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Abstract. The paper examines the effects of higher public investments in and for digital transformation and Big Data (BD) on the economic output in EMU countries as a possible policy action able to respond efficiently to the decline in global activity due to the COVID-19 pandemic. The adverse effects on economic growth are expected to be very significant; mobility fell substantially in all states, even ones that have not adopted major distancing mandates since the beginnings. Thus, larger investments accelerating the digital transformation in EMU countries might generate a positive GDP effect countervailing the COVID-19 crisis. In order to test this hypothesis, we develop a dataset able to represent among GDP determinants, the contribution of public investments in digital evolution and related technologies in EMU countries, and build an architecture via Artificial Neural Networks through a Deep Learning experiment using Python software to test it. The results confirm that a significant change in public investments on digital technologies and BD will generate a positive change in GDP in an acceleration process. This outcome advises policymakers to use forthcoming public resources from the European Recovery Funds also in accelerating the EMU economies' digital transformation by investing in the healthcare sector, investee companies, and throughout the modernization of the Central Public Administration.

Keywords: EMU Countries, Covid-19, Big Data, Economic Growth, Artificial Neural Networks.

1 Introduction

The economy and the global system are experiencing a deep crisis due to the international pandemic from COVID-19. The consequential outbreak has generated an unprecedented worldwide shock on economy and society. On top of the hundreds of thousands of deaths, and related social problems, this recent unexpected pandemic is likely to cause huge economic losses of about 9 trillion dollars for 2020. Global growth is projected at -4.9 % in 2020 [13], with a worse performance in the EMU countries (-10.2%),

especially in Italy, France and Spain (-12.8%), compared to United States and other advanced economies (-8%). The economic fallout has revealing to be more severe than it was predictable at the beginnings.
Unlike the past economic and financial crises, this time the international economic system has been hit symmetrically and simultaneously both, on the supply and the demand side [3, 8, 10]. Consumption and services output have fallen significantly due to a unique combination of factors: voluntary social distancing, lockdowns needed to slow global value transmission chains and allow health care systems to handle rapidly rising caseloads, steep income losses, and weaker consumer confidence. Firms have also cut back on investments, when faced with vertical demand losses, supply interruptions, and uncertain future earnings situations. This scenario has driven to a broad-based aggregate demand shock, compounding near-term supply disruptions due to lockdowns. First impact advanced economies' response has been providing sizable fiscal support through budgetary measures, as well as off-budget liquidity.
The belief that the health emergency and the economic crisis make a rapid recovery are less likely, as nothing of what we observe nowadays has ever been experienced before. Recent estimates expect a fall in the world trade volumes of goods and services of -11.9%, and even higher in the advanced economies (-13.4%) [13]. The recession generated by the pandemic - as noted by the IMF - "is unprecedented," and its adverse effects are much higher than the ones during the global financial crisis of 2007-2008.
Although this pandemic-economic crisis is touching all countries, the Eurozone remain among the major economic areas affected since the end of February 2020. The lockdown and the mandatory mobility restrictions have had an asymmetric impact worldwide, especially on labor markets, with the most negative effects concentrating on those EMU countries already vulnerable before the outbreak. Therefore, the main concern is to stimulate their economic activity to react, and to lessen some negative impacts on GDP that show a strong variation from one country to another, but the epidemiological damage caused by the pandemic, since they largely depend on the economic characteristics of each country. One response to lessen these impacts is the EU Commission's Coronavirus Response Initiative Plus, which introduces flexibility in the use of structural funds to support those regions most in need. The market conditions call for targeted policy responses and reactions, both at the EU and at Member State levels. Policymakers must cooperate to address the economic issues underlying trade and technology tensions as well as gaps in the rules-based multilateral trading system.
Our proposal for a stable economic recovery of the EMU counties is to consider higher public investments in digital transformation and Big Data (BD) as a good policy action since they would be able to accelerate GDP positive response. In particular, compared to other different actions on the determinants of growth, a BD action would enhance GDP acceleration in a phase of decline in global activity due to the COVID-19.
Why an acceleration in digital policies and BD did might be a good tool of action?
Digital technologies could help respond to the crisis and prevent future pandemics, as state the major four world's technology companies – Alphabet, Amazon, Facebook and Google – quarterly earnings (NYTimes 2020.07.30). The COVID-19 crisis is further strengthening the position of some digitally qualified companies, while challenging many traditional firms, emphasizing the increased reliance of the new business models

based on digital platforms and services during the pandemic. In fact, as governments work to offset the virus and mitigate the economic recession, digital technologies and new business models have allowed many firms to avoid a complete shutdown, accelerating our transition to a digitalized future. Connectivity and digital technologies have a critical role to play in responding to and recovering from the 2020 pandemic crisis.
In this paper, through a Deep Learning (DL) approach with Artificial Neural Networks (ANN), we try to show if an active support by policy interventions from the EMU countries on BD investments and related technologies can generate a positive GDP acceleration, recovering their economies from the adverse effects of the international crisis caused by Covid-19. The remainder of this paper is organized as follow. Section 2 present a review on BS concept and definitions, while Section 3 explains the model and the data used. In addition to generating the ANN, we have created a proxy able to synthetize investments in BD and the current digitalization process in the Euro area. Our hypothesis is confirmed by the results tested with the latest indication of models in DL in Section 4. Some policy evaluation concludes the paper.

2 Big Data's Definitions, Advantages and Challenges

There exists a widespread confidence that, using digital technologies and BD, economies under stress can accelerate their efforts to go digital in response to the COVID-19 crisis. To sustain economic recovery in the medium-term, though significant uncertainties remain, most of the countries are turning their attention into digital policies. While some recent policy actions, public and private, such as temporary access to spectrum or solidarity schemes to help firms generate short-term revenue, are like to be part of a temporary, emergency response to the crisis, other policies in the digital sector, such as programs around teleworking, e-learning or online business models, may prove to be longer lasting. All these actions need an enormous amount of data, a large database to run. This process of research into massive amounts of data to reveal hidden patterns and secret correlations named as BD analytics.
Although the term BD is still hidden by some conceptual vagueness, usually we refer to massive data sets having large, more varied and complex structure, with the difficulties of storing, analyzing and visualizing for further processes or results [23, 7, 26]. It is an abstract concept, mainly used to describe enormous datasets, but a wide range of concepts, from the technological ability to store, aggregate, and process data, to the cultural shift that is pervasively invading business and society, both drowning in information overload.
The lack of a formal definition has led academic researchers and practitioners to evolve into multiple and, sometimes, inconsistent paths, even if it has been believed from the beginnings the next frontier for innovation, competition, and productivity [6, 11, 16]. BD has been defined as early as 2001 associating a "3 Vs Model" [14]. The Vs are the key criteria that define the dimensions of BD: volume, velocity, and variety. From a business perspective, BD differs from traditional data. What makes the difference in generating and collecting masses of data is their utility in terms of data scale that becomes increasingly big (volume), whether and how high data velocity are relevant and

useful to maximize the BD commercial value (velocity), and how the various type of "digital data content" can be used to create business value (variety).

In 2011, another definition has been proposed. "Big data technologies describe a new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling the high-velocity capture, discovery, and/or analysis" [9], stressing another relevant characteristics of BD. As a result, it was add another V to the 3Vs Model to highlight the value essence of these enormous datasets (huge value but very low density). This new enriched definition with 4Vs indicates the most critical problem in BD: how to discover values from datasets with an enormous scale, various types, and rapid generation. In a business-oriented definition, we count BD, in general, each data set so large in the 4Vs, and of such complexity, that it cannot be accomplished using traditional IT and software/hardware tools within a tolerable time [22]. A traditional database manages data in rows and columns, but BD cannot be considered permanent, because they are not available in a structured form. They can be documents, values detected by IoT sensors, metadata, and geographic locations. BD are not only "Big" for size and variety, but for how important they are for the companies and entities that analyze and use them producing an advantage over the market competition [18].

BD role have significantly increased over the past years; they helped economists and practitioners to a better understanding of the real world, and to an in-depth knowledge of the economy, of the standards of living, and businesses. In EMU countries, for instance, there was a recent massive improvement in how to gather information to understand the economic dynamics of the region by investing more in the tools of data collection, transmission, storage, and analysis. These new ways of data collection and analysis have driven the production of new goods and services such as customized shoes, quick innovation via a shorter research and development cycle, optimization of business processes, effective management of the organization, and useful marketing strategies that apply customer feedback in designing products [12, 21].

The impact of BD on business activities does not affect consumers only, but companies adopting data-driven decisions and innovations (DDI). Such companies achieve 5% higher productivity and growth output than other firms do not use it [21]. Adopting digital technologies and BD in making financial decisions, major EMU countries have also registered improvements in asset utilization, market value, and return on equity. According toWilliams, the implementation of data policies could increase the annual income of EMU countries by roughly $800 billion per year, with an advantage for the region in terms of reduced corruption, improved foreign trade, increased energy efficiency, and enhanced workplace conditions [26].

BD have also made a massive improvement in the advertising industry by making marketing more efficient, matching customers' interests and needs, and reducing barriers to entry by enabling small companies to get the right data for their market. According to Savastano et al., "retailers' increasing data integration and big data analytics capacities improve their understanding of consumers' cross-channel shopping behavior (and contrast the phenomenon of research shopping), supporting them to observe, measure and leverage how the synergies across channels influence consumer behavior and value perception" [24, p.487]. In Williams' view, free internet services facilitated data retrieval, enabling entrepreneurs to make a more accurate judgment about their business [26]. The social surplus associated to data retrieved online is estimated to be roughly 120 billion euros [25] for EMU countries, being the consumers who majorly benefited from it. The present digital transformation in EMU countries has generated several job opportunities. Among them, data analysis is considered as one of the most exciting jobs in the 21st century, estimated to have more than 500,000 employees related to data collection, data cleaning and analysis within the area [19]. BD usage is also likely to foster productivity and wages. With the continuous improvement in the technological process, the collection, transmission, storage, and analysis of data have become more comfortable, and this has resulted in the creation of new products and services.

Looking at the challenges, BD offers a great opportunity and massive risk at the same time, although the latter did not receive enough political attention between EMU countries so far. Above all, they negatively affect individuals, whose data have been collected, sometimes misusing personal information [2]. By the use of algorithmic profiling, a way of combining multiple forms of data sets, data of different persons are extensively collected without their knowledge as they travel, search, visit sites, and buy goods. The sorting most of the time goes under the radar, but at times, the data is exposed to brokers who use it for other purposes.

BD is gaining massive impetus as technological development in the business and academic sectors of EMU countries. Because of their extensive nature, data is always difficult to process, and it often leads to a misleading conclusion if not adequately evaluated [2]. By using advanced analytics technologies, organizations within EMU countries can utilize BD in developing innovative products, insights, and services [28]. Abdullah et al. state that the opportunities that stem from BD analytics are essential in the operation of organizations, the primary force of change in an environment of networked business [1]. They also believe that organizations will massively gain in different domains, such as security, e-commerce, health, and e-government if they embrace the use of data in their decision-making process. Williams states that data is a source of innovative services, products, and opportunities in the industry [26]. Information about people is also critical in increasing efficiency and effectiveness of business operations such as optimization of supply chain flows, error minimization and quality improvement, identification of the best price for products and services and selection of the best workers for specific tasks [4].

The process of data collection is also riddled with frequent inconsistencies such as failure of face recognition systems to identify people of color. The issue is becoming increasingly important since security systems, police, and government agencies currently use facial and finger recognition tools. The discrimination posed by the use of BD is not just limited to skin color but also to gender. Xue et al. found that men and women get different job advertisement, with men receiving job offers with higher pay as compared to women. Additionally, the inclusion of vagrancy in crime prediction models disorients the process of analysis and generates a wrong feedback loop by inserting more rules in arrears where there is a high likelihood of homelessness. Such actions result in more punishment and increased crime rates in those arrears [27].

There is a vast gap between the potential effects of data-driven information and its real use to mitigate social problems that can be solved faster using BD. The use of traffic data to control highway traffic in Spain and Italy is one of them recently used in EMU countries [1]. Most organizations are currently using advancement information technology backed up on BD applications. This enables them to solve most financial problems and be accessed to extreme customer information, which allows them to understand their demand. The social BD effects within the EMU countries also come in the form of data and system errors. In Spain and Italy, BD blacklisting and watch-lists have led to wrongful identification of people. It has been established that wrongful identification of individuals negatively affects their ability to secure jobs, their ability to travel and, in some cases, illegal deportation or detention [26][1].

3 The Model

To test the effects of larger investments in digital transformation and BD on EMU economic growth, we use a DL approach with ANN on a production function. We use Oryx protocol 2.0.8 on a data set that exemplifies the variables able to generate a positive GDP acceleration (see Table 1). The variables represent a panel in time series (not counted as such by the neural networks) that cover the period from 1990 to 2019 for all 27 EMU countries.

Table 1. List of Variables

Variable	Explanation	Source
GDP	GDP per capita in 2000 US$ (converted at Geary Khamis PPPs)	FRED Data
K	Gross Capital Formation (constant 2010 US$)	FRED Data
L	Labor Force	FRED Data
Open	Exports + Imports % on GDP	WBD
Expenditure	Government Expenditure (in real term)	IMF
Big Data	Public Investments in Digitalization&BigData	Our elaboration

We use the following variables where *GDP* is the per capita GDP (at constant 2010 US$), *K* stands for the Gross capital formation (at constant 2010 US$), *L* is the Labor force, *Open* is the degree of openness of the country measured by the balance of payments on GDP in %, and *Expenditure* is the Government expenditure in real terms. The variable *Big Data* represents the EMU investments in the DDI. Because of the lack of homogeneous sources, it was generated *ad hoc*, using as a source the data of Interoperability Solutions for European Public Administrations, and the Digital Economy and

[1] In Austria, there was an investigation about the debt recovery system that is currently used by the government after a series of complains about errors and unfair targeting of its citizens. In Latvia, the mechanical system failures once devastating the lives of its citizens; people lost access to their benefits, Medicaid, and food stamps [25].

Society Index, weighed with the public expenditure for services, health, and public participation in companies. The result is a proxy in time series capable to catch EMU countries investments in BD.

Following Minsky and Papert, we use a multilayer Neural Network (NN) model with definition of perceptrons [15]. These are feedforward networks with layers of units between inputs and outputs, which do not interact directly with the external environment. For this reason, we call these nodes hidden units and they are the key point for overcoming the limits of computational systems. In fact, they allow elaborating an internal representation of the input vectors, useful for realizing non-linearly separable transformations between input and output units [17].

In Minsky and Papert's view, a multilayer network with a single layer of hidden units is always able to carry out the transformation required for any Boolean function to be computed. The general architecture of a multilayer network, also called generalized perceptron, contains multiple layers of hidden units, where the interconnections are unidirectional, and they range from the units of a particular layer to those of a higher-level layer, i.e. closer to the output layer. The x state of a neuron belongs to the range (0, 1) and the activation function is given by:

$$x_j = g\left(\sum_k^n w_{jk} x_k\right) \qquad [1]$$

where the function g is differentiable.

For each configuration x of the input layer, the network calculates a configuration y of the output layer. Therefore, a transformation f is established between the input configurations and those of exit. Random initial weights are also set. By way of providing the network with a sequence of stimuli $[x_k]$, it changes the weights of the connections so that, after a finite number N of so-called learning steps, the network function, i.e. the output y_k, coincides with $f[x_k]$ for each $k>N$, with the desired precision. The logical passage allows the modification of the weights to take place to minimize the discrepancies between the network response and the pursued one.

Therefore, following the theoretical settings of a multilayer NN, we generate a neural network on a dataset containing the variables listed in Table 1. In addition, we increased the number of data (according to the postulation of a DP model), and generated the logarithms and the variations in the differences between the variables. In this way, the neural network can process n combinations of inputs concerning a target. Overall, the model generated 1,764,322,560[2] possible combinations.

4 The Results

The statistical-neural analysis produced 16 inputs with respect to a single Target, with no variables omitted. Out of 15 variables combined by them, one variable (which does not appear) represents the substrate (see Table 2).

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[2] Result = $DR_{n,k}$. In this case, k, a positive integer, can also be greater than or equal to n.

Table 2. Variables Bars Chart.

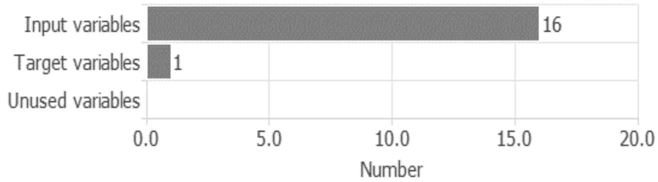

Figure 1 explains the use of all instances in the data set in details. The result has been divided into three different subsets for a total number of instances equals to 30. The number of training instances is 18 (60%), and they are the design of the model through various different settings. In other words, we built models with different architectures and, then, compared their performances. The number of selection instances is 6 (20%). Instead, these instances choose the NN with the best generalization properties. The number of testing instances is 6 (20%). These instances validate the operation of the model. Finally, the number of unused instances is 0 (0%). This result is significant, since it highlights no outliers presence in the data that can make the NN malfunctioning.

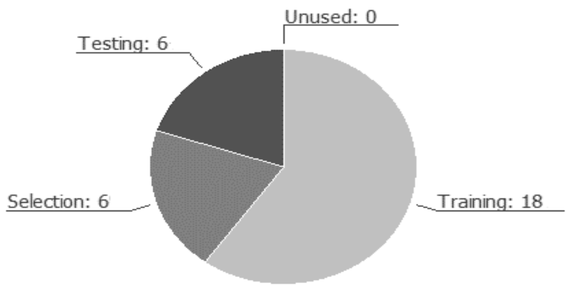

Fig. 1. Instances Pie Chart.

From the behavior of the datasets regarding the processing in Machine Learning of our algorithm, we can analyze the ANN results (Fig. 2). The ANNs graph contains a scaling layer, a NN and an unscaling layer. The yellow circles represent the scaling neurons, the blue circles perceptron neurons, and the red circles the unscaling neurons. The number of inputs is 13, where the number of output is 1. The degree of complexity, represented by the numbers of hidden neurons, is 16: 10: 8: 6: 1. Each neuron is interconnected one to the other, and between the perceptrons of the subsequent networks. The absence of anomalous values allowed a pyramid interconnection without the presence of anomalous perceptron networks such that they were more significant than the first NN. From the NN result, the pre-set target was *dGdp*, that is the best choice, compared to $DR_{n,k}$ possible combinations of inputs, to generate a target necessary for the analysis.

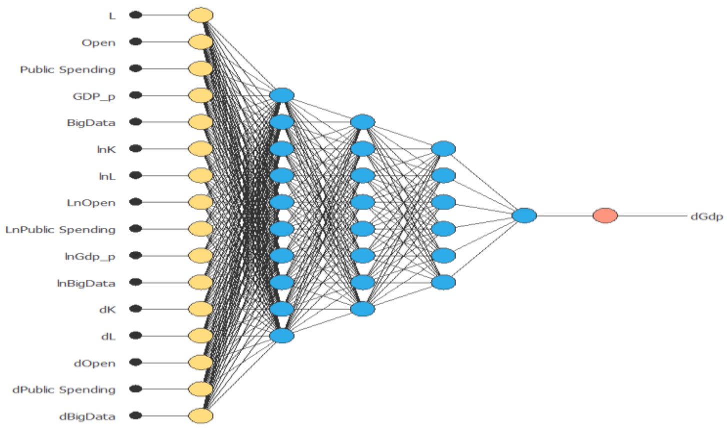

Fig. 2. Neural Network graph[3].

The Confusion Matrix corroborates the previous result gained through NNs (see Table 3).

Table 3. Confusion Matrix.

	Predicted Positive	**Predicted Negative**
Actual Positive	8.547	877
Actual Negative	851	8.531

These results confirm the goodness of the previous outcomes (see Fig. 2). The quality is very high. The expected values, compared to the actual positive values, cause a change in the target 90.69 times every 100 combinations between the inputs. Therefore, compared to the actual positive values, there is only a 9.3% probability of being able to choose a different target than the one selected in the NNs analysis (*dGDP*). We obtain the same result by observing, in the confusion matrix, the results between the predicted positive and negative values with the actual negative values. In this case, the probability of obtaining a different target is lower, only 9 %.
Finally, to check for errors in the prediction process, we test the model through the Quasi-Newton method that is based on Newton's method; although it does not require the calculation of second derivatives (see Fig. 3). Instead, the Quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm, by only using the gradient information. The blue line represents the training error, and the orange line the selection error. The initial value of the training error is 4.15595, and the final value after 10 epochs is 0.051782. The initial value of the selection error was 6.81115, and the final value after 11 epochs is 0.057160. Again, this analysis, confirming the previous one, highlights how the whole selection and training process of the neural network presents (almost) a cancellation of errors as the eras increase.

[3] On request are available the Training Test, the ANNs error test, and the Predicted Regression test.

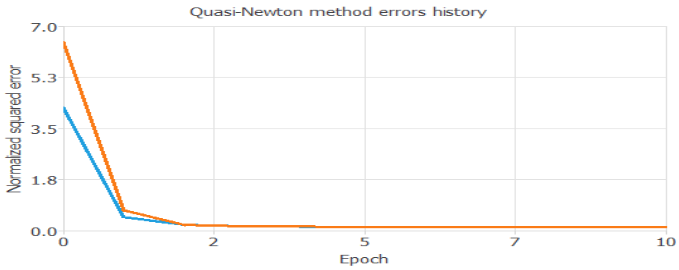

Fig. 3. The Training Process Test.

Now, since the ANN analysis revealed a large relationship between the investigated variables (60%), we evaluate which is the one most significant on the Target (*dGdp*). To this end, we performed the "importance test" on the ANNs algorithm (see Fig. 4).

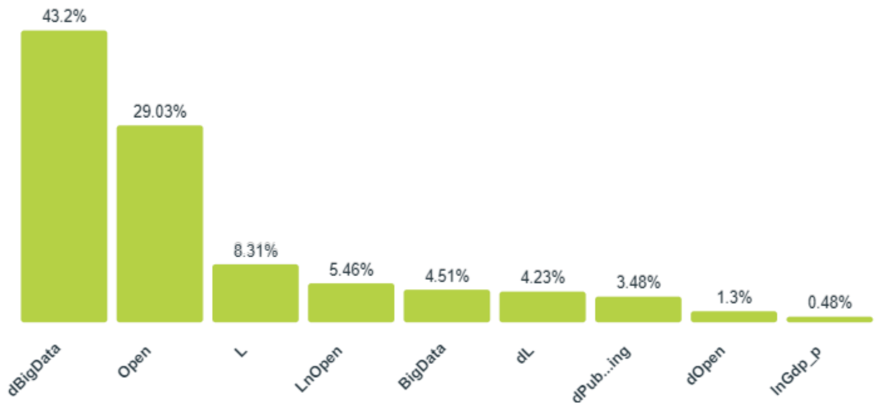

Fig. 4. Importance test[4]

As we can see, the change in the prediction of *dBig Data* represents the variable that generates the most significant effect in the change in *dGdp* (Target). However, also the Open variable has a high value in the test (29.03%). This result underlines how, at the level of predictive influence, the international business's opening rate impacts on the acceleration of GDP for about one third.

Therefore, these results open to two essential interpretations. First, we can affirm that an economic policy action that chooses public investments in BD could be the best initiative to face the economic crisis caused by COVID-19. In other words, EMU should make the best use of its own BD ability to promote recovery and growth in the medium-long term. It could pass precisely from the innovation of data to the software of health information systems, a sector that has been severely affected by the Coronavirus crisis. Secondly, policies capable of influencing EMU's international trade would

[4] In the test, there are only 9 variables out of 16. The result is reasonable to the degree that the other variables were not very important for Target.

be a good driver for economic growth. Observing the Importance test results, we can affirm how these two variables are most likely capable to assist each other. In fact, if we look at the so-called megatrends, investments for digitalization would be essential and enabling factors to accelerate markets' growth and foster product innovation. This last factor would represent an element of the new international trade theory traceable to the Vernon model. Therefore, a strong investment in BD could support the growth of EMU international trade. The positive surpluses in the balance of payments current account could be finalized to finance projects precisely in BD policies.

5 Conclusions

This work is an experiment based on a Deep Learning model that uses Artificial Neural Networks. Thanks to it, we have shown the potential positive role of BD and data analytics for the creation of significant competitive advantage and for the formation of knowledge-based capital, which can drive innovation and sustainable growth across the EMU economy during the COVID-19 recession. It is possible to act on this specific variable to accelerate the GDP rate of growth even during the pandemic economic crisis. The current pandemic, according to [13], will determine an unprecedented worldwide shock on economy and society with a dramatic collapse in the Eurozone of GDP performance. Even if the epidemiological damage caused by it largely depends on the economic characteristics of the regions, EMU area remains the most affected one.
"A crisis like no other, an uncertain recovery" titles WEO in June [13]. Because of the COVID-19 pandemic, public debt and labour market will be more under stress. The disposable income of European households would fall by 5.9% on average in 2020, if no policy emergency responses to the crisis were put in place to alleviate the impacts, especially in those countries already called PIGS (Portugal, Italy, Greece, and Spain) where tight fiscal constraints occur. Policy interventions at large scale, in particular through the European Recovery Package, could absorb a significant share of the economic and social shock. Among these actions, we recommend a smart investment on digital technologies, and BD. Temporary measures such as income subsidies, tax rebates and unemployment benefits will not be sufficient in the medium-long run.
In order to test this proposal, we have carried out a model that would assist policymakers in choosing to implement efficient economic policies to face the crisis. Starting from a production function that considered some determinants of economic growth, we built a variable able to represent potential public investments in BD. The results of the Neural Networks confirm that a significant change in public investments on digital technologies and BD will generate a positive change in GDP in an acceleration process.
This outcome advises policymakers to use forthcoming public resources from the European Recovery Funds also in accelerating the EMU economies' digital transformation by investing in the healthcare sector, investee companies, and throughout the modernization of the Central Public Administration. In this way, EMU countries could counter the fall in GDP in 2020-2021 caused by COVID-19. Further, we have observed that the "Open variable" (openness degree to international trade) also returns to the neural network signal from the inputs to the target with a very high value (29.03%) compared to

others. This result would represent a glue with the one obtained from the “BD variable”. More investments in policy innovation and BD would produce positive externalities to international trade itself, as they would trigger Vernon's product cycle.

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