence (54), Education and Human health activities (55)], in which the effects are generally higher than in the rest of the economy.

The results of the second exercise, which uses the third final demand structure, are shown in Figures 8 and 9. In comparison to the case with the first demand structure, the effects are much tinier. They are positive (or slightly negative, at worst) for workers with digital competences (see Figure 8). In the case of workers with high-school diploma and digital competences, impacts range from 0.04% (for males) and 0.07% (for females) and they rise to 0.11% and to 0.15% respectively when the educational attainment is a degree.

Industries that employ highly-skilled labour (with digital competences) more intensively tend to contribute positively to the labour related value added components, with a particularly marked effect for Public administration and defence (54), Education and

[5] These figures are authors' own calculations and are not shown in Figure 6.

Figure 6. Effects of an increase by 1% in final demand using final-demand structure 1.

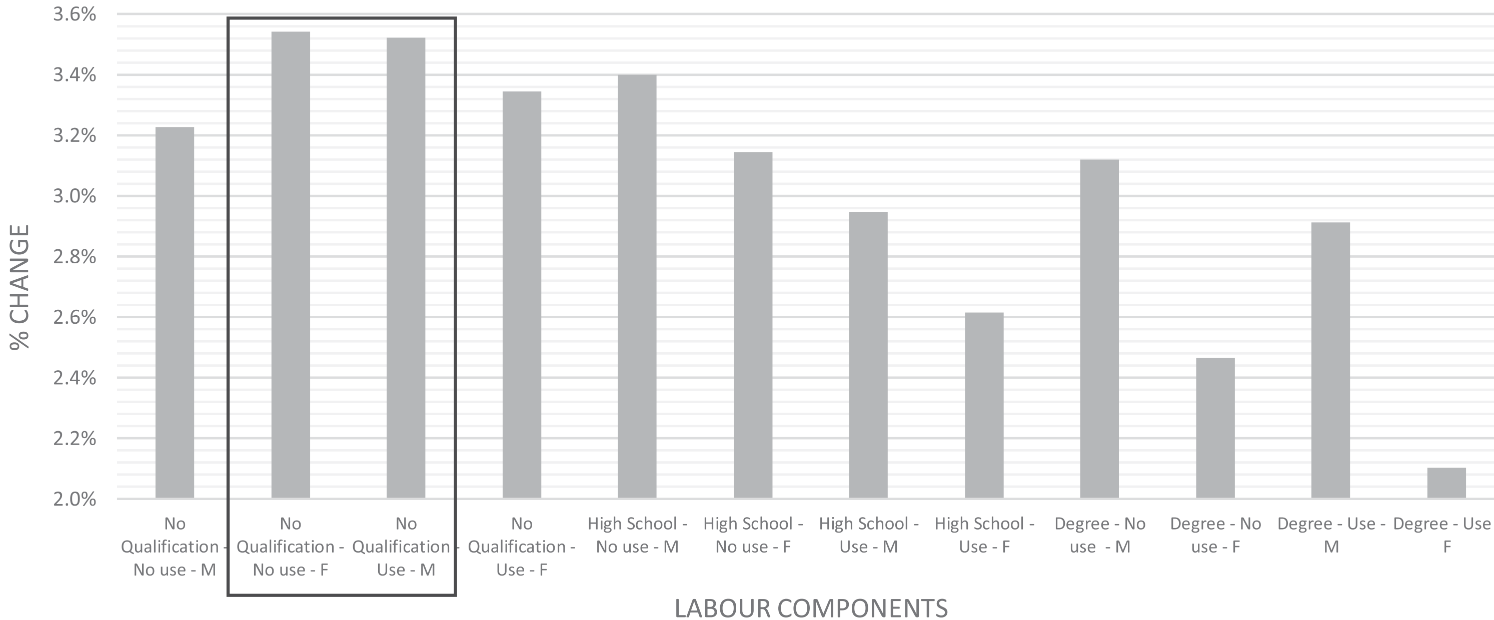


Figure 7. Effect on the labour components by industry of an increase by 1% of the final demand using structure 1.

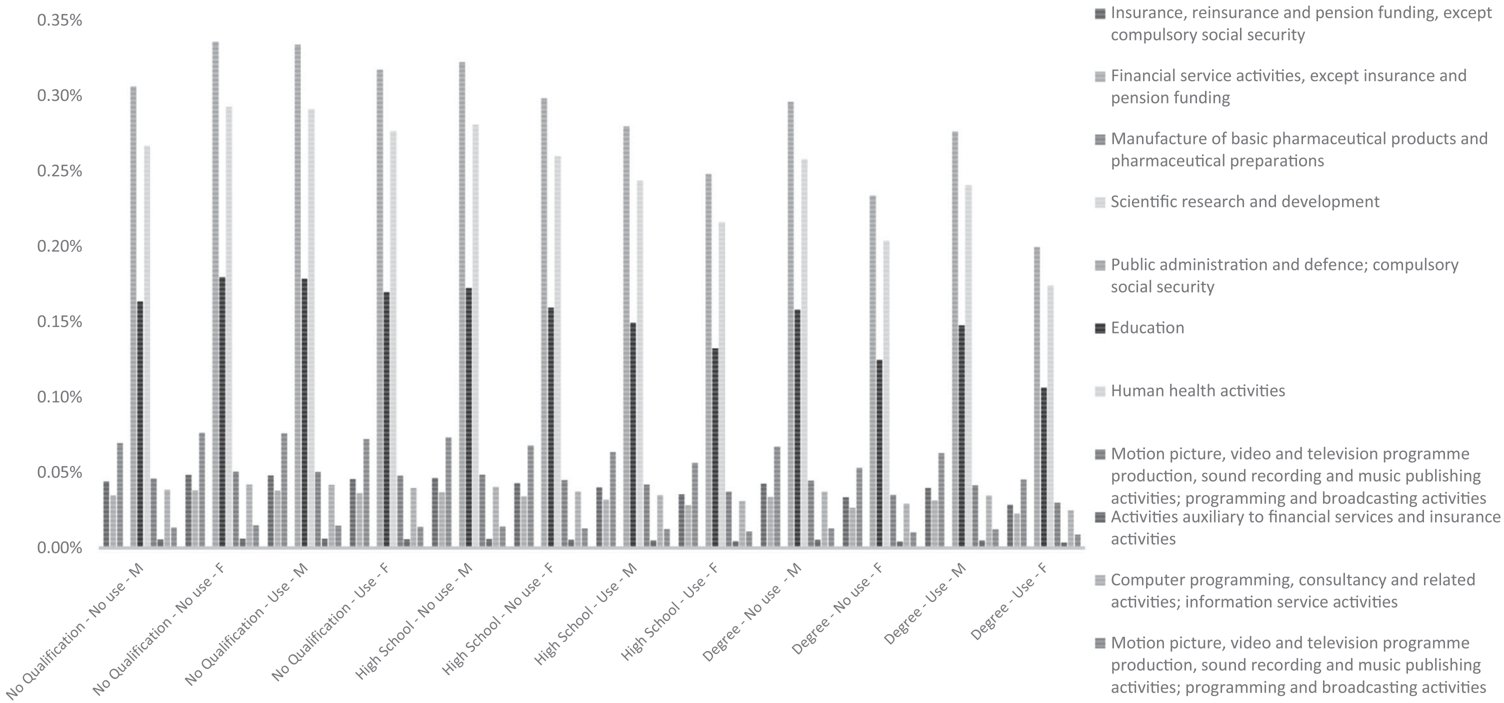
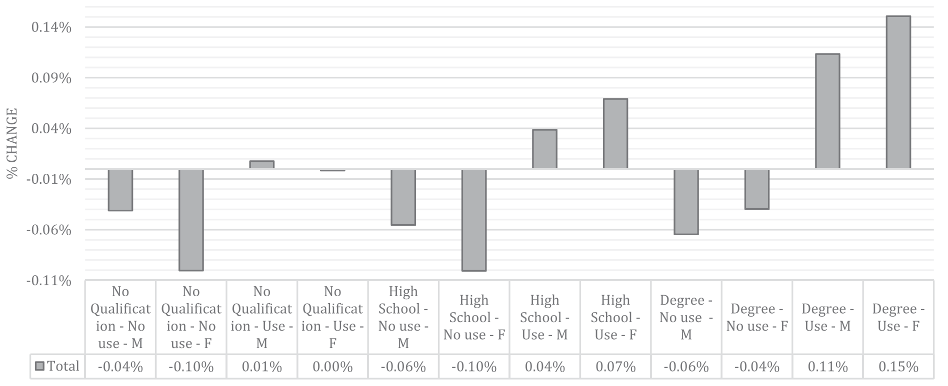


Figure 8. Effect on the labour components of an increase by 1% of the final demand using the structure 3.



Human health activities (55)(see Figure 9). A noticeable exception in this picture seems to be Scientific research and development, probably because of the low weight that this industry renders on Italy's total output. In the case of 'Other Activities', the overall impact on labour categories with digital competences tends to be negative.

In the last exercise, we construct a linear combination of the first and the third demand structure. The weights are 0.2 for the first demand structure and 0.8 for the third. Such a combination maximises the effects on highly-skilled labour with digital competences (see Figure 10). The highest impacts (ranging around 0.20 percent) are in fact on highly-educated workers digital competences, followed by workers with lower education attainment and the same level of digital competences (around 0.15 percent). Overall, the effects on labour categories with digital competences are higher than those on their counterparts without these competences. Among labour categories with digital competences, the effects on highly- and medium-skilled labour are similar to those on low-skilled labour (they all lie in the range between 0.15 and 0.20 percent). This result can be read as a sign of the complementary between highly-/medium-skilled and low-skilled labour.

As Figure 10 shows, the positive effect on highly-skilled labour (with digital competences) tends to be hand-in-hand with the effect on medium- and low-skilled labour. This complementarity is also visible in Figure 11 and is likely due to the structure of the production function in industries such as Education, Public administration (54) and (to a lesser extent) Manufacture of basic pharmaceutical products (12). Figure 11 also shows that industries with the largest effect on highly-skilled labour with digital competences are in Insurance (42), Financial service activities (41), Manufacture of basic pharmaceutical products (12), Education and Public administration (54). Among these industries, Education and Human health activities are seemingly the ones with higher female employment. These industries are relevant both in terms of size and share of highly-skilled labour compensation on the total labour compensation. In *Other Activities* by contrast, there seems to be more room for low-skilled labour without digital competences, which might be a confirmation of the Italian specialisation in industries that do not require digital competences. As also in the second exercise, notice Scientific research and development, which seems to be quite unaffected by the policy.

Figure 9. Effect on the labour components by industry of an increase by 1% of the final demand using structure 3.

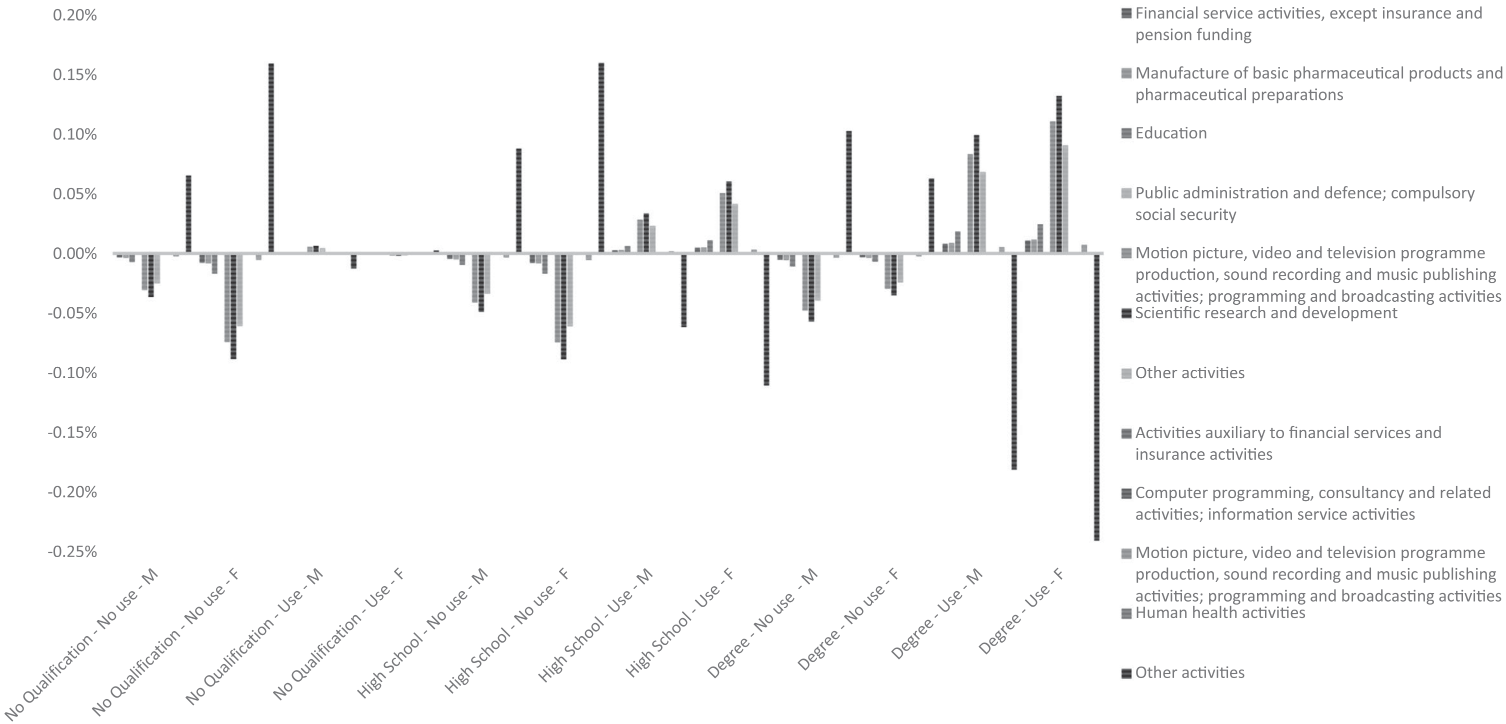
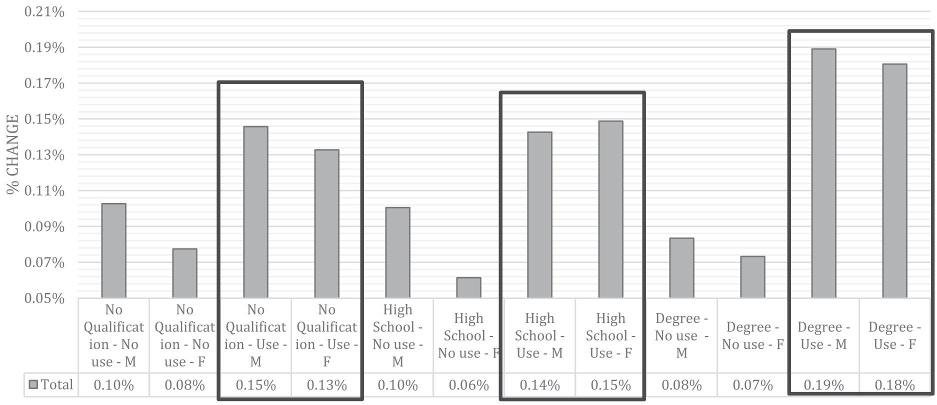


Figure 10. Effect on the labour components of an increase by 1% of the final demand using a combination of structures 1 and 3 (weights: 0.2; 0.8).



6. Policy implications and conclusion

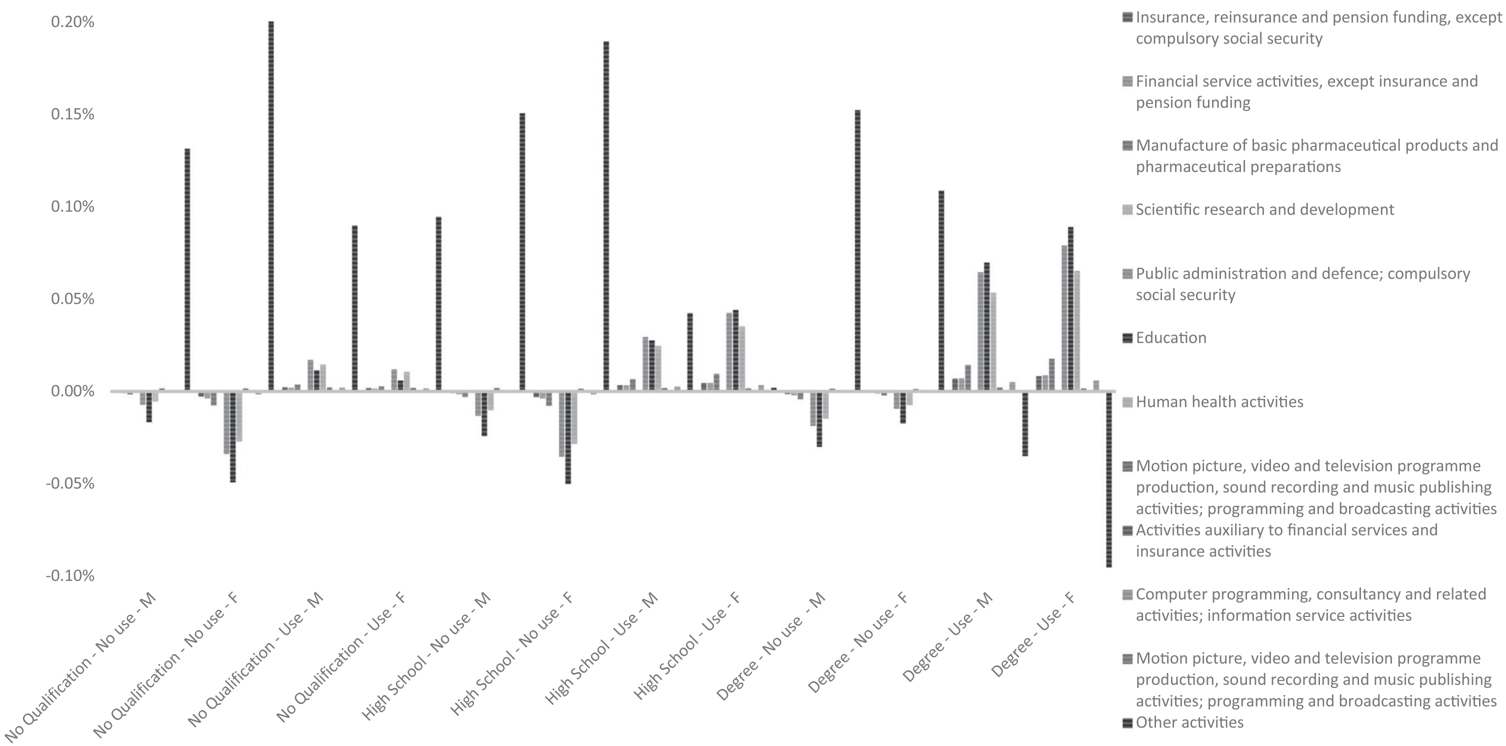
This article illustrates the potential of the disaggregated multisectoral analysis with the Macro Multiplier approach as a tool of economic policy. It focuses on the Italian economy and it shows that this approach may be useful for designing a number of policy measures aiming at increasing highly-skilled employment with digital competences. To this scope, it uses Miyazawa's (1976) basic multi-industry, multi-factor, multi-sector setting, further extended along the lines of Ciaschini and Socci (2007). The dataset is the 2013 SAM for Italy.

The paper contributes to the literature on the relationship between technological (specifically digital) development and labour market dynamics. Indeed, it is well recognised in the literature that technological development changes the composition of labour used, that is it polarised returns from highly-skilled labour with digital competences and from low-skilled labour that lacks digital competences. Specifically, a labour force with digital competences seems to determine growth, as it yields a country a more favourable position in the international division of labour. For this reason, both international organisations and governments have been promoting digitalisation.

In the case of Italy, our results indicate that Public administration (54), Education and Human health activities (55) are the industries in which highly-skilled labour with digital competences could increase most as a consequence of such promotion. By contrast, the typical high-tech industries as Scientific research and development (47), Telecommunications (39), Financial service activities (41), Insurance reinsurance and pension funding (42), Manufacture of basic pharmaceutical products (12) would change least in terms of their use of digitally-skilled labour.

In broader terms, sector-specific policies that support innovation and the use of highly-skilled workers (with digital competences) may eventually catalyse innovative private undertakings, and thereby reduce the digital skills gap and, hence, the division of labour between southern and northern European countries (see OECD, 2017). To this end, governments could make tax incentives available to innovative firms in order to encourage an inflow of FDI or otherwise launch public investment plans that aim to expand innovative

Figure 11. Effect on the value added components by industry of an increase by 1% of the final demand using a combination of structures 1 and 3 (weights: 0.2; 0.8).



activities. Such policy measures would likely affect labour demand by eventually raising the need for highly-skilled labour with digital competences. On the supply side of the labour market, it might stimulate both greater needs for education as well as for digital competences. Bridging the gap between the digital skills of graduates in southern Europe and graduates from Scandinavia or the Netherlands suggests enhancing sophisticated logical competencies that ICT innovation typically requires and that most firms also demand.

Disclosure statement

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