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COVID-19 emergency: a comprehensive overview of the economic classification systems for the manufacturing industry
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Editorial Preface

In this issue of the *Rivista di statistica ufficiale* the first scientific article deals with Big Data sources and is authored by Fabrizio De Fausti, Francesco Pugliese and Diego Zardetto.

Over the last few years, the relevance of the possible role of innovative data sources has increased enormously, both because of the opportunity scale it poses for official statistics and because of the more critical aspects, thus representing a huge challenge for experts and researchers.

In the light of that, this article illustrates targeted studies conducted by the Italian National Institute of Statistics – Istat, especially focussing on the activities that enterprises carry out using their websites. The main purpose is that of exploiting massive amounts of textual data scraped automatically from the websites of Italian enterprises, in order to predict a set of target variables which are currently observed in a traditional way, in particular through the Istat survey on *Information and Communication Technology – ICT Usage in Enterprises*.

The authors show that *Deep Learning* techniques can successfully meet this need by performing a text classification task, using a sophisticated processing pipeline they developed and evaluating its performance through wide-ranging experiments.

This pipeline makes use of *Convolutional Neural Networks* and relies on *Word Embedding* models so as to encode raw texts into grayscale images. Original contributions enable it to reach good classification results, proving that this proposal is more effective than all the alternative *Machine Learning* solutions already tested at Istat for the same issues.

As part of the second article, Francesca Alonzi, Simone Ambroselli and Alberto Valery continue with an in-depth examination of official statistics, especially from the point of view of the international statistical classification systems in the face of the 2020 health emergency.

Since the first months of this year, indeed, the international scenario has been dominated by the COVID-19 pandemic. As a direct consequence, several medical supplies and other related goods has suddenly become unavailable, making clear the importance of manufacturing of products useful to contain this worldwide critical situation.

In this context, on the one hand the World Customs Organization - WCO together with and the World Health Organization – WHO listed the most relevant products for prevention, testing and medical treatment of COVID-19. On the other, the World Trade Organization – WTO provided a comprehensive overview of trade and tariffs imposed on medical goods, many of which in severe shortage during certain phases of this health emergency.

As reference international classification for the COVID-19 medical supplies, all these contributions make use of the Harmonised System, which is part of an integrated system of economic classifications, developed within the activities coordinated by the United Nations Statistics Division.

This system guarantees comparability at world level of all the statistics produced according to the different classifications of products and economic activities.

The analyses illustrated aim at sharing a comprehensive overview in terms of industries and goods belonging to the medical and medical-related devices production largely affected during the pandemic. The findings highlighted are very useful for experts involved in the classification activities and constitute a valid support for research activities concerning COVID-19, in order to evaluate the impacts on both the production and the international trade systems.

Patrizia Cacioli
Editor

Nadia Mignolli
Coordinator of the Editorial board

Towards automated website classification by Deep Learning

Fabrizio De Fausti, Francesco Pugliese, Diego Zardetto [1]

Abstract

In recent years, the interest in Big Data sources has been steadily growing within the Official Statistics community. The Italian National Institute of Statistics - Istat is currently carrying out several Big Data studies. One of these studies, the ICT Big Data project, resulted in 2018 in the publication of a first set of experimental statistics on the activities that enterprises carry out through their websites (web ordering, job vacancy advertisement, use of social media, etc.). This project aims at exploiting massive amounts of textual data automatically scraped from the websites of Italian enterprises in order to predict a set of target variables (e.g. "e-commerce") that are routinely observed by the traditional ICT Survey. In this paper, we show that Deep Learning techniques can successfully address this problem. Essentially, we tackle a text classification task: an algorithm must learn to infer whether an Italian enterprise performs e-commerce from the textual content of its website. To reach this goal, we developed a sophisticated processing pipeline and evaluated its performance through extensive experiments. Our pipeline uses Convolutional Neural Networks and relies on Word Embeddings to encode raw texts into grayscale images (i.e. normalised numeric matrices). Web-scraped texts are huge and have very low signal to noise ratio: to overcome these issues, we adopted a framework known as False Positive Reduction, which has seldom (if ever) been applied before to text classification tasks. Several original contributions enable our processing pipeline to reach good classification results. Empirical evidence shows that our proposal outperforms all the alternative Machine Learning solutions already tested in Istat for the same task.

Keywords: Deep Learning, Convolutional Neural Networks, Big Data, Web Scraping, Text Classification, Word Embeddings, False Positive Reduction.

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1. Introduction

In recent years, a new research field known under the name of *Big Data* has emerged (Manyika *et al.*, 2011). In common meaning, Big Data are huge, heterogeneous collections of data sets that are difficult to handle by using state-of-the-art data processing approaches and traditional data management tools (*e.g.* relational databases). Doug Laney popularised “Volume, Velocity and Variety” (known as 3Vs) to characterise the concept of Big Data (Laney, 2001). “Volume” refers to the size of data sets, “Velocity” indicates the speed of data flows, and “Variety” describes the diversity of data types and sources. Big Data continuously grow in size because they are increasingly being generated by disparate sources, such as people posting messages on social networks, users publishing documents on the Web, ubiquitous information-sensing mobile devices, search engines and software logs, sensor networks, e-commerce and stock market transactions, large-scale scientific experiments, and so on. Owing to the speed of these data sets’ growth, devising effective methods for processing and analysing Big Data is still an open problem. An even bigger challenge is, perhaps, the one of extracting useful insights from this typically unstructured, noisy and heterogeneous mass of information.

In the last seven years, the Official Statistics community has been converging towards the consensus that Big Data must be one of the pillars of the ongoing modernisation efforts put in place by National Statistical Institutes (NSIs). For instance, the “Scheveningen Memorandum” (ESS, DGINS, 2013) acknowledges that Big Data sources represent new opportunities and challenges for the European Statistical System (ESS), therefore compelling European NSIs to explore the potential of Big Data for the production of official statistics. At present, similar initiatives are in place worldwide within the statistical systems of all advanced countries.

The Italian National Institute of Statistics - Istat is currently carrying out several Big Data studies, as schematically reported in Table 1. In the present paper we will focus on the “*ICT Big Data project*”. This project essentially aims at exploiting textual data automatically scraped from the websites of Italian enterprises in order to predict a set of target variables (*e.g.* “e-commerce”) falling within the scope of the Italian “Survey on ICT Usage in Enterprises”. The motivation of the project lies in the fact that a powerful and reliable prediction model could be applied, after careful validation, to the whole target population of the ICT survey (as of 2014, about 190,000 enterprises according to Istat's Business Register ASIA, 70% of which was estimated to own a website by the 2014 round of the ICT survey). This, in turn, would enable Istat to: (*i*) enrich the Italian Business Register, and (*ii*) increase the quality of the output estimates produced by the ICT survey (*e.g.* by reducing their Mean Square Error via composite estimators). This line of research eventually resulted in late 2018 in the publication of a first set of experimental statistics on the activities that enterprises carry out through their websites (web ordering, job vacancy advertisement, use of social media, etc.), see *e.g.* Barcaroli and Scannapieco 2019, and references therein.

Table 1 - Main studies on Big Data currently ongoing at Istat

Big Data Source	Official Statistics Domain	Maturity Level
Scanner data	Consumer Prices	Production
Internet data (web scraping)	ICT Usage in Enterprises	Experimental Statistics
Social media (Twitter)	Social Mood on Economy	Experimental Statistics
Open street map	Road Accidents Indicators	Experimental Statistics
Mobile phone data (Call Detail Records)	Mobility and Tourism statistics	Proof of Concept
Satellite images	Land Cover Statistics and Maps	Proof of Concept
Search engine queries (Google Trends)	Labour Force statistics	Research
Traffic cameras (online webcams)	Road Traffic and Accidents statistics	Research

Source: Our processing

In this work, we will describe a novel, experimental approach to address the prediction task of the ICT Big Data project, based on *Deep Learning* techniques.

The rest of the paper is organised as follows: Section 2 provides examples of Big Data Analytics and outlines the challenges Big Data pose to Machine Learning; Section 3 introduces Deep Learning and discusses it in a Big Data perspective; Section 4 offers background information about Istat's ICT Big Data project, with a focus on its prediction task; Section 5 introduces our Deep Learning proposal and sets our model of choice: *Convolutional Neural Networks*; Section 6 studies the feasibility of our approach, and illustrates preliminary results of a first naïve implementation; Section 7 describes in depth the development of our processing pipeline, from design principles to methods and technical details; Section 8 empirically evaluates the performance of our processing pipeline; Section 9, finally, hints at ongoing work and draws some conclusions.

2. Big Data Analytics and Machine Learning

In 2011 there were about 2.5 quintillion bytes of data created every day (Hilbert and Lopez, 2011), and this number still keeps increasing rapidly. Today, Big Data applications are involved in many scientific and industrial fields, and *Big Data Analytics* (Wilder-James, 2012) is often perceived as one of the most relevant business battlefields. Many leading companies all over the world are currently investing resources on sophisticated *Machine Learning* (ML) techniques, striving to mine the value hidden inside Big Data, with the goal of improving pricing strategies and advertising campaigns (Chen and Zhang, 2014). Similarly, the ESS is right now exploring the potential of selected Big Data sources to enhance the quality of existing official statistics, to investigate new phenomena and to produce innovative statistical products. The most promising sources identified so far within the ESSnet Big Data project[2] include: (*i*) enterprise websites (for statistics about job vacancies and enterprise characteristics); (*ii*) smart meters (for statistics about energy, census housing and the environment); (*iii*) AIS, *i.e.* shipboard Automatic Identification System data (for statistics about maritime transport); (*iv*) mobile phone data (for statistics about population, mobility and tourism); (*v*) social media (for statistics about consumer confidence, social tension and economic mood); (*vi*) satellite imagery (for statistics about agriculture and the environment). Just like it is happening in the private sector, ML techniques are destined to play a central role in processing Big Data within NSIs. Interestingly, this is something the whole Official Statistics community agrees on, *despite* the development of sound methodologies to extract valid statistical information from Big Data is still fairly embryonic. However, traditional ML approaches have often shown severe limits when faced with the objective of analysing and exploiting the today's jungle of Big Data. For instance, the fact that many promising Big Data sources generate *unstructured* data, *e.g.* natural language texts (Gentzkow *et al.*, 2017), poses a major challenge to Big Data Analytics. Indeed, most ML approaches require input data to be organised according to a "case by variable" data-model, whereas a natural notion of "variable" no longer exists for entirely unstructured data. As a consequence, meaningful features have to be somehow extracted from raw data before analysis. Unfortunately, human intervention and domain knowledge are needed to

2 ESSnet Big Data website: https://webgate.ec.europa.eu/fpfis/mwikis/essnetbigdata/index.php/Main_Page

perform this data-preparation step, known as *feature engineering*. But feature engineering is costly, impairs automation and hinders scalability. From this premise, the necessity arises for the creation and adoption of a "universal framework" able to deal with the inherent diversity, complexity and hugeness of Big Data, possibly in a highly scalable way. In this respect, Deep Learning naturally emerges as a really promising candidate, owing to its remarkable ability to automatically extract from raw data features that prove useful for a wide range of learning tasks (Goodfellow *et al.*, 2016).

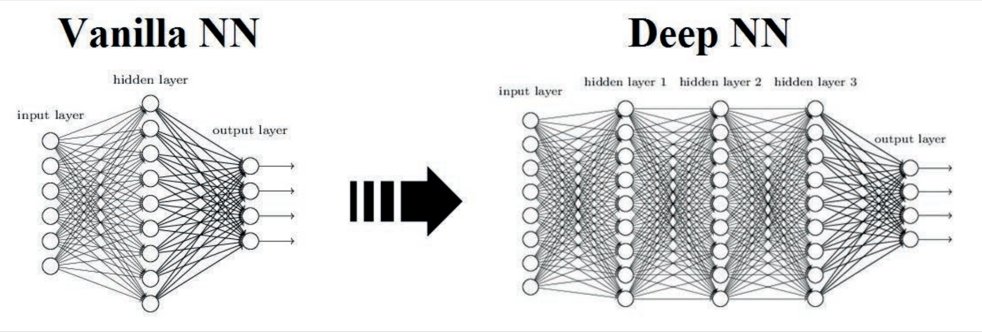
3. Deep Learning

Since around 5 years, *Deep Learning* (DL) is emerging as a promise land for Big Data Analytics, in that it seems excellently fit to distill useful insight from Big Data. Deep Learning typically (though not exclusively) relies on Artificial Neural Networks (ANN). In the past, ANNs have attracted great attention both in mathematical statistics (*e.g.* as universal approximation models of arbitrary nonlinear functions) (Hornik *et al.*, 1989) and in economics (*e.g.* for time series forecasting, see the seminal paper (Kuan and White, 1994) and the literature review (Herbrich *et al.*, 1999).

However, the traditional literature on ANNs mostly focussed on shallow multi-layer feedforward architectures characterised by fully connected neurons, while todays DL research explores a much wider range of alternative topologies and connectivity patterns. Deep Artificial Neural Networks are ANNs characterised by *multiple* hidden layers of neurons which are connected according to a *hierarchical* architecture. Figure 1 depicts the transition from old fashioned neural networks (also known as “Vanilla” or “Shallow” NNs) to *Deep* Neural Networks (DNN). DNNs are right now emerging as a scalable, robust and reliable machine learning paradigm, especially after last years’ hardware breakthroughs (GPU computing), new model regularisation (Data-augmentation, Dropout, Batch Normalisation) and training methodologies (Stochastic Gradient Descent, Adam, RMSProp). Specifically, the reason of the success of Deep Learning in Big Data Analytics originates from three major advantages that this approach provides:

- **Robust**: no need to design the features (data representations) ahead of time. Features are automatically learned to be optimal to the task at hand. Robustness to natural variations in the data is automatically learned.
- **Versatile**: the same Deep Learning approach can be used for many different applications and data types. For example, an algorithm performing very well in computer vision will likely lead to pretty good results in speech recognition or in text classification (and vice versa).
- **Scalable**: performance improves with more data. Furthermore the method is massively parallelizable. This makes Deep Learning a perfect fit for parallel computing architectures like GPUs.

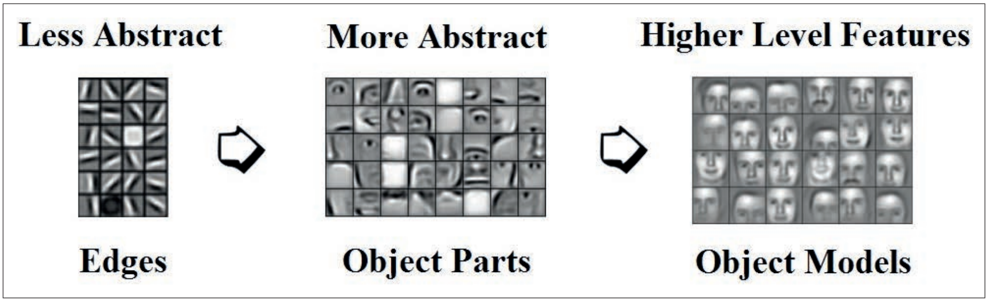
Figure 1 - From Vanilla Neural Networks (one hidden layer) to Deep Neural Networks (multiple hidden layers)



Source: Our processing on Nielsen, 2015

Deep Learning refers to techniques that *automatically* extract meaningful (from a human perspective) complex data representations (features) at high levels of abstraction (Bengio and LeCun, 2007). Such a methodology discovers and learns task-specific data features in a layered, hierarchical fashion. In other words, simpler (less abstract) data features are extracted by lower layers of the neural network and passed to the next layer, where they are combined to form higher-level (more abstract) features, and so on (Bengio *et al.*, 2013). This mechanism is depicted in Figure 2 for a DNN tackling a face recognition task. While the early hidden layers are only able to learn quite simple image features (*e.g.* edges and light or dark spots), these simple features get smartly assembled within the middle hidden layers, where more articulated representations start to form, like eyes, mouths, noses, and other face parts. In the higher hidden layers we can eventually catch sight of raw faces: a “face model” has been distilled, which provides an abstract and high-level synthesis of all the invariant elements of the faces acquired by the DNN during the training phase.

Figure 2 - Illustration of the features formation within deep hierarchical layers, from less abstract to more abstract data representations



Source: Our processing on Lee *et al.*, 2011

The hierarchical learning architecture of Deep Learning algorithms inspires to the deep layered organisation of the primary sensorial areas of the neocortex in the human brain (which is indeed a *natural* Big Data analyser) (Arel *et al.*, 2010). According to many cognitive scientists, hierarchical processing plays a fundamental role in the cortical computation (Hinton, 2007) and it *must* be the key factor for all the biologically inspired computational models (Riesenhuber, and Poggio, 1999).

From an algorithmic point of view, there is growing empirical evidence that data representations obtained by connecting *many* nonlinear feature extractors in series (as in *Deep* ANNs) generally yields better results as compared to traditional machine learning approaches (Larochelle *et al.*, 2009).

Stated very concisely, the more the layers, the more complicated non-linear transformations can be learned. Moreover, as shown in Figure 2, DNNs are entirely *data-driven*, namely they extract high-level abstractions and representations *without* any human intervention. On the contrary, classical machine learning algorithms are often unable to identify the complex and non-linear patterns that are observed in Computer Vision, Speech Recognition and Natural Language Processing tasks, thus requiring feature engineering (*i.e.* human intervention and domain knowledge) to reach effective results.

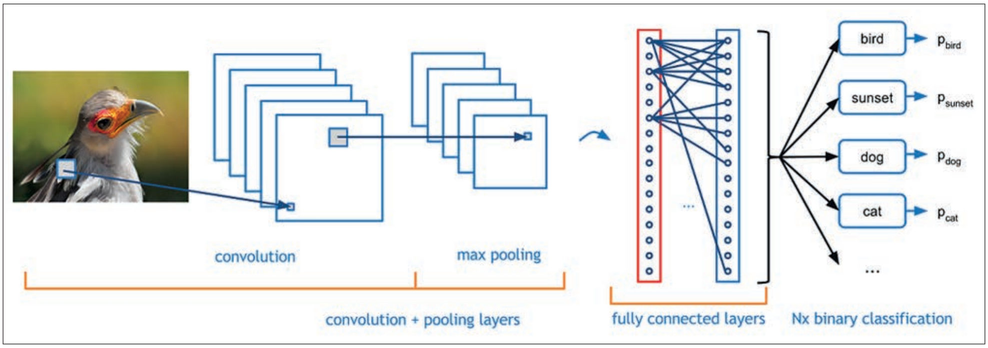
By automatically extracting features and abstractions from the underlying data, Deep Learning algorithms can address many important problems in Big Data Analytics (Najafabadi *et al.*, 2015). Furthermore, in contrast to more conventional machine learning and feature engineering algorithms, Deep Learning has the advantage of potentially providing a solution to tackle data analysis and learning problems found in massive volumes of *unsupervised* input data (Najafabadi *et al.*, 2015). This makes Deep Learning especially attractive, since nowadays the overwhelming majority of Big Data is made of extremely diverse and complex raw data, which are largely *unlabelled* and *un-categorised* (National Research Council, 2013).

According to the supervised or unsupervised nature of the learning process, DNNs can be divided in two classes:

- **Unsupervised Learning**: In 2006, Hinton proposed deep architectures whose learning process worked in an unsupervised, greedy, layer-wise manner (Hinton *et al.*, 2006). These deep architectures are called *Deep Belief Networks*. Basically, they are a stack of *Restricted Boltzmann Machines* and/or autoassociators called *Autoencoders* (Hinton and Zemel, 1994).
- **Supervised Learning**: In 1989, LeCun proposed the first simple stack of *convolutional* layers and fully connected layers known as LeNet for discriminative and supervised learning purposes (LeCun *et al.*, 1989). This model was enhanced by deeper and more accurate models like *AlexNet* in 2012 (Krizhevsky *et al.*, 2012), *GoogleNet* in 2014 (Szegedy *et al.*, 2015), and Microsoft Research's *Residual Neural Networks* in 2015, which reached super-human capabilities in some Computer Vision tasks (He *et al.*, 2016).

All the supervised learning DL models cited above belong to the *Convolutional Neural Networks* (CNN) family. The connectivity pattern between neurons of CNNs was originally inspired by the organisation of the visual cortex of mammals (see Figure 3). Unsurprisingly, CNNs typically show excellent performance on even very hard image recognition tasks.

Figure 3 - A schematic representation of a generic Convolutional Neural Network, highlighting the topology and the main building blocks of this kind of deep architecture



Source: Our processing on Deshpande, 2016

4. Background: Istat's Big Data Project on the ICT Survey

The annual "Survey on ICT Usage in Enterprises" ("ICT survey" for short) is carried out in Italy – as in many EU member states – under Eurostat regulations. It collects data on the usage of Information and Communication Technologies, the Internet, e-business and e-commerce in enterprises. The target population covers all the active enterprises with at least 10 employees. Enterprises with size 10-249 are sampled, whereas those with size 250 or more are all observed. The sampling design is one-stage stratified simple random sampling, with strata defined by crossing economic activity (NACE), enterprise size and geographical region (NUTS1). The sample is drawn from ASIA, the Istat archive of about 4.5 million Italian active enterprises. In the 2014 round of the survey, the planned sample size was about 30,000 units and the response rate was roughly 63%, yielding a respondent sample of nearly 19,000 enterprises (*i.e.* about 10% of the overall target population).

As discussed in Barcaroli *et al.* (2015 e 2016), Istat is actively investigating ways to:

1. Automatically scrape massive amounts of textual data from the websites of those enterprises, among the ones taking part to the ICT survey, which actually provided their website's URL through the survey questionnaire;
2. Train a machine learning algorithm to *learn* how to *predict* a survey variable Y (*e.g.* whether the enterprise has e-commerce facilities deployed on its own website) using, as input information X, the text scraped from the enterprise website.

With respect to the second objective, only *supervised* learning approaches have been experimented so far. This means that the candidate machine learning algorithm is always fed with a *labelled training set* of (Y_i, X_i) pairs, where Y_i is the *observed* survey value of the target variable of enterprise i, and X_i is the corresponding web-scraped text. The performance of the trained algorithm is subsequently *tested* comparing its predictions Y^*_j – based on a set of *unlabelled* X_j values, which were never used before during training – to the corresponding *gold-standard* survey values Y_j.

Many learners have already been considered in Barcaroli *et al.* (2015 e 2016), ranging from statistical parametric models (the Logistic model), to ensemble learners (Random Forest, Adaptive Boosting, Bootstrap Aggregating), and including well known, traditional algorithms like Naïve Bayes and Support Vector Machines (SVM), as well as a new approach named SLAD (Statistical and Logical Analysis of Data). The obtained results for variable *Y = "e-commerce (yes/no)"* are schematically reported in Table 2, along with a preliminary result of the new Deep Learning approach proposed here (highlighted in italic). Note that competing ML approaches have been ranked in Table 2 by *F-measure* (namely the harmonic mean of Precision and Recall), as the latter is the most reliable quality measure for the "e-commerce" classification task. This directly follows from the significant class imbalance of the gold-standard distribution of the target variable Y: 19% 'e-commerce' vs. 81% 'non-e-commerce'.

How to best encode the raw input data is a fundamental issue influencing the final performance of any ML algorithm. The optimal choice typically depends both on the learning task at hand and on specific characteristics qualifying the selected ML approach. In this respect, it must be stressed that all the learners studied in Barcaroli *et al.* (2015 e 2016) adopted the *same* encoding strategy, based on the traditional *bag-of-words* model. In such a model, which deliberately neglects word ordering and grammar rules, a text document is regarded as a simple set of terms and related frequencies. Therefore, a whole *corpus* of documents can be encoded into a Term-Document Matrix (TDM). Rows and columns of the TDM represent documents and terms occurring within them, respectively. The (*i*, *j*) cell score of a TDM depends on the frequency of occurrence of term j within document i and (possibly) across the entire *corpus*. These scores can be computed according to multiple schemes, giving rise to TDMs of different flavors, *e.g. binary*, *frequency* and *Tf-Idf* (Term frequency-Inverse document frequency)3.

It is worth specifying that, despite the number of distinct terms occurring within the raw web-scraped text *X* was huge (several millions), the TDMs used in Barcaroli *et al.* (2015 e 2016) for the "e-commerce" classification task were always reduced to 1,000 columns, thanks to a preliminary heavy-

3 The Tf-Idf scheme (Ramos, 2003) is often preferred in Text Mining applications, owing to its ability to increase the importance of a term proportionally to the term frequency inside the document, while penalising terms that are found to be very common in the whole *corpus*.

filtering step. Besides standard information retrieval preprocessing (*e.g.* tokenisation, stop words removal, stemming and lemmatisation), this filtering step used Correspondence Analysis (see *e.g.* Benzécri, 1973) to hopefully identify the 1,000 words having higher predictive power on the values of the target variable *Y*.

5. A new proposal based on Deep Learning

As anticipated in the Introduction, we propose to adopt cutting-edge Deep Learning techniques in order to address the prediction task of the ICT Big Data project. Our line of research, which is still ongoing, involves exploiting a CNN to solve the “e-commerce” classification problem. As this is essentially a supervised binary *text categorisation* problem, one could wonder why we decided to tackle it with a Deep Learning model originally designed for *image recognition*. The answer lies in the amazing *versatility* of DL models, which we mentioned in Section 3. As a matter of fact, there is a rich ongoing stream of scientific literature investigating the potentialities of CNNs in text classification (see *e.g.* Kim, 2014, and references therein).

Our work on CNN architectures encompassed two sequential phases. The first phase can be understood as a *feasibility study*, the second phase as the *actual implementation* of a production-ready processing pipeline. The next section explains the rationale of the feasibility study, describes its experimental setup and discusses its outcomes. The actual implementation of our proposal is illustrated in Section 7.

6. Feasibility study and preliminary results

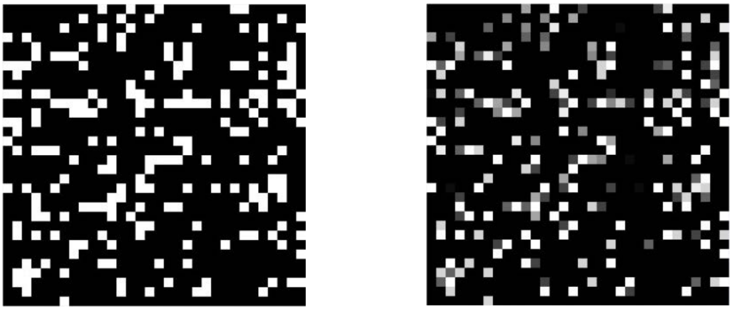
Within the DL research community, CNNs are nowadays among the dominant approaches to text classification. Most of the recent literature in the field relies on *Word Embedding* models in order to encode input texts into a *rich* data representation that is actually able to capture many important *semantic* and *syntactic* relationships between words (see Section 7.1). Compelling evidence shows that word embedding models outperform more traditional text encoding techniques, like bag-of-words, in a wide variety of tasks. Moreover, the richer input data representation provided by these models turns out to be highly beneficial for CNNs.

Despite being aware of these findings, we decided *not* to rely on word-embedding techniques for our initial experiments. Instead, we committed ourselves to feed our CNN model with exactly the same input Term-Document Matrices used in Barcaroli *et al.* (2015 e 2016). This choice had a threefold objective: (*i*) it allowed us to directly compare our results to those already obtained with other ML approaches; (*ii*) it helped us gain familiarity with sophisticated DL techniques, by letting us initially focus on a low-complexity solution; and (*iii*) it freed us from the need of exploring different word-embedding setups and assessing their impact on the obtained results.

Going into technical details, the ICT Big Data project successfully scraped 10,164 enterprise websites, giving rise to TDMs of size (10,164 x 1,000). They were randomly split into a *training* TDM and a *testing* TDM of almost identical sizes: (5,082 x 1,000) and (5,083 x 1,000) respectively. This split was consistently preserved across experiments (*i.e.* different ML approaches) and TDM flavors (*i.e.* binary, frequency and Tf-Idf).

In order to feed our first CNN model, we *folded* each TDM's row (*i.e.* the bag-of-words content of the website of a given enterprise) into a square image of (32 x 32) = 1,024 pixels. Every pixel, within the image, "depicts" the TDM score of a given word, as illustrated in Figure 4.

Figure 4 - Two images (32 x 32 = 1024 pixels) encoding alternative bag-of-words representations of the same web-scraped text (a). The left image is built upon one row of the *binary* TDM, the right one on the same row of the *Tf-Idf* version of the same TDM

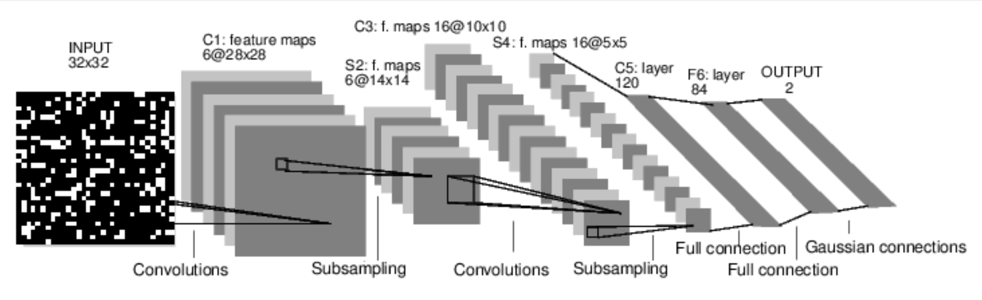


Source: Our processing
(a) The left image is built upon one row of the binary TDM, the right one on the same row of the Tf-Idf version of the same TDM.

For a *binary* TDM, a score of 1 (meaning *presence* of the word) is mapped to a *white* pixel, whereas a score of 0 (meaning *absence* of the word) is mapped to a *black* pixel. For *frequency* and *Tf-Idf* TDMs, the scores are mapped to *grayscale* colors (upon normalisation): the higher the score, the brighter the pixel tonality. Note that, since the size of our input images (*i.e.* 1,024 pixels) exceeded the number of columns (=words) of the TDMs that we inherited from Barcaroli *et al.* (2015 e 2016; *i.e.* 1,000 columns), we padded the residual 24 pixels with meaningless black pixels (*i.e.* artificial 0 scores).

Coming to the CNN model, for our feasibility study we chose to adopt a *LeNet* (LeCun *et al.*, 1989), which was appropriate to the moderate resolution of our input images. The architecture of this CNN is schematically illustrated in Figure 5. We encoded the results of the softmax output layer (Duan *et al.*, 2003) into a “one-hot” two component vector: <0,1> for ‘e-commerce’, and <1,0> for ‘non-e-commerce’. Moreover, for our first bunch of experiments, we selected as loss function the Categorical Cross-Entropy (Botev *et al.*, 2007). As training algorithm, we focussed on Adam Gradient Descent (Adam) (Kingma and Ba, 2015). To build and evaluate our experimental CNN architecture we used the Keras Python Deep Learning API running on top of Theano (Chollet, 2015; Al-Rfou *et al.*, 2016).

Figure 5 - The topology of the LeNet Convolutional Neural Network adopted in the feasibility study



Source: Our processing on Deshpande, 2016

The top performance achieved by our first CNN model on the "e-commerce" classification problem is reported in Table 2, where it is highlighted in italic and compared to previous ML approaches (see Section 4). Note that our CNN attained its top performance when it was fed with *frequency* TDMs[4], consistently with previous findings concerning other ML models (Barcaroli *et al.*, 2016). The 0.57 F-measure score obtained by our LeNet architecture ranked our Deep Learning approach 3rd, only slightly below SVM (0.59) and SLAD (0.60). Recall that, owing to the substantial class imbalance affecting the target variable (19% 'e-commerce' vs. 81% 'non-e-commerce'), the *F-measure* is a much more reliable quality measure than *Accuracy* for the present task[5].

4 Binary and Tf-Idf TDMs led to slightly lower F-measure scores (~ 0.56), but we did not investigate these results in depth, because they were not essential to our feasibility study.

5 Moreover, the F-measure $F = 2/(\mathrm{Prec}^{-1} + \mathrm{Rec}^{-1})$ is a *conservative* quality measure, as it can reach high values only when *both* Precision and Recall are high.

Table 2 - Machine Learning approaches tested so far within Istat's Big Data project on the ICT survey (see also Section 4) (a)

ML approach	F-measure	Precision	Recall	Accuracy
SLAD	0.60	0.58	0.62	0.84
SVM	0.59	0.55	0.64	0.83
Deep Learning	*0.57*	*0.47*	*0.70*	*0.79*
Random Forest	0.55	0.57	0.53	0.83
Logistic	0.53	0.53	0.53	0.83
ANN	0.52	0.52	0.52	0.82
Boosting	0.50	0.50	0.50	0.81
Bagging	0.48	0.53	0.44	0.82
Naïve Bayes	0.46	0.46	0.46	0.80

Source: Our processing
(a) The DL approach proposed in the feasibility study is highlighted in italic.

Although a 0.57 F-measure score may not seem an impressive result, we took it as a quite encouraging starting point for our Deep Learning line of research. The first reason was that, for the sake of comparability, we had until then restricted our CNN model to operate on bag-of-words text representations (*i.e.* Term-Document Matrices), which inevitably translated into cluttered images with very little spatial structure (as evident in Figure 4). The second reason was that the only ML approaches beating our initial proposal, *i.e.* SVM and SLAD, had required a fine-tuning of parameters to reach their top performances (as documented in Barcaroli *et al.*, 2016), something we had not yet done for our LeNet architecture.

Fortunately, we were confident that both issues affecting our initial CNN approach could be overcome. To reach this goal we decided, on the one hand, to dismiss the TDM approach and to switch to richer text representations, taking advantage of self-learned word-embeddings. Of course, we were aware that such a change would have required us to devise some smart *automatic summarisation* algorithm, in order to reduce the web-scraped text of each enterprise. Otherwise, the incorporation of word-embeddings would have inevitably led to very high resolution input images (see Section 7.1), with exploding computational costs. On the other hand, we planned to run more extensive experiments in order to optimise the hyperparameters of our candidate Deep Learning architectures, *e.g.* via grid search.

The next section shows how we turned the simple CNN architecture tested in the feasibility study into a much more sophisticated and better performing processing pipeline.

7. Processing pipeline

So far, we described our early attempts to solve the "e-commerce" classification task of the ICT Big Data project by means of Deep Learning techniques. Essentially, we fed a simple CNN architecture with web-scraped texts that previously underwent numerical encoding via the *bag-of-words* model. The overall approach was deliberately naïve, as appropriate for a feasibility study, but it yielded encouraging results. This section provides an overview of the work we carried out to design a more advanced DL pipeline that proved able to overcome the limits highlighted in Section 6.

Two main pillars underpin the processing pipeline we propose here. The first pillar is the adoption of *Word Embeddings* (WE). The second pillar is the adoption of a conceptual framework known as *False Positive Reduction* (FPR).

Next sections 7.1 and 7.2 introduce WE and FPR in isolation. A complete explanation of the way these pillars interact within our processing pipeline can be found in Section 7.3.

7.1 Word Embeddings

Modern WE models are generated by unsupervised learning algorithms – typically shallow neural networks, like Word2Vec (Mikolov *et al.*, 2013) or GloVe (Pennington *et al.*, 2014) – trained on very large text corpora. WE algorithms map words to vectors of a metric space in a very smart way, so that the resulting numeric representation of input texts effectively captures and preserves a wide range of semantic and syntactic relationships between words. Stated very simply: words that are strongly related from a syntactic and/or semantic point of view are mapped to embedding vectors that are almost parallel to each other; conversely, words that are syntactically and/or semantically loosely related are mapped to nearly perpendicular embedding vectors. Since the metric structure of embedding spaces is induced by the "cosine distance", WE algorithms are able to transform the notion of syntactic/semantic similarity between words into the notion of geometric closeness between the corresponding embedding vectors. This is an amazing achievement and clearly motivates the adoption of WE models as representational basis for many downstream Natural Language Processing tasks.

In principle, it is straightforward to use a WE model to turn a *text* into an *image*. Given a text of length n, that is an *ordered* sequence of words (w_1, …, w_n), and a WE space of dimension d, one simply encodes the text into a (d x n) numeric matrix, whose i-th column represents the coordinates of the embedding vector of the i-th word w_i. This (d x n) numeric matrix can, in turn, be seen as a grayscale image of (d x n) pixels. In most applications, the dimension of the embedding space d is set to values in the range 100-300 (Mikolov, *et al.*, 2013).

In practice, however, the very large size of our web-scraped input texts complicates the inclusion of a WE layer inside our processing pipeline. Indeed, each scraped websites amounts on average to $n \sim 10^4$ words and embedding vectors have usually $d \sim 10^2$ components, so that our input images would have typical size (d x n)$\sim 10^6$, *i.e.* several megapixel. Because processing such high resolution images with a CNN would result in unaffordable computational costs, we had to develop a clever *automatic summarisation* algorithm to shorten our input texts. Technical details on this algorithm can be found in Section 7.3.1, where its role within the FPR approach will also become clear. For the time being, just note that the operation of *shortening* a text and then converting the obtained summary to an image via WE actually produces a *segmentation* of the image that would have been generated from the original text.

7.2 False Positive Reduction: Intuition and Rationale

The *False Positive Reduction* (FPR) conceptual framework is the second pillar underpinning our processing pipeline. Since – to the best of our knowledge – the FPR approach has seldom (if ever) been applied before to text classification tasks, we offer here an intuitive insight into its working mechanism. The rationale for the adoption of the FPR framework in our application scenario should also emerge from this preamble, whereas technical details are deferred to later sections.

FPR is a popular training modality in the field of biomedical image classification, *e.g.* computer detection of lung cancer from thorax CT scans (Ge *et al.*, 2005). Our interest in FPR lies in the fact that the task of training a ML algorithm to classify thorax CT scans as ‘cancer’ or ‘non-cancer’ actually shares many challenges with our objective of classifying websites as 'e-commerce' or 'non-e-commerce'.

First, thorax CT scans contain an enormous amount of data about complex anatomical structures (*e.g.* lungs, airways, vessels, soft tissues), whereas the relevant information for cancer detection is mostly concentrated within few very small image parts, namely pulmonary *nodules*[6]. In other words, from a ML perspective, CT scans have a very low *signal-to-noise ratio*. Web-scraped texts suffer exactly the same issue: they are huge collections of words (up to order 106), where sentences identifying a website as 'e-commerce' are invariably overwhelmed by background noise.

Second, CT scans are very high resolution images. Unless exceptional hardware resources are available, this makes almost impractical to analyse them *as a whole* with a CNN, due to exploding computational costs. As anticipated in Section 7.1, the same would happen to our huge web-scraped texts, if we tried to *directly* encode them into the richer data representation provided by modern WE models.

The FPR framework offers a viable solution to both the aforementioned challenges.

FPR encompasses three main steps: (1) *input data segmentation*, (2) *training on data-segments with inherited labels*, (3) *class prediction of original data*. Let us exploit again the problem of cancer detection from CT scans as a guide to highlight the purpose of each step.

1. *Input data segmentation*. A first algorithm identifies pulmonary *nodules* within thorax CT scans. This way, each input CT scan is mapped into *a set* of nodule images. Note that while *gold-standard* cancer/non-cancer labels coming from radiological diagnoses are available for thorax CT scans, *no* such labels are instead available for the derived nodules. Nevertheless, segmentation dramatically decreases the complexity of the original images, with a simultaneous striking gain in terms of signal-to-noise ratio.

2. *Training on data-segments with inherited labels*. After segmentation, a ML algorithm is trained to classify nodules (*instead* of thorax CT

6 Note, indeed, that real-world radiological screening of lung cancer typically focusses on the analysis of pulmonary nodules.

scans) as cancer/non-cancer. Since no knowledge is actually available about the benign or malignant nature of the nodules, each nodule of the training set can only *inherit* the label of the CT scan from which it originated. Therefore, *all* the nodules derived from a *positive* CT scan (*i.e.* a case of cancer) will be labelled as 'cancer', irrespective of their actual benign or malignant nature. As a result, many *negative* (*i.e.* benign) nodules of the training set will be *wrongly* annotated as *positives* (*i.e.* malignant) in the gold-standard. This proliferation of *False Positive* labels in the training set is the price one has to pay for the benefits of segmentation[7].

3. *Class prediction of original data*. Once trained on nodules, the ML algorithm can natively only predict 'cancer' probabilities of *nodules*. This means that the ML predictions have to be suitably modified, if one wants to enable detection of lung cancer from thorax CT scans. A very simple, though often effective, adjustment amounts to assigning to each CT scan of the test set the highest 'cancer' probability observed among its nodules.

The key underlying assumption of the FPR framework is that the adopted ML algorithms are *tolerant* to misclassified training examples, *i.e.* they can achieve accurate predictions *despite* the proliferation of contaminating false positives induced by the segmentation step (whereby the name of the method: False Positive *Reduction*). In the biomedical field, this key assumption has been recently shown to hold for specific Deep Learning algorithms, *e.g.* the Multi-View ConvNets proposed in (Setio *et al.*, 2016).

7.3 Technical Implementation

Let us now switch to the technical implementation of our processing pipeline. The aim of this section is to describe: (*i*) how we took advantage of WE models, and (*ii*) how we deployed the FPR framework into our e-commerce detection application. To make the presentation easier, the implementation of each step of the FPR approach will be detailed in a dedicated subsection.

7 Note, incidentally, that *no False Negatives* can be generated as a byproduct of segmentation, as 'non-cancer' (*i.e.* negative) CT scans do not contain *any* malignant (*i.e.* positive) nodules.

7.3.1 Data Segmentation

In the *segmentation step* of the FPR approach, we map each scraped website into a small-cardinality set of *sentences* of equal length. These sentences are generated by an original automatic summarisation algorithm that we developed on purpose (as already mentioned in Sections 6 and 7.1). To identify relevant sentences within the text, the algorithm exploits a set of *marker words* with high discriminative power for the detection of e-commerce facilities in the website. Whenever one marker word is found in the text, all the surrounding words up to k positions away from the marker are kept. This way, each website is segmented into a variable number of synthetic sentences of common length $2k + 1$. In our experiments, we typically use $k \sim 10$.

Evidently, the core of the summarisation algorithm lies in the way *marker words* are recruited. To perform this task, we implemented two methods of different complexity. For presentation convenience, in what follows we will call these methods the '*simple strategy*' and the '*advanced strategy*'. To automatically build the set of marker words that guide the segmentation, both strategies leverage *self-trained*[8] word-embeddings.

First, a WE algorithm is trained on the *corpus* of 5,082 web-scraped texts belonging to the training set of the ICT Big Data project. Then, a handful of e-commerce specific words (*e.g.* 'cart', 'account', 'pay', 'online') are selected as marker *seeds* by the user, and their embedding vectors are summed. The resulting sum vector is subsequently used as a "*bait*" to attract new words inside the markers set. The '*simple strategy*' and the 'advanced strategy' only differ in the way they use the "bait vector" to probe the embedding space and to attract new marker words. While the 'simple strategy' emphasises *exploitation*, the 'advanced strategy' emphasises *exploration*.

The '*simple strategy*' is straightforward: the m embedding vectors that are *nearest* to the "bait vector" are identified in a single shot, and the corresponding words (*e.g.* 'order', 'wishlist', 'payment', 'checkout', 'shop', 'paypal', 'shipping', …) are directly recruited and join the ranks of the markers.

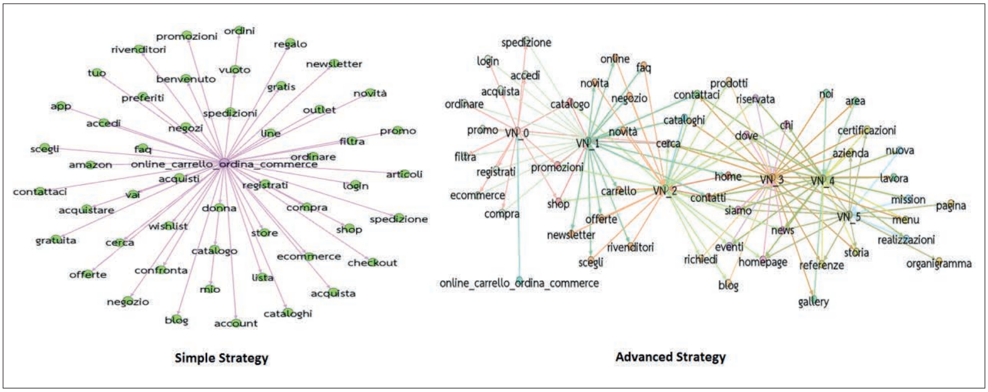
8 We also tested *pre-trained* word-embeddings (which we obtained with Word2Vec, using the Italian version of Wikipedia as training *corpus*) but they consistently *underperformed* self-trained ones.

The ‘*advanced strategy*’, is more sophisticated. The underlying algorithm relies on graph theory and cannot be thoroughly explained in this paper (we documented it elsewhere; see De Fausti *et al.*, 2018).

What deserves to be stressed here is that the ‘advanced strategy’ does not identify the best *m* embedding vectors in a single shot. Marker words are instead recruited *progressively* during subsequent iterations. The goal is to perform a wider-range exploration of the neighborhood of the “bait vector”. Of course, attention has been paid to prevent the algorithm from losing the initial semantic focus (set by the seed words) too quickly along the iterations.

Figure 6 provides one example of marker words generated by the ‘*simple strategy*’ and by the ‘*advanced strategy*’. Note that, in both cases, the same 4 seed words (‘online’, ‘carrello’, ‘ordina’, ‘commerce’) have been used to define the “bait vector”. The cardinality of the marker sets is also the same, *m* = 50. However, the results are noticeably different, as expected.

Figure 6 - Two graphs depicting m = 50 marker words identified by the ‘*simple strategy*’ (left graph) and by the ‘*advanced strategy*’ (right graph) (a)



Source: Our processing
(a) Although the same 4 seed words (‘online’, ‘carrello’, ‘ordina’, ‘commerce’) have been used, the two strategies clearly led to different sets of markers words and, therefore, to different segmentations of scraped websites.

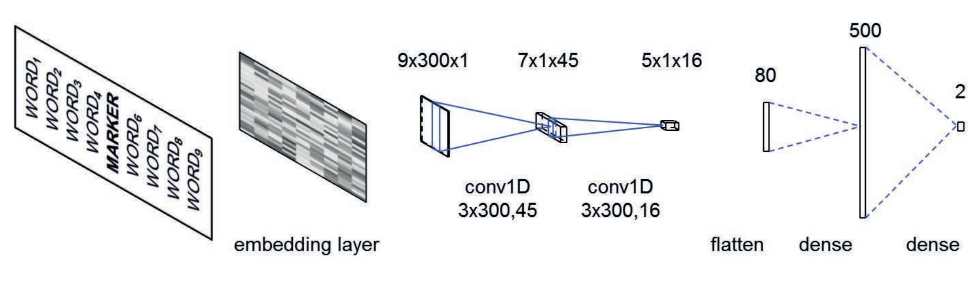
A few comments on the described segmentation strategies are in order. *First*, given the outstanding ability of word-embeddings to capture similarities between words, both strategies generate marker words characterised by good e-commerce *detection power*, likewise the original seeds. *Second*, marker words with high discriminative power for the detection of e-commerce help us *reduce*, since the beginning, the *False Positive* rate induced by the segmentation step of the FPR framework. That is, most of our segmented sentences will be *true* positives, akin to *malignant* nodules in the lung cancer analogy. *Third*, the algorithms that extract marker words are almost entirely *data-driven*: the analyst has only to provide few domain specific words as initial seeds. *Fourth*, the segmentation of websites into a set of synthetic sentences is entirely *automated*.

7.3.2 Training on Segments

After the segmentation step, our processing pipeline trains a CNN to classify *sentences* as 'e-commerce' or 'non-e-commerce' along the lines of Kim, 2014. Of course, as it is typical of the FPR approach, each sentence of the training set inherits its label Y_i from the original website. Moreover, as sketched in Section 7.1, the text of each sentence is encoded into an ordered sequence of embedding vectors, namely a grayscale image X_i of $(2k + 1)$ x d pixels, being d the dimension of the embedding space. Note that, as $k \sim 10$ and $d \sim 10^2$, these images are of size $\sim 10^3$ and processing them with a CNN does not pose any computational problems.

The architecture of the CNN we designed is schematically illustrated in Figure 7. Observe that this is actually a specific kind of CNN, known as *Conv1D*. The choice of a Conv1D CNN is easily motivated as follows. Typically, the convolution layers of CNNs (see Figure 3 and Figure 5) involve learnable filters that slide over the *whole* input image by moving in 2D, *i.e.* through horizontal *and* vertical translations. Conv1D CNNs, instead, only allow the filters to slide in 1D, *e.g. just* vertically. Of course, in our application, filters must be constrained to only move *horizontally*: this way, they can only slide over *full* columns of the input image, namely over words (= embedding vectors). As a result, the integrity of embedding vectors is preserved. Note that this property is easily recognised in Figure 7, where it is conveyed by blue rectangles in the convolutional layers.

Figure 7 - The topology of the Conv1D CNN used within the proposed False Positive Reduction framework (a)



Source: Our processing
(a) In this figure k = 4 is assumed, so that each website is segmented into a set of synthetic sentences of (2k + 1) = 9 words. Moreover, the embedding vectors used to turn sentences into images have dimension d=300.

As shown in Figure 7, our Conv1D CNN has a receptive field of size 3 x 300, uses a stride of length 1, and involves two convolutional layers. The first convolutional layer learns 45 filters, the second one 16 filters, and no pooling layers have been inserted between them (unlike for the LeNet architecture tested in Section 6). The fully connected part of the network consists of two hidden layers. The number of neurons of the first fully connected layer is a function of the length of the input sentence (2k + 1): in Figure 7, for instance, k=4 implies 80 neurons. The number of neurons of the second fully connected layer is instead fixed to 500. The output layer has two neurons, which return 'e-commerce' and 'non-e-commerce' probabilities of *sentences*.

We use ReLUs as activation functions for all the hidden layers of our Conv1D CNN model (be they convolutional or fully connected), and softmax for the output layer. As loss function, we adopt the Categorical Cross-Entropy. As training algorithm, we employ RMSProp with mini-batches of size 1,024 and a validation split of 25%.To prevent overfitting, training is performed for *very few* epochs, 10 at most, with an early stopping criterion ('patience') of 1 epoch. For the same reason, dropout regularisation is applied to all the layers with a *very high* rate of 50%. Indeed, while overfitting is a general concern in ML, it is even more serious in a FPR framework, because the training set is always contaminated by false positives introduced during the segmentation step. To implement and evaluate our model, we use Keras on top of Theano.

7.3.3 Class Prediction of Original Data

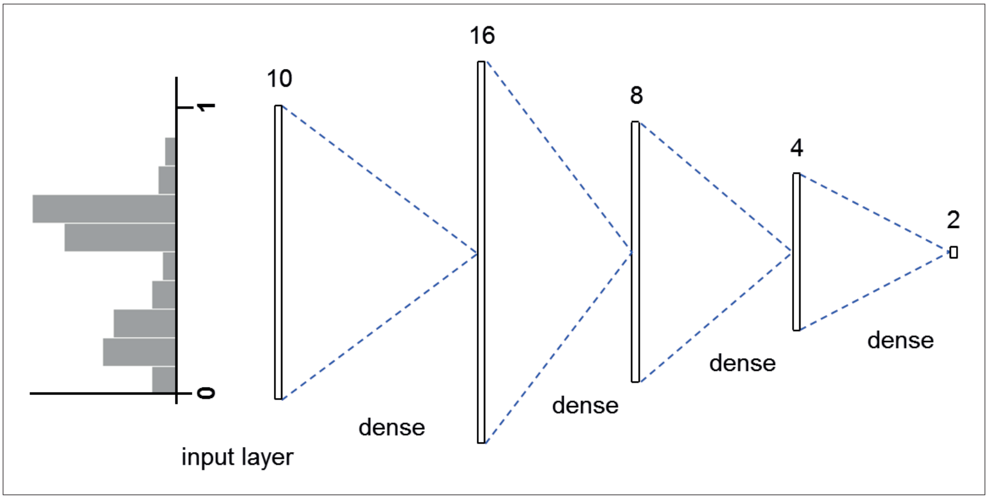
After having trained the Conv1D CNN on *sentences*, our processing pipeline suitably *modifies* its predictions, in order to enable the modified model to detect e-commerce at the *website* level. The goal is essentially to determine the 'e-commerce' probability of a website, given the predicted 'e-commerce' probabilities of its segments, *i.e.* sentences. We have explored and implemented two different methods to pursue this objective, which represents the final step of the FPR framework.

The *first method* is rather conventional: it simply assigns to each test website a predicted 'e-commerce' probability which equals the *highest* probability observed among its segmented sentences. For convenience, let us call this method the '*Max Rule*'.

The *second method* is original and more complex. It relies on a second dedicated Neural Network – specifically, a multilayer perceptron (MLP) – which is added to the pipeline just after the Conv1D CNN. This MLP is fed with labelled pairs (Y_i, Z_i), where Y_i is the 'e-commerce'/'non-e-commerce' status of the *i*-th website, and Z_i is the *histogram* of the predicted probabilities of its segmented sentences. The MLP is then trained to find a hopefully *optimal decision rule* to map 'e-commerce' probabilities from the sentence level to the website level. The intuition behind the adoption of a dedicated MLP is, of course, that the optimal decision rule may actually turn out to be much more complicated than the naive '*Max Rule*', and could even depend on the *whole* distribution of sentence-wise probabilities of each website (which is summarised by the histogram). For the sake of conciseness, let us refer to this second method as the '*Histogram Rule*'.

The architecture of the MLP implementing the '*Histogram Rule*' is schematically illustrated in Figure 8. For consistency, the number of input neurons must of course match the number of bins used to construct the histograms. Thus, since we used 10 bins of equal width for the histograms, the input layer of the MLP contains 10 neurons. The MLP has 3 hidden layers, made up of 16, 8, and 4 neurons respectively. The output layer has two neurons, which return 'e-commerce' and 'non-e-commerce' probabilities of *websites*.

Figure 8 - The topology of the MLP used to implement the 'Histogram Rule' (a)



Source: Our processing
(a) The MLP learns to reconstruct the 'e-commerce' probability of a website, given the predicted 'e-commerce' probabilities of its constituting segments, *i.e.* sentences. The sentence-level probabilities are fed to the MLP through a histogram with 10 equal-width bins.

All the hidden layers of the MLP use ReLUs as activation functions, while the output layer uses a softmax. The Categorical Cross-Entropy is employed as loss function, and RMSProp as optimisation algorithm, with mini-batches of size 600 and a validation split of 40%. Training is performed for at most 800 epochs, with an early stopping criterion ('patience') of 1 epoch. To prevent overfitting, L2 regularisation (with lambda 8·10-6) and dropout (with rate 25%) have been applied. To implement and evaluate our model, we use Keras on top of Theano. Observe that overfitting (albeit still undesirable) is not as dire a threat for the MLP as it was for the Conv1D CNN. This is because the Conv1D CNN was trained on *sentences* whose "e-commerce" labels were *inherited* and therefore *contaminated* by false positives, whereas the MLP is trained on *genuine* and *uncontaminated* "e-commerce" labels of *websites*. This explains why more epochs and lower dropout rates are used for the MLP as compared to the Conv1D CNN.

Both the '*Max Rule*' and the '*Histogram Rule*' eventually return predicted 'e-commerce' *probabilities* of websites. But the final output of our processing pipeline must actually be the *decision* of classifying each test websites as either 'e-commerce' or 'non-e-commerce'. To this end, a *classification threshold* has to be set, which allows for an additional degree of freedom within our pipeline. The simplest choice would be to set the threshold to 0.5: this would assign each website to the class to which it has the highest predicted probability of belonging. A more sophisticated alternative could be to explicitly take into account the inherent *class imbalance* of the “e-commerce” distribution, as known by the *training set* (about 19% ‘yes’ vs. 81% ‘no’). In this case, the classification threshold could be *adjusted* to best reproduce the gold-standard proportion of ‘e-commerce’ observed in the *training set*. Both these classification thresholds have been implemented in our processing pipeline: in what follows, we will refer to them as the ‘*Unadjusted Threshold*’ and the ‘*Adjusted Threshold*’ respectively. Note that the ‘*Adjusted Threshold*’ method has an interesting side-effect: it tends to equalize the Precision and the Recall of the classifier, which often results in a better F-measure score than the one induced by the ‘*Unadjusted Threshold*’.

8. Experiments

In this section, we empirically evaluate the performance of the Deep Learning processing pipeline documented in Section 7. We also provide insights on the impact of the most important tunable hyperparameters of our approach.

Likewise the feasibility study of Section 6, experiments focus here on the "e-commerce" prediction task of Istat's ICT Big Data project. Recall that available data amount to 10,164 pairs (Y_i, X_i), where Y_i is the "e-commerce" label of enterprise *i* (derived from the traditional ICT survey), and X_i is the corresponding web-scraped text. Recall also that these 10,164 pairs were randomly split into a *training set* and a *test set* of almost identical sizes: 5,082 and 5,083 respectively.

Word Embeddings (WE) are the first pillar underpinning our proposal: they provide the representational basis to turn texts into images (Section 7.1), and play a central role in the automatic summarisation algorithm that segments scraped websites into synthetic sentences (Section 7.3.1). Our pipeline only relies on *self-trained* WE, which we obtained with Word2Vec, using as training *corpus* the collection of 5,082 web-scraped texts of the *training set*. Note that our approach conventionally maps to the *null vector* of the embedding space those words belonging to websites of the *test set* that happen to be *absent* from the vocabulary of self-learned WE. We report here the configuration of **Word2Vec**'s main parameters (Levy *et al.*, 2015) that we settled in our experiments:

- Embedding space dimension: **d = 300**.
- Window size: **8 words**.
- Learning model: **CBOW with negative sampling**.

Because our pipeline is quite sophisticated and involves several hyperparameters that can be tuned to improve classification performance, we carried out an extensive grid-search. To make the presentation of the grid-search results easier, we provide here a synopsis of the hyperparameters we tested (their meaning is documented in Sections 7.3.1, 7.3.2 and 7.3.3). The synopsis below lists the hyperparameter values that have been explored (reported in bold), along with the logical building-blocks to which each hyperparameter belongs (reported in italic):

1. *Marker words selection*: 'Simple Strategy' / 'Advanced Strategy'
2. *Marker words cardinality*: m = (50, 100, 150)
3. *Sentence width (2k + 1)*: k = (2, 4, 8)
4. *Website probability reconstruction*: 'Max Rule' / 'Histogram Rule'
5. *Website classification threshold*: 'Unadjusted' / 'Adjusted'

Hyperparameters 1 and 2 govern the way marker words are automatically recruited starting from few seed words specified by the user. In all experiments we used the *same 4 seed words* (see Figure 6): **'online'**, **'carrello'**, **'ordina'**, **'commerce'**.

According to the synopsis above, our grid-search probed (2*3*3*2*2) = 72 distinct hyperparameter configurations. For each configuration, we tested the performance of our processing pipeline on the ICT Big Data project. Even after setting all the hyperparameters to specific values, the results of a Deep Learning algorithm are always affected by some residual random variability. This is because *e.g.* the network weights are initialised randomly, and stochastic optimisation algorithms are used to optimise the weights during training. To control for the impact of this residual variability on the performance of our algorithms, we performed 50 runs of our processing pipeline for each hyperparameter configuration tested in the grid-search. Therefore, the grid-search eventually resulted in (72*50) = 3,600 runs: for each run we measured the quality of obtained results in terms of Precision, Recall, F-measure and Accuracy. Note that, for each run, we *re-trained* both the Conv1D CNN and (if required by the hyperparameter configuration being tested) the MLP.

Table 3 - F-measure scores obtained in the grid-search, conditional to tested hyperparameter values (a)

Hyperparameter	Value	F-measure Distribution Summary						Nobs
		Min	1st Q	Median	Mean	3rd Q	Max	
Marker words selection	Simple Strategy	0.02	0.60	0.62	0.60	0.67	0.71	1,800
	Advanced Strategy	0.33	0.61	0.65	0.61	0.68	0.73	1,800
Marker words cardinality	m = 50	0.04	0.59	0.62	0.60	0.67	0.71	1,200
	m = 100	0.02	0.61	0.63	0.61	0.67	0.71	1,200
	m = 150	0.04	0.61	0.65	0.61	0.68	0.73	1,200
Sentence width (2k + 1)	k = 2	0.02	0.60	0.62	0.60	0.67	0.71	1,200
	k = 4	0.04	0.61	0.64	0.61	0.68	0.73	1,200
	k = 8	0.04	0.61	0.63	0.61	0.67	0.71	1,200
Website probability reconstruction	Max Rule	0.44	0.53	0.60	0.59	0.63	0.69	1,800
	Histogram Rule	0.02	0.64	0.67	0.65	0.68	0.73	1,800
Website classification threshold	Unadjusted	0.44	0.44	0.62	0.56	0.65	0.73	1,800
	Adjusted	0.02	0.61	0.66	0.65	0.68	0.72	1,800
–	–	*0.02*	*0.61*	*0.63*	*0.61*	*0.68*	*0.73*	*3,600*

Source: Our processing
(a) For convenience, the overall (*i.e.* unconditional) F-measure distribution is reported in italic in the last row. Column 'Nobs' gives the number of grid-search runs performed while holding fixed a given hyperparameter.

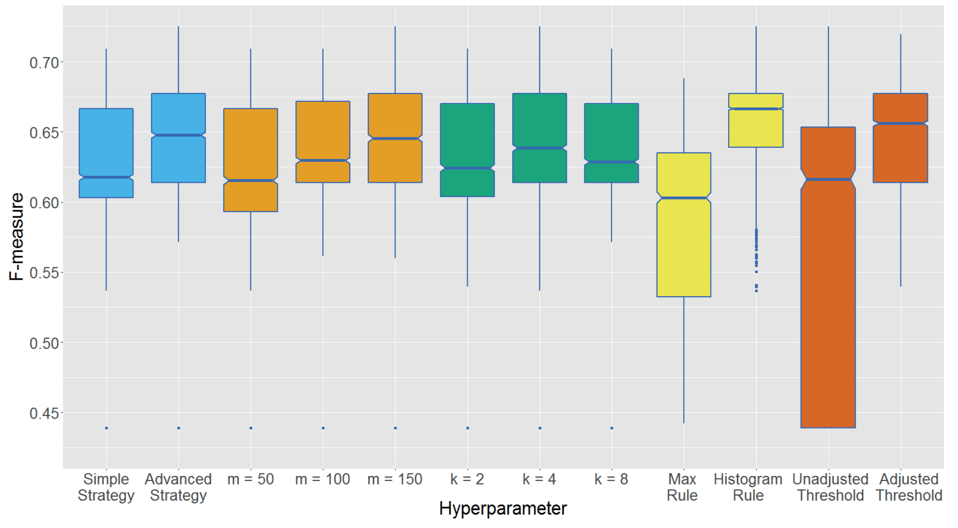
Table 3 above condenses the F-measure scores we obtained from the grid-search. More precisely, the table reports a summary of the (*conditional*) F-measure distribution obtained for each tested hyperparameter value. The overall (*i.e. unconditional*) F-measure distribution is also reported for convenience (last row, in italic).

With a top F-measure score of 0.73 reached in the grid-search, our pipeline clearly outperforms previous ML approaches listed in Table 2 of Section 6, and even subsequent attempts reported in Barcaroli and Scannapieco 2019 (top F-measure 0.63, achieved using Random Forest on comparable – albeit not identical – data collected in the 2017 round of the ICT survey). Note that this is a very robust result, as the top performances of competing ML approaches consistently lie below the average (and median) performance level attained by our proposal (despite occasional "unfortunate" runs occurred in the grid-search).

The same information provided in Table 3 is conveyed visually in Figure 9, which shows boxplots of F-measure scores by hyperparameter values.

Different values of the same hyperparameter correspond to boxplots of the same color. The *marginal effect* of each tested hyperparameters on the F-measure scores obtained in the grid-search emerges quite clearly from the plot.

Figure 9 - Boxplots of F-measure scores by hyperparameter values. Boxplots related to different values of the same hyperparameter share the same color (a)



Source: Our processing
(a) Boxplots related to different values of the same hyperparameter share the same color. This plot illustrates the marginal effect of each tested hyperparameters on the F-measure scores obtained in the grid-search.

The evidence from Figure 9 can be summarised as follows:

1. The 'Histogram Rule' largely outperforms the naïve 'Max Rule'. This fully repays the design and computational extra costs of including an additional MLP in our pipeline.
2. The 'Adjusted Threshold' stands out as a much better alternative than the 'Unadjusted Threshold'. This comes as no surprise, given the substantial class imbalance of the "e-commerce" distribution.
3. The 'Advanced Strategy' for recruiting marker words that guide the segmentation is significantly better than the 'Simple Strategy'.

4. Performance monotonically grows with the number of marker words, at least in the range explored in the grid-search, m = (50, 100, 150). This suggests that a further increase of *m* might lead our pipeline to even higher F-measure scores. However, a growth in *m* results in heightened computational costs. Therefore, more experiments would be needed to find an optimal tradeoff limit for *m*.

5. Sentences of intermediate length (9 words, k = 4) perform better than either shorter (5 words, k = 2) and longer (17 words, k = 8) ones.

Up to now we only analysed the *marginal effects* of each tested hyperparameters on the F-measure scores obtained in the grid-search. However, the main reason to perform a grid-search is to evaluate the *interaction effects* of all hyperparameters, namely to find the best possible *combination* of hyperparameter values. Due to space restrictions, we cannot report here performance statistics for all the 72 configurations explored in the grid-search. Instead, we study in some detail the behavior of the top-2 configurations. The hyperparameter configurations that achieved highest maximum F-measure in the grid-search are the following:

- **TOP-1** (maximum F-measure = 0.73):
  Advanced Strategy | m = 150 | k = 4 | Histogram Rule | Unadjusted Threshold.

- **TOP-2** (maximum F-measure = 0.72):
  Advanced Strategy | m = 150 | k = 4 | Histogram Rule | Adjusted Threshold.

The TOP-1 and TOP-2 configurations only differ in the way they set the final website classification threshold. Somewhat unexpectedly in the light of observation (*ii*) above, TOP-1 does *not* adjust the threshold. However, one should not overlook that TOP-1 and TOP-2 are actually very close in both maximum F-measure and maximum Accuracy. This can be seen in Table 4.

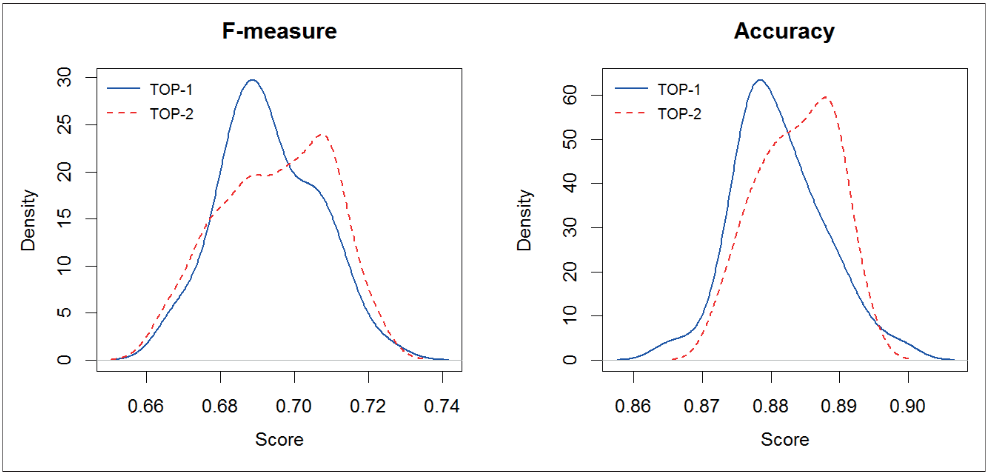
Table 4 - F-measure and Accuracy scores of the top-2 hyperparameter configurations found in the grid-search. For both configurations 50 runs were executed

Hyperparameter Configuration	Performance Measure	Distribution Summary					
		Min	1st Q	Median	Mean	3rd Q	Max
TOP-1	F-measure	0.67	0.68	0.69	0.69	0.70	0.73
TOP-2	F-measure	0.67	0.69	0.70	0.70	0.71	0.72
TOP-1	Accuracy	0.86	0.88	0.88	0.88	0.89	0.90
TOP-2	Accuracy	0.87	0.88	0.89	0.88	0.89	0.89

Source: Our processing

Table 4 shows subtle but interesting differences between the F-measure and Accuracy distributions of TOP-1 and TOP-2. These differences can be more easily recognised visually through Figure 10, where TOP-1 and TOP-2 are compared using F-measure and Accuracy density plots. There, blue continuous lines identify TOP-1 density plots and red dashed lines identify TOP-2 ones.

Figure 10 - Density plots of F-measure (left panel) and Accuracy (right panel) scores for the top-2 hyperparameter configurations found in the grid-search (a)



Source: Our processing
(a) The TOP-1 configuration densities are plotted with a blue continuous line; the TOP-2 ones, with a red dashed line. For both configurations 50 runs were executed.

The F-measure distribution of TOP-2 is clearly more concentrated at higher scores than the one of TOP-1, and has equal variance. The Accuracy distributions exhibit a similar pattern: TOP-2 peaks at higher scores, but is also less dispersed than TOP-1. Overall, the classification performance of TOP-2 appears at least as good as the one of TOP-1, but more stable. In the light of these considerations, and taking into account that the maximum F-measure and Accuracy scores of TOP-2 are only slightly below those of TOP-1, we are led to the conclusion that the best configuration of our processing pipeline is actually TOP-2.

Coming back to Table 4, it is worth stressing that all the *top* performances of previous ML approaches (listed in Table 2 of Section 6) consistently lie *below the minimum* performance level attained in 50 runs by the best configuration of our pipeline (*i.e.* TOP-2). This is a clear indication of the scale of the improvement achieved by our Deep Learning approach. We conclude the section by reporting below the top Precision, Recall, F-measure and Accuracy scores reached by our pipeline in the grid-search.

Table 5 - Best hyperparameter configuration and top performance of the Deep Learning processing pipeline proposed in the work

Best Hyperparameter Configuration	F-measure	Precision	Recall	Accuracy
• Advanced Strategy • m = 150 • k = 4 • Histogram Rule • Adjusted Threshold	0.72	0.73	0.72	0.89

Source: Our processing

As shown by Table 5 and Table 2, our processing pipeline achieved a relative gain in classification performance of +26% in terms of F-measure and +13% in terms of Accuracy with respect to our naïve model of Section 6.

With respect to the best competitor among previously tested ML approaches, the relative classification gain set by our proposal is +20% in terms of F-measure and +6% in terms of Accuracy.

Finally, it is worthwhile to note that our proposal even outperforms subsequent results achieved by Barcaroli and Scannapieco 2019 using Random Forest on comparable, albeit not identical, data collected in the 2017 round of the ICT survey. These authors report a top F-measure of 0.63 and a top Accuracy of 0.83. Therefore, with respect to these scores, our pipeline still seems ahead, with relative gains of +14% in terms of F-measure and +7% in terms of Accuracy.

9. Ongoing work and conclusions

In this paper, we showed that Deep Learning techniques can successfully address the "e-commerce" prediction task of Istat's ICT Big Data project. To reach this goal, we developed a sophisticated processing pipeline and evaluated its performance through extensive experiments. Empirical evidence shows that our proposal outperforms all the alternative Machine Learning solutions already tested in Istat for the same task. Besides good classification performance, our pipeline exhibits other desirable properties:

1. *It is entirely automated*. Useful text features for the detection of e-commerce are learned by the CNN without any human intervention, directly from the Word Embedding representation of scraped websites.
2. *It is almost entirely data-driven*. The only domain knowledge assumed is required to identify a handful of e-commerce specific words to be used as initial seeds by the automatic summarisation algorithm.
3. *It is generalizable*. The applicability to other binary classification tasks, besides "e-commerce", is obvious. Only minor adjustments would be required to enable multinomial classification of websites (essentially, the user would have to pass to the system class-specific seed words).
4. *Can take advantage of non-textual input*. Since CNNs can process both texts and images, our pipeline can be extended to leverage also the images scraped from the websites of Italian enterprises.

At the moment, our research focusses on point (4.). The rationale behind this line of research is that an ensemble of two Deep Learning classifiers – the first one extracting features from texts, the second from pictures – could achieve better predictive accuracy than either of the original classifiers. Let us hint at how our FPR approach may be applied to digital images scraped from enterprise websites. Since a large part of the paper has already been devoted to the FPR framework, we focus here only on the *differences* between processing texts and processing digital images.

Segmentation. As digital images embedded into most websites are easily identified within HTML files through their filename extensions (*e.g.* .jpeg, .gif, .bmp, etc.), segmentation of websites into images is straightforward and can be directly performed by the web-scraping system.

Image Scaling. Web-scraped images come up in widely varying sizes. This is at odds with the constant length synthetic sentences we extracted from scraped texts. Since CNNs generally benefit from constant size input examples, all the scraped images have to be scaled (up or down) to a common format, *e.g.* to square images of size 256 x 256 pixels.

DL architecture. We are currently studying and testing the *Residual Neural Networks* (ResNet) models proposed in (He *et al.*, 2016), which are our best candidate until now. ResNet are very deep and sophisticated CNN architectures that achieved record-breaking accuracies in Computer Vision, even outperforming humans in some image recognition tasks.

Training modality. Given the wide variety of goods and services that Italian enterprises can either sell (in the 'e-commerce' case) or only showcase (in the 'non-e-commerce' case) on their websites, our web-scraped images will span a tremendous range of diverse subjects. As a consequence, it will be extremely hard to train a CNN to either (*i*) identify few special images having high 'e-commerce' detection power (*e.g.* shopping cart icons), or (*ii*) discover useful latent correlations between the e-commerce/non-e-commerce status of websites and image subjects (*e.g.* smartphones are more frequently sold online than pets). ResNet models have the potential to cope with such complex problems, but they need *enormous* training sets of labelled examples to reach successful results (*e.g.* the ImageNet database[9] stores *over ten million* hand-annotated images). This is a serious concern, since our ICT training set only amounts to *few thousands* labelled websites. We believe that *Transfer Learning* (see *e.g.* Pan and Yang, 2010) can be a viable countermeasure to this issue. The base idea of Transfer Learning is to first train a CNN on a different (though not entirely unrelated) problem for which a huge training set is available, and to subsequently exploit the pre-trained model as a starting point to solve the real problem of interest, for which limited labelled examples are available. The intuition is that the knowledge gained in the first phase (and stored inside the weights of the pre-trained network) could be further enriched and fine-tuned in the second phase, therefore boosting the final prediction accuracy of the CNN. At the moment, we are running experiments in which a ResNet model pre-trained on ImageNet is retrained to classify our web-scraped images as 'e-commerce'/'non-e-commerce'.

9 ImageNet website: http://www.image-net.org/.

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COVID-19 emergency: a comprehensive overview of the economic classification systems for the manufacturing industry

Francesca Alonzi, Simone Ambroselli, Alberto Valery [1]

Abstract

Starting from the first months of 2020, the international scenario was dominated by the health emergency. Some medical supplies and other COVID-19 related products suddenly became hard to find bringing considerable attention to manufacturing of products to be used to contain this worldwide emergency. In this scenario, the World Customs Organization (WCO) and the World Health Organization (WHO) listed the products to be considered relevant in the prevention, testing and medical treatment of COVID-19 disease while the World Trade Organization (WTO) provided a comprehensive overview of trade and tariffs imposed on medical goods, many of which appeared to be in severe shortage during some phases of the crisis. The present paper is embedded in the context of official statistics and, in particular, focusses on the stream of research concerning international statistical classification systems. It offers a comprehensive overview in terms of industries and products of the medical and medical-related devices production mainly affected in the first phase (before vaccines' phase) of the COVID-19 emergency.

Keywords: COVID-19, Statistical classifications, Official Statistics, Correspondence tables, International Trade, Manufacturing sector.
JEL classification: C18, F00, L60.

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1. Introduction

During the COVID-19 worldwide emergency some medical supplies have suddenly become hard to find bringing considerable attention to manufacturing of medical products to be used for prevention, testing and treatment.

Several production systems, such as the Italian one, have faced lacks of some important supplies, for instance hand sanitisers and even run out of some other necessary items, such as face masks. As the pandemic worsened, some critical issues also emerged in the provision of medical ventilators and other specific equipment for hospitals. The provision of COVID-19 test kits and diagnostic instruments was challenging, too; at the beginning obstacles were related to the availability of equipped clinical laboratories and then chemical reagents needed for the tests have become scarce.

In this scenario, the World Customs Organization (WCO), in cooperation with the World Health Organization (WHO) has prepared a list of products which are considered relevant in the prevention, testing and medical treatment of COVID-19 disease in general. At the same time, the World Trade Organization (WTO) has provided a comprehensive overview of trade and tariffs imposed on medical goods in general, many of which appear to be in severe shortage as a result of the current crisis.

More recently, the WCO and the WHO have also produced lists of medical supplies and medicines for COVID-19 with the intent of helping customs and economic operators identify them.

All the contributions make use of the Harmonised System (HS) as the reference international classification for COVID-19 medical supplies.

HS is part of an integrated system of economic classifications, developed mainly under the auspices of the United Nations Statistical Division; the system ensures comparability at world level of statistics produced on the basis of the different classifications of products and economic activities.

Nevertheless, an evaluation of the potential economic activities related to the manufacturing of the above-mentioned products is still lacking. Such an assessment is indeed important to estimate the impact of enterprises restructuring generated by the COVID-19 emergency on the production system. In Italy, these processes of industrial conversion have also been expedited by containment measures adopted by the Government to limit contagion: many large companies have added new specific products related to the COVID-19 emergency to their main activity, while some smaller enterprises have totally reconverted their activities to devote themselves to products in greater demand during the pandemic period.

Based on the international references cited above, the main objective of the paper is to offer a comprehensive overview in terms of industries and products of the medical and medical-related devices production mainly affected in the first phase of the COVID-19 emergency.

Contributions are twofold: from one side, findings are useful for experts involved in the classification activities (both administrative and statistical units); secondly, findings constitute a valid support for research activities concerning the COVID-19 period in order to evaluate the impacts on the production and international trade systems.

With regard to the methodology, it should be noted that the output is of a high degree of reliability since it is based on the rigorous application of official correspondence tables and on the respect of hierarchical constraints existing between the different standard classifications that have been considered in this research work.

The contents of this work are divided into six Sections. Apart from the first Section that is devoted to the introduction, the second one is intended to review the most significant literature, focussing on the definition of statistical classification and presenting the recent advancements on the issue. The third Section is centred on the international system of economic classification that represents the basis on which the empirical analysis has been developed. Main business statistics domains and their pivotal relationships with classification systems are briefly described in the second part of the third Section. All data and methods used in the study are presented in the fourth Section while the major results are described in the fifth Section. Finally, the last Section contains the main conclusive remarks on the issues dealt with in this study presenting and critically discussing the output; some possible future research developments are also introduced.

2. Background

In order to investigate the economic system, we need to be able to assign units and activities into sets of discrete, exhaustive and mutually exclusive categories in the collection of data and presentation of statistics to policy makers, analysts and researchers, to describe the characteristics of a particular population (Hancock, 2013). Classifications group and organise information meaningfully and systematically into a standard format that is useful for determining the similarity of objects or persons (Hoffmann and Chamie, 1999); statistical classifications are used in the production and presentation of statistics.

More specifically, *"All economic phenomena that are to be described in the form of statistics require systematic classification. Classifications are, so to speak, the system of languages used in communication about, and statistical processing of, the phenomena concerned. They divide the universe of statistical data into categories that are as homogeneous as possible with respect to those characteristics that are the objects of the statistics in question"* (United Nations, 2008).

In particular, the objective of standard (or framework) classifications is to provide a recognised framework that makes it possible to accommodate for various sets of data coming from different sources and surveys and make them comparable (Eurostat, 2019).

In the case of COVID-19, governments call for reliable data on the effects of the emergency on the labour market, production system, and the economy in general. But there can be no economic analysis without a classification (Guibert *et al.*, 1971). To this aim, and in order to promote research and ensure high level of comparability between the data produced in this field, it is thus necessary to use classification systems for products and economic activities that are universally recognised and shared among users.

Taking into account the evidence that the pandemic unfortunately has a worldwide presence, international statistical classifications constitute a valid support in this sense.

This study builds on the recent notes prepared by the World Trade Organization (WTO) and the World Customs Organization (WCO), in cooperation with the World Health Organization (WHO) to list and categorise medical supplies and medicines relevant to the COVID-19 response. They represent a first, internationally agreed recommendation to list all medical products directly involved in the COVID-19 pandemic. The sources are presented in Table 1.

Table 1 - Informative sources

Authors	Edition	Release date	Living document	Type of products	N. of product sections	N. of HS products
WTO	1	3rd April 2020	No	Medical supplies and medicines	4	92
WCO and WHO	3.01	2nd June 2020	Yes	Medical supplies	8	100
WCO and WHO	1	30th April 2020	Yes	Medicines	3	47
WCO and WHO	Special edition	26th October 2020	Yes	Medicines	1	7

Source: Authors' elaboration on the basis of WCO and WTO data, 2020

The informative note prepared by the WTO and published in the early days of April 2020 lists a set of 92 products categorised into four groups: 1. Medicines (Pharmaceuticals) – including both dosed and bulk medicines; 2. Medical supplies – refers to consumables for hospital and laboratory use (*e.g.* alcohol, syringes, gauze, reagents, etc); 3. Medical equipment and technology; and 4. Personal protective products – hand soap and sanitiser, face masks, protective spectacles.

The WCO-WHO list for COVID-19 medical supplies includes more than 80 products grouped in eight different sections: I. COVID-19 Test kits/ Instruments and apparatus used in Diagnostic Testing; II. Protective garments and the like; III. Disinfectants and sterilisation products; IV. Oxygen Therapy equipment and pulse oximeters; V. Other medical devices and equipment; VI. Other Medical Consumables; VII. Vehicles and VIII. Other.

The WCO-WHO list of priority medicines organises medicines in three categories: 1. Medicines used in the general management of hospitalised patients with COVID-19; 2. Medicines which are used as part of the direct treatment against COVID-19 in hospitalised patients; 3. Medicines where interrupted supply could result in serious health consequences.

The WCO-WHO list of medicines released in October 2020 contains a list of other 25 substances pertinent to the COVID-19 pandemic.

All the documents present the products at 6-digit subheading according to the Harmonised System (HS) classification that is a multi-purpose international product classification developed by the WCO; it is a systematic list of commodities applied by most trading nations (and also used for international trade negotiations). To each product listed in the first document (WTO) it corresponds a unique HS code while the products listed in the second note (WCO-WHO medical supplies) are linked to 100 HS codes. In the third document (WCO-WHO medicines) 47 HS codes have been detected. Finally, the latest document provides 7 HS codes.

Starting from the contents of the above cited notes, the aim of our study is twofold: to derive nationally used statistical classifications of products and, at the same time, to identify a list of possible economic activities involved in the prevention, testing and treatment of COVID-19 in the manufacturing section without ignoring the fact that purposes of product classifications somehow differ from classifications of economic activities. From the one hand, product classifications are designed to categorise products that have common characteristics; they provide the basis for collecting and calculating statistics on the production, distributive trade, consumption, international trade, and transport of such products. On the other hand, activities are primarily grouped together when they share a common process for producing goods or services, using similar technologies; industries differ not just according to products produced but they have specific characteristics, histories and dynamics (Porter, 1979).

Our study will provide both producers and users of statistics with a useful tool for analysing the impact of COVID-19 in the manufacturing industry. The derived tool, a list of COVID-19 related products and economic activities, could be used in different fields both in the administrative and private economy context. More specifically, it could be used to measure the development of specific industrial sectors in times of COVID-19 in different countries thus the policy value of this information would be significant. From the point of view of analysts, such a tool would be useful to explain potential outliers or irregular trends which could have not been predictable.

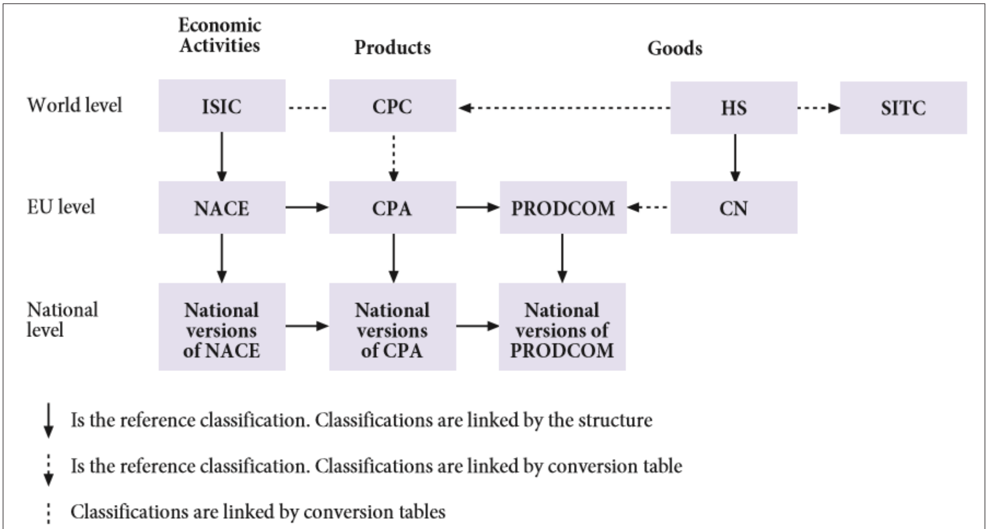
3. The international system of economic classifications and business statistics

3.1 The international system of economic classifications

Although a one-to-one correspondence does not exist between products and activities, there is a close relationship between the two that is ensured by their belonging to the international system of economic classifications, an integrated system of statistical classifications (Figure 1), developed mainly under the auspices of the United Nations Statistical Division (UNSD).

Classifications belonging to the system are linked by the structure or by conversion (also known as correspondence, concordance, mapping or correlation) tables. Correspondence tables are produced through the systematic comparison of one classification (A) to another (B) to determine how a statistical unit classified to a detailed category in A should be classified to the most detailed category possible in B (Hoffmann and Chamie, 1999). As presented by Eurostat (2019) they consist in establishing links between the codes in a source classification with the corresponding codes in a target classification.

Figure 1 - The international system of economic classification



Source: Eurostat, 2008

The international system of economic classifications is presented in Figure 1. Apart from the HS 2017, that has been presented in the background (Section 2), the following classifications[2] have been considered in the study.

1. Product classifications
    a. The *Central Product Classification (CPC)* constitutes a complete product classification covering goods and services. It serves as an international standard for assembling and tabulating all kinds of data requiring product detail.
    b. The *Statistical Classification of Products by Activity (CPA)* is the European version of the CPC and the purposes it serves are in line with those of the CPC. Although the CPA is the European counterpart of the CPC, it differs from the latter not only in that it is more detailed but also concerning its structuring. The view at European level is that a central product classification should be structured according to the criterion of economic activity, with the framework (and thus the definition of the economic activities) being based on NACE, the Statistical classification of economic activities in the European Community.
    c. The *Prodcom list* is the list of products of the European Community used to provide statistics on the production of manufactured goods. The term comes from the French "PRODuction COMmunautaire" (Community Production). Prodcom covers mining, quarrying and manufacturing: sections B and C of the NACE. Prodcom statistics aim at providing a full picture at EU level of developments in industrial production for a given product or for an industry in a comparable manner across countries.
    d. The *Combined Nomenclature (CN)* is the goods classification used within the EU for the purposes of foreign trade statistics and for intra-EU trade statistics. It is also used by Directorate General "Taxation and Customs Union" of the European Commission for customs duty purposes.

2 In general, classifications are revised more or less regularly; the indication after the name or acronym of the classification indicates the version of the classification itself. For instance, HS 2017 means the Harmonised System classification, version 2017.

2. Classifications of economic activities
   a. The *International Standard Industrial Classifications of All Economic Activities (ISIC)* is the international reference classification of economic activities. Its main purpose is to provide a set of activity categories that can be utilised for the collection and reporting of statistics according to such activities.
   b. The *Statistical classification of economic activities in the European Community (NACE)* is the classification of economic activities corresponding to ISIC at European level. Though more disaggregated than ISIC, NACE is completely in line with it and can thus be regarded as its European version.
   c. The *Classificazione delle Attività Economiche (Ateco)* is the national version of the NACE classification but is more detailed than the NACE having two more levels. At national level it is used both for statistical and administrative purposes.

3.2 Business statistics and classification systems

In the field of business and economic statistics, classifications play a crucial role both as stratification and dissemination variables. Probably the main and clearest examples to understand the ubiquitous role of the classifications are those concerning economic activities (NACE and Ateco, for the present paper). As national Statistical Business Registers (nSBRs) should be considered as the backbone for business statistics (Unece, 2015), classifying the statistical units according to the economic activity they carry out is certainly one of the main elements that guarantees that role. First of all, the economic activity classifications codes contribute to the coverage of the Registers. Secondly, as stratification variables they help in extracting samples and grossing-up. Thirdly, they can help in defining special statistical units, such as ancillary units. For the above reasons, NACE (or other code of economic activity) is a key variable that allows SBRs to be the backbone of business and economic statistics.

Structural Business Statistics (SBS), for what concerns EU countries, are compiled in modules defined by sectors derived from economic activities codes while indicators within the Short-Term Statistics (STS), such as turnover or prices, are in some cases produced according to the different type of industry.

Concerning the product classifications, Prodcom codes are the units of analysis useful to collect and disseminate data on the physical volume of production sold and the value of production sold during the survey period. Finally, also for trade classifications, it can be noted as classifications such as the CN constitute the central aspect that is collected and disseminated through international trade statistics.

4. Data and methods

The lists of COVID-19 related products presented in the informative notes prepared by the WTO and the WCO-WHO constitute the starting point of this research work. In order to consider a set as complete as possible, although not exhaustive as pointed out by the WCO[3], a total of 185 HS codes have been considered. 3 of them are cited in all the sources apart from the last one (WCO-WHO medicines special edition) while 128 in one document only, respectively: 40 have been detected only in the note prepared by the WTO, 59 only in the second document (WCO-WHO medical supplies) and 30 in the third one (WCO-WHO medicines). Table 2 presents the number of detected HS codes by source while all HS codes derived by the analysis of the informative notes are listed in Annex 1.

Table 2 - Number of HS codes by source

WTO medical supplies and medicines	WCO-WHO medical supplies	WCO-WHO medicines	WCO-WHO medicines special edition	N. of HS codes
Yes	Yes	Yes	No	3
Yes	Yes	No	No	37
Yes	No	No	Yes	2
Yes	No	No	No	40
Yes	No	Yes	Yes	1
Yes	No	Yes	No	9
No	Yes	Yes	No	1
No	Yes	No	No	59
No	No	Yes	Yes	3
No	No	Yes	No	30

Source: Authors' elaboration on the basis of WCO and WTO data, 2020

Through the application of a set of rules derived from both hierarchical relationships and official conversion tables, products have been codified according to other classification systems used at international, European and national level and an attempt to define also related economic activities has been developed. Official conversion tables are made available by the United Nations Statistical Division (UNSD) on its website[4] and by Eurostat directly on RAMON[5], its classification server.

3 As stated in the frontispiece of the document prepared by the WCO: "This list is provided as an indicative list only and only includes a limited number of items. It does not have a legal status".

4 The UNSD page that contains resources related to classifications on economic statistics is https://unstats.un.org/unsd/classifications/econ/

5 RAMON, Reference And Management Of Nomenclatures, is available at https://ec.europa.eu/eurostat/ramon

The following steps have been applied in order to derive different codes according to the above described classifications. Comparisons are always done two at a time, classification A to classification B; the input (or source) classification system is presented on the left while the derived (or target) classification is on the right. Only codes at the highest level of detail have been taken into account.

a) HS 2017 - CN 2020

b) CN 2020 - CN 2019

c) CN 2019 - Prodcom list 2019

d) CN 2019 - CPA 2.1

e) CPA 2.1 - NACE Rev.2

f) NACE Rev. 2 - Ateco 2007

g) NACE Rev. 2 - ISIC Rev. 4

h) HS 2017 - CPC 2.1

More specifically, HS 2017 codes have been converted in CN 2020 codes by using the hierarchical relationships between the two classifications (a). CN is an EU further development of international HS system. In fact, CN covers special EU-specific subdivisions (digits 7 and 8) starting from the HS 6-digit level. For this reason, the nature of the links may be (1) “one-to-one”, meaning that the whole content of a position in the source classification corresponds exactly to the whole content of a position in the target classification, or (2) “one-to-many”, meaning in the latter case that the content of a position in the HS 2017 (source classification) is distributed over more than one position in the target classification CN 2020. The objectives of this first step have been threefold: moving into the European dimension, obtaining more details, and involving a classification (CN) linked to others by direct correspondence tables. Starting from the latest CN version (CN 2020), the obtained codes have been compared with the list of changes (new, deleted or reused codes) that have occurred between the 2019 and 2020 versions of the CN itself; thus, the correspondent list of CN 2019 codes has been derived (b).

The subsequent steps (c and d) take advantage of the correspondence tables available in RAMON. According to step (c), starting from CN 2019 the most updated version and currently used, version of Prodcom has been obtained. Moving from CN 2019 to Prodcom 2019, “many-to-one” links have been tackled since the content of several positions in the CN 2019 is grouped into a single position in the Prodcom 2019.

The derived list of COVID-19 products codified according to the Prodcom list has never been used as an input classification; nevertheless, it has been produced in order to support current economic statistics at national and European level. No further national details of the classification have been found.

The next step (d) has been intended to derive CPA codes; to this aim, after evaluating alternative options, the existing correspondence table between the CN 2019 and the CPA 2.1 was exploited. Prodcom headings are coded using an eight-digit numerical code, the first six digits of which are identical to those of the CPA code. The Prodcom list is therefore also consistent with the CPA, while further detailing the CPA product categories. A detailed analysis has shown that if the conversion had been done by following the structural links, some differences with the first method would have been highlighted. In particular, three cases have been recorded; one of them also generates a change at the level of class (Prodcom code 13.92.29.99 is linked to CPA 32.50.50 rather than to CPA 13.92.29).

Shifting the focus towards economic activities (e), it should be noted that the CPA classification is based on the NACE in the sense that the CPA takes the 4 digits of the NACE and subdivides them into a 5th and 6th digit, thus specifying the products related to the economic activity classified in the NACE. For this reason, the step e) from CPA 2.1 to NACE Rev. 2 has been done in dropping the last two CPA positions.

In a similar way, the national version of the NACE classification is perfectly consistent with the NACE at the level of class, thus, it has been sufficient to link the two standards by NACE codes (f). Ateco 2007 is more detailed than the NACE; as a consequence, it has caused an increase of the total records.

In order to make the results of our analysis be used by a larger audience of users, two more correspondence tables have been applied with the aim of providing data according to the ISIC international classification (g) as well as the CPC (h). Links with the ISIC have been derived by the NACE classification through a bottom-up approach (from the European level to the world level) by using hierarchical links. CPC codes have, instead, been obtained directly from HS codes through the use of the official conversion table made available by the UNSD.

5. Results

As already described in the previous Section, starting from a list of 185 HS 2017 codes, a complete correspondence table (Annex 2) between products and economic activities presented through different classification systems has been derived. It includes those products and economic activities that are considered to be relevant for the prevention, testing and treatment of COVID-19 in the manufacturing sector, thus offering an almost complete overview of the economic sectors potentially involved in the management of the COVID-19 health emergency.

The output, formed by 736 records, has been derived through a step-by-step logic by integrating a set of correspondence tables between two classifications at a time.

First of all, the 185 HS codes have generated 348 CN 2020 codes (a). For the products under analysis, 87 “one-to-one” and 98 “one-to-many” have been found between HS 2017 and CN 2020. A few differences between the two versions of the Combined Nomenclature (b) have been detected: they only interest 5 codes that generate many-to-one links in the sense that 12 different CN 2019 codes merge into 5 CN 2020 codes[6].

179 product codes according to the Prodcom list 2019 have been derived from the CN 2019 (c). Nonetheless, moving from CN 2019 to Prodcom some links were missed; in particular, for the following CN codes no correspondence has been found in the conversion table: 2501 00 10, 8703 21 90, 8703 22 90, 8703 23 90, 8703 24 90, 8703 31 90, 8703 32 90, 8703 33 90, 8703 40 90, 8703 60 90 and 8703 80 90. While the first one, 2501 00 10, identifies “Sea water and salt liquors”, the others all refer to chapter 87 - vehicles other than railway or tramway rolling stock, and parts and accessories thereof, in particular to used motor cars and other motor vehicles principally designed for the transport of persons. In order to have a complete overview of the items involved in the prevention, testing and treatment of the COVID-19 disease, the complete list of the Prodcom codes is provided in Annex 3.

6 The changes between the CN 2019 and the CN 2020 are the following: 3926 90 92 and 3926 90 97 are merged into 3926 90 97; 9011 10 10 and 9011 10 90 are merged into 9011 10 00; 9025 19 20 and 9025 19 80 are merged into 9025 19 00; 9027 80 11 and 9027 80 99 are merged into 9027 80 20; 9027 80 13, 9027 80 17, 9027 80 91 and 9027 80 99 are merged into 9027 80 80.

The detected Prodcom codes correspond to 92 CPA (d). For the following 10 CN codes no correspondence has been found in the conversion table: 8703 21 90, 8703 22 90, 8703 23 90, 8703 24 90, 8703 31 90, 8703 32 90, 8703 33 90, 8703 40 90, 8703 60 90 and 8703 80 90.

The 92 CPA codes have generated 36 NACE codes (e) belonging to 17 NACE divisions (2-digit level); see Annex 4 for the complete list.

The 36 NACE classes have developed 67 Ateco categories at the 5th digit level (f); in this way, it has been possible to draw up an inventory of manufacturing economic activities potentially involved in the prevention, testing and treatment of COVID-19 at national level. This goal represents the principal aim of the study.

Moving the attention to the international layer, 27 ISIC (g) and 70 CPC codes (h) have been identified.

A complete overview of the various actions is presented in Table 3.

Table 3 - Correspondence tables applied in the research work

Correspondences		N. of records	Derived classification	Number of unique codes
	HS 2017	185	-	-
a)	HS 2017 - CN 2020	348	CN 2020	348
b)	CN 2020 - CN 2019	355	CN 2019	354
c)	CN 2019 - Prodcom list 2019	357	Prodcom list 2019	179
d)	CN 2019 - CPA 2.1	357	CPA 2.1	92
e)	CPA 2.1 - NACE Rev. 2	357	NACE Rev. 2	36
f)	NACE Rev. 2 - Ateco 2007	736	Ateco 2007	67
g)	NACE Rev. 2 - ISIC Rev. 4	736	ISIC Rev. 4	27
h)	HS 2017 - CPC 2.1	736	CPC 2.1	70

Source: Authors' elaboration

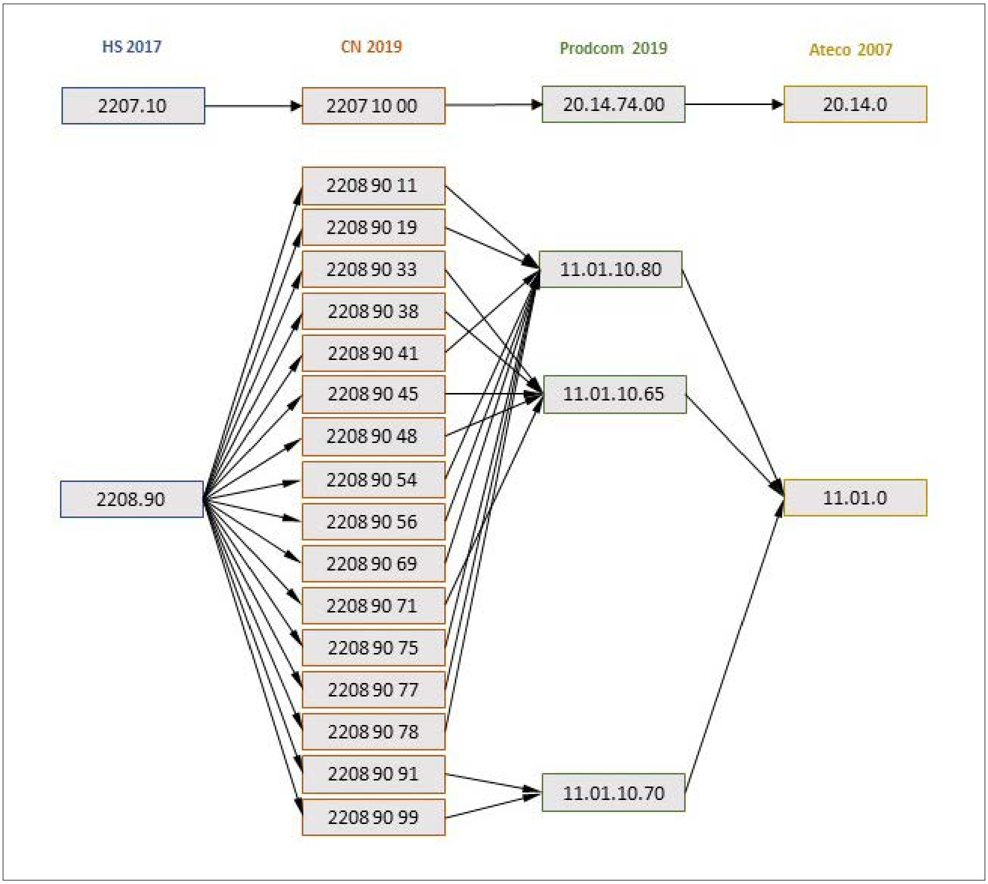
At the end of the procedure, HS 2017 products are generally codified in a single NACE division except for the following four: 2501.00, 3006.10, 3824.99 and 9025.11. In the first case, mining and quarrying sector (division 08) and food manufacturing activities (division 10) are involved. Products related to HS 3006.10 concern pharmaceutical industries (division 20) and other industries (division 32) while in the third both chemical (division 20) and pharmaceutical (division 21) are considered. In the latter case, NACE division 26 (manufacture of computer, electronic and optical products) and 32 (other manufacturing) are involved.

The derived correspondence table (Annex 2) between products and economic activities that are considered relevant for the prevention, testing and treatment of the COVID-19 is open to interpretation for several uses and different users. A possible way to analyse its data is by observing the positioning of some specific products. To this aim, some examples are provided below; they are about products that have been frequently cited by the media in the health emergency phase and that have activated more or less significant industrial conversion processes: ethyl alcohol, face masks and gowns.

In the HS 2017 classification ethyl alcohol is identified with two different codes (2207.10 and 2208.90) and the difference is given by the alcoholic strength by volume in relation to the 80% threshold. The types of industry activated by the two codes are very different, the chemical industry (division 20 according to the NACE classification) and the beverage industry (division 11). As shown in Figure 2, some relationships are one to one, such as the link of the product 2207.10 (HS 2017) while others are more complex. For example, HS code 2208.90 has further 16 EU specific subdivisions that correspond to 3 Prodcom 2019 codes (m to n relationships) but, even in this case, only a NACE class and a national fifth-digit level (Ateco 2007) has been involved.

Among personal protective equipment for the face, masks are certainly the main product that should be considered. They are classified according to the following two HS 2017 codes: 6307.90 identifies textile masks or without a replaceable filter or mechanical parts, and 9020.00 represents those masks with filters or other mechanical parts. These products are potentially related to enterprises operating in the following NACE classes: 13.92 Manufacture of made-up textile articles, except apparel; 32.50 Manufacture of medical and dental instruments and supplies; 32.99 Other manufacturing n.e.c. It is important to note that this example contains the codes described in Section 4 (step d) for which some differences according to the different conversion method have been found. The informative input note regarding medical supplies prepared by the WCO and WHO takes also into consideration cellulose or paper masks; their HS 2017 code is 4818.90 and it is related to NACE class 17.22 Manufacture of household and sanitary goods and of toilet requisites. Nevertheless, cellulose or paper masks produced by such an industry are hard to be considered as protective equipment.

Figure 2 - Ethyl alcohol: linking products and economic activities



Source: Authors' elaboration

Finally, concerning the identification of gowns, the following HS 2017 codes, all related to "protective garments" should be taken into consideration: 3926.20, 4015.90, 4818.50, 6210.10 and 6210.50. Even in this case, different industries are involved: NACE 22.29 Manufacture of other plastic products; 22.19 Manufacture of other rubber products; 17.22 Manufacture of household and sanitary goods and of toilet requisites; 14.19 Manufacture of other wearing apparel and accessories.

6. Discussion and conclusions

In the study of economic phenomena, taking all elements into account simultaneously is not always possible. For the purposes of analysis, certain elements need to be chosen and grouped according to particular characteristics (United Nations, 2008). Official statistical classifications are used for this purpose and serve to compare phenomena that otherwise would not be possible to measure.

This research work, inspired by the COVID-19 emergency and the changing business practices in reaction to it, is intended to identify, within the official economic classification systems, the economic activities of the manufacturing sector and the products considered relevant for the prevention of COVID-19 and medical treatment in general. In light of the recent pandemic events the document follows a strict structure as to allow other statisticians to replicate and integrate the analysis; it provides relevant background information, explanation of methods used and the presentation of the results of the study (Annex 2).

The output, a comprehensive correspondence table between codes of different classifications, may be used by researchers and statistical offices to make analysis on the manufacturing sector at the time of COVID-19 disease. Taking into account the fact that the COVID-19 has caused a worldwide emergency, the aim of the study, besides deriving informative systems to be used at national level by Istat, has been intended to provide an almost complete overview of the different classification systems used at international level.

The work, based on four notes prepared by the World Trade Organization and the World Customs Organization in cooperation with the World Health Organization, is the result of the application of a set of official conversion tables and structural links existing between different classifications, or different versions of the same classification; the starting point is the list of products cited in the above international notes.

The output is of a high degree of reliability since it is based on the rigorous application of official correspondence tables and on the respect of hierarchical constraints existing between the different classifications that have been considered in this research work; their being part of an integrated system of economic classifications developed mainly under the auspices of the Statistical Division of the United Nations ensures comparability at world, European and national level of statistics on products and economic activities.

Nevertheless, although product-activity links favoured by the existence of internationally harmonised classifying systems and official conversion tables have been respected, the analysis is affected by the limitations due to the different statistical purposes of classifications of products versus classifications of economic activities. While the former classifications are mainly based on the physical characteristics of the goods produced, the latter group together economic activities when they share a common process for producing goods or services, using similar technologies.

It should be noted that product classifications are more detailed than the classifications of economic activities; thus, they are able to catch changes, that risk to be temporary, in the production processes of small enterprises as well as medium-sized ones. On the other hand, classifications of economic activities are of a great importance because they are used to classify economic units in national Statistical Business Registers (nSBRs). In general, in nSBRs, units are classified according to their principal activity since it is not always possible to define also secondary productions. However, if it is possible that the COVID-19 disease has made some small and medium enterprises reconvert, even only for a limited period, their production processes, thus implying a change in the activity code registered in nSBRs, this may not be the case for larger companies. In this case, they may have developed some collateral activities by making some minor changes to their processes, but this will not imply a change at the level of ISIC/NACE or Ateco code.

In May 2020 and in October 2020, Istat conducted a special survey[7] on a representative sample of enterprises in order to evaluate their current situation and their perspectives concerning COVID-19 health emergency. As far as our purpose is concerned, the results of a specific qualitative question concerning the strategy enterprises have adopted or are about to adopt in a short term offer interesting hints for future research. In fact, the latest results show that 3 per cent of the manufacturing enterprises in the sample have added new

7 Istat. 2020. "Situazione e prospettive delle imprese nell'emergenza sanitaria COVID-19". *Statistiche Report*. May edition available at https://www.istat.it/it/archivio/244378
October edition available at https://www.istat.it/it/archivio/251618
At the time of writing this paper, the results of the survey had been disseminated in Italian only.

products and/or new processes related to COVID-19 emergency but within the industry they currently operate while more than 8 per cent of the enterprises (8.2 per cent) have enlarged their product range within their sector but for production unrelated to the emergency. It is also interesting noting that some of the manufacturers in the sample have afforded the crisis radically changing their main economic activity; analysing the survey results we are not able to understand in which way they have converted their activities but this could be a possible new field of research. The development of some economic activities as well as the decline of others, despite being not directly related to the COVID-19 emergency, could have been affected by new needs and habits.

Also the National Central Bank of Italy has detected some cases (4 per cent of enterprises in its sample) where Italian enterprises have converted their production activities especially in the textile and wearing apparel sectors. Similar findings have been discovered by Confindustria[8] and emerge in the second edition of a special survey on the effects of COVID-19 according to which more than 33 per cent of Italian enterprises in the sample would change the basket of products they produce or sell in order to react to the economic crisis.

Results seem to confirm that most of these changes of activity in some companies are not necessarily definitive but may well be ephemeral, limited to the COVID-19 emergency period. More in general, as highlighted by Carnazza and Giorgio (2020) the Italian Government has supported and encouraged these reconversions by providing subsidies.

Unfortunately, from a statistical point of view, it is not easy to measure also these temporary changes because they may cause difficulties for the statistical production especially for STS. In effect, at national level, statistics are being produced following the guidelines provided by Eurostat[9]; an example[10] is the "Guidance on estimation and imputation of missing data for short-term statistics in the context of the COVID-19 crisis" which states the following: *"Some statistical units temporarily have taken up alternative activities, e.g. producing disinfectants, protective masks, offering home delivery services. It is not recommended to reclassify them at this point since these will be only*

8 Confindustria. 2020. "Seconda edizione dell'indagine sugli effetti della pandemia da *COVID-19* per le imprese italiane". https://www.confindustria.it/notizie/dettaglio-notizie/Indagine-sugli-effetti-del-Covid-19-per-le-imprese-italiane

9 https://ec.europa.eu/eurostat/data/metadata/covid-19-support-for-statisticians

10 https://ec.europa.eu/eurostat/documents/10186/10693286/Estimation-imputation_of_missing_data_for_STS.pdf

temporary activities and might not affect the business structure in the long term. Although information on temporary conversions of businesses will be interesting, STS is not the right statistical domain for this purpose". Such methodological solution guarantees the STS domain but at the same time it does not solve the informative gap concerning the development of new products and economic activities emerged during the COVID-19 period.

All the above considered, the output scheme is a useful support for researchers to investigate the evolution of the above cited process of production conversions during the COVID-19 emergency by looking for examples of enterprises that have helped increasing the production of lacking medical products and equipment. At the same time, is it a useful tool for the users of economic statistical classification in finding the most appropriate classification code for products that are necessary for the management of the current emergency and economic activities related to their production (not only staff from nSBRs but also administrative sources which are used as inputs for the nSBRs). In addition, by considering different classification systems, it makes possible to compare statistics produced in different domains such as short-term business statistics or national accounts. The tool could be also particularly useful to introduce additional lenses in analysing international trade statistics in order to evaluate imports and exports comparing data pre-crisis and post-crisis.

In addition to the preliminary results of the special survey conducted by Istat on enterprises facing difficulties derived by COVID-19 health emergency, there is a certain evidence that a lot of national and multinational enterprises, both small and large, have temporarily changed their short-term strategies to convert, partially or totally, their production. Such an evidence is provided by leading Italian newspapers in business, financial and regulatory information[11]. What is more, during the emergency, in order to evaluate the

11 Some examples are provided in the following articles by IlSole24Ore:
Cinque imprese del Sud: pronte a convertire le linee per produrre respiratori (23 March 2020) https://www.ilsole24ore.com/art/cinque-imprese-sud-pronte-convertire-linee-produrre-respiratori-AD2W2GF
Mascherine e respiratori, ecco le fabbriche che si riconvertono (24 March 2020) https://www.ilsole24ore.com/art/da-miroglio-menarini-fabbriche-che-si-riconvertono-contro-coronavirus-ADLIFdD
Dalla grappa agli igienizzanti, l'alcol delle distillerie contro il coronavirus (24 March 2020) https://www.ilsole24ore.com/art/dalla-grappa-igienizzanti-l-alcol-distillerie-contro-coronavirus-ADnyxMF
Dai motorini dei tergicristalli nascono i respiratori per il Coronavirus (1 April 2020) https://www.ilsole24ore.com/art/dai-motorini-tergicristalli-nascono-respiratori-il-coronavirus-ADyxqVH
Invitalia, a 50 aziende incentivi alla riconversione per produrre mascherine (25 April 2020) https://www.ilsole24ore.com/art/invitalia-50-aziende-incentivi-riconversione-produrre-mascherine-ADgh0ZM

proper allocation of their new productions, some enterprises have consulted an early version of our tool, which was made available on the official website of the Italian National Institute of Statistics[12]. In that phase, requests have mainly concerned textile and apparel industries that started to produce face masks and gowns. Later on, in line with the adoption of new Government measures[13] (in force since June 2020) on distillation of wine in case of crisis we have supported wine-related industries interested in changing the activity codes for their new products (hand sanitisers and ethyl alcohol) since that Italy, as well other European countries, has authorised producers to transform cheaper wines in order to empty the cellars to leave space for the next harvest.

The obtained correspondence table is intended to be maintained regularly as to update official links between products and economic activities that are relevant in the prevention, testing and medical treatment of the COVID-19 pandemic. Such a tool, whose results are freely available in the annexes to this document, could be shared for testing and application in other countries.

Taking into account the most recent developments on the issue, such as the advancements undertaken by the European Commission[14] and the evidence that the Combined Nomenclature 2021 has included new codes all related to

12 The informative notes used as input sources in this study date back to the end of October 2020 and refer to the most critical time period for the COVID-19 disease in Italy and in the rest of the world. More specifically, this contribution represents a progress of the research work undertaken by the authors on the issue that was based only on the documentation available up to the end of April. The previous works are available at
https://www.istat.it/it/archivio/242495
https://www.istat.it/it/archivio/250131
https://www.istat.it/it/archivio/250136

13 Please refer to the following link for more information on the national regulation on distillation of wine in case of crisis https://www.politicheagricole.it/flex/cm/pages/ServeBLOB.php/L/IT/IDPagina/15714 which is derived from the COMMISSION DELEGATED REGULATION (EU) 2020/592 of 30 April 2020 on temporary exceptional measures derogating from certain provisions of Regulation (EU) No 1308/2013 of the European Parliament and of the Council to address the market disturbance in the fruit and vegetables and wine sectors caused by the COVID-19 pandemic and measures linked to it.

14 An example is provided by the live document “COVID-19 - Indicative list of products to be imported duty – VAT free” provided by the European Commission (2020).

COVID-19[15], an attempt to systematise all latest contributions on economic classifications related to COVID-19 would be desirable at international level as it could provide a more comprehensive picture of all products and economic activities heavily involved in the emergency. In effect, taking into account that the pandemic has spread rapidly around the world, and that we are still in the middle of the crisis and new developments may appear, the potential usefulness of applying a common classification tool internationally to identifying COVID-19 related manufacturing activities should be taken into consideration. Efforts could also be addressed to expand the tool beyond manufacturing, whether this logic is needed.

15 All the changes between the Combined Nomenclature 2020 and the updated version to 2021 are cases in which one CN2020 code has been split in two or more codes to better represent some medical supplies and medicines used during the COVID-19 pandemic. All the amendments are provided below where the first row is the CN2020 code while the following rows are the derived CN2021 codes.

3002 20 00 Vaccines for human medicine

3002 20 10 Vaccines against SARS-related coronaviruses "SARS-CoV species", for human medicine

3002 20 90 Vaccines for human medicine (excl. vaccines against SARS-related coronaviruses)

3926 90 97 Articles of plastics and articles of other materials of heading 3901 to 3914, n.e.s.

3926 90 60 Protective face shields/visors of plastics

3926 90 97 Articles of plastics and articles of other materials of heading 3901 to 3914, n.e.s.

6307 90 98 Made-up articles of textile materials, incl. dress patterns, n.e.s. (excl. of felt, knitted or crocheted, and single-use drapes used during surgical procedures made up of nonwovens)

6307 90 93 Filtering facepieces (FFP) according to EN149, and other masks conforming to a similar standard for masks as respiratory protective devices to protect against particles

6307 90 95 Protective face masks (excl. filtering facepieces FFP according to EN149, and other masks conforming to a similar standard for masks as respiratory protective devices to protect against particles)

6307 90 98 Made-up articles of textile materials, incl. dress patterns, n.e.s. (excl. of felt, knitted or crocheted, single-use drapes used during surgical procedures made up of nonwovens, and protective face masks)

9019 20 00 Ozone therapy, oxygen therapy, aerosol therapy, artificial respiration or other therapeutic respiration apparatus

9019 20 10 Mechanical ventilation apparatus, capable of providing invasive ventilation

9019 20 20 Mechanical ventilation apparatus, non-invasive

9019 20 90 Ozone therapy, oxygen therapy, aerosol therapy, artificial respiration or other therapeutic respiration apparatus, incl. parts and accessories (excl. mechanical ventilation apparatus)

9020 00 00 Breathing appliances and gas masks (excl. protective masks having neither mechanical parts nor replaceable filters, and artificial respiration or other therapeutic respiration apparatus)

9020 00 10 Gas masks (excl. protective masks having neither mechanical parts nor replaceable filters)

9020 00 90 Breathing appliances, incl. parts and accessories (excl. artificial respiration or other therapeutic respiration apparatus).

Annex 1 - HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
2207.10	Undenatured ethyl alcohol, of actual alcoholic strength of >= 80%	Yes	Yes	No	No
2208.90	Ethyl alcohol of an alcoholic strength of < 80% vol, not denatured; spirits and other spirituous beverages (excl. compound alcoholic preparations of a kind used for the manufacture of beverages, spirits obtained by distilling grape wine or grape marc, whiskies, rum and other spirits obtained by distilling fermented sugar-cane products, gin, geneva, vodka, liqueurs and cordials)	No	Yes	No	No
2501.00	Salts, incl. table salt and denatured salt, and pure sodium chloride, whether or not in aqueous solution or containing added anti-caking or free-flowing agents; sea water	No	No	Yes	No
2804.40	Oxygen	No	Yes	Yes	No
2847.00	Hydrogen peroxide, whether or not solidified with urea	Yes	Yes	No	No
2905.12	Alcohols; saturated monohydric, propan-1-ol (propyl alcohol) and propan-2-ol (isopropyl alcohol)	No	Yes	No	No
2907.19	Monophenols (excl. phenol “hydroxybenzene” and its salts, cresols and their salts, octylphenol, nonylphenol and their isomers and salts thereof and naphthols and their salts)	No	No	Yes	No
2915.11	Acids; saturated acyclic monocarboxylic acids; formic acid	No	Yes	No	No
2915.12	Acids; saturated acyclic monocarboxylic acids; salts of formic acids	No	Yes	No	No
2918.21	Acids; carboxylic acids, (with phenol function but without other oxygen function), salicylic acid and its salts	No	Yes	No	No
2920.90	Esters of inorganic acids of non-metals and their salts; their halogenated, sulphonated, nitrated or nitrosated derivatives (excl. esters of hydrogen halides, phosphoric esters, phosphite esters, and thiophosphoric esters “phosphorothioates”, their salts and their halogenated, sulphonated, nitrated or nitrosated derivatives, endosulfan “ISO” and inorganic or organic compounds of mercury)	No	No	Yes	No
2922.29	Amino-naphthols and other amino-phenols, their ethers and esters; salts thereof (excl. those containing > one kind of oxygen function; aminohydroxynaphthalenesulphonic acids and their salts)	No	No	Yes	No
2922.50	Amino-alcohol-phenols, amino-acid-phenols and other amino-compounds with oxygen function (excl. amino-alcohols, amino-naphthols and other amino-phenols, their ethers and esters and salts thereof, amino-aldehydes, amino-ketones and amino-quinones, and salts thereof, amino-acids and their esters and salts thereof)	No	No	Yes	No
2923.90	Quaternary ammonium salts and hydroxides (excl. choline and its salts, tetraethylammonium perfluorooctane sulphonate and didecyldimethylammonium perfluorooctane sulphonate)	No	No	Yes	No
2924.29	Cyclic amides, incl. cyclic carbamates, and their derivatives; salts thereof (excl. ureines and their derivatives, salts thereof, 2-acetamidobenzoic acid “N-acetylanthranilic acid” and its salts, ethinamate “INN” and alachlor “ISO”)	No	No	Yes	No
2925.29	Imines and their derivatives; salts thereof (excl. chlordimeform [ISO])	No	No	Yes	No
2932.19	Heterocyclic compounds with oxygen hetero-atom[s] only, containing an unfused furan ring, whether or not hydrogenated, in the structure (excl. tetrahydrofuran, 2-furaldehyde “furfuraldehyde”, furfuryl alcohol, tetrahydrofurfuryl alcohol and sucralose)	No	No	Yes	No
2933.29	Heterocyclic compounds with nitrogen hetero-atom[s] only, containing an unfused imidazole ring, whether or not hydrogenated, in the structure (excl. hydantoin and its derivatives, and products of subheading 3002 10)	No	No	Yes	No

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Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
2933.33	Alfentanil “INN”, anileridine “INN”, bezitramide “INN”, bromazepam “INN”, difenoxin “INN”, diphenoxylate “INN”, dipipanone “INN”, fentanyl “INN”, ketobemidone “INN”, methylphenidate “INN”, pentazocine “INN”, pethidine “INN”, pethidine “INN” intermediate A, phencyclidine “INN” “PCP”, phenoperidine “INN”, pipradol “INN”, piritramide “INN”, propiram “INN” and trimeperidine “INN”, and salts thereof	No	No	Yes	No
2933.39	Heterocyclic compounds with nitrogen hetero-atom[s] only, containing an unfused pyridine ring, whether or not hydrogenated, in the structure (excl. pyridine, piperidine, alfentanil “INN”, anileridine “INN”, bezitramide “INN”, bromazepam “INN”, difenoxin “INN”, diphenoxylate “INN”, dipipanone “INN”, fentanyl “INN”, ketobemidone “INN”, methylphenidate “INN”, pentazocine “INN”, pethidine “INN”, pethidine “INN” intermediate A, phencyclidine “INN” “PCP”, phenoperidine “INN”, pipradol “INN”, piritramide “INN”, propiram “INN”, trimeperidine “INN”, and salts thereof, and inorganic or organic compounds of mercury)	No	No	Yes	No
2933.49	Heterocyclic compounds with nitrogen hetero-atom[s] only, containing in the structure a quinoline or isoquinoline ring-system, whether or not hydrogenated, but not further fused (excl. levorphanol “INN” and its salts, and inorganic or organic compounds of mercury)	No	No	Yes	Yes
2933.59	Heterocyclic compounds with nitrogen hetero-atom[s] only, containing a pyrimidine ring, whether or not hydrogenated, or piperazine ring in the structure (excl. malonylurea “barbituric acid” and its derivatives, allobarbital “INN”, amobarbital “INN”, barbital “INN”, butalbital “INN”, butobarbital “INN”, cyclobarbital “INN”, methylphenobarbital “INN”, pentobarbital “INN”, phenobarbital “INN”, secbutabarbital “INN”, secobarbital “INN”, vinylbital “INN”, loprazolam “INN”, mecloqualone “INN”, methaqualone “INN” and zipeprol “INN”, and salts thereof)	No	No	Yes	No
2933.79	Lactams (excl. 6-hexanelactam “epsilon-caprolactam”, clobazam “INN”, methyprylon “INN”, and inorganic or organic compounds of mercury)	No	No	Yes	No
2933.91	Alprazolam “INN”, camazepam “INN”, chlordiazepoxide “INN”, clonazepam “INN”, clorazepate, delorazepam “INN”, diazepam “INN”, estazolam “INN”, ethyl loflazepate “INN”, fludiazepam “INN”, flunitrazepam “INN”, flurazepam “INN”, halazepam “INN”, lorazepam “INN”, lormetazepam “INN”, mazindol “INN”, medazepam “INN”, midazolam “INN”, nimetazepam “INN”, nitrazepam “INN”, nordazepam “INN”, oxazepam “INN”, pinazepam “INN”, prazepam “INN”, pyrovalerone “INN”, temazepam “INN”, tetrazepam “INN” and triazolam “INN”, and salts thereof	No	No	Yes	No
2933.99	Heterocyclic compounds with nitrogen hetero-atom[s] only (excl. those containing an unfused pyrazole, imidazole, pyridine or triazine ring, whether or not hydrogenated, a quinoline or isoquinoline ring-system, not further fused, whether or not hydrogenated, a pyrimidine ring, whether or not hydrogenated, or piperazine ring in the structure, and lactams, alprazolam “INN”, camazepam “INN”, chlordiazepoxide “INN”, clonazepam “INN”, clorazepate, delorazepam “INN”, diazepam “INN”, estazolam “INN”, ethyl loflazepate “INN”, fludiazepam “INN”, flunitrazepam “INN”, flurazepam “INN”, halazepam “INN”, lorazepam “INN”, lormetazepam “INN”, mazindol “INN”, medazepam “INN”, midazolam “INN”, nimetazepam “INN”, nitrazepam “INN”, nordazepam “INN”, oxazepam “INN”, pinazepam “INN”, prazepam “INN”, pyrovalerone “INN”, temazepam “INN”, tetrazepam “INN” and triazolam “INN”, salts thereof and azinphos-methyl “ISO”)	No	No	Yes	No
2934.10	Heterocyclic compounds containing an unfused thiazole ring, whether or not hydrogenated, in the structure	No	No	Yes	No

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Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
2934.30	Heterocyclic compounds containing in the structure a phenothiazine ring-system, whether or not hydrogenated, but not further fused	No	No	Yes	No
2934.99	Nucleic acids and their salts, whether or not chemically defined; heterocyclic compounds (excl. with oxygen only or with nitrogen hetero-atom[s] only, compounds containing in the structure an unfused thiazole ring or a benzothiazole or phenothiazine ring-system, not further fused and aminorex “INN”, brotizolam “INN”, clotiazepam “INN”, cloxazolam “INN”, dextromoramide “INN”, haloxazolam “INN”, ketazolam “INN”, mesocarb “INN”, oxazolam “INN”, pemoline “INN”, phendimetrazine “INN”, phenmetrazine “INN”, sufentanil “INN”, and salts thereof, and inorganic or organic compounds of mercury whether or not chemically defined, and products of 3002 10)	No	No	Yes	Yes
2937.19	Polypeptide hormones, protein hormones and glycoprotein hormones, their derivatives and structural analogues, used primarily as hormones (excl. somatropin, its derivatives and structural analogues, and insulin and its salts)	No	No	Yes	Yes
2937.21	Cortisone, hydrocortisone, prednisone “dehydrocortisone” and prednisolone “dehydrohydrocortisone”	No	No	Yes	No
2937.23	Oestrogens and progestogens	No	No	Yes	No
2937.29	Steroidal hormones, their derivatives and structural analogues, used primarily as hormones (excl. cortisone, hydrocortisone, prednisone “dehydrocortisone”, prednisolone “dehydrohydrocortisone”, halogenated derivatives of corticosteroidal hormones, oestrogens and progestogens)	No	No	Yes	No
2937.90	Hormones, natural or reproduced by synthesis; derivatives and structural analogues thereof, used primarily as hormones (excl. polypeptide hormones, protein hormones, glycoprotein hormones, steroidal hormones, catecholamine hormones, prostaglandins, thromboxanes and leukotrienes, their derivatives and structural analogues, and amino-acid derivatives, and products of 3002 10)	No	No	Yes	No
2939.11	Concentrates of poppy straw; buprenorphine “INN”, codeine, dihydrocodeine “INN”, ethylmorphine, etorphine “INN”, heroin, hydrocodone “INN”, hydromorphone “INN”, morphine, nicomorphine “INN”, oxycodone “INN”, oxymorphone “INN”, pholcodine “INN”, thebacon “INN” and thebaine, and salts thereof	No	No	Yes	No
2939.19	Alkaloids of opium and their derivatives, and salts thereof (excl. concentrates of poppy straw; buprenorphine “INN”, codeine, dihydrocodeine “INN”, ethylmorphine, etorphine “INN”, heroin, hydrocodone “INN”, hydromorphone “INN”, morphine, nicomorphine “INN”, oxycodone “INN”, oxymorphone “INN”, pholcodine “INN”, thebacon “INN” and thebaine, and salts thereof)	No	No	Yes	No
2939.79	Vegetable alkaloids, natural or reproduced by synthesis, and their salts, ethers, esters and other derivatives (excl. alkaloids of opium, alkaloids of cinchons, theophylline, aminophylline “theophylline-ethylenediamine” alkaloids of rye ergot and their salts and derivatives, cocaine, ecgonine, levometamfetamine, metamfetamine “INN”, metamfetamine racemate, and salts, esters and other derivatives thereof, caffeine and ephedrines, and their salts)	No	No	Yes	No
2941.10	Penicillins and their derivatives with a penicillanic acid structure; salts thereof	No	No	Yes	No
2941.30	Tetracyclines and their derivatives; salts thereof	No	No	Yes	No
2941.40	Chloramphenicol and its derivatives; salts thereof	No	No	Yes	No

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Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
2941.90	Antibiotics (excl. penicillins and their derivatives with a penicillanic acid structure, salts thereof, streptomycins, tetracyclines, chloramphenicol and erythromycin, their derivatives and salts thereof)	No	No	Yes	No
3001.20	Extracts of glands or other organs or of their secretions, for organo-therapeutic uses	Yes	No	No	No
3001.90	Dried glands and other organs for organo-therapeutic uses, whether or not powdered; heparin and its salts; other human or animal substances prepared for therapeutic or prophylactic uses, n.e.s.	Yes	No	Yes	No
3002.12	Antisera and other blood fractions	Yes	No	No	No
3002.13	Immunological products, unmixed, not put up in measured doses or in forms or packings for retail sale	Yes	No	Yes	Yes
3002.14	Immunological products, mixed, not put up in measured doses or in forms or packings for retail sale	Yes	No	No	No
3002.15	Immunological products, put up in measured doses or in forms or packings for retail sale	Yes	Yes	Yes	No
3002.19	Immunological products, n.e.s. (code possibly empty, preceding subheadings seem exhaustive)	Yes	No	No	No
3002.20	Vaccines for human medicine	Yes	No	No	Yes
3002.90	Human blood; animal blood prepared for therapeutic, prophylactic or diagnostic uses; toxins, cultures of micro-organisms and similar products (excl. yeasts and vaccines)	Yes	No	No	No
3003.10	Medicaments containing penicillins or derivatives thereof with a penicillanic acid structure, or streptomycins or derivatives thereof, not in measured doses or put up for retail sale	Yes	No	Yes	No
3003.20	Medicaments containing antibiotics, not in measured doses or put up for retail sale (excl. medicaments containing penicillins or derivatives thereof with a penicillanic acid structure, or streptomycins or derivatives thereof)	Yes	No	Yes	No
3003.31	Medicaments containing insulin, not in measured doses or put up for retail sale	Yes	No	No	No
3003.39	Medicaments containing hormones or steroids used as hormones, not containing antibiotics, not in measured doses or put up for retail sale (excl. those containing insulin)	Yes	No	No	No
3003.41	Medicaments containing ephedrine or its salts, not containing hormones, steroids used as hormones or antibiotics, not in measured doses or put up for retail sale	Yes	No	No	No
3003.42	Medicaments containing pseudoephedrine “INN” or its salts, not containing hormones, steroids used as hormones or antibiotics, not in measured doses or put up for retail sale	Yes	No	No	No
3003.43	Medicaments containing norephedrine or its salts, not containing hormones, steroids used as hormones or antibiotics, not in measured doses or put up for retail sale	Yes	No	No	No
3003.49	Medicaments containing alkaloids or derivatives thereof, not containing hormones, steroids used as hormones or antibiotics, not in measured doses or put up for retail sale (excl. containing ephedrine, pseudoephedrine “INN”, norephedrine or their salts)	Yes	No	No	No

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Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
3003.60	Medicaments containing any of the following antimalarial active principles: artemisinin “INN” for oral ingestion combined with other pharmaceutical active ingredients, or amodiaquine “INN”; artelinic acid or its salts; artenimol “INN”; artemotil “INN”; artemether “INN”; artesunate “INN”; chloroquine “INN”; dihydroartemisinin “INN”; lumefantrine “INN”; mefloquine “INN”; piperaquine “INN”; pyrimethamine “INN” or sulfadoxine “INN”, not containing hormones, steroids used as hormones or antibiotics, not in measured doses or put up for retail sale	Yes	No	No	No
3003.90	Medicaments consisting of two or more constituents mixed together for therapeutic or prophylactic uses, not in measured doses or put up for retail sale (excl. antibiotics containing hormones or steroids used as hormones, but not containing antibiotics, alkaloids or derivatives thereof, hormones, antibiotics, antimalarial active principles or goods of heading 3002, 3005 or 3006)	Yes	No	No	No
3004.10	Medicaments containing penicillins or derivatives thereof with a penicillanic acid structure, or streptomycins or derivatives thereof, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale	Yes	No	Yes	No
3004.20	Medicaments containing antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale (excl. medicaments containing penicillins or derivatives thereof with a penicillanic structure, or streptomycines or derivatives thereof)	Yes	No	Yes	No
3004.31	Medicaments containing insulin but not antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale	Yes	No	No	No
3004.32	Medicaments containing corticosteroid hormones, their derivatives or structural analogues but not antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale	Yes	No	Yes	No
3004.39	Medicaments containing hormones or steroids used as hormones but not antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale (excl. medicaments containing insulin or corticosteroid hormones, their derivatives or structural analogues)	Yes	No	Yes	No
3004.41	Medicaments containing ephedrine or its salts, not containing hormones, steroids used as hormones or antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale	Yes	No	No	No
3004.42	Medicaments containing pseudoephedrine “INN” or its salts, not containing hormones, steroids used as hormones or antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale	Yes	No	No	No
3004.43	Medicaments containing norephedrine or its salts, not containing hormones, steroids used as hormones or antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale	Yes	No	No	No
3004.49	Medicaments containing alkaloids or derivatives thereof, not containing hormones, steroids used as hormones or antibiotics, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale (excl. containing ephedrine, pseudoephedrine “INN”, norephedrine or their salts)	Yes	No	Yes	No

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Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
3004.50	Medicaments containing provitamins, vitamins, incl. natural concentrates and derivatives thereof used primarily as vitamins, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale (excl. containing antibiotics, hormones, alkaloids, or their derivatives)	Yes	No	No	No
3004.60	Medicaments containing any of the following antimalarial active principles: artemisinin “INN” for oral ingestion combined with other pharmaceutical active ingredients, or amodiaquine “INN”; artelinic acid or its salts; artenimol “INN”; artemotil “INN”; artemether “INN”; artesunate “INN”; chloroquine “INN”; dihydroartemisinin “INN”; lumefantrine “INN”; mefloquine “INN”; piperaquine “INN”; pyrimethamine “INN” or sulfadoxine “INN”, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale (excl. containing antibiotics, hormones, alkaloids, provitamins, vitamins, or their derivatives)	Yes	No	Yes	No
3004.90	Medicaments consisting of mixed or unmixed products for therapeutic or prophylactic purposes, put up in measured doses “incl. those for transdermal administration” or in forms or packings for retail sale (excl. containing antibiotics, hormones or steroids used as hormones, alkaloids, provitamins, vitamins, their derivatives or antimalarial active principles)	Yes	Yes	Yes	No
3005.10	Adhesive dressings and other articles having an adhesive layer, impregnated or covered with pharmaceutical substances or put up for retail sale for medical, surgical, dental or veterinary purposes	Yes	Yes	No	No
3005.90	Wadding, gauze, bandages and the like, *e.g.* dressings, adhesive plasters, poultices, impregnated or covered with pharmaceutical substances or put up for retail sale for medical, surgical, dental or veterinary purposes (excl. adhesive dressings and other articles having an adhesive layer)	Yes	Yes	No	No
3006.10	Sterile surgical catgut, similar sterile suture materials, incl. sterile absorbable surgical or dental yarns, and sterile tissue adhesives for surgical wound closure; sterile laminaria and sterile laminaria tents; sterile absorbable surgical or dental haemostatics; sterile surgical or dental adhesion barriers, whether or not absorbable	Yes	No	No	No
3006.20	Reagents for determining blood groups or blood factors	Yes	No	No	No
3006.30	Opacifying preparations for x-ray examinations; diagnostic reagents for administration to patients	Yes	No	No	No
3006.50	First-aid boxes and kits	Yes	No	No	No
3006.70	Gel preparations designed to be used in human or veterinary medicine as a lubricant for parts of the body for surgical operations or physical examinations or as a coupling agent between the body and medical instruments	Yes	Yes	No	No
3401.11	Soap and organic surface-active products and preparations, in the form of bars, cakes, moulded pieces or shapes, and paper, wadding, felt and nonwovens, impregnated, coated or covered with soap or detergent, for toilet use, incl. medicated products	Yes	Yes	No	No
3401.20	Soap in the form of flakes, granules, powder, paste or in aqueous solution	No	Yes	No	No
3401.30	Organic surface-active products and preparations for washing the skin, in the form of liquid or cream and put up for retail sale, whether or not containing soap	Yes	Yes	No	No
3402.12	Cationic organic surface-active agents, whether or not put up for retail sale (excl. soap)	Yes	No	No	No
3402.13	Non-ionic organic surface-active agents, whether or not put up for retail sale (excl. soap)	Yes	No	No	No

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Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
3402.20	Surface-active preparations, washing preparations, auxiliary washing preparations and cleaning preparations put up for retail sale (excl. organic surface-active agents, soap and organic surface-active preparations in the form of bars, cakes, moulded pieces or shapes, and products and preparations for washing the skin in the form of liquid or cream)	Yes	No	No	No
3504.00	Peptones and their derivatives; other protein substances and their derivatives, n.e.s.; hide powder, whether or not chromed (excl. organic or inorganic compounds of mercury whether or not chemically defined)	Yes	No	No	No
3507.90	Enzymes and prepared enzymes, n.e.s. (excl. rennet and concentrates thereof)	Yes	No	No	Yes
3701.10	Photographic plates and film in the flat, sensitised, unexposed, for X-ray (excl. of paper, paperboard and textiles)	Yes	Yes	No	No
3702.10	Photographic film in rolls, unexposed, for X-ray (excl. of paper, paperboard or textiles)	Yes	Yes	No	No
3808.94	Disinfectants, put up in forms or packings for retail sale or as preparations or articles (excl. goods of subheading 3808.59)	Yes	Yes	Yes	No
3821.00	Prepared culture media for the development or maintenance of micro-organisms “incl. viruses and the like” or of plant, human or animal cells	Yes	Yes	No	No
3822.00	Diagnostic or laboratory reagents on a backing, prepared diagnostic or laboratory reagents whether or not on a backing, and certified reference materials (excl. compound diagnostic reagents designed to be administered to the patient, blood-grouping reagents, animal blood prepared for therapeutic, prophylactic or diagnostic uses and vaccines, toxins, cultures of micro-organisms and similar products)	Yes	Yes	No	No
3824.99	Chemical products and preparations of the chemical or allied industries, incl. those consisting of mixtures of natural products, n.e.s.	Yes	No	No	No
3905.99	Polymers of vinyl esters and other vinyl polymers, in primary forms (excl. those of vinyl chloride or other halogenated olefins, poly”vinyl acetate”, vinyl acetate copolymers and poly”vinyl alcohol”, whether or not containing unhydrolised acetate groups)	No	No	Yes	No
3923.29	Articles for the conveyance or packaging of goods, of plastics (excl. boxes, cases, crates and similar articles; sacks and bags, incl. cones; carboys, bottles, flasks and similar articles; spools, spindles, bobbins and similar supports; stoppers, lids, caps and other closures)	No	Yes	No	No
3926.20	Articles of apparel and clothing accessories produced by the stitching or sticking together of plastic sheeting, incl. gloves, mittens and mitts (excl. goods of 9619)	Yes	Yes	No	No
3926.90	Articles of plastics and articles of other materials of heading 3901 to 3914, n.e.s. (excl. goods of 9619)	Yes	Yes	No	No
4014.90	Hygienic or pharmaceutical articles, incl. teats, of vulcanised rubber (excl. hard rubber), with or without fittings of hard rubber, n.e.s. (excl. sheath contraceptives and articles of apparel and clothing accessories, incl. gloves, for all purposes)	Yes	No	No	No
4015.11	Surgical gloves, of vulcanised rubber (excl. fingerstalls)	Yes	Yes	No	No
4015.19	Gloves, mittens and mitts, of vulcanised rubber (excl. surgical gloves)	Yes	Yes	No	No
4015.90	Articles of apparel and clothing accessories, for all purposes, of vulcanised rubber (excl. hard rubber and footwear and headgear and parts thereof, and gloves, mittens and mitts)	No	Yes	No	No

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Annex 1 continued - **HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
4016.99	Rubber; vulcanised (other than hard rubber), articles n.e.c. in heading no. 4016, of non-cellular rubber	No	Yes	No	No
4818.50	Articles of apparel and clothing accessories, of paper pulp, paper, cellulose wadding or webs of cellulose fibres (excl. footwear and parts thereof, incl. insoles, heel pieces and similar removable products, gaiters and similar products, headgear and parts thereof)	No	Yes	No	No
4818.90	Paper, cellulose wadding or webs of cellulose fibres, of a kind used for household or sanitary purposes, in rolls of a width <= 36 cm, or cut to size or shape; articles of paper pulp, paper, cellulose wadding or webs of cellulose fibres for household, sanitary or hospital use (excl. toilet paper, handkerchiefs, cleansing or facial tissues and towels, tablecloths, serviettes, sanitary towels and tampons, napkins and napkin liners for babies and similar sanitary articles)	No	Yes	No	No
5603.11	Nonwovens; whether or not impregnated, coated, covered or laminated, of man-made filaments, (weighing not more than 25g/m^2)	No	Yes	No	No
5603.12	Nonwovens; whether or not impregnated, coated, covered or laminated, of man-made filaments, (weighing more than 25g/m^2 but not more than 70g/m^2)	No	Yes	No	No
5603.13	Nonwovens; whether or not impregnated, coated, covered or laminated, of man-made filaments, (weighing more than 70g/m2 but not more than 150g/m^2)	No	Yes	No	No
5603.14	Nonwovens; whether or not impregnated, coated, covered or laminated, of man-made filaments, (weighing more than 150g/m^2)	No	Yes	No	No
5603.91	Nonwovens; whether or not impregnated, coated, covered or laminated, not of man-made filaments, (weighing not more than 25g/m^2)	No	Yes	No	No
5603.92	Nonwovens; whether or not impregnated, coated, covered or laminated, not of man-made filaments, (weighing more than 25g/m^2 but not more than 70g/m^2)	No	Yes	No	No
5603.93	Nonwovens; whether or not impregnated, coated, covered or laminated, not of man-made filaments, (weighing more than 70g/m^2 but not more than 150g/m^2)	No	Yes	No	No
5603.94	Nonwovens; whether or not impregnated, coated, covered or laminated, not of man-made filaments, (weighing more than 150g/m^2)	No	Yes	No	No
6116.10	Gloves, mittens and mitts, impregnated, coated or covered with plastics or rubber, knitted or crocheted	No	Yes	No	No
6210.10	Garments made up of felt or nonwovens, whether or not impregnated, coated, covered or laminated (excl. babies' garments and clothing accessories)	No	Yes	No	No
6210.40	Men's or boys' garments of textile fabrics, rubberised or impregnated, coated, covered or laminated with plastics or other substances (excl. of the type described in subheading 6201,11 to 6201,19, and babies' garments and clothing accessories)	No	Yes	No	No
6210.50	Women's or girls' garments of textile fabrics, rubberised or impregnated, coated, covered or laminated with plastics or other substances (excl. of the type described in subheading 6202,11 to 6202,19, and babies' garments and clothing accessories)	No	Yes	No	No
6211.42	Track suits and other garments n.e.c.; women's or girls', of cotton (not knitted or crocheted)	No	Yes	No	No
6216.00	Gloves, mittens and mitts, of all types of textile materials (excl. knitted or crocheted and for babies)	No	Yes	No	No
6306.22	Tents; of synthetic fibres	No	Yes	No	No
6306.29	Tents; of textile materials other than synthetic fibres	No	Yes	No	No

Source: Authors' elaboration on the basis of WCO and WTO data, 2020
(*) WCO MS = WCO medical supplies, WCO M = WCO medicines and WCO M SE = WCO medicines special edition

Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
6307.90	Made-up articles of textile materials, incl. dress patterns, n.e.s.	Yes	Yes	No	No
6505.00	Hats and other headgear, knitted or crocheted, or made up from lace, felt or other textile fabric, in the piece (but not in strips), whether or not lined or trimmed; hairnets of any material, whether or not lined or trimmed (excl. headgear for animals, and toy and carnival headgear)	No	Yes	No	No
7017.10	Laboratory, hygienic or pharmaceutical glassware, whether or not graduated or calibrated, of fused quartz or other fused silica (excl. containers for the conveyance or packing of goods, measuring, checking or medical instruments and apparatus of chapter 90)	Yes	Yes	No	No
7017.20	Laboratory, hygienic or pharmaceutical glassware, whether or not graduated or calibrated, having a linear coefficient of expansion <= 5 x 10 -6 per kelvin within a temperature range of 0°C to 300°C (excl. glass of fused quartz or other fused silica, containers for the conveyance or packing of goods, measuring, checking or medical instruments and apparatus of chapter 90)	Yes	Yes	No	No
7017.90	Laboratory, hygienic or pharmaceutical glassware, whether or not graduated or calibrated (excl. glass having a linear coefficient of expansion <= 5 x 10 -6 per kelvin within a temperature range of 0°C to 300°C or of fused quartz or other fused silica, containers for the conveyance or packing of goods, measuring, checking or medical instruments and apparatus of chapter 90)	Yes	Yes	No	No
7311.00	Containers of iron or steel, for compressed or liquefied gas (excl. containers specifically constructed or equipped for one or more types of transport)	No	Yes	No	No
7324.90	Sanitary ware, incl. parts thereof (excl. cans, boxes and similar containers of heading 7310, small wall cabinets for medical supplies or toiletries and other furniture of chapter 94, and fittings, complete sinks and washbasins, of stainless steel, complete baths and fittings)	No	Yes	No	No
7613.00	Aluminium containers for compressed or liquefied gas	No	Yes	No	No
8413.19	Pumps for liquids, fitted or designed to be fitted with a measuring device (excl. pumps for dispensing fuel or lubricants, of the type used in filling stations or in garages)	No	Yes	No	No
8419.20	Medical, surgical or laboratory sterilizers	Yes	Yes	No	No
8421.39	Machinery and apparatus for filtering or purifying gases (excl. isotope separators and intake air filters for internal combustion engines)	No	Yes	No	No
8424.89	Mechanical appliances; for projecting, dispersing or spraying liquids or powders, for other than agricultural or horticultural use, whether or not hand-operated	No	Yes	No	No
8539.49	Lamps; ultra-violet or infra-red lamps, (excluding arc-lamps)	No	Yes	No	No
8539.50	Lamps; light-emitting diode (LED) lamps	No	Yes	No	No
8543.70	Electrical machines and apparatus; having individual functions, not specified or included elsewhere in this chapter, n.e.c. in heading no. 8543	No	Yes	No	No
8703.10	Vehicles for the transport of <10 persons on snow; golf cars and similar vehicles	No	Yes	No	No
8703.21	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only spark-ignition internal combustion reciprocating piston engine of a cylinder capacity <= 1.000 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No

Source: Authors' elaboration on the basis of WCO and WTO data, 2020
(*) WCO MS = WCO medical supplies, WCO M = WCO medicines and WCO M SE = WCO medicines special edition

Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
8703.22	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only spark-ignition internal combustion reciprocating piston engine of a cylinder capacity > 1.000 cm³ but <= 1.500 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.23	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only spark-ignition internal combustion reciprocating piston engine of a cylinder capacity > 1.500 cm³ but <= 3.000 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.24	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only spark-ignition internal combustion reciprocating piston engine of a cylinder capacity > 3.000 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.31	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only diesel engine of a cylinder capacity <= 1.500 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.32	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only diesel engine of a cylinder capacity > 1.500 cm³ but <= 2.500 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.33	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only diesel engine of a cylinder capacity > 2.500 cm³ (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.40	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with both spark-ignition internal combustion reciprocating piston engine and electric motor as motors for propulsion (excl. vehicles for travelling on snow, other specially designed vehicles of subheading 8703.10 and plug-in hybrids)	No	Yes	No	No
8703.50	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with both diesel engine and electric motor as motors for propulsion (excl. vehicles for travelling on snow, other specially designed vehicles of subheading 8703.10 and plug-in hybrids)	No	Yes	No	No
8703.60	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with both spark-ignition internal combustion reciprocating piston engine and electric motor as motors for propulsion, capable of being charged by plugging to external source of electric power (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.70	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with both diesel engine and electric motor as motors for propulsion, capable of being charged by plugging to external source of electric power (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No

Source: Authors' elaboration on the basis of WCO and WTO data, 2020
(*) WCO MS = WCO medical supplies, WCO M = WCO medicines and WCO M SE = WCO medicines special edition

Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
8703.80	Motor cars and other motor vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with only electric motor for propulsion (excl. vehicles for travelling on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8703.90	Motor cars and other vehicles principally designed for the transport of <10 persons, incl. station wagons and racing cars, with engines other than internal combustion piston engine or electric motor (excl. vehicles for the transport of persons on snow and other specially designed vehicles of subheading 8703.10)	No	Yes	No	No
8705.90	Special purpose motor vehicles (other than those principally designed for the transport of persons or goods and excl. concrete-mixer lorries, fire fighting vehicles, mobile drilling derricks and crane lorries)	No	Yes	No	No
8713.10	Carriages for disabled persons, not mechanically propelled	No	Yes	No	No
8713.90	Carriages for disabled persons, motorised or otherwise mechanically propelled (excl. specially designed motor vehicles and bicycles)	No	Yes	No	No
9004.90	Spectacles, goggles and the like, corrective, protective or other (excl. spectacles for testing eyesight, sunglasses, contact lenses, spectacle lenses and frames and mountings for spectacles)	Yes	Yes	No	No
9010.50	Apparatus and equipment for photographic or cinematographic laboratories, n.e.s.; negatoscopes	Yes	No	No	No
9011.10	Stereoscopic optical microscopes	Yes	No	No	No
9011.80	Optical microscopes (excl. for photomicrography, cinephotomicrography or microprojection, stereoscopic microscopes, binocular microscopes for ophthalmology and instruments, appliances and machines of heading 9031)	Yes	No	No	No
9018.11	Electro-cardiographs	Yes	Yes	No	No
9018.12	Ultrasonic scanning apparatus	Yes	Yes	No	No
9018.13	Magnetic resonance imaging apparatus	Yes	Yes	No	No
9018.14	Scintigraphic apparatus	Yes	Yes	No	No
9018.19	Electro-diagnostic apparatus, incl. apparatus for functional exploratory examination or for checking physiological parameters (excl. electro-cardiographs, ultrasonic scanning apparatus, magnetic resonance imaging apparatus and scintigraphic apparatus)	Yes	Yes	No	No
9018.20	Ultraviolet or infra-red ray apparatus used in medical, surgical, dental or veterinary sciences	Yes	Yes	No	No
9018.31	Syringes, with or without needles, used in medical, surgical, dental or veterinary sciences	Yes	Yes	No	No
9018.32	Tubular metal needles and needles for sutures, used in medical, surgical, dental or veterinary sciences	Yes	Yes	No	No
9018.39	Needles, catheters, cannulae and the like, used in medical, surgical, dental or veterinary sciences (excl. syringes, tubular metal needles and needles for sutures)	Yes	Yes	No	No
9018.41	Dental drill engines, whether or not combined on a single base with other dental equipment	No	Yes	No	No
9018.49	Instruments and appliances used in dental sciences, n.e.s.	No	Yes	No	No
9018.50	Ophthalmic instruments and appliances, n.e.s.	No	Yes	No	No

Source: Authors' elaboration on the basis of WCO and WTO data, 2020
(*) WCO MS = WCO medical supplies, WCO M = WCO medicines and WCO M SE = WCO medicines special edition

Annex 1 continued **- HS 2017 codes used to identify COVID-19 products in the notes prepared by WTO and WCO**

HS 2017	Description	WTO	WCO MS*	WCO M*	WCO M SE*
9018.90	Instruments and appliances used in medical, surgical or veterinary sciences, n.e.s.	Yes	Yes	No	No
9019.20	Ozone therapy, oxygen therapy, aerosol therapy, artificial respiration or other therapeutic respiration apparatus	Yes	Yes	No	No
9020.00	Breathing appliances and gas masks (excl. protective masks having neither mechanical parts nor replaceable filters, and artificial respiration or other therapeutic respiration apparatus)	Yes	Yes	No	No
9021.50	Pacemakers for stimulating heart muscles (excl. parts and accessories)	Yes	No	No	No
9022.12	Computer tomography apparatus	Yes	Yes	No	No
9022.14	Apparatus based on the use of X-rays, for medical, surgical or veterinary uses (excl. for dental purposes and computer tomography apparatus)	Yes	No	No	No
9022.19	Apparatus based on the use of X-rays (other than for medical, surgical, dental or veterinary uses)	Yes	No	No	No
9022.21	Apparatus based on the use of alpha, beta or gamma radiations, for medical, surgical, dental or veterinary uses	Yes	No	No	No
9022.29	Apparatus based on the use of alpha, beta or gamma radiations (other than for medical, surgical, dental or veterinary uses)	Yes	No	No	No
9022.30	X-ray tubes	Yes	No	No	No
9022.90	X-ray generators other than X-ray tubes, high tension generators, control panels and desks, screens, examination or treatment tables, chairs and the like, and general parts and accessories for apparatus of heading 9022, n.e.s.	Yes	No	No	No
9025.11	Thermometers, liquid-filled, for direct reading, not combined with other instruments	Yes	No	No	No
9025.19	Thermometers and pyrometers, not combined with other instruments (excl. liquid-filled thermometers for direct reading)	Yes	Yes	No	No
9026.80	Instruments or apparatus for measuring or checking variables of liquids or gases, n.e.s.	No	Yes	No	No
9027.80	Instruments and apparatus for physical or chemical analysis, or for measuring or checking viscosity, porosity, expansion, surface tension or the like, or for measuring or checking quantities of heat, sound or light, n.e.s.	Yes	Yes	No	No
9028.20	Liquid meters, incl. calibrating meters therefor	No	Yes	No	No
9030.20	Oscilloscopes and oscillographs	Yes	No	No	No
9402.90	Operating tables, examination tables, and other medical, dental, surgical or veterinary furniture (excl. dentists' or similar chairs, special tables for X-ray examination, and stretchers and litters, incl. trolley-stretchers)	Yes	Yes	No	No

Source: Authors' elaboration on the basis of WCO and WTO data, 2020
(*) WCO MS = WCO medical supplies, WCO M = WCO medicines and WCO M SE = WCO medicines special edition

Annex 2 - Correspondence table between COVID-19 products and economic activities

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
2207.10	2207 10 00	2207 10 00	20.14.74.00	20.14.74	20.14	20.14.0	2011	24110
2208.90	2208 90 11	2208 90 11	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 19	2208 90 19	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90				11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 38	2208 90 38	11.01.10.65	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 41	2208 90 41	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 45	2208 90 45	11.01.10.65	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 48	2208 90 48	11.01.10.65	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 54	2208 90 54	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 56	2208 90 56	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 69	2208 90 69	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 71	2208 90 71	11.01.10.65	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 75	2208 90 75	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 77	2208 90 77	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 78	2208 90 78	11.01.10.80	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 91	2208 90 91	11.01.10.70	11.01.10	11.01	11.01.0	1101	24139
2208.90	2208 90 99	2208 90 99	11.01.10.70	11.01.10	11.01	11.01.0	1101	24139
2501.00	2501 00 10	2501 00 10		08.93.10	08.93	08.93.0	0893	16200
2501.00	2501 00 31	2501 00 31	08.93.10.00	08.93.10	08.93	08.93.0	0893	16200
2501.00	2501 00 51	2501 00 51	08.93.10.00	08.93.10	08.93	08.93.0	0893	16200
2501.00	2501 00 91	2501 00 91	10.84.30.00	10.84.30	10.84	10.84.0	1079	16200
2501.00	2501 00 99	2501 00 99	08.93.10.00	08.93.10	08.93	08.93.0	0893	16200
2804.40	2804 40 00	2804 40 00	20.11.11.70	20.11.11	20.11	20.11.0	2011	34210
2847.00	2847 00 00	2847 00 00	20.13.63.00	20.13.63	20.13	20.13.0	2011	34280
2905.12	2905 12 00	2905 12 00	20.14.22.20	20.14.22	20.14	20.14.0	2011	34139
2907.19	2907 19 10	2907 19 10	20.14.24.10	20.14.24	20.14	20.14.0	2011	34139
2907.19	2907 19 90	2907 19 90	20.14.24.10	20.14.24	20.14	20.14.0	2011	34139
2915.11	2915 11 00	2915 11 00	20.14.32.50	20.14.32	20.14	20.14.0	2011	34140
2915.12	2916 12 00	2916 12 00	20.14.32.50	20.14.32	20.14	20.14.0	2011	34140
2918.21	2918 21 00	2918 21 00	21.10.10.30	21.10.10	21.10	21.10.0	2100	35210
2920.90	2920 90 10	2920 90 10	20.14.53.80	20.14.53	20.14	20.14.0	2011	34180
2920.90	2920 90 70	2920 90 70	20.14.53.80	20.14.53	20.14	20.14.0	2011	34180
2922.29	2922 29 00	2922 29 00	20.14.42.90	20.14.42	20.14	20.14.0	2011	34150
2922.50	2922 50 00	2922 50 00	20.14.42.90	20.14.42	20.14	20.14.0	2011	34150
2923.90	2923 90 00	2923 90 00	21.10.20.40	21.10.20	21.10	21.10.0	2100	35220
2924.29	2924 29 10	2924 29 10	21.10.20.70	21.10.20	21.10	21.10.0	2100	35220
2924.29	2924 29 70	2924 29 70	21.10.20.70	21.10.20	21.10	21.10.0	2100	35220
2925.29	2925 29 00	2925 29 00	20.14.43.40	20.14.43	20.14	20.14.0	2011	34150
2932.19	2932 19 00	2932 19 00	20.14.52.25	20.14.52	20.14	20.14.0	2011	34160
2933.29	2933 29 10	2933 29 10	20.14.52.30	20.14.52	20.14	20.14.0	2011	34160
2933.29	2933 29 90	2933 29 90	20.14.52.30	20.14.52	20.14	20.14.0	2011	34160

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
2933.29	2933 29 90	2933 29 90	20.14.52.30	20.14.52	20.14	20.14.0	2011	34160
2933.33	2933 33 00	2933 33 00	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 10	2933 39 10	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 20	2933 39 20	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 25	2933 39 25	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 35	2933 39 35	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 40	2933 39 40	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 45	2933 39 45	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 50	2933 39 50	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 55	2933 39 55	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.39	2933 39 99	2933 39 99	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.49	2933 49 10	2933 49 10	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.49	2933 49 30	2933 49 30	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.49	2933 49 90	2933 49 90	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.59	2933 59 10	2933 59 10	21.10.31.59	21.10.31	21.10	21.10.0	2100	35230
2933.59	2933 59 20	2933 59 20	21.10.31.59	21.10.31	21.10	21.10.0	2100	35230
2933.59	2933 59 95	2933 59 95	21.10.31.59	21.10.31	21.10	21.10.0	2100	35230
2933.79	2933 79 00	2933 79 00	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.91	2933 91 10	2933 91 10	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.91	2933 91 90	2933 91 90	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.99	2933 99 20	2933 99 20	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.99	2933 99 50	2933 99 50	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2933.99	2933 99 80	2933 99 80	20.14.52.80	20.14.52	20.14	20.14.0	2011	34160
2934.10	2934 10 00	2934 10 00	20.14.52.90	20.14.52	20.14	20.14.0	2011	34160
2934.30	2934 30 10	2934 30 10	21.10.31.80	21.10.31	21.10	21.10.0	2100	35230
2934.30	2934 30 90	2934 30 90	21.10.31.80	21.10.31	21.10	21.10.0	2100	35230
2934.99	2934 99 60	2934 99 60	20.14.52.90	20.14.52	20.14	20.14.0	2011	34160
2934.99	2934 99 90	2934 99 90	20.14.52.90	20.14.52	20.14	20.14.0	2011	34160
2937.19	2937 19 00	2937 19 00	21.10.52.00	21.10.52	21.10	21.10.0	2100	35250
2937.21	2937 21 00	2937 21 00	21.10.52.00	21.10.52	21.10	21.10.0	2100	35250
2937.23	2937 23 00	2937 23 00	21.10.52.00	21.10.52	21.10	21.10.0	2100	35250
2937.29	2937 29 00	2937 29 00	21.10.52.00	21.10.52	21.10	21.10.0	2100	35250
2937.90	2937 90 00	2937 90 00	21.10.52.00	21.10.52	21.10	21.10.0	2100	35250
2939.11	2939 11 00	2939 11 00	21.10.53.00	21.10.53	21.10	21.10.0	2100	35250
2939.19	2939 19 00	2939 19 00	21.10.53.00	21.10.53	21.10	21.10.0	2100	35250
2939.79	2939 79 10	2939 79 10	21.10.53.00	21.10.53	21.10	21.10.0	2100	35250
2939.79	2939 79 90	2939 79 90	21.10.53.00	21.10.53	21.10	21.10.0	2100	35250
2941.10	2941 10 00	2941 10 00	21.10.54.00	21.10.54	21.10	21.10.0	2100	35250
2941.30	2941 30 00	2941 30 00	21.10.54.00	21.10.54	21.10	21.10.0	2100	35250
2941.40	2941 40 00	2941 40 00	21.10.54.00	21.10.54	21.10	21.10.0	2100	35250

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
2941.90	2941 90 00	2941 90 00	21.10.54.00	21.10.54	21.10	21.10.0	2100	35250
3001.20	3001 20 10	3001 20 10	21.10.60.20	21.10.60	21.10	21.10.0	2100	35270
3001.20	3001 20 90	3001 20 90	21.10.60.20	21.10.60	21.10	21.10.0	2100	35270
3001.90	3001 90 20	3001 90 20	21.10.60.40	21.10.60	21.10	21.10.0	2100	35270
3001.90	3001 90 91	3001 90 91	21.10.60.40	21.10.60	21.10	21.10.0	2100	35270
3001.90	3001 90 98	3001 90 98	21.10.60.40	21.10.60	21.10	21.10.0	2100	35270
3002.12	3002 12 00	3002 12 00	21.20.21.25	21.20.21	21.20	21.20.0	2100	35270
3002.13	3002 13 00	3002 13 00	21.20.21.25	21.20.21	21.20	21.20.0	2100	35270
3002.14	3002 14 00	3002 14 00	21.20.21.25	21.20.21	21.20	21.20.0	2100	35270
3002.15	3002 15 00	3002 15 00	21.20.21.25	21.20.21	21.20	21.20.0	2100	35270
3002.19	3002 19 00	3002 19 00	21.20.21.25	21.20.21	21.20	21.20.0	2100	35270
3002.20	3002 20 00	3002 20 00	21.20.21.45	21.20.21	21.20	21.20.0	2100	35270
3002.90	3002 90 10	3002 90 10	21.10.60.55	21.10.60	21.10	21.10.0	2100	35270
3002.90	3002 90 30	3002 90 30	21.10.60.55	21.10.60	21.10	21.10.0	2100	35270
3002.90	3002 90 50	3002 90 50	21.10.60.55	21.10.60	21.10	21.10.0	2100	35270
3002.90	3002 90 90	3002 90 90	21.10.60.55	21.10.60	21.10	21.10.0	2100	35270
3003.10	3003 10 00	3003 10 00	21.20.11.30	21.20.11	21.20	21.20.0	2100	35260
3003.20	3003 20 00	3003 20 00	21.20.11.50	21.20.11	21.20	21.20.0	2100	35260
3003.31	3003 31 00	3003 31 00	21.20.12.30	21.20.12	21.20	21.20.0	2100	35260
3003.39	3003 39 00	3003 39 00	21.20.12.50	21.20.12	21.20	21.20.0	2100	35260
3003.41	3003 41 00	3003 41 00	21.20.13.10	21.20.13	21.20	21.20.0	2100	35260
3003.42	3003 42 00	3003 42 00	21.20.13.10	21.20.13	21.20	21.20.0	2100	35260
3003.43	3003 43 00	3003 43 00	21.20.13.10	21.20.13	21.20	21.20.0	2100	35260
3003.49	3003 49 00	3003 49 00	21.20.13.10	21.20.13	21.20	21.20.0	2100	35260
3003.60	3003 60 00	3003 60 00	21.20.13.20	21.20.13	21.20	21.20.0	2100	35260
3003.90	3003 90 00	3003 90 00	21.20.13.20	21.20.13	21.20	21.20.0	2100	35260
3004.10	3004 10 00	3004 10 00	21.20.11.60	21.20.11	21.20	21.20.0	2100	35260
3004.20	3004 20 00	3004 20 00	21.20.11.80	21.20.11	21.20	21.20.0	2100	35260
3004.31	3004 31 00	3004 31 00	21.20.12.60	21.20.12	21.20	21.20.0	2100	35260
3004.32	3004 32 00	3004 32 00	21.20.12.70	21.20.12	21.20	21.20.0	2100	35260
3004.39	3004 39 00	3004 39 00	21.20.12.70	21.20.12	21.20	21.20.0	2100	35260
3004.41	3004 41 00	3004 41 00	21.20.13.40	21.20.13	21.20	21.20.0	2100	35260
3004.42	3004 42 00	3004 42 00	21.20.13.40	21.20.13	21.20	21.20.0	2100	35260
3004.43	3004 43 00	3004 43 00	21.20.13.40	21.20.13	21.20	21.20.0	2100	35260
3004.49	3004 49 00	3004 49 00	21.20.13.40	21.20.13	21.20	21.20.0	2100	35260
3004.50	3004 50 00	3004 50 00	21.20.13.60	21.20.13	21.20	21.20.0	2100	35260
3004.60	3004 60 00	3004 60 00	21.20.13.80	21.20.13	21.20	21.20.0	2100	35260
3004.90	3004 90 00	3004 90 00	21.20.13.80	21.20.13	21.20	21.20.0	2100	35260
3005.10	3005 10 00	3005 10 00	21.20.24.20	21.20.24	21.20	21.20.0	2100	35270
3005.90	3005 90 10	3005 90 10	21.20.24.40	21.20.24	21.20	21.20.0	2100	35270

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3005.90	3005 90 31	3005 90 31	21.20.24.40	21.20.24	21.20	21.20.0	2100	35270
3005.90	3005 90 50	3005 90 50	21.20.24.40	21.20.24	21.20	21.20.0	2100	35270
3005.90	3005 90 99	3005 90 99	21.20.24.40	21.20.24	21.20	21.20.0	2100	35270
3006.10	3006 10 10	3006 10 10	21.20.24.30	21.20.24	21.20	21.20.0	2100	35290
3006.10	3006 10 30	3006 10 30	32.50.50.30	32.50.50	32.50	32.50.1	3250	35290
3006.10	3006 10 30	3006 10 30	32.50.50.30	32.50.50	32.50	32.50.2	3250	35290
3006.10	3006 10 30	3006 10 30	32.50.50.30	32.50.50	32.50	32.50.3	3250	35290
3006.10	3006 10 30	3006 10 30	32.50.50.30	32.50.50	32.50	32.50.4	3250	35290
3006.10	3006 10 30	3006 10 30	32.50.50.30	32.50.50	32.50	32.50.5	3250	35290
3006.10	3006 10 90	3006 10 90	32.50.50.30	32.50.50	32.50	32.50.1	3250	35290
3006.10	3006 10 90	3006 10 90	32.50.50.30	32.50.50	32.50	32.50.2	3250	35290
3006.10	3006 10 90	3006 10 90	32.50.50.30	32.50.50	32.50	32.50.3	3250	35290
3006.10	3006 10 90	3006 10 90	32.50.50.30	32.50.50	32.50	32.50.4	3250	35290
3006.10	3006 10 90	3006 10 90	32.50.50.30	32.50.50	32.50	32.50.5	3250	35290
3006.20	3006 20 00	3006 20 00	21.20.23.20	21.20.23	21.20	21.20.0	2100	35270
3006.30	3006 30 00	3006 30 00	21.20.23.40	21.20.23	21.20	21.20.0	2100	35270
3006.50	3006 50 00	3006 50 00	21.20.24.60	21.20.24	21.20	21.20.0	2100	35290
3006.70	3006 70 00	3006 70 00	32.50.50.20	32.50.50	32.50	32.50.1	3250	35290
3006.70	3006 70 00	3006 70 00	32.50.50.20	32.50.50	32.50	32.50.2	3250	35290
3006.70	3006 70 00	3006 70 00	32.50.50.20	32.50.50	32.50	32.50.3	3250	35290
3006.70	3006 70 00	3006 70 00	32.50.50.20	32.50.50	32.50	32.50.4	3250	35290
3006.70	3006 70 00	3006 70 00	32.50.50.20	32.50.50	32.50	32.50.5	3250	35290
3401.11	3401 11 00	3401 11 00	20.42.19.15	20.42.19	20.42	20.42.0	2023	35321
3401.20	3401 20 10	3401 20 10	20.41.31.50	20.41.31	20.41	20.41.1	2023	35321
3401.20	3401 20 10	3401 20 10	20.41.31.50	20.41.31	20.41	20.41.2	2023	35321
3401.20	3401 20 90	3401 20 90	20.41.31.80	20.41.31	20.41	20.41.1	2023	35321
3401.20	3401 20 90	3401 20 90	20.41.31.80	20.41.31	20.41	20.41.2	2023	35321
3401.30	3401 30 00	3401 30 00	20.42.19.30	20.42.19	20.42	20.42.0	2023	35321
3402.12	3402 12 00	3402 12 00	20.41.20.30	20.41.20	20.41	20.41.1	2023	35310
3402.12	3402 12 00	3402 12 00	20.41.20.30	20.41.20	20.41	20.41.2	2023	35310
3402.13	3402 13 00	3402 13 00	20.41.20.50	20.41.20	20.41	20.41.1	2023	35310
3402.13	3402 13 00	3402 13 00	20.41.20.50	20.41.20	20.41	20.41.2	2023	35310
3402.20	3402 20 20	3402 20 20	20.41.32.40	20.41.32	20.41	20.41.1	2023	35322
3402.20	3402 20 20	3402 20 20	20.41.32.40	20.41.32	20.41	20.41.2	2023	35322
3402.20	3402 20 90	3402 20 90	20.41.32.50	20.41.32	20.41	20.41.1	2023	35322
3402.20	3402 20 90	3402 20 90	20.41.32.50	20.41.32	20.41	20.41.2	2023	35322
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.1	2029	35420
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.2	2029	35420
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.3	2029	35420

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.4	2029	35420
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.5	2029	35420
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.6	2029	35420
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.7	2029	35420
3504.00	3504 00 10	3504 00 10	20.59.51.00	20.59.51	20.59	20.59.9	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.1	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.2	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.3	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.4	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.5	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.6	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.7	2029	35420
3504.00	3504 00 90	3504 00 90	20.59.51.00	20.59.51	20.59	20.59.9	2029	35420
3507.90	3507 90 30	3507 90 30	20.14.64.70	20.14.64	20.14	20.14.0	2011	34170
3507.90	3507 90 90	3507 90 90	20.14.64.70	20.14.64	20.14	20.14.0	2011	34170
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.1	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.2	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.3	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.4	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.5	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.6	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.7	2029	48341
3701.10	3701 10 00	3701 10 00	20.59.11.30	20.59.11	20.59	20.59.9	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.1	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.2	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.3	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.4	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.5	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.6	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.7	2029	48341
3702.10	3702 10 00	3702 10 00	20.59.11.50	20.59.11	20.59	20.59.9	2029	48341
3808.94	3808 94 10	3808 94 10	20.20.14.30	20.20.14	20.20	20.20.0	2021	34664
3808.94	3808 94 20	3808 94 20	20.20.14.50	20.20.14	20.20	20.20.0	2021	34664
3808.94	3808 94 90	3808 94 90	20.20.14.90	20.20.14	20.20	20.20.0	2021	34664
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.1	2029	35440
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.2	2029	35440
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.3	2029	35440
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.4	2029	35440
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.5	2029	35440

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.6	2029	35440
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.7	2029	35440
3821.00	3821 00 00	3821 00 00	20.59.52.70	20.59.52	20.59	20.59.9	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.1	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.2	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.3	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.4	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.5	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.6	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.7	2029	35440
3822.00	3822 00 00	3822 00 00	20.59.52.10	20.59.52	20.59	20.59.9	2029	35440
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 10	3824 99 10	20.59.59.10	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 15	3824 99 15	20.59.59.10	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 20	3824 99 20	20.59.59.10	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 25	3824 99 25	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.1	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.2	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.3	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.4	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.5	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.6	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.7	2029	35499
3824.99	3824 99 30	3824 99 30	20.59.57.30	20.59.57	20.59	20.59.9	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 45	3824 99 45	20.59.59.40	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 50	3824 99 50	20.59.59.53	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 55	3824 99 55	20.59.59.57	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 56	3824 99 56	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 57	3824 99 57	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 58	3824 99 58	21.20.13.80	21.20.13	21.20	21.20.0	2100	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 61	3824 99 61	20.59.59.63	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 62	3824 99 62	20.59.59.63	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 64	3824 99 64	20.59.59.63	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.3	2029	35499

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 65	3824 99 65	20.59.59.65	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 70	3824 99 70	20.59.59.67	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 75	3824 99 75	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 80	3824 99 80	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 85	3824 99 85	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 86	3824 99 86	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 92	3824 99 92	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 93	3824 99 93	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.1	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.2	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.3	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.4	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.5	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.6	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.7	2029	35499
3824.99	3824 99 96	3824 99 96	20.59.59.94	20.59.59	20.59	20.59.9	2029	35499
3905.99	3905 99 10	3905 99 10	20.16.52.70	20.16.52	20.16	20.16.0	2013	34790
3905.99	3905 99 90	3905 99 90	20.16.52.70	20.16.52	20.16	20.16.0	2013	34790
3923.29	3923 29 10	3923 29 10	22.22.12.00	22.22.12	22.22	22.22.0	2220	36410
3923.29	3923 29 90	3923 29 90	22.22.12.00	22.22.12	22.22	22.22.0	2220	36410
3926.20	3926 20 00	3926 20 00	22.29.10.10	22.29.10	22.29	22.29.0	2220	28243
3926.90	3926 90 50	3926 90 50	22.29.26.30	22.29.26	22.29	22.29.0	2220	36990
3926.90	3926 90 97	3926 90 92	22.29.29.50	22.29.29	22.29	22.29.0	2220	36990
3926.90	3926 90 97	3926 90 97	22.29.29.95	22.29.29	22.29	22.29.0	2220	36990
4014.90	4014 90 00	4014 90 00	22.19.71.30	22.19.71	22.19	22.19.0	2219	36270
4015.11	4015 11 00	4015 11 00	22.19.60.00	22.19.60	22.19	22.19.0	2219	36260
4015.19	4015 19 00	4015 19 00	22.19.60.00	22.19.60	22.19	22.19.0	2219	36260

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
4015.90	4015 90 00	4015 90 00	22.19.60.00	22.19.60	22.19	22.19.0	2219	36260
4016.99	4016 99 52	4016 99 52	22.19.73.45	22.19.73	22.19	22.19.0	2219	36270
4016.99	4016 99 57	4016 99 57	22.19.73.47	22.19.73	22.19	22.19.0	2219	36270
4016.99	4016 99 91	4016 99 91	22.19.73.49	22.19.73	22.19	22.19.0	2219	36270
4016.99	4016 99 97	4016 99 97	22.19.73.65	22.19.73	22.19	22.19.0	2219	36270
4818.50	4818 50 00	4818 50 00	17.22.12.50	17.22.12	17.22	17.22.0	1709	32193
4818.90	4818 90 10	4818 90 10	17.22.12.90	17.22.12	17.22	17.22.0	1709	32193
4818.90	4818 90 90	4818 90 90	17.22.12.90	17.22.12	17.22	17.22.0	1709	32193
5603.11	5603 11 10	5603 11 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.11	5603 11 90	5603 11 90	13.95.10.10	13.95.10	13.95	13.95.0	1399	27922
5603.12	5603 12 10	5603 12 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.12	5603 12 90	5603 12 90	13.95.10.20	13.95.10	13.95	13.95.0	1399	27922
5603.13	5603 13 10	5603 13 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.13	5603 13 90	5603 13 90	13.95.10.30	13.95.10	13.95	13.95.0	1399	27922
5603.14	5603 14 10	5603 14 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.14	5603 14 90	5603 14 90	13.95.10.50	13.95.10	13.95	13.95.0	1399	27922
5603.91	5603 91 10	5603 91 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.91	5603 91 90	5603 91 90	13.95.10.10	13.95.10	13.95	13.95.0	1399	27922
5603.92	5603 92 10	5603 92 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.92	5603 92 90	5603 92 90	13.95.10.20	13.95.10	13.95	13.95.0	1399	27922
5603.93	5603 93 10	5603 93 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.93	5603 93 90	5603 93 90	13.95.10.30	13.95.10	13.95	13.95.0	1399	27922
5603.94	5603 94 10	5603 94 10	13.95.10.70	13.95.10	13.95	13.95.0	1399	27922
5603.94	5603 94 90	5603 94 90	13.95.10.50	13.95.10	13.95	13.95.0	1399	27922
6116.10	6116 10 20	6116 10 20	14.19.13.00	14.19.13	14.19	14.19.1	1410	28229
6116.10	6116 10 20	6116 10 20	14.19.13.00	14.19.13	14.19	14.19.2	1410	28229
6116.10	6116 10 80	6116 10 80	14.19.13.00	14.19.13	14.19	14.19.1	1410	28229
6116.10	6116 10 80	6116 10 80	14.19.13.00	14.19.13	14.19	14.19.2	1410	28229
6210.10	6210 10 10	6210 10 10	14.19.32.00	14.19.32	14.19	14.19.1	1410	28250
6210.10	6210 10 10	6210 10 10	14.19.32.00	14.19.32	14.19	14.19.2	1410	28250
6210.10	6210 10 92	6210 10 92	14.19.32.00	14.19.32	14.19	14.19.1	1410	28250
6210.10	6210 10 92	6210 10 92	14.19.32.00	14.19.32	14.19	14.19.2	1410	28250
6210.10	6210 10 98	6210 10 98	14.19.32.00	14.19.32	14.19	14.19.1	1410	28250
6210.10	6210 10 98	6210 10 98	14.19.32.00	14.19.32	14.19	14.19.2	1410	28250
6210.40	6210 40 00	6210 40 00	14.19.32.00	14.19.32	14.19	14.19.1	1410	28250
6210.40	6210 40 00	6210 40 00	14.19.32.00	14.19.32	14.19	14.19.2	1410	28250
6210.50	6210 50 00	6210 50 00	14.19.32.00	14.19.32	14.19	14.19.1	1410	28250
6210.50	6210 50 00	6210 50 00	14.19.32.00	14.19.32	14.19	14.19.2	1410	28250
6211.42	6211 42 10	6211 42 10	14.12.30.23	14.12.30	14.12	14.12.0	1410	28236
6211.42	6211 42 31	6211 42 31	14.19.22.20	14.19.22	14.19	14.19.1	1410	28236

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
6211.42	6211 42 31	6211 42 31	14.19.22.20	14.19.22	14.19	14.19.2	1410	28236
6211.42	6211 42 41	6211 42 41	14.19.22.20	14.19.22	14.19	14.19.1	1410	28236
6211.42	6211 42 41	6211 42 41	14.19.22.20	14.19.22	14.19	14.19.2	1410	28236
6211.42	6211 42 42	6211 42 42	14.19.22.20	14.19.22	14.19	14.19.1	1410	28236
6211.42	6211 42 42	6211 42 42	14.19.22.20	14.19.22	14.19	14.19.2	1410	28236
6211.42	6211 42 90	6211 42 90	14.19.22.20	14.19.22	14.19	14.19.1	1410	28236
6211.42	6211 42 90	6211 42 90	14.19.22.20	14.19.22	14.19	14.19.2	1410	28236
6216.00	6216 00 00	6216 00 00	14.19.23.70	14.19.23	14.19	14.19.1	1410	28238
6216.00	6216 00 00	6216 00 00	14.19.23.70	14.19.23	14.19	14.19.2	1410	28238
6306.22	6306 22 00	6306 22 00	13.92.22.30	13.92.22	13.92	13.92.1	1392	27160
6306.22	6306 22 00	6306 22 00	13.92.22.30	13.92.22	13.92	13.92.2	1392	27160
6306.29	6306 29 00	6306 29 00	13.92.22.30	13.92.22	13.92	13.92.1	1392	27160
6306.29	6306 29 00	6306 29 00	13.92.22.30	13.92.22	13.92	13.92.2	1392	27160
6307.90	6307 90 10	6307 90 10	13.92.29.99	13.92.29	13.92	13.92.1	1392	27190
6307.90	6307 90 10	6307 90 10	13.92.29.99	13.92.29	13.92	13.92.2	1392	27190
6307.90	6307 90 91	6307 90 91	13.92.29.99	13.92.29	13.92	13.92.1	1392	27190
6307.90	6307 90 91	6307 90 91	13.92.29.99	13.92.29	13.92	13.92.2	1392	27190
6307.90	6307 90 92	6307 90 92	13.92.29.99	32.50.50	32.50	32.50.1	3250	27190
6307.90	6307 90 92	6307 90 92	13.92.29.99	32.50.50	32.50	32.50.2	3250	27190
6307.90	6307 90 92	6307 90 92	13.92.29.99	32.50.50	32.50	32.50.3	3250	27190
6307.90	6307 90 92	6307 90 92	13.92.29.99	32.50.50	32.50	32.50.4	3250	27190
6307.90	6307 90 92	6307 90 92	13.92.29.99	32.50.50	32.50	32.50.5	3250	27190
6307.90	6307 90 98	6307 90 98	13.92.29.99	13.92.29	13.92	13.92.1	1392	27190
6307.90	6307 90 98	6307 90 98	13.92.29.99	13.92.29	13.92	13.92.2	1392	27190
6505.00	6505 00 10	6505 00 10	14.19.42.30	14.19.42	14.19	14.19.1	1410	28262
6505.00	6505 00 10	6505 00 10	14.19.42.30	14.19.42	14.19	14.19.2	1410	28262
6505.00	6505 00 30	6505 00 30	14.19.42.70	14.19.42	14.19	14.19.1	1410	28262
6505.00	6505 00 30	6505 00 30	14.19.42.70	14.19.42	14.19	14.19.2	1410	28262
6505.00	6505 00 90	6505 00 90	14.19.42.70	14.19.42	14.19	14.19.1	1410	28262
6505.00	6505 00 90	6505 00 90	14.19.42.70	14.19.42	14.19	14.19.2	1410	28262
7017.10	7017 10 00	7017 10 00	23.19.23.30	23.19.23	23.19	23.19.1	2310	37195
7017.10	7017 10 00	7017 10 00	23.19.23.30	23.19.23	23.19	23.19.2	2310	37195
7017.10	7017 10 00	7017 10 00	23.19.23.30	23.19.23	23.19	23.19.9	2310	37195
7017.20	7017 20 00	7017 20 00	23.19.23.30	23.19.23	23.19	23.19.1	2310	37195
7017.20	7017 20 00	7017 20 00	23.19.23.30	23.19.23	23.19	23.19.2	2310	37195
7017.20	7017 20 00	7017 20 00	23.19.23.30	23.19.23	23.19	23.19.9	2310	37195
7017.90	7017 90 00	7017 90 00	23.19.23.30	23.19.23	23.19	23.19.1	2310	37195
7017.90	7017 90 00	7017 90 00	23.19.23.30	23.19.23	23.19	23.19.2	2310	37195
7017.90	7017 90 00	7017 90 00	23.19.23.30	23.19.23	23.19	23.19.9	2310	37195
7311.00	7311 00 11	7311 00 11	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
7311.00	7311 00 13	7311 00 13	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220
7311.00	7311 00 19	7311 00 19	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220
7311.00	7311 00 30	7311 00 30	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220
7311.00	7311 00 91	7311 00 91	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220
7311.00	7311 00 99	7311 00 99	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220
7324.90	7324 90 00	7324 90 00	25.99.11.31	25.99.11	25.99	25.99.1	2599	42911
7324.90	7324 90 00	7324 90 00	25.99.11.31	25.99.11	25.99	25.99.2	2599	42911
7324.90	7324 90 00	7324 90 00	25.99.11.31	25.99.11	25.99	25.99.3	2599	42911
7324.90	7324 90 00	7324 90 00	25.99.11.31	25.99.11	25.99	25.99.9	2599	42911
7613.00	7613 00 00	7613 00 00	25.29.12.00	25.29.12	25.29	25.29.0	2512	42220
8413.19	8413 19 00	8413 19 00	28.13.11.25	28.13.11	28.13	28.13.0	2813	43220
8419.20	8419 20 00	8419 20 00	32.50.12.00	32.50.12	32.50	32.50.1	3250	48140
8419.20	8419 20 00	8419 20 00	32.50.12.00	32.50.12	32.50	32.50.2	3250	48140
8419.20	8419 20 00	8419 20 00	32.50.12.00	32.50.12	32.50	32.50.3	3250	48140
8419.20	8419 20 00	8419 20 00	32.50.12.00	32.50.12	32.50	32.50.4	3250	48140
8419.20	8419 20 00	8419 20 00	32.50.12.00	32.50.12	32.50	32.50.5	3250	48140
8421.39	8421 39 15	8421 39 15	28.25.14.50	28.25.14	28.25	28.25.0	2819	43914
8421.39	8421 39 25	8421 39 25	28.25.14.10	28.25.14	28.25	28.25.0	2819	43914
8421.39	8421 39 35	8421 39 35	28.25.14.40	28.25.14	28.25	28.25.0	2819	43914
8421.39	8421 39 85	8421 39 85	28.25.14.30	28.25.14	28.25	28.25.0	2819	43914
8424.89	8424 89 40	8424 89 40	28.29.22.40	28.29.22	28.29	28.29.1	2819	43923
8424.89	8424 89 40	8424 89 40	28.29.22.40	28.29.22	28.29	28.29.2	2819	43923
8424.89	8424 89 40	8424 89 40	28.29.22.40	28.29.22	28.29	28.29.3	2819	43923
8424.89	8424 89 40	8424 89 40	28.29.22.40	28.29.22	28.29	28.29.9	2819	43923
8424.89	8424 89 70	8424 89 70	28.29.22.40	28.29.22	28.29	28.29.1	2819	43923
8424.89	8424 89 70	8424 89 70	28.29.22.40	28.29.22	28.29	28.29.2	2819	43923
8424.89	8424 89 70	8424 89 70	28.29.22.40	28.29.22	28.29	28.29.3	2819	43923
8424.89	8424 89 70	8424 89 70	28.29.22.40	28.29.22	28.29	28.29.9	2819	43923
8539.49	8539 49 00	8539 49 00	27.40.15.70	27.40.15	27.40	27.40.0	2740	46510
8539.50	8539 50 00	8539 50 00	27.40.30.90	27.40.30	27.40	27.40.0	2740	46939
8543.70	8543 70 01	8543 70 01	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 02	8543 70 02	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 03	8543 70 03	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 04	8543 70 04	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 05	8543 70 05	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 06	8543 70 06	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 07	8543 70 07	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 08	8543 70 08	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 09	8543 70 09	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 10	8543 70 10	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
8543.70	8543 70 30	8543 70 30	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 50	8543 70 50	27.90.45.70	27.90.45	27.90	27.90.0	2790	46939
8543.70	8543 70 60	8543 70 60	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 70	8543 70 70	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8543.70	8543 70 90	8543 70 90	27.90.11.50	27.90.11	27.90	27.90.0	2790	46939
8703.10	8703 10 11	8703 10 11	29.10.52.00	29.10.52	29.10	29.10.0	2910	49116
8703.10	8703 10 18	8703 10 18	29.10.52.00	29.10.52	29.10	29.10.0	2910	49116
8703.21	8703 21 10	8703 21 10	29.10.21.00	29.10.21	29.10	29.10.0	2910	49113
8703.21	8703 21 90	8703 21 90						49113
8703.22	8703 22 10	8703 22 10	29.10.21.00	29.10.21	29.10	29.10.0	2910	49113
8703.22	8703 22 90	8703 22 90						49113
8703.23	8703 23 11	8703 23 11	29.10.22.50	29.10.22	29.10	29.10.0	2910	49113
8703.23	8703 23 19	8703 23 19	29.10.22.30	29.10.22	29.10	29.10.0	2910	49113
8703.23	8703 23 90	8703 23 90						49113
8703.24	8703 24 10	8703 24 10	29.10.22.30	29.10.22	29.10	29.10.0	2910	49113
8703.24	8703 24 90	8703 24 90						49113
8703.31	8703 31 10	8703 31 10	29.10.23.10	29.10.23	29.10	29.10.0	2910	49113
8703.31	8703 31 90	8703 31 90						49113
8703.32	8703 32 11	8703 32 11	29.10.23.53	29.10.23	29.10	29.10.0	2910	49113
8703.32	8703 32 19	8703 32 19	29.10.23.30	29.10.23	29.10	29.10.0	2910	49113
8703.32	8703 32 90	8703 32 90						49113
8703.33	8703 33 11	8703 33 11	29.10.23.55	29.10.23	29.10	29.10.0	2910	49113
8703.33	8703 33 19	8703 33 19	29.10.23.40	29.10.23	29.10	29.10.0	2910	49113
8703.33	8703 33 90	8703 33 90						49113
8703.40	8703 40 10	8703 40 10	29.10.24.10	29.10.24	29.10	29.10.0	2910	49113
8703.40	8703 40 90	8703 40 90						49113
8703.50	8703 50 00	8703 50 00	29.10.24.10	29.10.24	29.10	29.10.0	2910	49113
8703.60	8703 60 10	8703 60 10	29.10.24.30	29.10.24	29.10	29.10.0	2910	49113
8703.60	8703 60 90	8703 60 90						49113
8703.70	8703 70 00	8703 70 00	29.10.24.30	29.10.24	29.10	29.10.0	2910	49113
8703.80	8703 80 10	8703 80 10	29.10.24.50	29.10.24	29.10	29.10.0	2910	49113
8703.80	8703 80 90	8703 80 90						49113
8703.90	8703 90 00	8703 90 00	29.10.24.90	29.10.24	29.10	29.10.0	2910	49113
8705.90	8705 90 30	8705 90 30	29.10.59.90	29.10.59	29.10	29.10.0	2910	49119
8705.90	8705 90 80	8705 90 80	29.10.59.90	29.10.59	29.10	29.10.0	2910	49119
8713.10	8713 10 00	8713 10 00	30.92.20.30	30.92.20	30.92	30.92.1	3092	49922
8713.10	8713 10 00	8713 10 00	30.92.20.30	30.92.20	30.92	30.92.2	3092	49922
8713.10	8713 10 00	8713 10 00	30.92.20.30	30.92.20	30.92	30.92.3	3092	49922
8713.10	8713 10 00	8713 10 00	30.92.20.30	30.92.20	30.92	30.92.4	3092	49922
8713.90	8713 90 00	8713 90 00	30.92.20.90	30.92.20	30.92	30.92.1	3092	49922

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
8713.90	8713 90 00	8713 90 00	30.92.20.90	30.92.20	30.92	30.92.2	3092	49922
8713.90	8713 90 00	8713 90 00	30.92.20.90	30.92.20	30.92	30.92.3	3092	49922
8713.90	8713 90 00	8713 90 00	30.92.20.90	30.92.20	30.92	30.92.4	3092	49922
9004.90	9004 90 10	9004 90 10	32.50.42.90	32.50.42	32.50	32.50.1	3250	48312
9004.90	9004 90 10	9004 90 10	32.50.42.90	32.50.42	32.50	32.50.2	3250	48312
9004.90	9004 90 10	9004 90 10	32.50.42.90	32.50.42	32.50	32.50.3	3250	48312
9004.90	9004 90 10	9004 90 10	32.50.42.90	32.50.42	32.50	32.50.4	3250	48312
9004.90	9004 90 10	9004 90 10	32.50.42.90	32.50.42	32.50	32.50.5	3250	48312
9004.90	9004 90 90	9004 90 90	32.50.42.90	32.50.42	32.50	32.50.1	3250	48312
9004.90	9004 90 90	9004 90 90	32.50.42.90	32.50.42	32.50	32.50.2	3250	48312
9004.90	9004 90 90	9004 90 90	32.50.42.90	32.50.42	32.50	32.50.3	3250	48312
9004.90	9004 90 90	9004 90 90	32.50.42.90	32.50.42	32.50	32.50.4	3250	48312
9004.90	9004 90 90	9004 90 90	32.50.42.90	32.50.42	32.50	32.50.5	3250	48312
9010.50	9010 50 00	9010 50 00	26.70.19.10	26.70.19	26.70	26.70.1	2670	48329
9010.50	9010 50 00	9010 50 00	26.70.19.10	26.70.19	26.70	26.70.2	2670	48329
9011.10	9011 10 00	9011 10 10	26.70.22.70	26.70.22	26.70	26.70.1	2670	48314
9011.10	9011 10 00	9011 10 10	26.70.22.70	26.70.22	26.70	26.70.2	2670	48314
9011.10	9011 10 00	9011 10 90	26.70.22.70	26.70.22	26.70	26.70.1	2670	48314
9011.10	9011 10 00	9011 10 90	26.70.22.70	26.70.22	26.70	26.70.2	2670	48314
9011.80	9011 80 00	9011 80 00	26.70.22.70	26.70.22	26.70	26.70.1	2670	48314
9011.80	9011 80 00	9011 80 00	26.70.22.70	26.70.22	26.70	26.70.2	2670	48314
9018.11	9018 11 00	9018 11 00	26.60.12.30	26.60.12	26.60	26.60.0	2660	48121
9018.12	9018 12 00	9018 12 00	26.60.12.80	26.60.12	26.60	26.60.0	2660	48121
9018.13	9018 13 00	9018 13 00	26.60.12.80	26.60.12	26.60	26.60.0	2660	48121
9018.14	9018 14 00	9018 14 00	26.60.12.80	26.60.12	26.60	26.60.0	2660	48121
9018.19	9018 19 10	9018 19 10	26.60.12.80	26.60.12	26.60	26.60.0	2660	48121
9018.19	9018 19 90	9018 19 90	26.60.12.80	26.60.12	26.60	26.60.0	2660	48121
9018.20	9018 20 00	9018 20 00	26.60.13.00	26.60.13	26.60	26.60.0	2660	48122
9018.31	9018 31 10	9018 31 10	32.50.13.11	32.50.13	32.50	32.50.1	3250	48150
9018.31	9018 31 10	9018 31 10	32.50.13.11	32.50.13	32.50	32.50.2	3250	48150
9018.31	9018 31 10	9018 31 10	32.50.13.11	32.50.13	32.50	32.50.3	3250	48150
9018.31	9018 31 10	9018 31 10	32.50.13.11	32.50.13	32.50	32.50.4	3250	48150
9018.31	9018 31 10	9018 31 10	32.50.13.11	32.50.13	32.50	32.50.5	3250	48150
9018.31	9018 31 90	9018 31 90	32.50.13.11	32.50.13	32.50	32.50.1	3250	48150
9018.31	9018 31 90	9018 31 90	32.50.13.11	32.50.13	32.50	32.50.2	3250	48150
9018.31	9018 31 90	9018 31 90	32.50.13.11	32.50.13	32.50	32.50.3	3250	48150
9018.31	9018 31 90	9018 31 90	32.50.13.11	32.50.13	32.50	32.50.4	3250	48150
9018.31	9018 31 90	9018 31 90	32.50.13.11	32.50.13	32.50	32.50.5	3250	48150
9018.32	9018 32 10	9018 32 10	32.50.13.13	32.50.13	32.50	32.50.1	3250	48150
9018.32	9018 32 10	9018 32 10	32.50.13.13	32.50.13	32.50	32.50.2	3250	48150

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
9018.32	9018 32 10	9018 32 10	32.50.13.13	32.50.13	32.50	32.50.3	3250	48150
9018.32	9018 32 10	9018 32 10	32.50.13.13	32.50.13	32.50	32.50.4	3250	48150
9018.32	9018 32 10	9018 32 10	32.50.13.13	32.50.13	32.50	32.50.5	3250	48150
9018.32	9018 32 90	9018 32 90	32.50.13.15	32.50.13	32.50	32.50.1	3250	48150
9018.32	9018 32 90	9018 32 90	32.50.13.15	32.50.13	32.50	32.50.2	3250	48150
9018.32	9018 32 90	9018 32 90	32.50.13.15	32.50.13	32.50	32.50.3	3250	48150
9018.32	9018 32 90	9018 32 90	32.50.13.15	32.50.13	32.50	32.50.4	3250	48150
9018.32	9018 32 90	9018 32 90	32.50.13.15	32.50.13	32.50	32.50.5	3250	48150
9018.39	9018 39 00	9018 39 00	32.50.13.17	32.50.13	32.50	32.50.1	3250	48150
9018.39	9018 39 00	9018 39 00	32.50.13.17	32.50.13	32.50	32.50.2	3250	48150
9018.39	9018 39 00	9018 39 00	32.50.13.17	32.50.13	32.50	32.50.3	3250	48150
9018.39	9018 39 00	9018 39 00	32.50.13.17	32.50.13	32.50	32.50.4	3250	48150
9018.39	9018 39 00	9018 39 00	32.50.13.17	32.50.13	32.50	32.50.5	3250	48150
9018.41	9018 41 00	9018 41 00	32.50.11.30	32.50.11	32.50	32.50.1	3250	48130
9018.41	9018 41 00	9018 41 00	32.50.11.30	32.50.11	32.50	32.50.2	3250	48130
9018.41	9018 41 00	9018 41 00	32.50.11.30	32.50.11	32.50	32.50.3	3250	48130
9018.41	9018 41 00	9018 41 00	32.50.11.30	32.50.11	32.50	32.50.4	3250	48130
9018.41	9018 41 00	9018 41 00	32.50.11.30	32.50.11	32.50	32.50.5	3250	48130
9018.49	9018 49 10	9018 49 10	32.50.11.50	32.50.11	32.50	32.50.1	3250	48130
9018.49	9018 49 10	9018 49 10	32.50.11.50	32.50.11	32.50	32.50.2	3250	48130
9018.49	9018 49 10	9018 49 10	32.50.11.50	32.50.11	32.50	32.50.3	3250	48130
9018.49	9018 49 10	9018 49 10	32.50.11.50	32.50.11	32.50	32.50.4	3250	48130
9018.49	9018 49 10	9018 49 10	32.50.11.50	32.50.11	32.50	32.50.5	3250	48130
9018.49	9018 49 90	9018 49 90	32.50.11.50	32.50.11	32.50	32.50.1	3250	48130
9018.49	9018 49 90	9018 49 90	32.50.11.50	32.50.11	32.50	32.50.2	3250	48130
9018.49	9018 49 90	9018 49 90	32.50.11.50	32.50.11	32.50	32.50.3	3250	48130
9018.49	9018 49 90	9018 49 90	32.50.11.50	32.50.11	32.50	32.50.4	3250	48130
9018.49	9018 49 90	9018 49 90	32.50.11.50	32.50.11	32.50	32.50.5	3250	48130
9018.50	9018 50 10	9018 50 10	32.50.13.20	32.50.13	32.50	32.50.1	3250	48150
9018.50	9018 50 10	9018 50 10	32.50.13.20	32.50.13	32.50	32.50.2	3250	48150
9018.50	9018 50 10	9018 50 10	32.50.13.20	32.50.13	32.50	32.50.3	3250	48150
9018.50	9018 50 10	9018 50 10	32.50.13.20	32.50.13	32.50	32.50.4	3250	48150
9018.50	9018 50 10	9018 50 10	32.50.13.20	32.50.13	32.50	32.50.5	3250	48150
9018.50	9018 50 90	9018 50 90	32.50.13.20	32.50.13	32.50	32.50.1	3250	48150
9018.50	9018 50 90	9018 50 90	32.50.13.20	32.50.13	32.50	32.50.2	3250	48150
9018.50	9018 50 90	9018 50 90	32.50.13.20	32.50.13	32.50	32.50.3	3250	48150
9018.50	9018 50 90	9018 50 90	32.50.13.20	32.50.13	32.50	32.50.4	3250	48150
9018.50	9018 50 90	9018 50 90	32.50.13.20	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 10	9018 90 10	32.50.13.33	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 10	9018 90 10	32.50.13.33	32.50.13	32.50	32.50.2	3250	48150

Source: Authors’ elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
9018.90	9018 90 10	9018 90 10	32.50.13.33	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 10	9018 90 10	32.50.13.33	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 10	9018 90 10	32.50.13.33	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 20	9018 90 20	32.50.13.35	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 20	9018 90 20	32.50.13.35	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 20	9018 90 20	32.50.13.35	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 20	9018 90 20	32.50.13.35	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 20	9018 90 20	32.50.13.35	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 30	9018 90 30	32.50.13.53	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 30	9018 90 30	32.50.13.53	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 30	9018 90 30	32.50.13.53	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 30	9018 90 30	32.50.13.53	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 30	9018 90 30	32.50.13.53	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 40	9018 90 40	32.50.13.55	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 40	9018 90 40	32.50.13.55	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 40	9018 90 40	32.50.13.55	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 40	9018 90 40	32.50.13.55	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 40	9018 90 40	32.50.13.55	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 50	9018 90 50	32.50.13.63	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 50	9018 90 50	32.50.13.63	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 50	9018 90 50	32.50.13.63	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 50	9018 90 50	32.50.13.63	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 50	9018 90 50	32.50.13.63	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 60	9018 90 60	32.50.13.65	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 60	9018 90 60	32.50.13.65	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 60	9018 90 60	32.50.13.65	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 60	9018 90 60	32.50.13.65	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 60	9018 90 60	32.50.13.65	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 75	9018 90 75	32.50.13.70	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 75	9018 90 75	32.50.13.70	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 75	9018 90 75	32.50.13.70	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 75	9018 90 75	32.50.13.70	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 75	9018 90 75	32.50.13.70	32.50.13	32.50	32.50.5	3250	48150
9018.90	9018 90 84	9018 90 84	32.50.13.70	32.50.13	32.50	32.50.1	3250	48150
9018.90	9018 90 84	9018 90 84	32.50.13.70	32.50.13	32.50	32.50.2	3250	48150
9018.90	9018 90 84	9018 90 84	32.50.13.70	32.50.13	32.50	32.50.3	3250	48150
9018.90	9018 90 84	9018 90 84	32.50.13.70	32.50.13	32.50	32.50.4	3250	48150
9018.90	9018 90 84	9018 90 84	32.50.13.70	32.50.13	32.50	32.50.5	3250	48150
9019.20	9019 20 00	9019 20 00	32.50.21.80	32.50.21	32.50	32.50.1	3250	48160
9019.20	9019 20 00	9019 20 00	32.50.21.80	32.50.21	32.50	32.50.2	3250	48160

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
9019.20	9019 20 00	9019 20 00	32.50.21.80	32.50.21	32.50	32.50.3	3250	48160
9019.20	9019 20 00	9019 20 00	32.50.21.80	32.50.21	32.50	32.50.4	3250	48160
9019.20	9019 20 00	9019 20 00	32.50.21.80	32.50.21	32.50	32.50.5	3250	48160
9020.00	9020 00 00	9020 00 00	32.99.59.10	32.99.59	32.99	32.99.1	3290	48160
9020.00	9020 00 00	9020 00 00	32.99.59.10	32.99.59	32.99	32.99.2	3290	48160
9020.00	9020 00 00	9020 00 00	32.99.59.10	32.99.59	32.99	32.99.3	3290	48160
9020.00	9020 00 00	9020 00 00	32.99.59.10	32.99.59	32.99	32.99.4	3290	48160
9020.00	9020 00 00	9020 00 00	32.99.59.10	32.99.59	32.99	32.99.9	3290	48160
9021.50	9021 50 00	9021 50 00	26.60.14.50	26.60.14	26.60	26.60.0	2660	48172
9022.12	9022 12 00	9022 12 00	26.60.11.15	26.60.11	26.60	26.60.0	2660	48110
9022.14	9022 14 00	9022 14 00	26.60.11.15	26.60.11	26.60	26.60.0	2660	48110
9022.19	9022 19 00	9022 19 00	26.60.11.19	26.60.11	26.60	26.60.0	2660	48110
9022.21	9022 21 00	9022 21 00	26.60.11.30	26.60.11	26.60	26.60.0	2660	48110
9022.29	9022 29 00	9022 29 00	26.60.11.30	26.60.11	26.60	26.60.0	2660	48110
9022.30	9022 30 00	9022 30 00	26.60.11.50	26.60.11	26.60	26.60.0	2660	48110
9022.90	9022 90 20	9022 90 20	26.60.11.70	26.60.11	26.60	26.60.0	2660	48110
9022.90	9022 90 80	9022 90 80	26.60.11.70	26.60.11	26.60	26.60.0	2660	48110
9025.11	9025 11 20	9025 11 20	32.50.13.40	32.50.13	32.50	32.50.1	3250	48251
9025.11	9025 11 20	9025 11 20	32.50.13.40	32.50.13	32.50	32.50.2	3250	48251
9025.11	9025 11 20	9025 11 20	32.50.13.40	32.50.13	32.50	32.50.3	3250	48251
9025.11	9025 11 20	9025 11 20	32.50.13.40	32.50.13	32.50	32.50.4	3250	48251
9025.11	9025 11 20	9025 11 20	32.50.13.40	32.50.13	32.50	32.50.5	3250	48251
9025.11	9025 11 80	9025 11 80	26.51.51.10	26.51.51	26.51	26.51.1	2651	48251
9025.11	9025 11 80	9025 11 80	26.51.51.10	26.51.51	26.51	26.51.2	2651	48251
9025.19	9025 19 00	9025 19 20	26.51.51.35	26.51.51	26.51	26.51.1	2651	48251
9025.19	9025 19 00	9025 19 20	26.51.51.35	26.51.51	26.51	26.51.2	2651	48251
9025.19	9025 19 00	9025 19 80	26.51.51.39	26.51.51	26.51	26.51.1	2651	48251
9025.19	9025 19 00	9025 19 80	26.51.51.39	26.51.51	26.51	26.51.2	2651	48251
9026.80	9026 80 20	9026 80 20	26.51.52.83	26.51.52	26.51	26.51.1	2651	48252
9026.80	9026 80 20	9026 80 20	26.51.52.83	26.51.52	26.51	26.51.2	2651	48252
9026.80	9026 80 80	9026 80 80	26.51.52.89	26.51.52	26.51	26.51.1	2651	48252
9026.80	9026 80 80	9026 80 80	26.51.52.89	26.51.52	26.51	26.51.2	2651	48252
9027.80	9027 80 05	9027 80 05	26.70.24.90	26.70.24	26.70	26.70.1	2670	48253
9027.80	9027 80 05	9027 80 05	26.70.24.90	26.70.24	26.70	26.70.2	2670	48253
9027.80	9027 80 20	9027 80 11	26.51.53.81	26.51.53	26.51	26.51.1	2651	48253
9027.80	9027 80 20	9027 80 11	26.51.53.81	26.51.53	26.51	26.51.2	2651	48253
9027.80	9027 80 20	9027 80 99	26.51.53.95	26.51.53	26.51	26.51.1	2651	48253
9027.80	9027 80 20	9027 80 99	26.51.53.95	26.51.53	26.51	26.51.2	2651	48253
9027.80	9027 80 80	9027 80 13	26.51.53.83	26.51.53	26.51	26.51.1	2651	48253
9027.80	9027 80 80	9027 80 13	26.51.53.83	26.51.53	26.51	26.51.2	2651	48253

Source: Authors' elaboration

Annex 2 continued **- Correspondence table between COVID-19 products and economic activities**

HS 2017	CN 2020	CN 2019	Prodcom 2019	CPA 2.1	NACE Rev. 2	Ateco 2007	ISIC Rev. 4	CPC 2.1
9027.80	9027 80 80	9027 80 17	26.51.53.83	26.51.53	26.51	26.51.1	2651	48253
9027.80	9027 80 80	9027 80 17	26.51.53.83	26.51.53	26.51	26.51.2	2651	48253
9027.80	9027 80 80	9027 80 91	26.51.53.95	26.51.53	26.51	26.51.1	2651	48253
9027.80	9027 80 80	9027 80 91	26.51.53.95	26.51.53	26.51	26.51.2	2651	48253
9027.80	9027 80 80	9027 80 99	26.51.53.95	26.51.53	26.51	26.51.1	2651	48253
9027.80	9027 80 80	9027 80 99	26.51.53.95	26.51.53	26.51	26.51.2	2651	48253
9028.20	9028 20 00	9028 20 00	26.51.63.50	26.51.63	26.51	26.51.1	2651	48263
9028.20	9028 20 00	9028 20 00	26.51.63.50	26.51.63	26.51	26.51.2	2651	48263
9030.20	9030 20 00	9030 20 00	26.51.00.Z0	26.51.45	26.51	26.51.1	2651	48242
9030.20	9030 20 00	9030 20 00	26.51.00.Z0	26.51.45	26.51	26.51.2	2651	48242
9030.20	9030 20 00	9030 20 00	26.51.42.00	26.51.45	26.51	26.51.1	2651	48242
9030.20	9030 20 00	9030 20 00	26.51.42.00	26.51.45	26.51	26.51.2	2651	48242
9030.20	9030 20 00	9030 20 00	26.51.45.00	26.51.45	26.51	26.51.1	2651	48242
9030.20	9030 20 00	9030 20 00	26.51.45.00	26.51.45	26.51	26.51.2	2651	48242
9402.90	9402 90 00	9402 90 00	32.50.30.50	32.50.30	32.50	32.50.1	3250	48180
9402.90	9402 90 00	9402 90 00	32.50.30.50	32.50.30	32.50	32.50.2	3250	48180
9402.90	9402 90 00	9402 90 00	32.50.30.50	32.50.30	32.50	32.50.3	3250	48180
9402.90	9402 90 00	9402 90 00	32.50.30.50	32.50.30	32.50	32.50.4	3250	48180
9402.90	9402 90 00	9402 90 00	32.50.30.50	32.50.30	32.50	32.50.5	3250	48180

Source: Authors' elaboration

Annex 3 - COVID-19 products according to the Prodcom list 2019

Prodcom 2019	Description
08.93.10.00	Salt (including denatured salt but excluding salt suitable for human consumption) and pure sodium chloride, whether or not in aqueous solution or containing added anti-caking or free-flowing agents
10.84.30.00	Salt suitable for human consumption
11.01.10.65	Spirits distilled from fruit (excluding liqueurs, gin, geneva; grape wine or grape marc (important: excluding alcohol duty))
11.01.10.70	Pure alcohols (important: excluding alcohol duty)
11.01.10.80	Spirits, liqueurs and other spirituous beverages (excluding spirits distilled from grape wine, grape marc or fruit/whisky, rum, tafia, gin and geneva, Vodka of an alcoholic strength by volume of <= 45.4%, spirits distilled from fruit) (important: excluding alcohol duty)
13.92.22.30	Tents (including caravan awnings)
13.92.29.99	Floor-cloths, dish-cloths, dusters and similar cleaning cloths, knitted or crocheted; life-jackets, life-belts and other made up articles (excluding sanitary towels and napkins and similar articles)
13.95.10.10	Non-wovens of a weight ≤ 25 g/m² (including articles made from non-wovens) (excluding articles of apparel, coated or covered)
13.95.10.20	Non-wovens of a weight of > 25 g/m² but ≤ 70 g/m² (including articles made from non-wovens) (excluding articles of apparel, coated or covered)
13.95.10.30	Non-wovens of a weight of > 70 g/m² but ≤ 150 g/m² (including articles made from non-wovens) (excluding articles of apparel, coated or covered)
13.95.10.50	Non-wovens of a weight of > 150 g/m² (including articles made from non-wovens) (excluding articles of apparel, coated or covered)
13.95.10.70	Non-wovens, coated or covered (including articles made from non-wovens) (excluding articles of apparel)
14.12.30.23	Women’s or girls’ other garments, of cotton or man-made fibres, for industrial or occupational wear
14.19.13.00	Gloves, mittens and mitts, of knitted or crocheted textiles
14.19.22.20	Other women’s or girls’ apparel n.e.c., including tracksuits and jogging suits (excluding waistcoats, ski-suits, knitted or crocheted)
14.19.23.70	Gloves, mittens and mitts (excluding knitted or crocheted)
14.19.32.00	Garments made up of felt or non-wovens, textile fabrics impregnated or coated
14.19.42.30	Felt hats and other felt headgear, made from hat bodies or hoods and plateaux
14.19.42.70	Hats and other headgear, knitted or crocheted or made-up from lace, felt or other textile fabric in the piece (but not in strips); hair-nets of any material
17.22.12.50	Articles of apparel and clothing accessories of paper pulp; paper; cellulose wadding or webs of cellulose fibres (excluding handkerchiefs, headgear)
17.22.12.90	Household, sanitary or hospital articles of paper, etc., n.e.c.
20.11.11.70	Oxygen
20.13.63.00	Hydrogen peroxide
20.14.22.20	Propan-1-ol (propyl alcohol) and propan-2-ol (isopropyl alcohol)
20.14.24.10	Monophenols
20.14.32.50	Formic acid, its salts and esters
20.14.42.90	Oxygen-function amino-compounds (excluding amino-alcohols, their esters and ethers and salts thereof, lysine and its salts and esters, glutamic acid its salts and esters)
20.14.43.40	Imides and their derivatives, and salts thereof (excluding saccharin and its salts)
20.14.52.25	Heterocyclic compounds with oxygen only hetero-atom(s) (excluding other lactones)
20.14.52.30	Heterocyclic compounds with nitrogen only hetero-atom(s); containing an unfused imidazole ring (excluding hydantoin and its derivatives)

Source: Authors’ elaboration

Annex 3 continued **- COVID-19 products according to the Prodcom list 2019**

Prodcom 2019	Description
20.14.52.80	Compounds containing in the structure an unfused pyridine ring or a quinoline or isoquinoline ring-system, not further fused; lactames; other heterocyclic compounds with nitrogen hetero-atom(s) only (excluding compounds containing in the structure an unfused pyrazole ring, an unfused imidazole ring, a pyrimidine ring, a piperazine ring or an unfused triazine ring)
20.14.52.90	Nucleic acids and other heterocyclic compounds - thiazole, benzothiazole, other cycles
20.14.53.80	Esters of other inorganic acids of non-metals (excluding esters of hydrogen halides) and their salts; their halogenated, sulphonated, nitrated or nitrosated derivatives
20.14.64.70	Enzymes; prepared enzymes (not elsewhere specified or included) (excluding rennet and concentrates)
20.14.74.00	Undenatured ethyl alcohol of an alcoholic strength by volume >= 80 % (important: excluding alcohol duty)
20.16.52.70	Polymers of vinyl esters or other vinyl polymers, in primary forms (excluding vinyl acetate)
20.20.14.30	Disinfectants based on quaternary ammonium salts put up in forms or packings for retail sale or as preparations or articles (excluding hazardous pesticides)
20.20.14.50	Disinfectants based on halogenated compounds put up in forms or packings for retail sale or as preparations (excluding hazardous pesticides)
20.20.14.90	Disinfectants put up in forms or packings for retail sale or as preparations or articles (excluding those based on quaternary ammonium salts, those based on halogenated compounds and those being hazardous pesticides)
20.41.20.30	Cationic organic surface-active agents (excluding soap)
20.41.20.50	Non-ionic organic surface-active agents (excluding soap)
20.41.31.50	Soap in the form of flakes, wafers, granules or powders
20.41.31.80	Soap in forms excluding bars, cakes or moulded shapes, paper, wadding, felt and non-wovens impregnated or coated with soap/detergent, flakes, granules or powders
20.41.32.40	Surface-active preparations, whether or not containing soap, p.r.s. (excluding those for use as soap)
20.41.32.50	Washing preparations and cleaning preparations, with or without soap, p.r.s. including auxiliary washing preparations excluding those for use as soap, surface-active preparations
20.42.19.15	Soap and organic surface-active products in bars, etc., for toilet use
20.42.19.30	Organic surface-active products and preparations for washing the skin; whether or not containing soap, p.r.s.
20.59.11.30	Photographic plates and film in the flat, sensitised and unexposed, of any material; instant print film in the flat, sensitised and unexposed (excluding paper; paperboard or textiles)
20.59.11.50	Photographic film in rolls, sensitised, unexposed of any material; instant print film in rolls sensitised and unexposed (excluding paper, paperboard or textiles)
20.59.51.00	Peptones and their derivatives; other protein substances and their derivatives; hide powder including glutelins and prolamins, globulins, glycinin, keratins, nucleoproteids, protein isolates
20.59.52.10	Composite diagnostic or laboratory reagents, including paper impregnated or coated with diagnostic or laboratory reagents
20.59.52.70	Prepared culture media for development of micro-organisms
20.59.57.30	Naphthenic acids, their water-insoluble salts and their esters
20.59.59.10	Ion-exchangers; getters for vacuum tubes; petroleum sulphonates (excluding petroleum sulphonates of alkali metals, of ammonium or of ethanolamines); thiophenated sulphonic acids of oils obtained from bituminous minerals, and their salts
20.59.59.40	Anti-scaling and similar compounds
20.59.59.53	Preparations for electroplating
20.59.59.57	Mixtures of mono-, di- and tri-, fatty acid esters of glycerol (emulsifiers for fats)

Source: Authors’ elaboration

Annex 3 continued **- COVID-19 products according to the Prodcom list 2019**

Prodcom 2019	Description
20.59.59.63	Products and preparations for pharmaceutical or surgical uses
20.59.59.65	Auxiliary products for foundries (excluding prepared binders for foundry moulds or cores)
20.59.59.67	Fire-proofing, water-proofing and similar protective preparations used in the building industry
20.59.59.94	Other chemical products, n.e.c.
21.10.10.30	Salicylic acid and its salts
21.10.20.40	Quaternary ammonium salts and hydroxides; lecithins and other phosphoaminolipids, whether or not chemically defined
21.10.20.70	Cyclic amides and their derivatives, and salts thereof (including cyclic carbamates) (excluding ureines and their derivatives, and salts thereof)
21.10.31.59	Compounds containing a pyrimidine ring (whether or not hydrogenated) or piperazine ring in the structure (excluding malonylurea (barbituric acid) and its derivatives)
21.10.31.80	Compounds containing a phenothiazine ring-system (whether or not hydrogenated); not further fused
21.10.52.00	Hormones, prostaglandins, thromboxanes and leukotrienes, natural or reproduced by synthesis; derivatives and structural analogues thereof, including chain modified polypeptides, used primarily as hormones
21.10.53.00	Glycosides and vegetable alkaloids, natural or reproduced by synthesis, and their salts, ethers, esters and other derivatives
21.10.54.00	Antibiotics
21.10.60.20	Extracts of glands or other organs or of their secretions (for organo-therapeutic uses)
21.10.60.40	Glands and other organs or substances for therapeutic or prophylactic use, n.e.c. (excluding blood and extracts of glands or other organs)
21.10.60.55	Human blood; animal blood prepared for therapeutic, prophylactic or diagnostic uses; cultures of micro-organisms; toxins (excluding yeasts)
21.20.11.30	Medicaments containing penicillins or derivatives thereof, with a penicillanic acid structure, or streptomycins or their derivatives, for therapeutic or prophylactic uses, n.p.r.s.
21.20.11.50	Medicaments of other antibiotics, n.p.r.s.
21.20.11.60	Medicaments of penicillins, streptomycins or derivatives thereof, in doses or p.r.s.
21.20.11.80	Medicaments of other antibiotics, p.r.s.
21.20.12.30	Medicaments containing insulin but not antibiotics, for therapeutic or prophylactic uses, not put up in measured doses or for retail sale
21.20.12.50	Medicaments containing hormones but not antibiotics, for therapeutic or prophylactic uses, not put up in measured doses or for retail sale (excluding insulin)
21.20.12.60	Medicaments containing insulin but not antibiotics, for therapeutic or prophylactic uses, put up in measured doses or for retail sale
21.20.12.70	Medicaments containing corticosteroid hormones, their derivatives and structural analogues, put up in measured doses or for retail sale
21.20.13.10	Medicaments of alkaloids or derivatives thereof, n.p.r.s.
21.20.13.20	Other medicaments for therapeutic or prophylactic uses, of HS 3003, n.p.r.s.
21.20.13.40	Medicaments of alkaloids or derivatives thereof, p.r.s.
21.20.13.60	Medicaments containing vitamins, provitamins, derivatives and intermixtures thereof, for therapeutic or prophylactic uses, put up in measured doses or for retail sale
21.20.13.80	Other medicaments of mixed or unmixed products, p.r.s., n.e.c.
21.20.21.25	Antisera, other immunological products which are directly involved in the regulation of immunological processes and other blood fractions
21.20.21.45	Vaccines for human medicine

Source: Authors' elaboration

Annex 3 continued **- COVID-19 products according to the Prodcom list 2019**

Prodcom 2019	Description
21.20.23.20	Blood-grouping reagents
21.20.23.40	Opacifying preparations for X-ray examinations; diagnostic reagents designed to be administered to the patient
21.20.24.20	Adhesive dressings or similar articles; impregnated or coated with pharmaceutical substances; or put up in forms for retail sale
21.20.24.30	Sterile surgical catgut
21.20.24.40	Wadding, gauze, etc., with pharmaceutical substances, p.r.s., n.e.c.
21.20.24.60	First-aid boxes and kits
22.19.60.00	Articles of apparel and clothing accessories (including gloves, mittens and mitts), for all purposes, of vulcanised rubber other than hard rubber
22.19.71.30	Hygienic or pharmaceutical articles of rubber (excluding sheath contraceptives)
22.19.73.45	Rubber-to-metal bonded articles for tractors and motor vehicles
22.19.73.47	Moulded rubber articles for tractors and motor vehicles
22.19.73.49	Rubber-to-metal bonded articles for other uses than for tractors and motor vehicles
22.19.73.65	Articles of vulcanised solid rubber other than for tractors and motor vehicles
22.22.12.00	Plastic sacks and bags (including cones) (excluding of polymers of ethylene)
22.29.10.10	Plastic articles of apparel and clothing accessories (including headgear, gloves, raincoats, aprons, belts and babies' bibs) (excluding safety headgear)
22.29.26.30	Perforated buckets and similar articles used to filter water at the entrance to drains, of plastic
22.29.29.50	Other articles made from sheet
22.29.29.95	Other articles of plastic n.e.c. (excluding appliances identifiable for ostomy use)
23.19.23.30	Laboratory, hygienic or pharmaceutical glassware whether or not graduated
25.29.12.00	Containers for compressed or liquefied gas, of metal
25.99.11.31	Sanitary ware and parts of sanitary ware of iron or steel
26.51.00.Z0	Cathode-ray oscilloscopes and cathode-ray oscillographs; Instruments and apparatus for measuring or checking electrical quantities n.e.c.
26.51.42.00	Cathode-ray oscilloscopes and cathode-ray oscillographs
26.51.45.00	Instruments and apparatus for measuring or checking electrical quantities n.e.c.
26.51.51.10	Thermometers, liquid-filled, for direct reading, not combined with other instruments (excluding clinical or veterinary thermometers)
26.51.51.35	Electronic thermometers and pyrometers, not combined with other instruments (excluding liquid filled)
26.51.51.39	Thermometers, not combined with other instruments and not liquid filled, n.e.c.
26.51.52.83	Electronic instruments and apparatus for measuring variables of liquids/gases (including heat meters; excluding for measuring pressure/flow/level of liquids)
26.51.52.89	Non-electronic instruments for measuring or checking variables of liquids or gases (including heat meters; excluding for measuring or checking pressure/flow/level of liquids)
26.51.53.81	Electronic ph and rh meters, other apparatus for measuring conductivity and electrochemical quantities (including use laboratory/field environment, use process monitoring/control)
26.51.53.83	Other electronic instruments and apparatus for physical or chemical analysis n.e.c.
26.51.53.95	Other non-electronic instruments and apparatus for physical or chemical analyses, n.e.c.
26.51.63.50	Liquid supply or production meters (including calibrated) (excluding pumps)
26.60.11.15	Apparatus based on the use of X-rays, for medical, surgical, dental or veterinary uses (including radiography and radiotherapy apparatus)
26.60.11.19	Apparatus based on the use of X-rays (excluding for medical, surgical, dental or veterinary use)

Source: Authors' elaboration

Annex 3 continued **- COVID-19 products according to the Prodcom list 2019**

Prodcom 2019	Description
26.60.11.30	Apparatus based on the use of alpha, beta or gamma radiations, whether or not for medical, surgical, dental or veterinary uses, including radiography or radiotherapy apparatus
26.60.11.50	X-ray tubes (excluding glass envelopes for X-ray tubes)
26.60.11.70	X-ray generators, high tension generators, including parts of HS 9022
26.60.12.30	Electro-cardiographs
26.60.12.80	Electro-diagnostic, apparatus (excluding electro-cardiographs), n.e.c.
26.60.13.00	Ultraviolet or infrared apparatus used in medical, surgical, dental or veterinary sciences
26.60.14.50	Pacemakers for stimulating heart muscles (excluding parts and accessories)
26.70.19.10	Flashlights (including photographic flashbulbs, flashcubes and the like); photographic enlargers; apparatus for photographic laboratories; negastoscopes, projection screens
26.70.22.70	Compound optical microscopes, including those for photomicrography, cinephotomicrography or microprojection
26.70.24.90	Exposure meters, stroboscopes, optical instruments, appliances and machines for inspecting semiconductor wafers or devices or for inspecting photomasks or reticles used in manufacturing semiconductor devices, profile projectors and other optical instruments, appliances and machines for measuring or checking
27.40.15.70	Ultraviolet or infrared lamps, arc lamps
27.40.30.90	Electric lamps and lighting fittings, of plastic and other materials, of a kind used for filament lamps and tubular lamps, including lighting sets for Christmas trees and LED lamps
27.90.11.50	Machines with translation or dictionary functions, aerial amplifiers and other electrical machines and apparatus, having individual functions, not specified or included elsewhere in HS 85 (excluding accumulator chargers, sunbeds, sunlamps and similar suntanning equipment)
27.90.45.70	Sunbeds, sunlamps and similar suntanning equipment
28.13.11.25	Pumps fitted or designed to be fitted with a measuring device, for dispensing liquids (excl.pumps for dispensing fuel or lubricants, of the type used in filling stations or in garages)
28.25.14.10	Machinery and apparatus for filtering or purifying air (excluding intake filters for internal combustion engines)
28.25.14.30	Machinery and apparatus for filtering and purifying gases (other than air and excluding those which operate using a catalytic process, and isotope separators)
28.25.14.40	Machinery and apparatus for filtering or purifying gases by catalytic process (excluding intake air filters for internal combustion engines, machinery and apparatus for filtering or purifying air)
28.25.14.50	Machinery and apparatus for filtering and purifying gases with stainless steel housing, and with inlet and outlet tube bores with inside diameters not exceeding 1,3 cm (excluding intake filters for internal combustion engines)
28.29.22.40	Other mechanical appliances for projecting, dispersing or spraying
29.10.21.00	Vehicles with only spark-ignition engine of a cylinder capacity <= 1 500 cm³
29.10.22.30	Motor vehicles with only petrol engine > 1 500 cm³ (including motor caravans of a capacity > 3 000 cm³) (excluding vehicles for transporting >= 10 persons, snowmobiles, golf cars and similar vehicles)
29.10.22.50	Motor caravans with only spark-ignition internal combustion reciprocating piston engine of a cylinder capacity > 1 500 cm³ but <= 3 000 cm³
29.10.23.10	Motor vehicles with only diesel or semi-diesel engine <= 1 500 cm³ (excluding vehicles for transporting >=10 persons, snowmobiles, golf cars and similar vehicles)
29.10.23.30	Motor vehicles with only diesel or semi-diesel engine > 1 500 cm³ but <= 2 500 cm³ (excluding vehicles for transporting >=10 persons, motor caravans, snowmobiles, golf cars and similar vehicles)
29.10.23.40	Motor vehicles with only diesel or semi-diesel engine > 2 500 cm³ (excluding vehicles for transporting >= 10 persons, motor caravans, snowmobiles, golf cars and similar vehicles)

Source: Authors' elaboration

Annex 3 continued **- COVID-19 products according to the Prodcom list 2019**

Prodcom 2019	Description
29.10.23.53	Motor caravans with only compression-ignition internal combustion piston engine (diesel or semi-diesel) of a cylinder capacity > 1 500 cm³ but <= 2 500 cm³
29.10.23.55	Motor caravans with only compression-ignition internal combustion piston engine (diesel or semi-diesel) of a cylinder capacity > 2 500 cm³
29.10.24.10	Motor vehicles, with both spark-ignition or compression-ignition internal combustion reciprocating piston engine and electric motor as motors for propulsion, other than those capable of being charged by plugging to external source of electric power
29.10.24.30	Motor vehicles, with both spark-ignition or compression-ignition internal combustion reciprocating piston engine and electric motor as motors for propulsion, capable of being charged by plugging to external source of electric power
29.10.24.50	Motor vehicles, with only electric motor for propulsion
29.10.24.90	Other motor vehicles for the transport of persons (excluding vehicles with only electric motor for propulsion4818.50, vehicles for transporting >= 10 persons, snowmobiles, golf cars and similar vehicles)
29.10.52.00	Motor vehicles specially designed for travelling on snow, golf cars and similar vehicles
29.10.59.90	Other special-purpose motor vehicles n.e.c.
30.92.20.30	Invalid carriages not mechanically propelled
30.92.20.90	Invalid carriages motorised or mechanically propelled
32.50.11.30	Dental drill engines, whether or not combined on a single base with other dental equipment
32.50.11.50	Instruments and appliances used in dental sciences (excluding drill engines)
32.50.12.00	Medical, surgical or laboratory sterilisers
32.50.13.11	Syringes, with or without needles, used in medical, surgical, dental or veterinary sciences
32.50.13.13	Tubular metal needles, for medical, surgical, dental or veterinary sciences
32.50.13.15	Needles for sutures used in medical, surgical, dental or veterinary sciences
32.50.13.17	Needles, catheters, cannulae and the like used in medical, surgical, dental or veterinary sciences (excluding tubular metal needles and needles for sutures)
32.50.13.20	Ophthalmic instruments and appliances
32.50.13.33	Instruments and apparatus for measuring blood-pressure (including sphygmomanometers, tensiometers, oscillometers)
32.50.13.35	Endoscopes for medical purposes
32.50.13.40	Clinical or veterinary thermometers, liquid filled, for direct reading (excluding those combined with other instruments)
32.50.13.53	Renal dialysis equipment
32.50.13.55	Diathermic apparatus (including ultrasonic)
32.50.13.63	Transfusion apparatus (excluding special blood storage glass bottles)
32.50.13.65	Anaesthetic apparatus and instruments
32.50.13.70	Instruments and appliances used in medical, surgical or veterinary sciences, n.e.s.
32.50.21.80	Ozone therapy, oxygen therapy, aerosol therapy, respiration apparatus
32.50.30.50	Medical, surgical or veterinary furniture, and parts thereof (excluding tables and seats specialised for X-ray purposes)
32.50.42.90	Spectacles, goggles and the like, corrective, protective or other (excluding sunglasses)
32.50.50.20	Gel preparations for use in human or veterinary medicine as a lubricant for surgical operations or physical examinations or as a coupling agent between the body and medical instruments

Source: Authors' elaboration

Annex 3 continued **- COVID-19 products according to the Prodcom list 2019**

Prodcom 2019	Description
32.50.50.30	Sterile surgical or dental adhesion barriers, whether or not absorbable; sterile suture materials, including sterile absorbable surgical or dental yarns (excluding catgut); sterile tissue adhesives for surgical wound closure; sterile laminaria and sterile laminaria tents; sterile absorbable surgical or dental haemostatics
32.99.59.10	Breathing appliances and gas masks (excluding therapeutic respiration apparatus and protective masks having neither mechanical parts nor replaceable filters)

Source: Authors' elaboration

Annex 4 - COVID-19 economic activities according to the NACE Rev. 2 classification

Division	Class	Title
08		Other mining and quarrying
	08.93	Extraction of salt
10		Manufacture of food products
	10.84	Manufacture of condiments and seasonings
11		Manufacture of beverages
	11.01	Distilling, rectifying and blending of spirits
13		Manufacture of textiles
	13.92	Manufacture of made-up textile articles, except apparel
	13.95	Manufacture of non-wovens and articles made from non-wovens, except apparel
14		Manufacture of wearing apparel
	14.12	Manufacture of workwear
	14.19	Manufacture of other wearing apparel and accessories
17		Manufacture of paper and paper products
	17.22	Manufacture of household and sanitary goods and of toilet requisites
20		Manufacture of chemicals and chemical products
	20.11	Manufacture of industrial gases
	20.13	Manufacture of other inorganic basic chemicals
	20.14	Manufacture of other organic basic chemicals
	20.16	Manufacture of plastics in primary forms
	20.20	Manufacture of pesticides and other agrochemical products
	20.41	Manufacture of soap and detergents, cleaning and polishing preparations
	20.42	Manufacture of perfumes and toilet preparations
	20.59	Manufacture of other chemical products n.e.c.
21		Manufacture of basic pharmaceutical products and pharmaceutical preparations
	21.10	Manufacture of basic pharmaceutical products
	21.20	Manufacture of pharmaceutical preparations
22		Manufacture of rubber and plastic products
	22.19	Manufacture of other rubber products
	22.22	Manufacture of plastic packing goods
	22.29	Manufacture of other plastic products
23		Manufacture of other non-metallic mineral products
	23.19	Manufacture and processing of other glass, including technical glassware
25		Manufacture of fabricated metal products, except machinery and equipment
	25.29	Manufacture of other tanks, reservoirs and containers of metal
	25.99	Manufacture of other fabricated metal products n.e.c.
26		Manufacture of computer, electronic and optical products
	26.51	Manufacture of instruments and appliances for measuring, testing and navigation
	26.60	Manufacture of irradiation, electromedical and electrotherapeutic equipment
	26.70	Manufacture of optical instruments and photographic equipment
27		Manufacture of electrical equipment

Source: Authors’ elaboration

Annex 4 continued **- COVID-19 economic activities according to the NACE Rev. 2 classification**

Division	Class	Title
	27.40	Manufacture of electric lighting equipment
	27.90	Manufacture of other electrical equipment
28		Manufacture of machinery and equipment n.e.c.
	28.13	Manufacture of other pumps and compressors
	28.25	Manufacture of non-domestic cooling and ventilation equipment
	28.29	Manufacture of other general-purpose machinery n.e.c.
29		Manufacture of motor vehicles, trailers and semi-trailers
	29.10	Manufacture of motor vehicles
30		Manufacture of other transport equipment
	30.92	Manufacture of bicycles and invalid carriages
32		Other manufacturing
	32.50	Manufacture of medical and dental instruments and supplies
	32.99	Other manufacturing n.e.c.

Source: Authors' elaboration

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