HELLENIC COMPETITION COMMISSION

BRICS COMPETITION LAW&POLICY CENTRE

Computational Competition Law and Economics: Issues, Prospects

Inception Report

Computational Competition Law and Economics

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Directed by Ioannis Lianos

With contributions from
Hellenic Competition Commission staff (General Directorate of Competition), a team of external experts to the HCC, which included Vassilis Vassalos, Admir Demiraj, Lampis Tzai, Argyris Roumeliotis, Ioannis Rizos, Nancy Xagoni, Mihaly Fazekas, Natercia Fortuna, Bruno Carballa Schmichowski
and
a team from the **BRICS Competition Law and Policy Centre** which included Alexey Ivanov, Anna Pozdnyakova, Natalya Mosunova, Daria Kotova, Mikhail Shikhmuradov and Olga Gavrilova

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Computational competition law and economics

1. Introduction

This research report examines the impact of the use of computational techniques (e.g. Big Data, AI, machine learning, deep learning) and computational economics (e.g. complex economics, systems analysis) in competition law enforcement, and explores the possibilities for more active and targeted competition law enforcement if such techniques are systematically used in the future. Its goal is to engage with the challenges faced by competition authorities in integrating such techniques and advanced learning in the legal framework of competition law enforcement, examining in particular legal requirements with regard to the standard of proof, procedural rights and investigation procedures. The ambition is also to explore ways the implementation of these new technologies may change the direction of competition law, as reliance on new sources of learning and new measurement tools may enhance the ability of competition law to escape from the narrow confines of price theory and develop more analytical frameworks that may better engage with other dimensions of competition than price and the mechanisms of a complex economy[1]. From this perspective, the ambition of this project to explore the transformational impact of these new technologies and sources of knowledge is wider than that of other projects undertaken in the broader field of competition law and policy[2].

This is a topic of crucial importance in view of the increasingly significant use of computational techniques in competition law enforcement by different authorities around the world, as well as the significance of developing more appropriate methodological tools that would be more appropriate in a complex economy. This is often marked by network effects, intense learning effects through the increasing use of algorithms, and low frequency high impact events that produce very complex cascade effects, which spur changes beyond markets on sustainable development, in particular environmental sustainability.

In view of the recent emphasis put by competition authorities worldwide on climate change and environmental and social sustainability, which call for a broader methodological and analytical framework, including the expansion of competition law assessment to more than just analysing prices and output, and the difficulties emerging out of the Covid-19 pandemic, with regard to the possibility of competition authorities to investigate conduct, often now taking place in digital markets, through the traditional means of competition law enforcement, such as down raids, it becomes essential to engage with the possible use of new computational technologies in competition law enforcement. The impact of these new computational methods is not only felt in the competition law enforcement techniques, but also concerns the use of new analytical methods.

Competition law has not yet engaged with complex systems science, in particular the fields of computational economics[3], systems dynamics[4], evolutionary dynamics, network science[5], fractals and scaling, pattern formation[6], econophysics[7], nonlinear dynamics and chaos[8]. Such approaches become crucial the more competition authorities need to explore correlated systems, where (business) conduct occurs at various scales, 'so the complexity

[1] I. Lianos, Competition Law for a Complex Economy, (2019) 50 IIC International Review of Intellectual Property and Competition Law 643.
[2] See, for instance, the Stanford Computational Antitrust Project https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/computational-antitrust-project/ .
[3] L. Tesfatsion, Agent-Based Computational Economics: Growing Economies From the Bottom Up, (2002) 8(1) Artificial Life 55; L. Tesfatsion & K.L. Judd (eds.), Handbook of Computational Economics (North Holland, 2006).
[4] J. Sterman, Business Dynamics (Irwin/McGraw, 2010).
[5] A.L. Barabási, Netowkr Science (CUP, 2016).
[6] T.C. Shelling, Micromotives and Macrobehavior (Norton & Company, 2006)
[7] R.N. Mantegna & H.E> Stanley, Introduction to Econophysics: Correlations and Complexity in Finance (CUP, 1999).
[8] J. Gleick, Making a New Science (Open Road Media, 2011).

gradually increases as one examines the system in greater and greater detail'[9]. Indeed, issues relating to quality and variety competition, as well as the broader social costs arising out of the lack of competition, with the recent emphasis on sustainable development have been recurrent features in competition law scholarship and enforcement in recent years[10]. Introducing concerns over different dimensions of inequality in competition law also require new conceptual and methodological frameworks that break with the sole emphasis on economic efficiency[11] and call for a more 'polycentric' vision for competition law[12].

This new direction for the competition law enterprise is still work in progress. The aim of the report is to provide some examples where a complex systems approach may provide a significant added value to competition law enforcement and to explore possibilities its impact may expand in the future.

2. The use of computational techniques by competition authorities: a state of play

The research will aim to map the use of different computational techniques (Big Data, AI, machine learning, deep learning) by competition authorities around the world, focusing in particular on some selected competition authorities, in view of their different level of development, size and legal system in order to better understand the linkage between the use of these computational techniques and institutional change. For the purposes of this study the following authorities will be examined: the Russian Federal Antitrust Service, the Brazilian Administrative Council for Economic Defence (CADE), the South African Competition Commission and the Hellenic Competition Commission (HCC). The choice was made in view of the more or less systematic use of computational techniques in competition law enforcement by these authorities, the rapid introduction of such techniques during the period of crisis, and the institutional reforms that have taken place during the same time so as to facilitate the introduction of such new techniques in the work of these authorities.

The project team has engaged with the heads of these authorities and their staff in better understanding the challenges they faced, their specific choice of computational tool/technique, the way this was rolled out and integrated in the work of the authority, the collaboration between the "new" experts (those with a data science background, IT

[9] A. F. Siegenfeld, Y. Bar-Yam, An Introduction to Complex Systems Science and its Applications, (2020) Complexity arXiv:1912.05088, 3.

[10] See the recent emphasis on the role of competition law to protect privacy [N. Economides, & I. Lianos, Restrictions on Privacy and Exploitation in the Digital Economy: A Competition Law Perspective (August 30, 2019). Forthcoming, Journal of Competition Law and Economics, CLES Research Paper Series 5/2019, ISBN: 978-1-910801-29-1, NYU Stern School of Business, NET Institute Working Paper No. 21-02, Available at SSRN: https://ssrn.com/abstract=3474099]; or the role of competition law in promoting sustainable development [see https://www.epant.gr/en/enimerosi/competition-law-sustainability.html].

[11] I. Lianos, Competition Law as a Form of Social Regulation, (2020) 65(1) The Antitrust Bulletin 3.

[12] I. Lianos, Polycentric Competition Law, (2018) 71(1) Current Legal Problems 161.

engineers etc) with the more traditional experts usually found in competition law authorities (such as competition lawyers and economists), the institutional arrangements or legislative changes made in order to enable a more effective use of such techniques, for instance rules concerning hearings, investigations, standard of proof etc. Furthermore, it will be particularly important to understand the different technological choices made in the development of such techniques and screening tools in the various jurisdictions (for instance, is this a proprietary system or an open software? Does this collect real time data and how? What is the appropriate format for the data? What type of analyses can each of these tools perform? What have been the results of their usage by competition authorities and in which cases have they used them? Are these tools only used by case teams or can they also contribute to a better management of the authority and better case management?). The constitution of data platforms and competition screens in real time assessment of competitive interactions offer important opportunities to develop a more robust competition law and policy.

We will first examine the emergence of computational antitrust, in particular the systematic use by some competition authorities of screening tools and algorithms in order to detect anticompetitive collusive conduct. We will then examine how these screening tools may expand to other areas of competition law enforcement, by looking to the experience gained in the design of screening tools for the enforcement of competition law during the Covid-19 crisis in Greece. We will discuss a number of concrete examples where such tools have been used.

2.1. The emergence of computational antitrust

2.1.1. Employing screening tools and algorithms to detect collusive conduct

Competition authorities usually rely on 'market-based' evidence focusing on the detection of coordinated oligopolistic price elevation, including 'price patterns' in the industry, evidence of price elevation and facilitating practice. Econometric techniques using a structural approach (focusing on markets with traits thought to be conducive to collusion) have been used to help provide information as to where cartels may be located, as well as logit models or OLS predicting the probability or the number of cartels likely to exist in a specific industry[13]. Some authors have also emphasised behavioural approaches to detecting cartels, which also require the use of econometric techniques.[14]

[13] OFT773, 'Predicting cartels' (Economic discussion paper, March 2005). For an overview, see P Rey, 'On the Use of Economic Analysis in Cartel Detection', in C-D Ehlermann and I Atanasiu (eds), *Enforcement of Prohibition of Cartels, European Competition Law Annual 2006* (Hart Pub, 2007) 69–82; P A Grout and S Sonderegger, 'Structural Approaches to cartel Detection' in C-D Ehlermann and I Atanasiu (eds), *Enforcement of Prohibition of Cartels, European Competition Law Annual 2006* (Hart Pub, 2007) 83–104.
[14] J E Harrington, Jr, 'Detecting Cartels' (Department of Economics, John Hopkins University, 2005), available at econ.jhu.edu/wp-content/uploads/pdf/papers/wp526harrington.pdf ; J E Harington Jr 'Behavioral

Quantitative economic analysis includes, as a first step, an industry analysis with a scoring approach (looking to different variables, such as indicators of price, transparency, concentration and entry) in order to exclude from the sample cases where cartel activity is relatively improbable and, as a second step, a critical event analysis (with a focus on exogenous shocks or structural breaks) testing the collusive against the competitive scenario.

The OECD has reported a number of EU member States where cartel investigations were triggered based exclusively on economic indicators.[15] Most recent research has focused on the role of 'empirical', as opposed to 'structural' screening techniques in uncovering collusive oligopolistic interdependence[16]. As it is explained by Abrates-Metz, '(t)he purpose of screening is not to deliver the final evidence based on which colluders will be convicted, but instead to identify markets where empirical red flags are raised and which are worth further investigations'[17].

Algorithms offer additional opportunities for detecting collusion more accurately on the basis of Big Data evidence. They complement existing digital technologies used for competition law enforcement, such as online whistleblowers tools. Whistleblowers tools are online web forms to inform authorities about competition law violations. Although there have been some earlier examples[18] the EU Commission has introduced this tool as recently as in 2017.[19] As previously discussed screening relies on an econometric analysis of data. However, by-hand econometrics analysis has limitations, as it solely depends on human resources. The Korean Fair Trade Commission (hereinafter KFTC) observes that investigation of possible collusive bidding solely by humans is difficult, as the information 'was usually sent in written form which made it physically impossible for the KFTC to thoroughly review and analyze it'.[20] Digital technology developments shift manual analysis of data to automatic cartel detection. Software screening tools for cartel detection are

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Screening and the Detection of Cartels' in C-D Ehlermann & I Atanasiu (eds), *Enforcement of Prohibition of Cartels, European Competition Law Annual 2006* (Hart Pub, 2007) 51–68.

[15] See, for instance, the Italian baby milk case (where a cross-country price benchmarking was used): OECD, DAF/COMP/GF(2006)7, pp 22–24. See also the Dutch shrimps case (structural indicators were employed): J E Harrington, Jr, 'Detecting Cartels', op cit, pp 3–4.

[16] R Abrantes-Metz, OECD *Roundtable on Ex- Officio cartel investigations and the use of screens to detect cartels*, OECD DAF/COMP(2013)20 (noted omitted), pp 3–4.

[17] R Abrantes-Metz, OECD *Roundtable on Ex- Officio cartel investigations and the use of screens to detect cartels*, OECD DAF/COMP(2013)20 (noted omitted), pp 3–4.

[18] In 2012 an anonymous online whistleblower tool was implemented by the Bundeskartellamt in Germany. See https://www.bundeskartellamt.de/EN/Banoncartels/Whistle-blower/whistle-blower_node.html
Since 2017 anonymous whistleblowers tools exist in EU and UK https://cma-553899.workflowcloud.com/forms/c35b9608-b73d-464c-bbfa-0b3ccda758b2

[19] European Commission. Press release. March 2017. http://europa.eu/rapid/press-release_IP-17-591_en.htm

[20] https://one.oecd.org/document/DAF/COMP(2013)14/en/pdf P. 61.

applied by competition authorities in Russia, Korea, Brazil and the UK. They are currently under development in Spain[21] and Canada[22].

One of the first software screening tool was implemented in Korea in 2006. This software screening tool called Bid Rigging Indicator Analysis System (BRIAS) automatically analyses bid information obtained from 332 Korean public procurement agencies.[23] Amongst the successful BRIAS cases is the detection of collusion in the Seoul Subway Line 7 construction.[24] In 2017 two more software tools for cartel screening were introduced: FAS Russia announced the successful implementation of their software screening tool in mid-2017, and the UK Competition and Markets Authority (CMA) shared an open Screening for Cartels tool at the end of 2017. [25]

To date, the software screening tool developed by FAS Russia detected eighty cartels in e-procurement, including the most serious bid rigging in construction and medical supply e-procurements, which amounted to 197 billion rubles (circa $2 billion dollars).[26] The success of the FAS Russia screening resulted in a number of institutional changes with the establishment of a new department specializing in the use of the software screening tool.[27] This software tool was named "Big Digital Cat", as it detects "mouse", that is cartels, in the digital age.

The FAS software screening tool was named "Big Digital Cat", as it detects "mouse", that is cartels, in the digital age. The screening service automatically collects publicly available data (for example, from UIS, ETP mass media) and information that is not disclosed to the public (such as that from the Federal Tax Service database) and then use algorithms for establishing whether the collected data complies with specified criteria. Based on this analysis, Big Digital Cat also forms evidence according to the procedural law to be used in an inquiry and a trial.[28]

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[21] In May 2018 Spain National Authority for Markets and Competition (CNMC) officially reported the development of screening software in collaboration with professionals in statistics, computer and data science, https://www.cnmc.es/node/368434

[22] Matthew Boswell. Bid-rigging Detection and Prevention: Ensuring a Competitive and Innovative Procurement Process. Speech at Canadian Public Procurement Council Forum 2017: Innovation in Public Procurement. November 2017. Matthew Boswell in his November 2017 speech at Canadian Public Procurement Council Forum on innovation announced the development of software screening tool URL: https://www.canada.ca/en/competition-bureau/news/2017/11/bid-rigging_detectionandpreventionensuringacompetitiveandinnovat.html

[23] Korea Fair Trade Commission, Current Status of Operation of Bid Rigging Indicator Analysis System, http://www.ftc.go.kr/www/cmm/fms/FileDown.do?atchFileId=FILE_000000000079626&fileSn=0
, Roundtable on Ex Officio Cartel Investigations and the Use of Screens to Detect Cartels, OECD, https://one.oecd.org/document/DAF/COMP(2013)14/en/pdf P. 62.

[24] Korea Fair Trade Commission, Current Status of Operation of Bid Rigging Indicator Analysis System, P. 6.

[25] https://www.gov.uk/government/news/cma-launches-digital-tool-to-fight-bid-rigging

[26] https://fas.gov.ru/news/1690/export_to_file.pdf (in Russian).

[27] https://fas.gov.ru/news/26154 (in Russian).

[28] Федеральная антимонопольная служба. (2019, сентябрь 18). Андрей Цыганов: В раскрытии сговоров на торгах ФАС активно использует анализ открытых источников данных. https://fas.gov.ru/news/30480.

The Administrative Council for Economic Defense (CADE) in Brazil also developed the screening tool Projeto Cérebro, which was integrated into the federal electronic procurement system Comprasnet in 2018.[29] Projeto Cérebro helped CADE to effectively detect bid rigging in the supply of implantable cardiac pacemakers.[30]

Each jurisdiction takes a different approach in designing and implementing their software screening tools. First, screening tools may address different stakeholders. The CMA developed screening tool not only for CMA related work, but also for public and private procurers.[31] This tool should help procurers to flag suspicious procurement exercises in their tenders and notify CMA for further investigation. However, both the decision to use this tool and CMA notification are at the discretion of procurers. In contrast, in Korea, Russia and Brazil, the software tools for cartel detection aim competition authorities. Only competition authorities have direct access to the software tools implemented into the electronic public bidding systems. These software tools automatically transfer bidding information to the competition authorities. Procurers do not have access to the software screening tools.

Second, most competition authorities keep their screening tools private and share neither its source code nor binary executable. However, unlike most countries, the UK screening software is an open source software available for download by interested persons upon request. The black-box approach chosen by most competition authorities aims to avoid disclosure of implementation details to possible colluders. This secrecy makes it difficult for would be colluders to game the screening tool.

Third, software tools developed by competition authorities have different designs, as they differ in both set of collected bidding information and indicators they analyze.

To the best of our knowledge,[32] all parameetrs analyzed by screening tools might be grouped into four categories:

- Number and pattern of bidders;
- Suspicious pricing patterns;
- Low endeavor and similar submissions;
- Tenders' history data.

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[29] Cartel screening in the digital era – CADE Brazil – January 2018 OECD Workshop. https://www.slideshare.net/OECD-DAF/cartel-screening-in-the-digital-era-cade-brazil-january-2018-oecd-workshop See also http://www.lickslegal.com/clientalert/Newsletter_Antitrust_January2018.pdf P. 5. http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/LACF(2016)19&docLanguage=En p.3

[30] http://www.cade.gov.br/noticias/superintendencia-instaura-processos-para-apurar-cartel-no-mercado-de-orteses-proteses-e-materiais-medicos-especiais

[31] CMA launches digital tool to fight bid-rigging. Press release. https://www.gov.uk/government/news/cma-launches-digital-tool-to-fight-bid-rigging

[32] The CMA provided us access to the software screening tool source code, as the CMA screening tool is an open software available for download upon request. Thus, we analyzed the CMA screening tool source code in detail. Other software screening tools are not publicly available, and we revised them based on the information publicly disclosed by FAS Russia, KFTC and CADE in the conference proceedings and other publications.

To find suspicious tenders, the CMA screening tool analyses eight criteria and performs four combination tests. The category *Number and pattern of bidders* carries out the following tests: low number of bidders, which is triggered when the number of bidders is less than three; and single bid test. The category *Suspicious pricing patterns* includes: 1. the "winning price is outlier" test, which is triggered when winning price is more than in one standard deviation away from mean price of all bids; 2. The "similar pricing across bids" test is triggered when ratio of prices mean to standard deviation is less than fifteen; 3. the last criterion analyzed in this category is made up costs. This test verifies that all prices in the bid conform to Benford's law. This criterion is unique across software tools developed by other countries. By analyzing frequency of the first digit, it allows one to find out that the distribution of costs listed in the bid consists of made up numbers rather than real prices. The next category analyzed by CMA software tool is the *Low endeavor and similar submissions*. This category includes the following criteria: 1. The fact that there are same authors in more than one bid, which analyses author name according to the metadata of files submitted by the bidders. 2. The "low endeavor losing bids" test, which evaluates the ratio of submitted documents revision count to time spent editing the document. Both values are extracted from submitted documents metadata. 3. The "similar text in losing bids" test, which compares words frequency of two losing bids weighted by the inverse of overall word frequency in all bids.

Since the CMA tool analyses data of a single tender only, it does not carry out any tests from the *Tenders' history data* category. Each criterion is associated with its weight, which is added to the tender's "suspicious score".

Due to the limitations of such a simple linear score computation model, tool developers enriched the list of criteria by four combination tests. Each combination test relies on two basic tests and is triggered when both basic tests are triggered. The CMA combination tests are the following: similar text and word count in losing bids; low number of bidders and made up prices; winning price is outlier and made up prices; made up prices and low effort. While the linear "suspicious score" model appears to be used in all screening tools under review, only the CMA tool employs combination tests to overcome the limitations of the linear model. This makes the CMA tool more flexible.

Unlike the CMA tool, the FAS software analyses tenders 'history data in addition to the data of the current tender. This feature enables FAS Russia to detect bid-rigging techniques that cannot be discovered by analysing a single tender, for example, bid rotation and bid suppression. In the *number and pattern of bidders* category, the FAS tool executes only the "low number of bidders" test. In the "suspicious pricing patterns" category, the FAS tool analyses the difference between the winning bid price and market price. The FAS tool compares bidders 'IP addresses, sets of fonts used in the submission, number of characters in submitted documents and performs a rich analysis of metadata (comparing authors ' name, time of creation, and software version). The tool analyses text similarities (like the

CMA tool), and it appears to perform a deep analysis of implicit similarities (e.g. IP address, fonts, metadata).

A mathematical model has been developed for the analysis, clustering, indexing of big data that is necessary to detect and subsequently prove the conclusion and (or) implementation of cartels and other anticompetitive agreements. The FAS Russia tool's developers declared that it relies on the analysis of fifty criteria.[33] Unfortunately, only few criteria have been disclosed.

Unlike the CMA tool, the FAS software analyses tenders' history data in addition to the data of the current tender. This feature enables FAS Russia to detect bid rigging techniques that cannot be discovered by analysis of a single tender, for example, bid rotation and bid suppression. In the *number and pattern of bidders* category, the FAS tool executes only the "low number of bidders" test. In the "suspicious pricing patterns" category, the FAS tool analyses the difference between the winning bid price and market price. The FAS tool compares bidders' IP addresses, sets of fonts used in submission, number of characters in submitted documents, and performs a rich analysis of metadata (comparing authors' name, time of creation, and software version). There is no evidence that the FAS Russia tool analyzes text similarities (unlike the CMA tool), but it appears to perform a deep analysis of implicit similarities (e.g. IP address, fonts, metadata). This approach turns out to be fruitful, as it helped to detect dangerous collusion in the supply of medical expendables' procurement, which amounted to 197 billion rubles (circa $ 2 billion).[34] Thanks to analysis of historical data, FAS tool can perform tests from the *Tenders history data* category and detect bid rotation and companies which often win tenders.

The research for the model has examined 32 structural indicators, 12 behavioural signs, 29 indicators from the UIS and nine indicators from ETP and established that 14 features of UIS and ETP are highly informative; other parameters may be of lower relevance.

Cluster analysis has determined four different clusters. If a bidder or a buyer changes behaviour patterns of procurement, it results in changes in the number of clusters, their boundaries, and standards. The research also has proven that clustering depends on the industry (construction, medicine, food supplies, etc.).[35]

A conceptual model of bidders behaviour on the electronic platform has been examined to establish the sequence of their actions and the elements of risks to breach the law. To minimise the risk of error, the list of indicator which cannot be analysed mathematically has been introduced.

[33] Andrey Tsarikovskii, Alexey Ivanov, Elena Voinikanis, Ekaterina Semenova, Andrey Tenishev, Mukhammed Khamukov. Antitrust Regulation in the Digital Age. Competition Enforcement in the Context of Globalization and the Fourth Industrial Revolution. P. 153. doi: 10.17323/978-5-7598-1750-5 (in Russian);

[34] FAS Russia Deputy Head Andrey Tsarikovskii emphasized the role of FAS Russia software screening in the detection of collusion behavior in the "VALERIA" and "Egmed" bid rigging case.

[35]*https://fas.gov.ru/p/presentations/611?fbclid=IwAR2dFl_aLmULKksNXhA0Tc_TE14tcHmcxMGU2etCewL4_bsX2kxWYBP0Q4s*

In addition to discovering anticompetitive conspiracy in automatic mode, the software creates documents for further procedural stages of investigation (report, market analysis, case decision) and assesses the probability of collusion (scoring).[36]

Following the development of the 'Big Digital Cat' tool, in 2019, during the FAS's agenda to unify merger rules, a project was developed which enables companies to file electronic merger notifications, and the antimonopoly body - to analyze big data arrays using artificial intelligence.t was outlined that the final decision, anyway, would be made by a human. Similar to Big Digital Cat, the project was named Big Digital Dog[37]. However, the initiative is still in progress due to several reasons, one of which is serious concerns about the confidentiality of information sent to the agency through online forms

The Korean BRIAS is a non-public software tool used internally by the KFTC. The tool automatically collects information from the Korean e-procurement system KONEPS, used by multiple Korean procurers. To detect suspicious behavior, BRIAS checks a small number of bidders' criteria, and the winning price as the outlier criterion. More specifically, the winning price computes the gap between the winning price and the prices of the second and the third bidders. In the *Suspicious pricing patterns* category, similarly to FAS tool it also analyses the number of bids above the market price. The tool also carries out the test from tender's history data category and detects companies with a high winning rate. A strong point of the BRIAS is its integration with the national e-procurement system, enabling a completely automated screening pipeline.

Projecto Cerebro developed by CADE Brazil collects data for the analysis from 40 databases including prices and public procurement databases.[38] The collected data is used to perform tests from the suspicious pricing patterns category, such as cover bidding and superfluous losing bidders. It also detects low endeavor and similar submissions by searching for text and metadata (author, IP address) similarities. The tool is also advertised to analyze historical data and detect bid rotation, bid suppression and stable market share.[39] Table 1 summarizes the main features of the discussed software screenings.

Table 1.: Comparative table of software screening tools

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[36] *Tarkhova, K. V., Alifirov, V. I., & Gorokhova, O. N. (2020). The evolution of antitrust regulation in Russia in digital era. Digital Law Journal, 1(4), 38–55. https://doi.org/10.38044/2686-9136-2020-1-4-38-55*

[37] Regulatory rules should be improved in cooperation with the legal community / FAS. September 30, 2019. URL: http://en.fas.gov.ru/press-center/news/detail.html?id=54400

[38] LATIN AMERICAN AND CARIBBEAN COMPETITION FORUM, Session III: Promoting effective competition in public procurement -- Contribution from Brazil -- 12-13 April 2016. P.4. http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/LACF(2016)19&docLanguage=En

[39] Slides Cartel screening in the digital era – CADE Brazil – January 2018 OECD Workshop.

Analyzed criteria \ Screening tool	**UK CMA**	**Russia FAS**	**Korea BRIAS**	**Brazil CADE Projecto Cerebro**
Number and pattern of bidders	+	+	+	
Low number of bidders	+	+	+	
Single bid	+			
Suspicious pricing patterns	+	+	+	+
Winning price is outlier	+		+	
Non-market bids		+	+	+
Winning price is close to start price		+		
Similar pricing across bids	+			+
Made up costs	+			
Low endeavor and similar submissions	+	+		+
Text similarities	+			+
Similar word count	+	+		
Low endeavor losing bids	+			
Metadata similarities	+	+		+
Same fonts		+		
History of participation		+	+	+
Bid rotation		+		+
Bid suppression				+

Stable market share and/or constant winner		+	+	+
Combination tests	+			

We conclude that no screening tool outperforms other screening tools, since each tool has its strong and weak points. For example, the FAS Russia's tool main advantage is deep metadata analysis (e.g. fonts analysis). The Korea BRIAS' tool strong point is seamless integration with the e-procurement system, uniting administrative agencies, local governments and government companies. [40] The CMA tool uses combination tests, allowing it to overcome the limitations of linear model.

This observation highlights the need for collaboration between competition authorities to develop new generation software screening tools. Moreover, all the tools rely on a large amount of rather simple tests, that can be simply fooled by astute colluders. For example, metadata can be simply forged by bidders, thus rendering metadata-based tests useless. Colluders can also fool made up prices test by generating fake costs according to Benford's law. The wider use of screening tools inevitably leads to growth of colluders' awareness and the number of attempts to game these tools. This once again emphasizes the need for a collaborative development of new smarter tools by competition authorities, although one may also see some value in the existence of different systems that may be a source of experimentation.

Existing software screenings rely on a linear model and use simple tests, mostly easy to deceive by astute colluders. Big data and advanced machine learning techniques might offer a possible solution to this problem, as they provide the possibility to find nontrivial collusive patterns that econometrics could not foresee and they may build non-trivial tests on these patterns. As we mentioned above, the main advantage of current screening tools is the analysis of large amounts of procurement data, which is infeasible if this was done by humans. Advanced machine learning techniques should enable the employment of effective cartel detection criteria on the basis of Big Data which were previously unknown to econometrics.

However, the transition from a linear model with hand-crafted weights to advanced machine learning techniques (such as neural networks or random forests) requires big training data sets containing examples of collusive and competitive behaviour.

The creation of such data sets demands a huge number of man-hours to analyze procurement data and annotate whether it is competitive or not, and thus requires some collaboration between competition authorities. Rosa Abrantes-Metz analyses the

[40] P. 62. OECD 2013.

possibilities of machine learning aid in cartel detection asking whether "such a data set exist today – with a sufficient number of cases of both collusion and not-collusion, with the necessary data on price, cost, and drivers of supply and demand – or will we have to wait for it?".[41]

To our mind, in order to create a training data set containing collusive examples for neural networks and other machine learning methods, competition authorities should share data on cartels gained by the operation of existing software screenings, such as the Korea BRIAS, Brazil Projecto Cérebro, and FAS Russia software screening tools. Moreover, new suspicious behaviour criteria found during analysis of such a data set should also be shared across borders to improve the screening tools of all countries.

Notably, improvement and wider usage of the software screening tools will make colluders polish bid-rigging techniques to make them invisible to these tools. In its turn, the improvement of bid-rigging methods will require the development of better screening tools. Therefore, we are at the beginning of yet another sword and shield competition between competition authorities and colluders. Finally, to discourage over optimistic expectations from screening tools, we want to emphasize that disregarding any progress made in their improvement, screening tools enable to find only *suspicious* behavior. The final decision whether this is *collusive* behavior, should remain with the competition authority.[42]

2.1.2. Institutional changes in order to integrate computational techniques

2.1.2.1. Organisation of competition authorities

The use of screening tools by competition authorities is not the only manifestation of the computational turn, framed by some as the "more technological approach"[43], in competition law enforcement. More and more competition authorities hire data scientists and put in place special units in order to assist then in developing advanced forensic techniques and data analytics. This follows the pattern that was initiated with the new economic approach and the recourse to economic evidence in the 1908s in the US with the adoption of the 1982 Merger Guidelines and in the late 1990s-early 2000s in EU, during the era of modernisation of competition law enforcement, and the appointment of chief

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[41] Rosa M. Abrantes-Metz & Albert D. Metz. Can Machine Learning Aid in Cartel detection? CPI Antitrust Chronicle July 2018. P. 3. https://www.competitionpolicyinternational.com/wp-content/uploads/2018/07/CPI-A-M-Metz.pdf

[42] Lianos, Ioannis and Genakos, Christos, Econometric Evidence in EU Competition Law: An Empirical and Theoretical Analysis (October 1, 2012). CLES Research Paper series 06/12. Available at SSRN: https://ssrn.com/abstract=2184563 or http://dx.doi.org/10.2139/ssrn.2184563.

[43] R. Podszun, The More Technological Approach: Competition Law in the Digital Economy, in Surblytė G. (eds) Competition on the Internet. MPI Studies on Intellectual Property and Competition Law, vol 23. (2015, Springer), 101.

economists at the European Commission in 2003 and now in most competition authorities in the EU and beyond[44].

Some competition authorities in the EU have already proceeded to the appointment of a chief technology officer and specific units. Moreover some authorities have already acquired experience in using Big Data or AI (machine-learning or deep-learning solutions) in cartels detection and in the analysis of data obtained during a cartel investigation. In particular, in Finland a new ICT and a digital unit were established as of May 2020 in order to strengthen their capacity to meet new digitalisation challenges. The office is headed by a chief technology officer (CTO), who has a background in antitrust enforcement. This digital unit collaborates with other units of the authority, as well as with its Forensic IT functions, which is part of the cartel enforcement Unit. The Finish Competition and Consumer Authority (FCCA) had also launched a short POC (Proof-of-concept) project titled cartel-radar ("kartellitutka" in Finnish), in which the Authority tested textual parsing and analytics as a part of screening newsfeeds. Finland has also some open-source projects or portals to dig into some national data assets. For example, there is an "explore public spending" portal, which allows anyone to dig into the public procurement data of Finland's government agencies. While the portal cannot be regarded as AI or machine-learning, it is an example of a way to dig into Big Data[45].

The Dutch ACM has also appointed a Chief Data Officer with experience in cognitive science and artificial intelligence. The Chief Data officer is responsible for the DataHub, which groups 15~20 data engineers and data scientists, who are working in projects with and for all departments within ACM and also contribute to the development of the data strategy of the ACM. The authority has also a short experience in using Big Data, as it is currently working on the implementation of classifiers in the context of bid-rigging. The ACM has developed the implementation in-house. Furthermore the ACM has developed a proof-of-concept of technology assisted review in the context of e-discovery.

In January 2020, the French Competition Authority created a digital economy unit. This specialised unit will report directly to the General Rapporteur (the head of investigations at the French NCA) and will be tasked with developing in-depth expertise in all digital areas. The unit will be composed of a head of unit, an economist, a data scientist, a software engineer and a lawyer. The digital economy unit will take part in the Autorité's discussions and sector-specific inquiries on new issues related to the development of digital technology, in line with those already carried out on big data, online advertising and algorithms. The team will also be responsible for developing new digital investigation tools, based in particular on algorithmic technology, big data and artificial intelligence. The new

[44] For a critical analysis, I. Lianos, Judging' Economists: Economic Expertise in Competition Law Litigation - A European View, in I. Lianos & I.Kokkoris (eds.), New Challenges in EC Competition Law Enforcement (Kluwer, 2010), 185.

[45] Link to the aforementioned portal: https://tutkihankintoja.fi/?lang=en.

service will also provide support to the Autorité's investigation and inspection units that are handling cases with a significant digital dimension (mergers involving actors from the digital sector, breaches of competition law committed by digital means, problems with referencing, ranking bias or collusion through the use of algorithms). Finally, the digital economy unit will work in close cooperation with industry regulators, relevant government departments and other competition authorities at European and international level to develop convergent and standardised methods of analysis and intervention. It will also be responsible for developing discussions with the academic community and research institutions specialising in digital subjects.

In order to efficiently respond to the challenges and opportunities that digital platforms pose to the society, the Competition and Markets Authority (CMA) has also started setting up its new Data, Technology and Analytics (DaTA) unit aiming to ensure that CMA stays ahead, using the latest in data engineering, machine learning and artificial intelligence techniques. DaTA Unit was also in the priority focus areas of the general "Digital Markets Strategy" that CMA has launched[46]. The unit has in view to pioneer the use of these techniques internally aiming to increase the effectiveness of CMA while enabling it to understand how firms are using data, what their machine learning (ML) and AI algorithms are doing, the consequences of these algorithms and, ultimately, what actions authorities need to take. More specifically, CMA's DaTA Unit[47] has built a cutting-edge analytics platform in AWS using a bespoke implementation of JupyterHub. This enables the storage, processing and analysis of big and complex data speedily and flexibly. On top of this infrastructure, they have implemented an Agile operating model. The implementation of the above are already bringing insights into CMA, by developing machine learning tools to identify possible breaches of consumer law on digital platforms and applying the latest natural language processing techniques to sift and review 100,000s of internal documents from companies, which we receive in the context of our cases. In this context, the DaTA unit is growing in the key capabilities areas of Data Engineering and Data Science Innovation & Intelligence.

In particular, the Director of Data Science will have a prominent role as the most senior data scientist in the CMA. Among his responsibilities would be to oversee the development of algorithmic auditing capabilities, intelligence on technological developments in the markets and original research. The data scientists coordinated by the Director will lead a machine learning team with two functions, to use machine learning to improve what the

[46] CMA launches Digital Markets Strategy https://www.gov.uk/government/news/cma-launches-digital-markets-strategy and assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/814150/cma_digital_markets_strategy.pdf
See also https://www.bakermckenzie.com/en/insight/publications/2019/07/cma-launches-digital-markets-strategy

[47] "The CMA DaTA unit – we're growing!", Stefan Hunt, 28 May 2019 https://competitionandmarkets.blog.gov.uk/2019/05/28/the-cma-data-unit-were-growing/

CMA does and, importantly, to develop an analytical toolkit to understand how companies are using algorithms and when authorities should intervene. Additionally, the Head of Data Engineering will lead the engineering team, which will support the CMA in understanding the kinds of data used by the companies it investigates, what firms do with that data and how to obtain and wrangle that data. Recent types of data include clickstream data from websites, Instagram posts, large email caches and more. They will also help develop the CMA's thinking about the critical issues of data privacy, data access and the regulation of data. The Lead Technical Expert will be the team's 'Tech Guru', taking responsibility for maintaining a broad understanding of the latest machine learning and AI techniques used in commercial organisations. The Lead Technical Expert will use their knowledge and insight to help the CMA use these techniques and become a thought leader on the use of algorithms, including on issues such as algorithmic fairness, transparency and explainability[48].

In parallel, it is advisable to report on a new Digital Markets Taskforce in connection with the creation of an upcoming Digital Market Unit embedded within the CMA. In March 2020, the CMA was asked to lead a Digital Markets Taskforce[49], working closely with the Office of Communications (Ofcom) and the Information Commissioner's Office (ICO), to provide advice to the government on the design and implementation of a pro-competition regime for digital markets. The government was clear when commissioning this work that it should complement and build on the outputs of the Furman Review[50], as well as drawing evidence from the CMA's market study into online platforms and digital advertising. The Digital Markets Taskforce will be informing a new Digital Markets[51] Unit which will be set up within the CMA. The new unit will begin to operate in April 2021 while working closely with regulators including Ofcom and the ICO in order to introduce and enforce a new code to govern the behavior of platforms. In addition, the Digital Markets Unit could be given powers to suspend, block and reverse decisions of tech giants, order them to take certain actions to achieve compliance with the code, and impose financial penalties for non-compliance.

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[48]"CMA's new DaTA unit: exciting opportunities for data scientists", Stefan Hunt, 24 October 2018 https://competitionandmarkets.blog.gov.uk/2018/10/24/cmas-new-data-unit-exciting-opportunities-for-data-scientists/

[49] A new pro-competition regime for digital markets Advice of the Digital Markets Taskforce, par.1, https://assets.publishing.service.gov.uk/media/5fce7567e90e07562f98286c/Digital_Taskforce_-_Advice_--.pdf

[50] Report of the Digital Competition Expert Panel "Unlocking digital competition", Furman Review https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf

[51] New competition regime for tech giants to give consumers more choice and control over their data, and ensure businesses are fairly treated, https://www.gov.uk/government/news/new-competition-regime-for-tech-giants-to-give-consumers-more-choice-and-control-over-their-data-and-ensure-businesses-are-fairly-treated

The Office for the Protection of Competition of Czech Republic has also established an IT Unit. The Head of the IT Unit could be considered as CTO, as he works closely with other units during dawn raids and in particular investigations. The IT Unit provides equipment for data processing and technical support to the investigators. Within the Office, the Chief Economist could have similar competences as CDS or CINO. His unit analyses, case by case, problematic competition issues. Moreover, the Office for the Protection of Competition cooperates with the Masaryk University – Faculty of Economics and Administration, on basic detection software which should be helpful in detecting bid rigging cases. The Office tries to introduce some new obligations to contracting authorities in relation to publication of relevant data through the amendment to current Act on Public Procurement.

In 2009 the German Competition Authority[52] has also set up a Unit specialising on IT forensics[53], which assists the decision divisions in collecting and analysing IT data e.g. in conducting online surveys in major proceedings and seizing and evaluating IT data in cartel detections. The Unit is also responsible for developing further the forensic expertise in this area. Moreover the new "Digital Economy" unit cooperates with the IT Unit.

Some authorities have also included in their organizational structure an IT Forensic unit, such as the Austrian Federal Competition Authority[54] and the Italian Competition Authority[55], while the Hungarian Competition Authority[56] has established an IT and Document Management section. Furthermore, the Office of Competition and Consumer Protection in Poland[57] has set up an office of IT and security which is responsible for planning and implementing tasks related to the maintenance and development of IT systems of the Office and ensuring property protection. This Competition Authority does not have experience in using Big Data or AI to detect bid rigging, but it does have a project under way, aimed at devising and implementing a system of risk markers. So it has implemented datasets of large infrastructural tenders (several hundred tenders in total), which contain very rich information on the tenders in question.

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[52] Bundeskartellamt Annual Report 2019, https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Jahresbericht/Jahresbericht_2019.pdf?__blob=publicationFile&v=3 (p.12)
Organisation Chart of the Bundeskartellamt, 1 January 2021, https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/OrganizationalChart/Organisation%20Chart.pdf?__blob=publicationFile&v=46

[53] It is mentioned as "Information Technology Unit" in the New Organisation Chart of the Bundeskartellamt.

[54] Federal Competition Authority website, Organization of the Authority https://www.bwb.gv.at/en/federal_competition_authority/organisation/

[55] Italian Competition Authority, IT Operations and Forensic IT Office, https://en.agcm.it/en/about-us/organization/detail?id=32a1c931-ec76-4340-8691-0150005f74a9

[56] The Organisational Structure of the Hungarian Competition Authority, https://www.gvh.hu/en/gvh/legal_status_of_the_gvh/organigram

[57] Office of Competition and Consumer Protection website, https://www.uokik.gov.pl/departments.php#faq4136

The Swedish Competition Authority (SCA)[58] has a Communications and IT Unit which is responsible for external and internal communications, publications and press. The unit is also responsible for the Authority's overall management function of external tip-offs and enquiries and for the IT-support in the organisation. Moreover, SCA has set up a project group who is currently analysing the possibilities for the SCA to use AI in its investigations. So far, the main areas of potential use concern situations where the SCA needs to process and analyse obtained data using machine learning and text analysis. The Authority is in the early stages of developing a ML-tool aiming at organising a large number of documents based on their content. Such a tool would make it possible for a case team to quickly get an overview of the case file following an inspection where a lot of digital material has been collected.

The Spanish competition authority (CNMC)[59] has a Systems and Information and Communication Technologies unit, specialised in computer technologies, which provides support to all the units of the CNMC and which is responsible for the implementation of and permanent support for all technological infrastructure. Furthermore, in 2018 the CNMC created the Economic Intelligence Unit (EIU) with full time staff dedicated to the ex-officio detection of anticompetitive practices and a particular focus on the detection of cartels, especially in the field of public procurement. This unit, which is located in the Competition Directorate, is equipped with qualified staff and specific resources to promote the ex-officio detection of collusive behaviour, in particular of cartels affecting public contracts. The staff of this unit specialises in quantitative techniques, forensic analysis, open-source intelligence (OSINT) and cartel investigation and is responsible for the development of statistical tools and screening techniques to identify collusive patterns in the data. The type of analysis carried out depends on the data to be studied in each specific case. This means that while the use of relatively simple screens is sufficient in some cases, in others more complex statistical and econometric techniques, network analysis and machine learning methods, both supervised and unsupervised, are beginning to be applied. In some areas, where the availability of data is not so evident, case detection is much more limited. To address this, techniques such as web scraping or text mining can be used to increase data availability. The development and application of these techniques is carried out by the Competition Authority itself and specifically within the Economic Intelligence Unit. Statistical software, such as R, Python, SPSS, and Stata, are used to apply the above

[58] Organization Chart of Swedish Competition Authority https://www.konkurrensverket.se/en/omossmeny/about-us/organisation/

[59] Cani Fernandez interview in 27.09.2020 at https://www.competitionpolicyinternational.com/cpi-talks-with-cani-fernandez/

See also "Spain: Competition Authority", Lexology, 8 July 2020 https://www.lexology.com/library/detail.aspx?g=b909538a-4ef5-4933-9e21-909fb77727b2 and

OECD "LATIN AMERICAN AND CARIBBEAN COMPETITION FORUM – Session I: Digital Evidence Gathering in Cartel Investigations", Contribution from Spain, 28–29 September 2020, http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/LACF(2020)5&docLanguage=En paras. 4-10 and 33-35.

techniques. As inspection procedures have developed, gathering evidence on cartels during company inspections using various forensic analysis tools (off-the-shelf or developed in house by the CNMC's forensic IT experts) has become particularly important. These software applications are developed in close cooperation with competition inspectors, who are in charge of investigating cases. Among the tools used is the Nuix software platform, which enables analysis of multiple databases and offers a high-speed indexing engine. This software allows the use of various clustering algorithms and other machine learning techniques. Additionally, it offers the option of social network analysis, which can improve information filtering.

The Hellenic Competition Commission has also established as of October 2020 a forensic IT unit, which is headed by an economist and cooperates with number data scientists, who are acting as external experts for the authority. Moreover, the Commission is at the process of setting up an expandable Big Data Management Infrastructure Platform/dash-board, tailor made for the authority by an external contractor where real-time public data from different sources (Price Observatory of Supermarkets, fuel prices, vegetables and fruits prices, public procurement data, etc.) will be automatically uploaded. At the same time the Commission has appointed experts to design a program, drawing raw data from unstructured information available in the internet in pdf formats, as well as in other formats and extract it in csv files form. It will be gradually concluded possibly by mid next year. This data will be mainly used for cartel-detection but will also offer an integrated data analytics environment with various tools/apps on the basis of bespoke programmes and /or available off the shelf software tools to visualise and analyse data. The Commission has also employed contractors to develop an integrated data template and dashboards as well as bespoke software programs for the needs of the Authority.

In addition, two more NCAs have hired specialised experts in data science, although not in leadership roles at the Authority. The Portuguese competition authority includes a number of data scientists in their forensic IT team. Furthermore, the Danish competition authority has integrated data scientists in their investigation and cartel division, as well as in their market analysis and economics division and in our digital platforms division. In 2019, the Danish Competition Authority also launched a project in order to detect cartels and bid rigging by screening public procurement data. Moreover, it has established a new setup to bring together economists, investigators and data scientist and they use machine learning and different data-based testing methods to point out signs of collusion between the bidders. The authority has also developed its own software solutions, using Python as bid rigging detecting tool. For picture categorization it is mainly using ready-made software. This is combined with some Python coding for calculating and matching histograms. The Authority has started using the build in features of its IT Forensic software for picture categorization in data from dawn raids and picture categorization In

BlackLight[60] regarding mobile phones. This feature has been proven very powerful for identifying pictures of documents in a huge mixed dataset from several mobile phones. For picture categorization in data from computers it has used some features in Nuix Workstation[61]. They have used the features to categorize on skin tone and colour count. Assuming that pictures of documents, whiteboards etc. has a low number of colours and low amount of skin tone, they have tried to filter out these types of pictures, but this method has not been proven satisfying so far. The Authority is also working on a new approach to find pictures of documents etc., while its data scientist has calculated histograms of a big amount of this kind of pictures.

In addition to the EU Competition Authorities, some of the non-EU Commissions have also proceeded to the appointment of a chief technology officer and specific units. In particular, in July 2019, a Chief Digital Enforcement Officer has been hired by the Competition Bureau of Canada[62]. The officer supports the Bureau to monitor the digital landscape, as well as identify and evaluate new investigative techniques. The Chief Digital Enforcement Officer will provide advice on a wide variety of issues, including tools and skills development, in order to boost the Bureau's investigations in the digital economy. Moreover, the Bureau uses a wide range of technological tools for cartel detections. The Japan Fair Trade Commission[63] has also included in its organizational structure the position of a Counselor for Cybersecurity and Information Technology Management.

The Australian Competition and Consumer Commission (ACCC)[64],[65] has set up a Legal and Economic Division, which consists of the Legal Group, the Economic Group and the Strategic Data Analysis unit (including data governance and management functions). The Strategic Data Analysis Unit provides expert quantitative advice and support to line areas of the Commission. The unit members are working in basic research and issues where the use of complex data and analysis required. The unit also supports the context analysis and the identification of data sources. The Division also leads the data governance function that is becoming a significant part of the way the authority operates. Data generation plays an essential role in the economy. To address the challenges this poses, ACCC is investing in

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[60] https://www.blackbagtech.com/products/blacklight/

[61] https://www.nuix.com/products/nuixworkstation

[62] Competition Bureau Performance Measurement & Statistics Report 2019-20, https://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/04508.html
Message from the Commissioner, 25 July 2019, https://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/04480.html
Ibid, Matthew Boswell in his November 2017 speech, https://www.canada.ca/en/competition-bureau/news/2017/11/bid-rigging_detectionandpreventionensuringacompetitiveandinnovat.html

[63] Organisation Chart of the Japan Fair Trade Commission, https://www.jftc.go.jp/en/about_jftc/index_files/200929.pdf

[64] ACCC and AER Corporate Plan, 2020-2021, https://www.accc.gov.au/system/files/20-28RPT%2520ACCC%2520and%2520AER%2520Corporate%2520Plan%25202020-21_D05.pdf (p.16, 36)

[65] Speech of Mr Rod Sims, Chair, Gilbert & Tobin seminar, 26 November 2018 https://www.accc.gov.au/speech/gilbert-tobin-seminar-the-data-economy

data by strengthening its data governance processes, improving how it stores and accesses data across teams, as well as strengthening staff capability. In addition the Strategic Data Analysis Unit assists the Agency in analysing data and algorithms across a range of investigations, which concern both the competition and consumer areas.

The US Federal Trade Commission has also proceeded to the appointment of a specific division. The primary focus of the Technology Enforcement Division (TED) [66] [67] is to identify and investigate anticompetitive conduct (including consummated mergers) in markets in which digital technology is an important dimension of competition, such as online platforms, digital advertising, social networking, software, operating systems, and streaming services. The TED will leverage its existing expertise and work with other Commission staff, including technologists, to develop a deep understanding of some unique features of complex, dynamic digital markets[68].

In March 2020, the Mexican Federal Economic Competition Commission (COFECE)[69] announced the establishment of a Digital Markets Unit within its institutional structure with the purpose of advancing in the comprehension of the digitization of the Mexican economy to execute the powers bestowed upon it by the LFCE with greater effectiveness. In 2014, Competition Authority of Brazil (Cade) contracted external consultants with

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[66] Inside the Bureau of Competition August 2020, p.21 https://www.ftc.gov/system/files/attachments/inside-bureau-competition/inside_the_bureau_of_competition_updated_august_2020.pdf see also FTC Tehnology Enforcement Division and press release attached https://www.ftc.gov/news-events/press-releases/2019/02/ftcs-bureau-competition-launches-task-force-monitor-technology

[67] Also for TED in PREPARED STATEMENT OF THE FEDERAL TRADE COMMISSION: OVERSIGHT OF THE FEDERAL TRADE COMMISSION Before the COMMITTEE ON COMMERCE, SCIENCE, AND TRANSPORTATION UNITED STATES SENATE WASHINGTON DC in August 2020, p.34 https://www.ftc.gov/system/files/documents/public_statements/1578963/p180101testimonyftcoversight20200805.pdf

[68] In February 2019, the FTC created a task force entirely dedicated to address competition issues in the technology industry. The task force has since been converted into a permanent Bureau of Competition division called the Technology Enforcement Division (TED). In July 2019, Facebook disclosed that it was being investigated by the FTC, which the FTC subsequently confirmed was part of the TED's antitrust probe of multiple large technology firms classified as "multi-sided platforms." Several major media outlets have reported that Amazon is also a main focus of the FTC's ongoing investigation. In January 2020, FTC Chairman Joseph Simons revealed that the FTC was nearing a decision on whether it will bring a related enforcement action.While the TED was continuing its investigation, the FTC's Deputy Director, Daniel Francis, discussed the creation of the FTC's first new enforcement division in nearly twenty years during a panel discussion on September 12, 2019, titled, "Big Tech and Antitrust: What Lies Ahead." Mr. Francis explained that the TED was created to address the unique issues that big-tech firms present to antitrust enforcement in the United States, including the ever-evolving nature of digital platforms. Mr. Francis made clear that while the FTC is highly attuned to these issues, it will continue to pursue traditional, evidence-based cases to develop its enforcement response to digital platforms. https://www.winston.com/en/competition-corner/doj-and-ftc-lock-in-on-big-tech-firms-but-t-mobilesprint-merger-opinion-provides-a-potential-compelling-antitrust-defense.html

[69]COFECE's press release, Digital Strategy, 30 March 2020, https://www.cofece.mx/wp-content/uploads/2020/03/COFECE-013-2020-DIGITAL-STRATEGY-Vf.pdf and COFECE Digital Strategy, March 2020, https://www.cofece.mx/wp-content/uploads/2020/03/EstrategiaDigital_ENG_V10.pdf (p.15)

specialized knowledge in Statistics, IT, and data mining for the development of analytical tools. Cade has also established the creation of an Intelligence Unit. The Intelligence Unit is formed by senior case handlers and civil servants recruited in institutions responsible for criminal investigations. In this sense, the Intelligence Unit – by promoting training programs for planning and conduction of interviews and hearings, the use of analysis software, investigating and mapping, among others – acts in the consolidation of knowledge in the field of investigation, identifying among the various complaints received by Cade those that could give rise to effective investigations of violations to the economic order. The use of active techniques for cartel detection works as an additional element in the system of incentives of reactive tools. In other words, the consolidation of screening tools – via opening of administrative proceedings and eventual condemnations in the administrative sphere – will certainly work as an additional incentive for companies and individuals to apply for leniency, to propose Cease and Desist Agreements (TCC in its acronym in Portuguese), and to file complaints with Cade.[70]

The Competition Commission of South Africa has implemented a service dedicated to Information Technology (IT). The aim of this service is to understand the problems and needs of the Commission as the basis for determining how IT can be used to bring about improvements for the business, leading to improved business processes, improved information systems, new or improved computer applications and knowledge sharing[71],[72]. However there is a will of digital transformation in Competition Commission of South Africa in order to boost its ability to detect, examine digital cartels. In order to realize these outcomes, the Authority would develop applicable instruments for detecting digital cartels and assessing the results of agreements amongst rivals, build and employees a cartel forensic lab as well as develop tips for establishing the fee's jurisdiction in instances of digital collusion that have an impact in South Africa.

Moreover, in 2018[73] , Andrey Tsarikovskiy, Deputy Head of Federal Antimonopoly Service of the Russian Federation (FAS), had also reached a conclusion that it was necessary to establish a special team to investigate cases on cartels and other anticompetitive agreements in the digital field. The Anti-Cartel Department would form a special unit to deal with digital investigations. This special Unit is probably the "Division for Digital Investigations" which belongs to the Anti-cartel Department[74], however no further

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[70]OECD, "Latin America and Competition Forum, Session III: Promoting effective competition in public procurement –Contribution from Brazil", 12-13 April 2016 http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF%2FCOMP%2FLACF(2016)19&docLanguage=En&fbclid=IwAR3g7tbnfvfqIBaWDOzVkNSGr7kvKCDBFuYFmnt0yRgouqVKmqPOTET3gaA, para.8-22.

[71] Competition Commission's website http://www.compcom.co.za/information-and-system/

[72] "CompCom takes aim at 'digital markets", online article https://za.newschant.com/technology/compcom-takes-aim-at-digital-markets/

[73] FAS press release: FAS creates a new web-service: "Big Digital Cat", 22/10/2018 http://en.fas.gov.ru/press-center/news/detail.html?id=53478

[74] Structure of FAS, https://en.fas.gov.ru/about/structure/

information from FAS is released. It is noticed, also, that the “Big Digital Cat” web service belongs to the same Department.

The Turkish Competition Authority (TCA)[75] has recently empowered its already existing Strategy Development Department to meet with the new developments in digital markets. Considering the huge effects of competition law infringements through big data and algorithms, traditional applications and approaches are predicted to be insufficient in dealing with the new problems in this field. In that regard, TCA redesigned the responsibilities of its Strategy Development Department**,** with the aim of ensuring to act proactively. The new tasks of Strategy Development Department include assisting case handlers, providing opinions for investigations, providing support for competition probes relating to the digital economy, conducting trainings in relation to digital market-related matters, exchanging information and experience with national and international institutions, raising awareness regarding impacts of the digital economy and algorithm usage on both markets and consumers, contributing to the development of public policies in this regard by communicating with the relevant ministries, institutions and organisations[76] [77] .

Table 2: Computational capabilities in competition authorities (see Annex)

2.1.2.2. Procedural standards and standards of evidence

Of particular interest for the further development of such techniques is the adaptation of legal standards for initiating investigations and also the standards of evidence used in assessing such material.

With regard to the first issue, usually competition authorities act upon complaints or general market information that is provided to them either by market participants or through a systematic monitoring of different economic sectors, for instance by examining generalist or specialised press or through organised meetings with economic actors. However, the emergence of the Internet and the development of Big Data analytics provide competition authorities with multiple other sources of information that are publicly available or can be harvested through web-scraping tools. Scraping is a method for

[75]OECD, ‘‘Consumer data rights and competition – Note by Turkey’’ https://one.oecd.org/document/DAF/COMP/WD(2020)55/en/pdf paras.7-9

[76] TCA’s Press Release dated 30.01.2020. Available only in Turkish at: https://www.rekabet.gov.tr/tr/Guncel/rekabetkurumu-dijitallesme-ve-rekabet-p-874d77d25943ea118119005056b1ce21

[77] TCA’s press release dated 08.05.2020. Available only in Turkish at: https://www.rekabet.gov.tr/tr/Guncel/rekabetkurulu-dijital-ekonomiyi-mercek--61aedbe40a91ea11811a00505694b4c6. See also https://www.mondaq.com/turkey/antitrust-eu-competition-/934258/turkish-competition-authority-designates-its-strategy-unit-for-digital-markets and https://www.kinstellar.com/insights/detail/1129/turkish-competition-authority-designates-its-strategy-unit-for-digital-markets

crawling web sites and automatically extracting structured data on it. The use of algorithms may greatly facilitate the data collection process, as well as data analysis. Such tools have already been used in competition law investigations. For instance, in the Google Search investigation, the European Commission explored in order to build the anticompetitive effect of Google's conduct data on the traffic to Google's own comparison shopping service and traffic to competing comparison shopping services and merchant platforms, its own compilation of data from the approximately 380 services identified by Google as competing with Google Shopping[78]. Furthermore, the use of data visualization, natural language processing and predictive analytics may enable the systematic monitoring of entire economic sectors in order to decipher various patterns that may raise red flags with regard to the presence of anticompetitive behavior.

Particular applications include the use of Web-scraping enables in order to scale up evidence gathering, the use of geocoding that may enable competition authorities to analyse locations of competitors in merger analysis or develop mechanisms to facilitate e-discovery by using a machine learning models, such as TexRank, or by employing predictive coding tools, which use a subset of documents ("seed documents") in order to train computer algorithms to make predictions over the content of the other documents[79]. The software analyses documents and 'scores ' them for relevance to the issues in the case. The results of this categorisation exercise are then validated through a number of quality assurance exercises. These are based on statistical sampling, the sampling being fixed in advance depending on what confidence level and what margin of error are desired. This sampling is further reviewed (blind) by a human. The process of sampling is repeated as many times as required to bring the overturns to a level within agreed tolerances, and so as to achieve a stability pattern, each use of the predictive coding process being bespoke for that case. This technology saves time and reduces costs. Advanced network analysis may also facilitate the visualization and assessment of interactions between various economic players, as well as the analysis of large datasets of emails through specialized software, such as Tovek.

The use of such tools may require some adaptation to the legal standards put in place to limit the discretion of competition authorities to launch investigations and in particular initiate inspections. In the EU, according to the case law, the European Commission is prevented from going on "fishing expeditions"[80]. Furthermore, "(i)nformation obtained during investigations must not be used for purposes other than those indicated in the inspection warrant or decision"[81], although this does not limit competition authorities in the EU to issue inspection decisions that are broadly written and

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[78] European Commission, Case AT.39740 *Google Search (Shopping)*, paras 614-618.
[79] See, S. Hunt, Data, technology and analytics in competition enforcement: building a new professional capability and offering December 2019, available at PowerPoint Presentation (concorrencia.pt) .
[80] Case C-583/13P, Deutsche Bahn and Others v Commission, ECLI:EU:C:2015:404.
[81] Ibid., para. 57.

which cover multiple product markets and types of conduct, without the need for a legal qualification. The principle of proportionality also requires that any interference with an undertaking's business activities has to take the least onerous form possible. Inspection decisions have to be subject to specific requirements, in particular being "properly reasoned" through the existence of a sufficient suspicion of an infringement as well as a precise delineation of their scope[82]. They must provide a description, even broad, of the suspected infringement, the possible nature of the suspected restrictions of competition, and the broader markets or economic activity covered by the alleged infringement.

However, the Commission is not required to communicate a precise legal qualification of the alleged infringement, the period of the infringement or the precise delimitation of the market in question. It is sufficient to indicate the "essential features" of the suspected infringements[83]. It is not also "required to state the evidence and indicia on which the decision is based" but to only show "that it is in possession of information and evidence providing reasonable grounds for suspecting the infringement"[84]. In order to launch an inspection the Commission should however rely on sufficiently strong evidence in respect of the suspected behaviour and inspections. In some recent case law the Court has sanctioned the Commission for not having "reasonable grounds" for suspecting an infringement[85], or because it had insufficient evidence to form the basis for launching an inspection[86]. Although welcome from a 'rights of defence' perspective, such case law, if left uncalibrated, may put some barriers to the development of e-discovery and the more systematic use of Big Data techniques and data analytics technologies in order to monitor markets for discovering anticompetitive conduct.

Similar constraints may be put to the use of predictive approaches on the basis of data analytics in view of the required standards of evidence. The rules of evidence have been framed with the view that most evidence will be factual. Yet, sources of evidence are diverse and might include contemporaneous documents, such as emails or statements by market participants (competitors, customers and consumers), but also more complex evidence. The probative value attached to a piece of evidence depends on the —reliability of that evidence. For instance, complex evidence such as econometrics is assessed on the basis of some specific causal inferences (internal validity) made on the basis of some observations that are generalized, the last operation relating to the connection of these inferences to the real outside world (external validity), the main issue being if we can make

[82] Article 296 TFEU. Article 41(2)(c) of the Charter of Fundamental Rights of the European Union.
[83] Case T-339/04, France Telecom SA v Commission, ECLI:EU:T:2007:80 , paras 58 and 59 (this case law however concerns an Art. 20(4) Reg. 1/2003 decision).
[84] Ibid., paras 60 & 123.
[85] See, Case T-135/09, Nexans France SAS and Nexans SA v European Commission, ECLI identifier: ECLI:EU:T:2012:596.
[86] Case T-325/16, České dráhy a.s. v European Commission, ECLI:EU:T:2018:368; Cases T-249/17 Casino, Guichard-Perrachon and Achats Marchandises Casino SAS (AMC) v Commission, T-254/17, Intermarché Casino Achats v Commission and T-255/17, Les Mousquetaires and ITM Entreprises v Commission, ECLI:EU:T:2020:458

a causal claim in competition law based on econometric evidence[87]. Similar concerns may be raised with regard to evidential inferences made on the basis of data science, although descriptive uses of data analysis may not be judged problematic from a law of evidence perspective. Indeed, in this context we may be closer to the dominant conception of causality in law, which refers to causal connections between events and involves a concrete instantiation of a causal law on the particular occasion, regarding the existence of a causal link between the specific event A and the specific event B, rather than the more "theoretical" and categorical approach of causation followed in econometrics, where the inferential direction runs from theory to data requiring the matching of the remaining conditions in the set against the applicable causal generalization. However, some predictive data analytics techniques, such as predictive coding, may face similar difficulties to those confronted by econometrics. Courts should therefore develop a more hospitable tradition to such type of evidential material. This has already been the case in some jurisdictions, which has already accepted the technology of predictive coding or technology assisted review of documents. For instance, *in Pyrrho Investments Ltd v MWB Property Ltd*[88], not a competition law case, the UK High court accepted predictive coding as an acceptable technique to analyse document evidence, noting that "there will be greater consistency in using the computer to apply the approach of a senior lawyer towards the initial sample (as refined) to the whole document set, than in using dozens, perhaps hundreds, of lower-grade fee-earners, each seeking independently to apply the relevant criteria in relation to individual documents"[89]. It is likely that the greater use of data analytics and computational techniques will lead to the development of specific case law regarding the standards of proof applied in this context and in particular the assessment of the criterion of reliability of evidence.

2.2. Developing a screening tool for collusive practices and excessive pricing

There have been important efforts to develop operational screening tools for other practices than collusive conduct in the context of bid rigging investigations. More recently, the competition authority in Greece (Hellenic Competition Commission or HCC) commissioned a report to develop a screening method to detect anti-competitive practices – including cartels, excessive pricing and exclusionary pricing – from the analysis of market data (in particular prices), taking advantage of new

[87] For a discussion see, I. Lianos & C. Genakos, Econometrics in EU Competition Law: an empirical and theoretical analysis, in I. Lianos, D. Geradin (Eds.), Handbook in EU Competition Law – Enforcement and Procedure (Edward Elgar, 2013), 1.
[88] Pyrrho Investments Ltd v MWB Property Ltd, 2016] EWHC 256 (Ch).
[89] Ibid., para. 33. See also, *Irish Bank Resolution Corporation Ltd v Quinn* [2015] IEHC 175 (finding that predictive coding is at least as accurate as, and, probably more accurate than, the manual or linear method in identifying relevant documents).

legislation enabling the authority to have mandated access to primary data regarding prices by the main supermarkets in the country, the distribution system for petrol stations, and the Athens central market for vegetables and fruits. This enables the authority to follow daily the level of prices for more than 2000 thousands product codes across the country and to be able to use a time series since January 2020 and for some products a few years earlier.

2.2.1. The screen design

The objective of the report was to provide the Hellenic Competition Authority with an analytical tool to identify potential anti-competitive conduct at early stages and to prioritise cases worth of further investigation while taking into consideration existing constraints in resources and data availability. In order to achieve this goal, we attempted to design a screen with the three following characteristics:

- **Broad applicability**: the screen proposed is possible to implement in most product markets. A notable exception is a public procurement, where the price formation process is different and for which there are more appropriate screening methods proposed in the literature.
- **Low implementation cost**: the screen proposed has a low implementation cost, at least during its first step, requiring standard software and limited processing power.
- **Accuracy**: the accuracy of the method largely depends on the quality of data collected and on the ability of the authority to identify a relevant counterfactual. The authority can in any case tune the screen to minimise false positives (namely if resources are limited and if it is necessary to prioritise the main cases worth investigating) or to minimise false negatives (if it is important to scrutinise all potential competitive concerns). A limitation of the method is that it can only detect anti-competitive behaviours that either started or ended during the observed period. In other words, the method will fail to detect, for instance, a well-established cartel that sustains high prices over the entire observed period.

2.2.2. Methodology

The screen proposed was based on standard industrial economics principles and builds on top of existing screening methods to detect cartels. Most screens described in the literature are relatively sophisticated methods with large data requirements, frequently applied in isolation to a market where anti-competitive behaviour is already suspected. In that sense, traditional screens might not serve as a practical tool to detect anti-competitive behaviour on a systematic basis. For that reason, we developed an alternative method that the HCC could potentially implement despite the data and resources constraints of the project.

The screen proposed in this report was tested using simulation techniques. In other words, we produced simulated datasets that replicate how firms behave according to industrial economics theory. The advantage of using simulated data is that we know when firms are engaging in anti-competitive practices, enabling us to test whether the proposed screen can accurately identify those practices and to make adjustments in the method in order to obtain better results. After running several alternative versions of the method, we developed a final version that was able to identify anti-competitive conduct during the simulation tests successfully. Ideally, it would be useful also to test the screen using real-world data on past infringements of competition law, though this is out of the scope of this report.

2.2.3. A brief overview of the method

We propose a two-steps method comprising an initial screen to identify suspicious changes in pricing behaviour, followed by a verification step to confirm whether the change is indeed consistent with anti-competitive conduct or whether other market events can explain it.

- The first step of the method consists of a preliminary analysis of unusual and suspicious price changes **using a log diff-in-diff model**. This step requires only price data and the identification of a one on more relevant counterfactuals. A positive result at this stage suggests that further analysis is needed.
- The second step of the method consists of a more in-depth industry-specific analysis, which involves estimating a **pricing regression** using supply- and demand-side variables as regressors and testing for **structural breaks** in the series. This way, it is only necessary to carry out more complex analysis and to collect non-price data in case of suspected anti-competitive behaviour during the previous stage.

The intuition for the two-step method described above is the following: whenever a firm engages in anti-competitive behaviour, such as collusion, excessive pricing or exclusionary pricing, such behaviour will necessarily affect the pricing strategy of the firm and create a break in the dataset. This is true even if the firm attempts to hide the anti-competitive behaviour because a significant price change is a necessary condition for the success of the strategy.

As changes in pricing behaviour could also result from all types of demand and supply shocks, the use of a log diff-in-diff pricing model in the first stage enables us to control for market shocks that similarly affect firms and products. When market shocks cannot explain the change of pricing behaviour, the second step of the method assesses whether the price change can be attributed instead to an idiosyncratic shock in the firm's cost or individual demand curve. If price changes cannot be explained either by the market or idiosyncratic shocks in demand and supply, the only explanation left is a change in competitive behaviour.

It is important to note that even where the screen and verification steps generate a positive result, this is not enough to conclude that there was an infringement, as firms can unilaterally change their pricing strategies without necessarily violating competition laws. The screen and verification steps must, therefore, be followed by a prosecution step, which involves collecting additional evidence to assess whether the structural breaks in prices were the result of unlawful conduct. The screen and verification steps may nonetheless not only facilitate detection of anti-competitive behaviour but may also provide useful information and clues about the type of evidence that the authority should collect.

2.2.4. Data requirements

The first step of the screen requires the collection of pricing data in a panel format. The cross-section unit is the product/firm combination; that is, each individual corresponds to a product sold by a specific firm. The unit of the time series can be the year, trimester or month. The choice of a short time unit (e.g. daily or weekly data) could compromise the good functioning of the method, as firms may adjust their pricing strategies gradually over time in order to avoid detection. Besides, data should be collected in such a way that products are grouped in categories that can be used as counterfactuals. While this can create an additional burden during the data collection process, the choice of a good counterfactual is crucial to minimise false positives.

The second step of the method, apart from relying on pricing data, also requires the collection of supply- and demand-side data to use as controls. The variables incorporated in the pricing regression may vary with the particular industry under analysis and must hence be chosen on a case-by-case basis, subject to data availability. If demand-side variables are not available, the authority may consider using quantities transacted as an explanatory variable, though that may create an endogeneity problem. In that case, the completeness of the cost data is crucial to guarantee that the results obtained are unbiased.

Description of the first step – log diff-in-diff pricing model

The first step of the method requires the generation of **a log diff-in-diff pricing time series** for each product/firm combination:

$$DD_{it} = (\log P_{it} - \log P_{i,t-1}) - (\log CF_{it} - \log CF_{i,t-1}),$$

where $(\log P_{it} - \log P_{i,t-n})$ is the continuous growth rate of the price of the product/firm i between $t-1$ and t, and $(\log CF_{it} - \log CF_{i,t-n})$ is the continuous growth rate of the counterfactual of product/firm i over the same period. The series DD_{it} is thus the growth rate of the price of product/firm i in excess to its counterfactual.

The estimation of the time series DD_{it} assumes that the authority can identify one or more relevant counterfactuals for each of the product-firm combinations. The choice of the counterfactuals is probably the most important component of the analysis, as it will drive the quality of the results. If the authority has no means to identify a relevant counterfactual for each of the observations, it may consider a few alternative approaches:

- One option is to calculate the average price across all products or the average price by industry code. The main reasoning is that products within the same industry often react similarly to market shocks, though this is not always the case and may depend on the level of aggregation of the industry.
- Another option is to identify a counterfactual by looking at price patterns, namely by calculating the coefficient of correlation between the prices of different products/firms. When screening for anti-competitive unilateral conduct, the best counterfactual could be the most positively correlated product/firm, which is likely a close competitor that did not engage in the same strategy (given that the conduct was unilateral). However, when screening for cartels, closest competitors might all be involved in the conspiracy and may thus not serve as a counterfactual. In that case, it could be preferable to use as counterfactual the fifth or sixth most positively correlated product/firm, as cartels rarely involve more than five players.

Once the series DD_{it} is obtained, one can look for outliers that could reflect changes in pricing behaviour. A simple graphical analysis of the series DD_{it} could be helpful to identify outliers – for instance through the creation of boxplots or scatterplots. Nevertheless, in order to automatise the process and to deal with a very large number of observations, it may be desirable to develop also an analytical test to detect outliers and to report them whenever they occur.

As the outlier detection method, we propose running a t-student test for each of the observations of the series DD_{it} and automatically reporting every time the t-statistic exceeds the critical value for a specified significance level. The null hypothesis of the test is that the observation is not an outlier and is generated by the same distribution as all other observations. The sensitiveness of the test can be controlled by changing the significance level. A lower significance level implies a lower probability of rejecting the null when the null hypothesis is true – or, in other words, a lower number of false positives. Alternatively, the method can also report the n observations with the highest t-statistics, in order to identify the top cases worth investigating.

While the detection of outliers in a log dif-in-dif pricing model serves as a screen on its own, as robustness check it would be useful to run other simple screens on the pricing series. This way, if several screens generate a positive result for the same observation, there is a stronger indication of a change of competitive behaviour. In particular, it could be worth complementing the screen proposed here with a variance screen for collusion, which also only relies on pricing data, though its implementation is out of the scope of this report.

Description of the second step – structural break test on a price regression

The second step of the method involves estimating a price regression for any product/firm where at least one outlier was previously identified:

$$P_t = \beta_0 + \boldsymbol{\beta_1 C_t} + \boldsymbol{\beta_2 D_t} + u_t,$$

where P_t is the price of the product/firm under investigation, $\boldsymbol{C_t}$ is a row vector of cost or supply-side m regressors, *i.e.*, $\boldsymbol{C_t} = [\boldsymbol{C_{1t}} \quad \boldsymbol{C_{2t}} \quad \cdots \quad \boldsymbol{C_{mt}}]$, $\boldsymbol{\beta_1} = [\beta_{11} \quad \beta_{12} \quad \cdots \quad \beta_{1m}]^T$, $\boldsymbol{D_t} = [\boldsymbol{D_{1t}} \quad \boldsymbol{D_{2t}} \quad \cdots \quad \boldsymbol{D_{nt}}]$ is a row vector of demand-side n regressors, $\boldsymbol{\beta_2} = [\beta_{21} \quad \beta_{22} \quad \cdots \quad \beta_{2n}]^T$ and u_t is the error term. Choice of functional form and regressors is context-specific and has, therefore, to be adapted to the industry under analysis. Before conducting any tests on this regression, it is important to confirm whether the model has good explanatory power, namely by checking its global significance through an F-test.

After successfully estimating the regression, it is possible to use standard tests to infer whether there was a structural break in the coefficients of the time series. The most straightforward procedure is to run a modified Chow test at the period where the outlier was identified in the previous step. Rejection the null suggests that the beta regression coefficients are different before and after the outlier period, and thus that the pricing behaviour has changed. As a robustness check, it is also possible to conduct an augmented Dickey-Fuller test to verify the stationarity of the series (which follows similar principles to the Chow test but does not require knowledge *a priori* about the period when the break occurred). In this case, the null hypothesis is non-stationarity, and failure to reject the null suggests that the pricing behaviour is not stable over time.

If demand-side data is not available, one may consider using quantities transacted as a regressor. However, in that case, the estimated coefficients of time series could be biased due to mutual causality between the price and the quantity, resulting in an endogeneity problem. Indeed, unobserved cost shocks affect the price of the product, which in turn affects consumer demand and thus the quantity transacted. The resulting correlation between the error term and quantities implies that the estimated coefficient is biased. The higher is the variability of the error term the greater is the estimation bias, and in extreme cases, the estimated coefficient might have a negative value.

In light of the endogeneity problem and the lack of suitable instrument variables to correct it (assuming that demand-side data is not available), the identification of structural breaks in the time series could have one of two meanings. The first is that the pricing behaviour of the firm significantly changed over time. The second is that the firm under investigation did not provide the authority with relevant cost data that could explain the structural breaks and without which statistical inference is invalid. Either way, evidence of structural breaks in the time series is an indicator that further investigation is warranted, in order to assess whether the firm under investigation has engaged in anti-competitive conduct or failed to report relevant cost data.

2.2.5. Simulation results

The method proposed in this note successfully identified changes of competitive behaviour in several simulation tests, performing better than alternative versions of the method.

An important lesson from simulation experiments was that structural break tests should only be carried out during the verification step, after controlling for supply- and demand-side data. Attempting to run structural break tests in price series without controls leads to systematic false positives, because price series are generally not stationary, making statistical inference invalid. Running structural break tests on first-differences prices does not work either, because the first differences eliminate the effect of the change of competitive behaviour on all observations but one (the observation where the change occurred). However, structural break tests can only successfully identify breaks in the series if there are multiple observations affected by the change of competitive behaviour.

The use of simple outlier tests instead of structural break tests in the first step improved the method substantially, enabling us to detect changes of competitive behaviour even when using low significance levels (1% and 0.1%) to minimise false positives. In some occasions, we also identified outliers when there was no change of competitive behaviour – this is expected, as some false positives are inevitable when using a screening method that relies only on price data.

The simulations obtained good results when using the average price across all products as counterfactual. However, real data may include very heterogeneous products, whose prices react differently to market shocks. In that case, the choice of a better counterfactual might be important to guarantee the quality of results and to avoid false positives.

Finally, the use of structural break tests in the verification step enabled us to distinguish true positives from false positives. Nevertheless, the simulated variance of the error term was small, so caution should be applied when running this method on real-world data, especially in circumstances where the model has limited explanatory power.

2.3. The HCC Economic Intelligence Platform

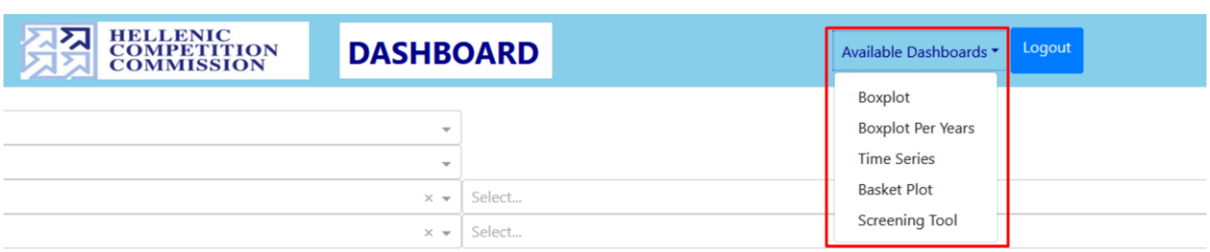
2.3.1. General Description

The Hellenic Competition Commission (HCC) is an independent authority responsible for the "Control of Monopolies and Oligopolies, and the Protection of free Competition". In order to comply with its duties the HCC has to explore multiple commercial sectors and data that have vast heterogeneity. This task requires a huge manual effort both for the collection of the data as well as for their exploration. The HCC Intelligence Platform is an effort to integrate and keep updated multiple external data sources in common database schema and provide visualization tools for data exploration and screening. The platform is being hosted within the premises of the HCC and is accessible here, given that the user has the appropriate access credentials.

2.3.2. User Guide

2.3.2.1. Dashboards Options

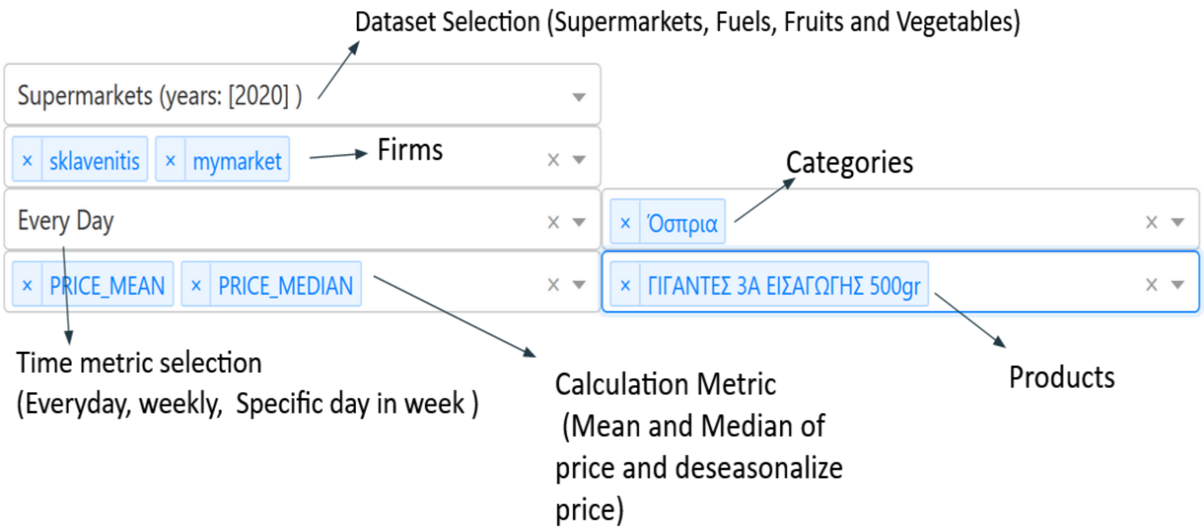
In the top-right of the page you can find a dropdown with available dashboards.



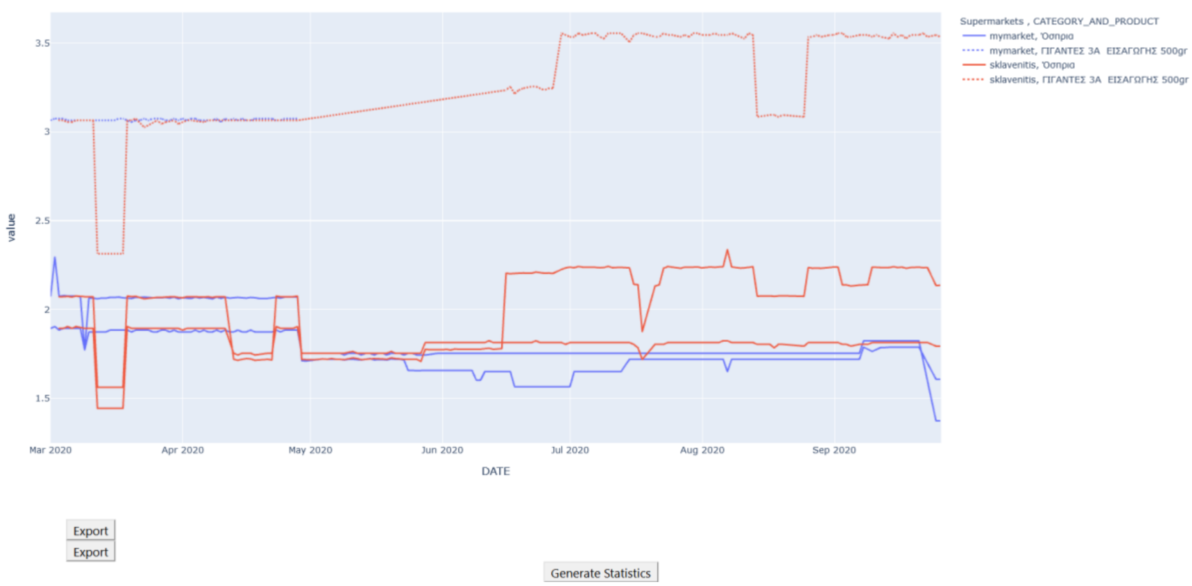
2.3.2.2. Time Series

In this plot we can identify the trends in category and product prices, for every Firm or multiple Firms. See price changes day-by-day or week-by-week. In the week-by-week analysis the specific weekday is provided in order to see if there are any special offers, and the average or median or both prices per day / week are used for the creation of the diagrams. Extra we can generate general statistics and to export data in excel form.

2.3.2.2.1. Time Series Options



2.3.2.2.2. Time Series Example



2.3.2.2.3. Time Series Generate Statistics and Export In Excel File

For every line in the above plot we can generate basic statistics like length (count), mean, standard deviation, minimum, maximum and quantiles 25%, 50%, 75% by pressing the button *Generate Statistics*.

CATEGORY_PRODUCT_SUPEMARKET	Count	Mean	Standard Deviation	Minimum Value	Quantile 25%	Quantile 50%	Quantile 75%	Maximum Valu
Όσπρια_mymarket_PRICE_mean	179	1.81	0.19	1.56	1.65	1.72	2.06	2.2
σπρια_sklavenitis_PRICE_mean	166	2.02	0.22	1.56	1.77	2.07	2.23	2.3
ΗΣ 500gr_mymarket_PRICE_mean	58	3.06	0.01	3.05	3.06	3.06	3.07	3.0
500gr_sklavenitis_PRICE_mean	119	3.3	0.32	2.31	3.06	3.53	3.54	3.5
Όσπρια_mymarket_PRICE_median	179	1.79	0.07	1.37	1.75	1.75	1.87	1.
ρια_sklavenitis_PRICE_median	166	1.8	0.08	1.44	1.79	1.81	1.81	1.
500gr_mymarket_PRICE_median	58	3.06	0.01	3.05	3.06	3.06	3.07	3.0
0gr_sklavenitis_PRICE_median	119	3.3	0.32	2.31	3.06	3.53	3.54	3.5

Except from basic statistics we display and the data which needed to create the plot.

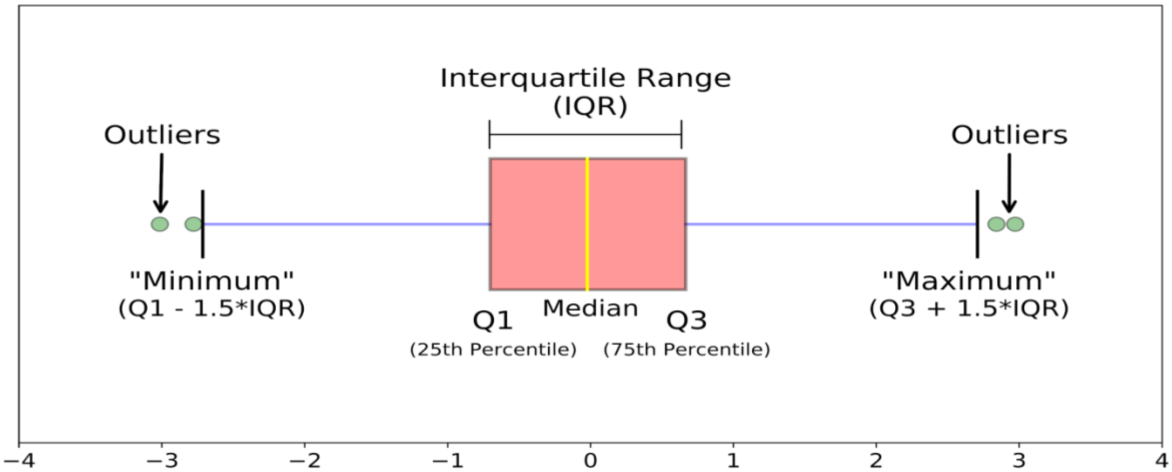
Export

index	CATEGORY_AND_PRODUCT	DATE	PRICE_mean	PRICE_median	SUPERMARKET
	Όσπρια	2020-03-01	2.07	1.89	mymarket
	ΓΙΓΑΝΤΕΣ 3Α ΕΙΣΑΓΩΓΗΣ 500gr	2020-03-01	3.06	3.06	mymarket
	Όσπρια	2020-03-02	2.29	1.9	mymarket
	ΓΙΓΑΝΤΕΣ 3Α ΕΙΣΑΓΩΓΗΣ 500gr	2020-03-02	3.07	3.07	mymarket
	Όσπρια	2020-03-03	2.07	1.88	mymarket
	Όσπρια	2020-03-03	2.07	1.89	sklavenitis
	ΓΙΓΑΝΤΕΣ 3Α ΕΙΣΑΓΩΓΗΣ 500gr	2020-03-03	3.06	3.06	sklavenitis
	ΓΙΓΑΝΤΕΣ 3Α ΕΙΣΑΓΩΓΗΣ 500gr	2020-03-03	3.07	3.07	mymarket
	Όσπρια	2020-03-04	2.07	1.89	mymarket
	ΓΙΓΑΝΤΕΣ 3Α ΕΙΣΑΓΩΓΗΣ 500gr	2020-03-04	3.06	3.06	sklavenitis

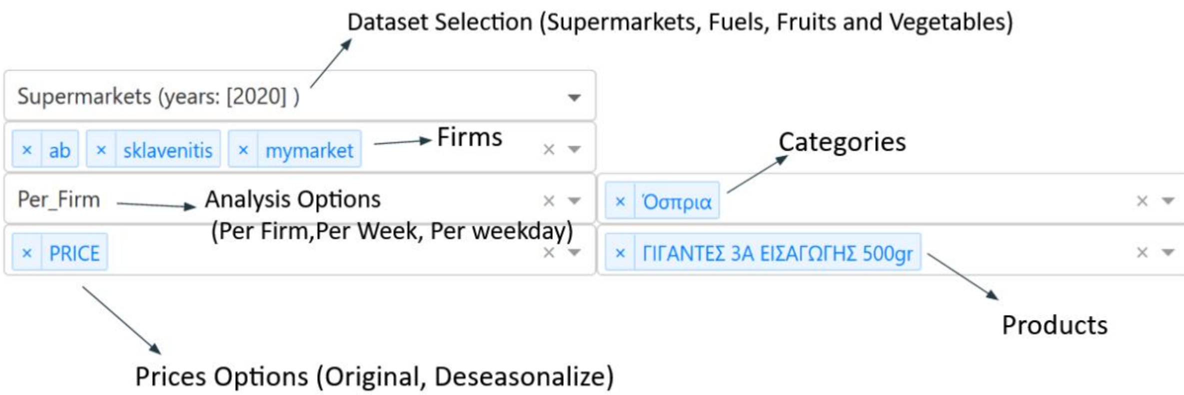
We can export both tables like excel file by pressing the button *Export* above of two tables.

2.3.2.3. Box-Plot

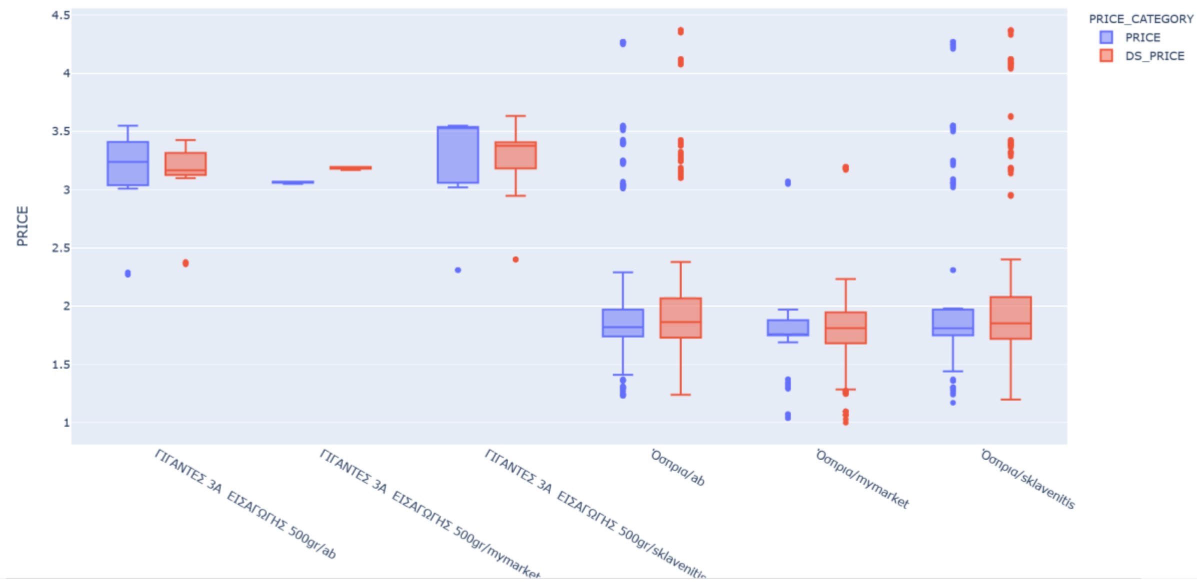
A more informative view of the price changes per category or product can be taken by using measures such as the percentiles, median, security threshold and outliers. Each price is used as a unique data point in the analysis (not an average price of the week). Below we describe all the measures employed in a box plot.



2.3.2.3.1. Box-Plot Options



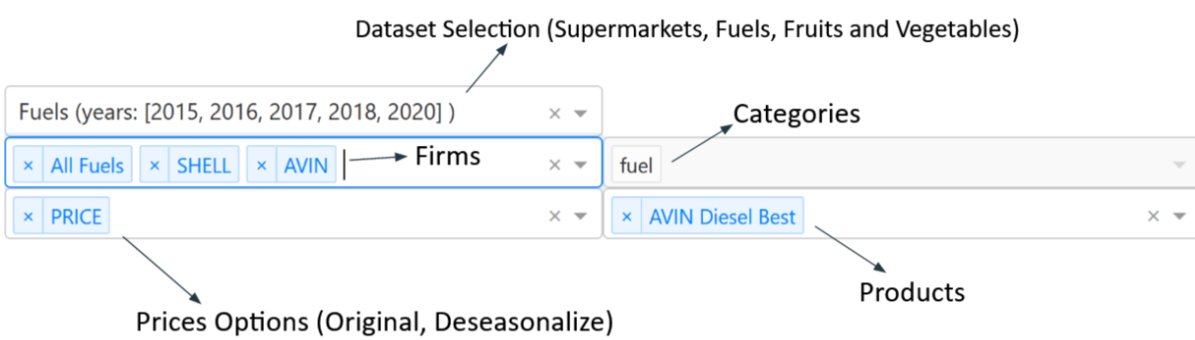
2.3.2.3.2. Box-Plot Example



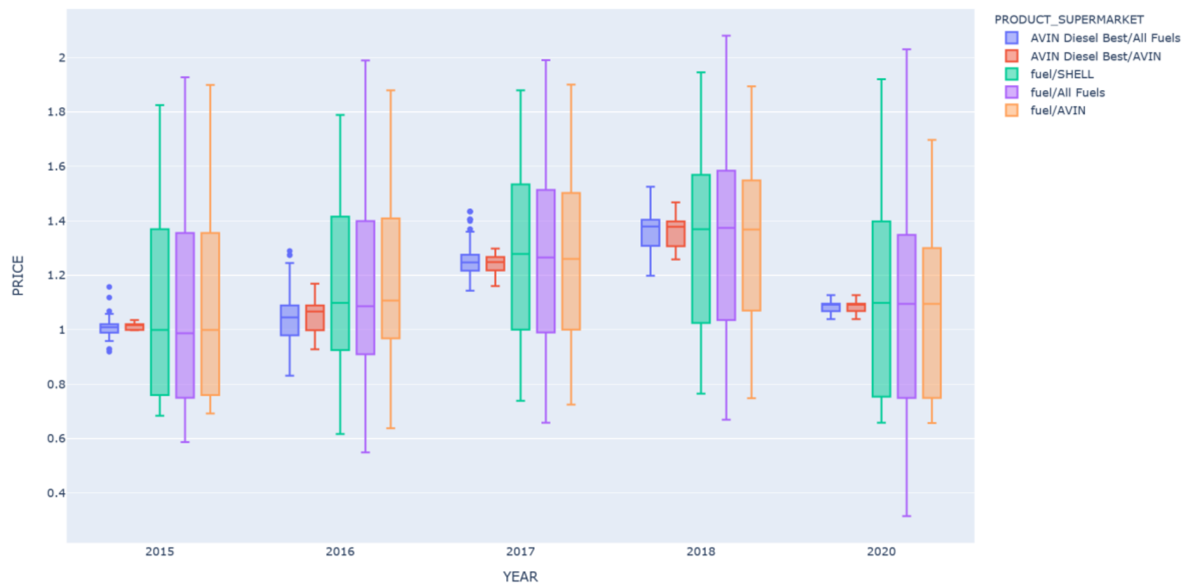
2.3.2.3.3. Box-Plot Per Year

In this plot we can provide a category price comparison of the previous years for each Firm or many Firms.

2.3.2.3.3.1. Box-Plot Per Year Options



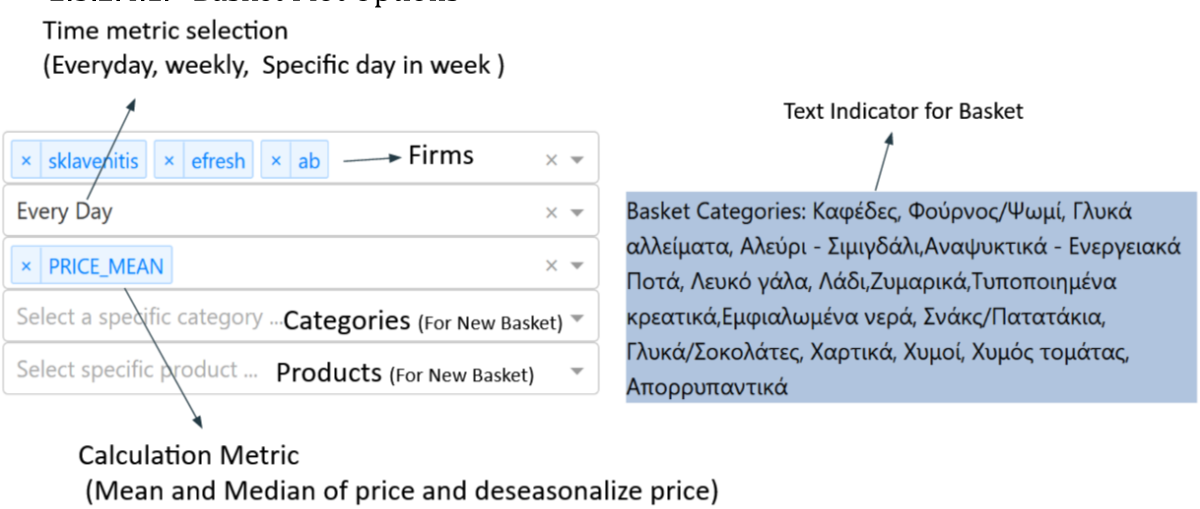
2.3.2.3.3.2. Box-Plot Per Year Example



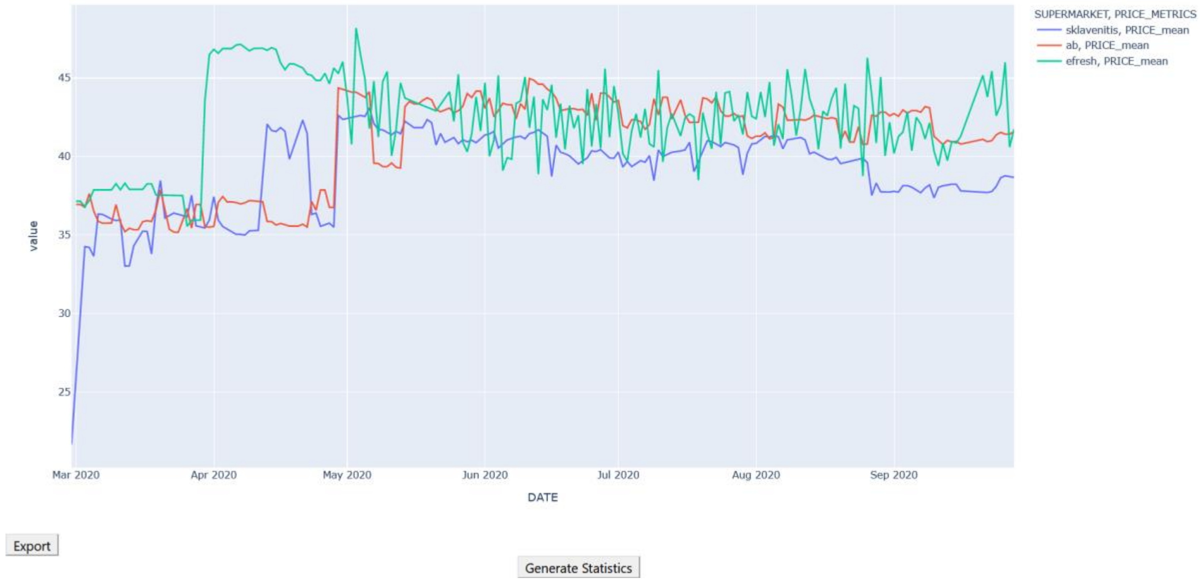
2.3.2.4. Basket Plot

A line plot with basket of products. We create a default basket with following 16 categories: *Coffee, Bread, Sweet Spices, Flour - Semolina, Soft drinks - Energy Drinks, White Milk, Oil , Pasta, Standard Meats, Bottled Water,Chips, Chocolate, PaperRoll, Juices, Tomato Juice, Detergents.* For every category we calculate the median price of products. Based on analysis of Research Institute of Retail Consumer Goods (" Ινστιτούτου Έρευνας Λιανεμπορίου Καταναλωτικών Αγαθών (ΙΕΛΚΑ)") weighted with Consumer Price Index of 2019 by Hellenic Statistical Authority (ΕΛΣΤΑΤ). Extra the user can create a new basket and to export statistics as excel file .

2.3.2.4.1. Basket Plot Options



2.3.2.4.2. Basket Plot Example



2.3.2.4.3. Basket Plot Generate Statistics and Export In Excel File

For every line in the above plot we can generate basic statistics like length (count), mean, standard deviation, minimum, maximum and quantiles 25%, 50%, 75% by pressing the button *Generate Statistics*. We can export table like excel file by pressing the button *Export* above of table.

Export

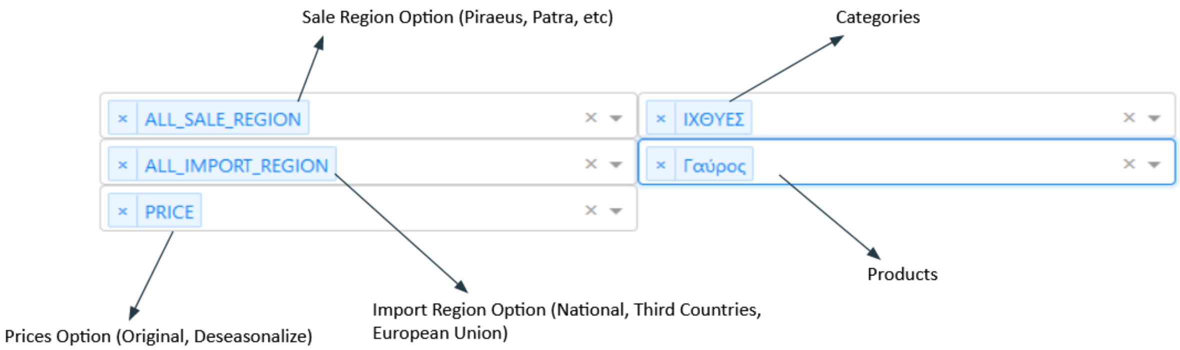
ndex	SUPERMARKET	Count	Mean	Standard Deviation	Minimum Value	Quantile 25%	Quantile 50%	Quantile 75%	Maximum Val
0	ab_PRICE_mean	201	40.75	3.04	35.16	37.14	42.18	43.05	44.
1	efresh_PRICE_mean	199	42.31	2.91	35.55	40.48	42.52	44.7	48
2	sklavenitis_PRICE_mean	166	39.12	2.76	21.65	37.73	39.93	41.11	43.

Generate Statistics

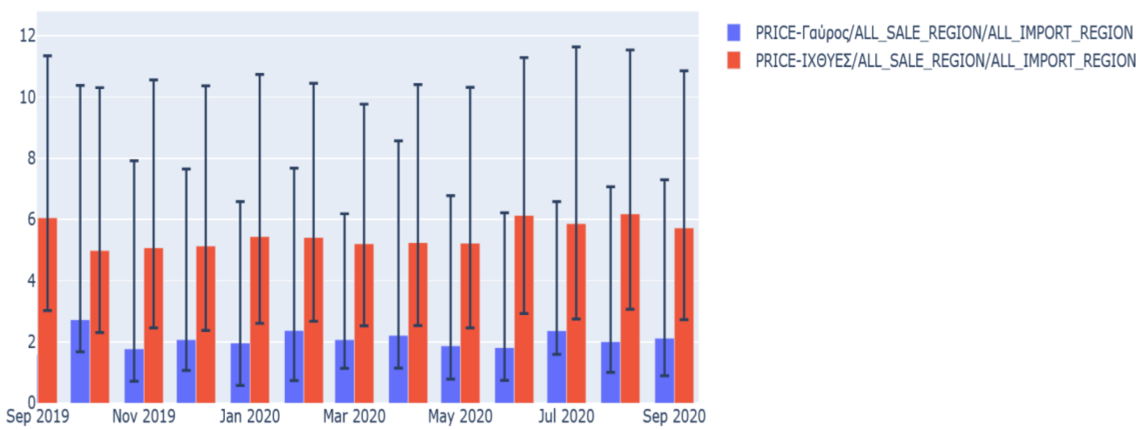
2.3.2.5. Fish-Data-Error-Bar

In this plot we try to make use of all the given information about the fish data. For every month we have the minimum, the average and the maximum price of selling fish products. Therefore we create an error bar per month. Error bars are graphical representations of the variability of data. They give a general idea of variation of selling products. Moreover, if we hover above a specific bar the total quantity of the particular product or category is being shown.

2.3.2.5.1. Fish-Data-Error-Bar Options



2.3.2.5.2. Fish-Data-Error-Bar Example



2.3.2.5.3. Fish-Data-Error-Bar Generate Statistics and Export In Excel File

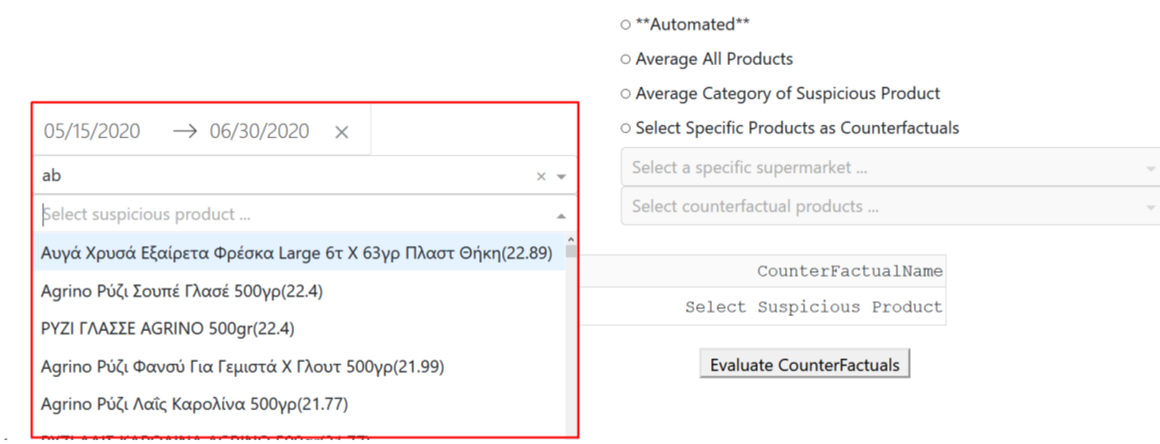
For every bar and for every minimum, average and maximum price in the above plot we can generate basic statistics like length (count), mean, standard deviation, minimum, maximum and quantiles 25%, 50%, 75% by pressing the button *Generate Statistics*. We can export the depicted table as an excel file by pressing the button *Export* that is above the table. Except from basic statistics we display and the data which needed to create the plot.

2.3.2.6. Screening Tool

Implementation of a two-steps screen to detect anti-competitive practices (collusion, excessive pricing and exclusionary pricing).

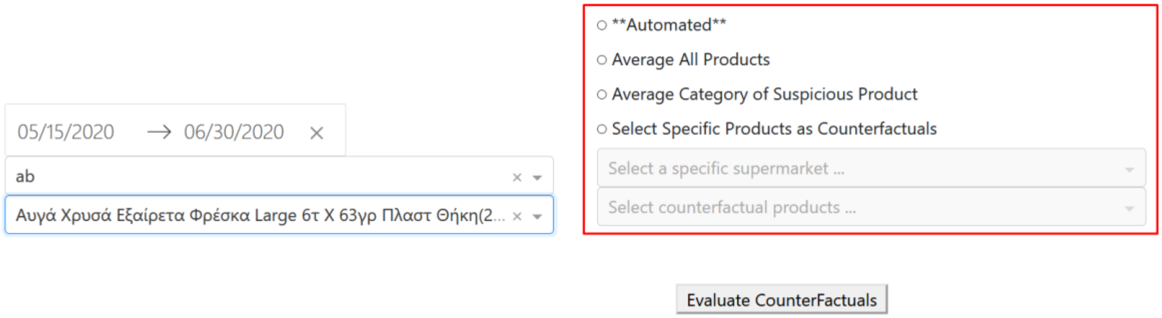
- **First Step:** preliminary analysis of unusual and suspicious price changes
- **Second step:** is a test for structural break in the price series.

A user selects a time period (preferable larger than a month) and a supermarket and automatically calculated the t-statistic from the t-test for all the products of that supermarket. The t-statistic indicates which products had the largest price variation when taking into account the price before and during the suspicious period. Positive t-statistic means price growth and vice versa. Below we have an example with period 15 May 2020 -- 30 June 2020, with selected supermarket the "ab" and in dropdown display the products sorted with absolute value of t-statistics.



After a user chooses the suspicious product, the user can select one of the following ways to produce counterfactuals (products that we expect to have similar price variations as the suspicious product but are not considered to be suspicious themselves).

- **Automated** (the correlation between the suspicious product and all other products from each supermarket and select the top 10 products that have highest correlation)
- **Average all products** (use as a counterfactual the average of all products)
- **Average category** (average price from the category of the suspicious product)
- **Manual selection** (select products from specific supermarkets manually)

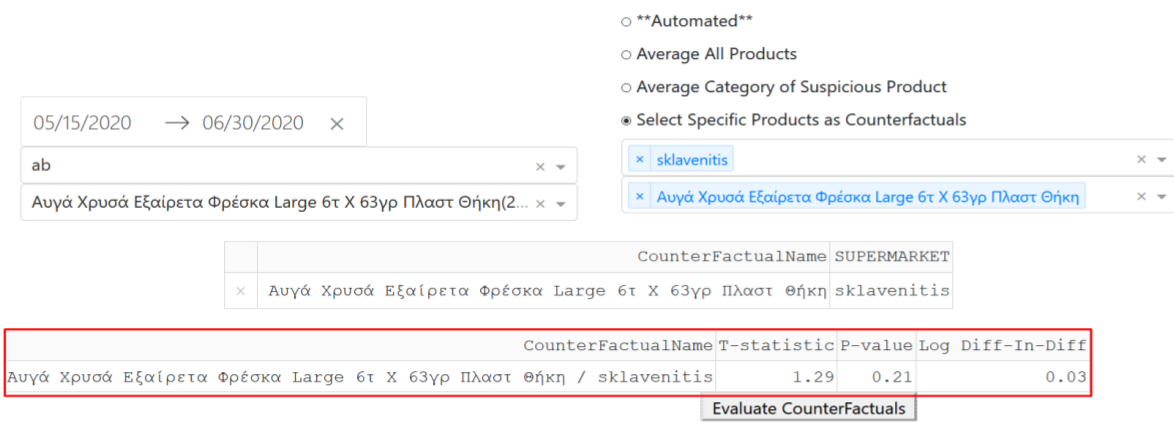


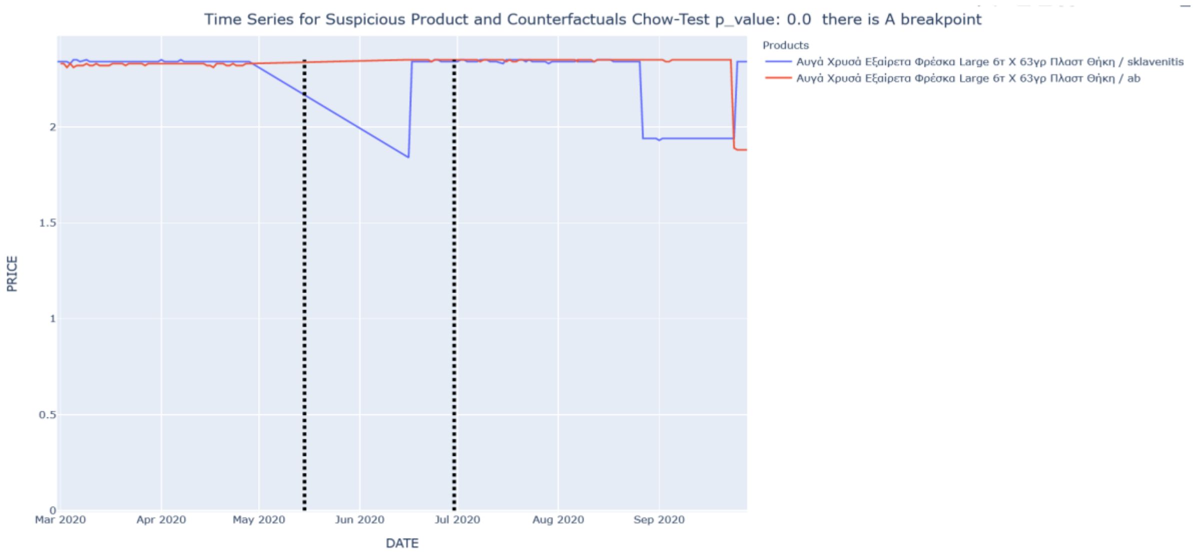
When the user chooses the counterfactual the app produces various metrics like t-statistic, P-value of t-test and log-diff-in-diff and a diagram to help the user evaluate whether the counterfactuals have the price changes as the suspicious product with pressing the button Evaluate CounterFactuals .

The log-diff-in-diff is define as:

$$DD_{it} = (log\, P_{it} - log\, P_{i,t-1}) - (log\, CF_{it} - log\, CF_{i,t-1})$$

where $(log\, P_{it} - log\, P_{i,t-1})$ is the continuous growth rate of the price of the product/firm i between t-1 and t, and $(log\, CF_{it} - log\, CF_{i,t-1})$ is the continuous growth rate of the counterfactual of product/firm i over the same period.

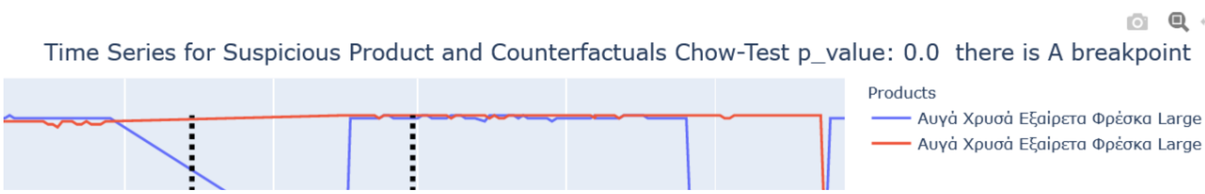




The black dotted lines are the specific time period which have been chosen by the user. The app above the plot calculates the expected price of the suspicious product and outputs whether there are any structural breaks. The expected price is define as follow:

$$P_t \; = \; \beta_1 \, Pr_{cf_1} + \ldots . + \beta_n \, Pr_{cf_n} + e$$

where P_t price of suspicious product in t, Pr_{cf_i} price of counterfactual i in t, β_i the coefficient in linear regression and e the error term. In this manner we can calculate the chow test which checks if any breaking points indicate between the coefficients before and during a suspicious period. Thus, if there are breaking points so the counterfactual/s and suspicious product have different behaviour before and during a suspicious period.

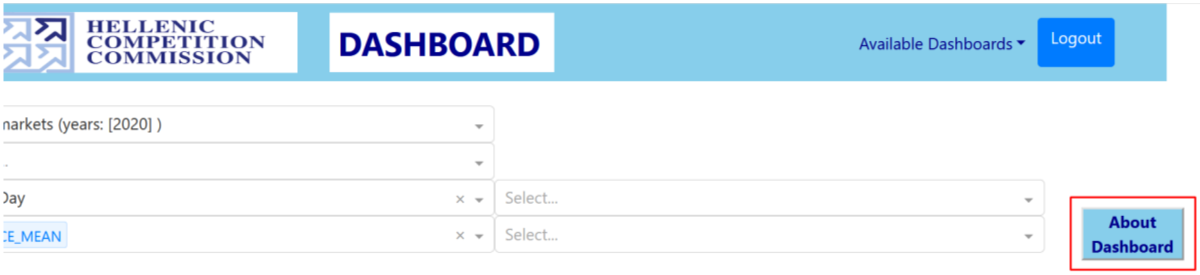


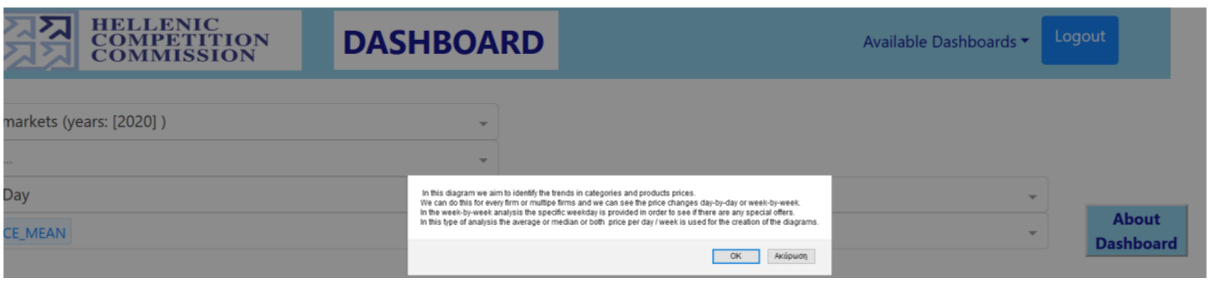
We can not consider this result valid because the expected value was predicted by a regression model based on counterfactual prices but the market dependent and for many other parameters like (cost or demand).

2.3.2.7. Extra Features in Every Dashboard

2.3.2.7.1. About Dashboard

In every dashboard in the right corner we can find a button named About Dashboard which the user can press it and it will pop up a window with information about the specific dashboard





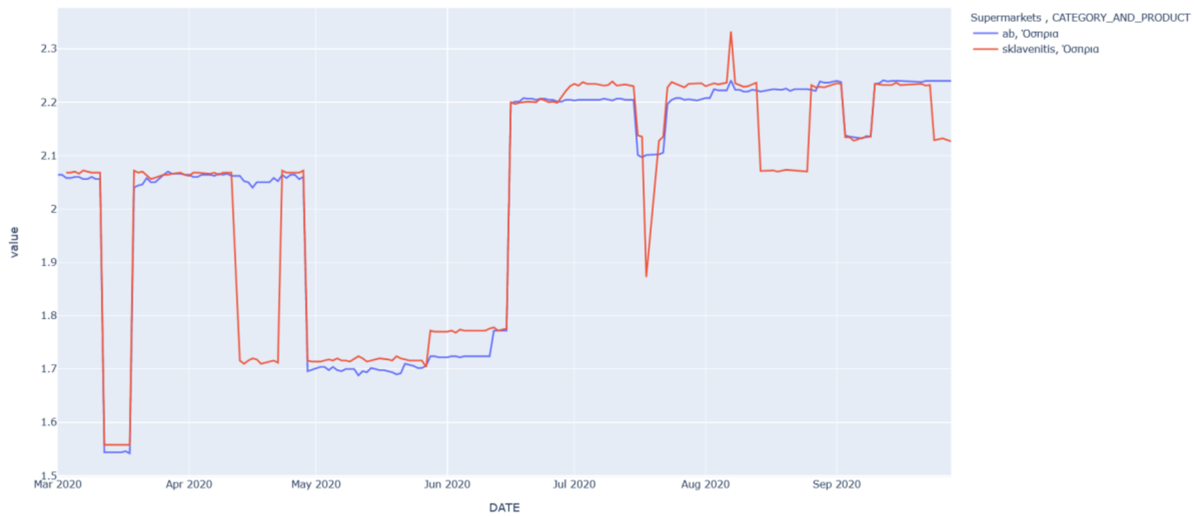
2.3.2.7.2. Help Menu Options

In every dashboard plot in the right-corner of the plot we have some extra helpful features.

Download The Plot as PNG

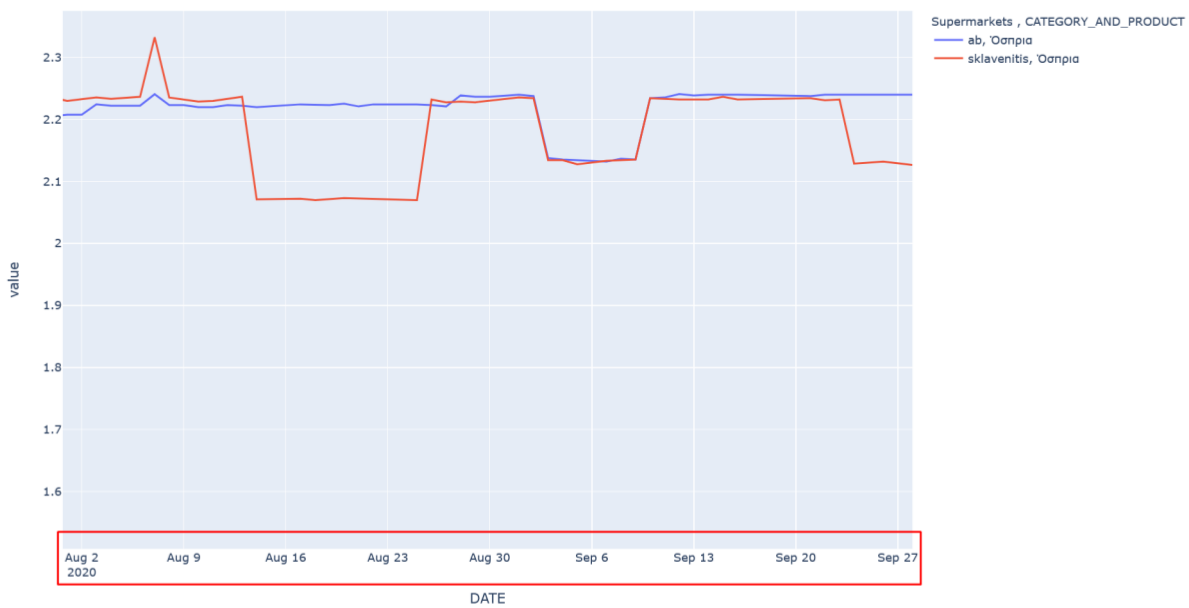
Zoom in/out

Original plot:



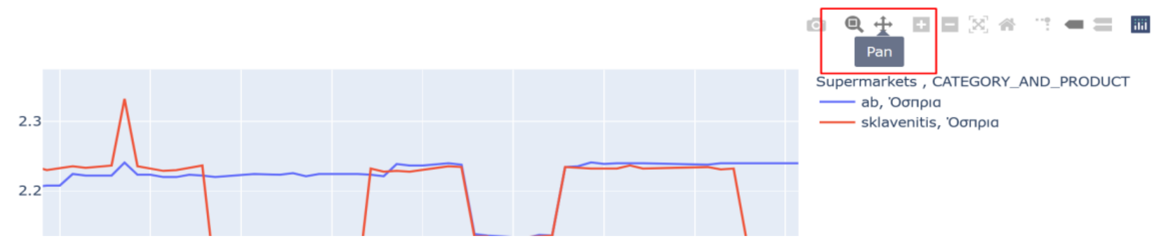
With to hold left click mouse inside in plot we can zoom in in specific time period

After zoom plot:

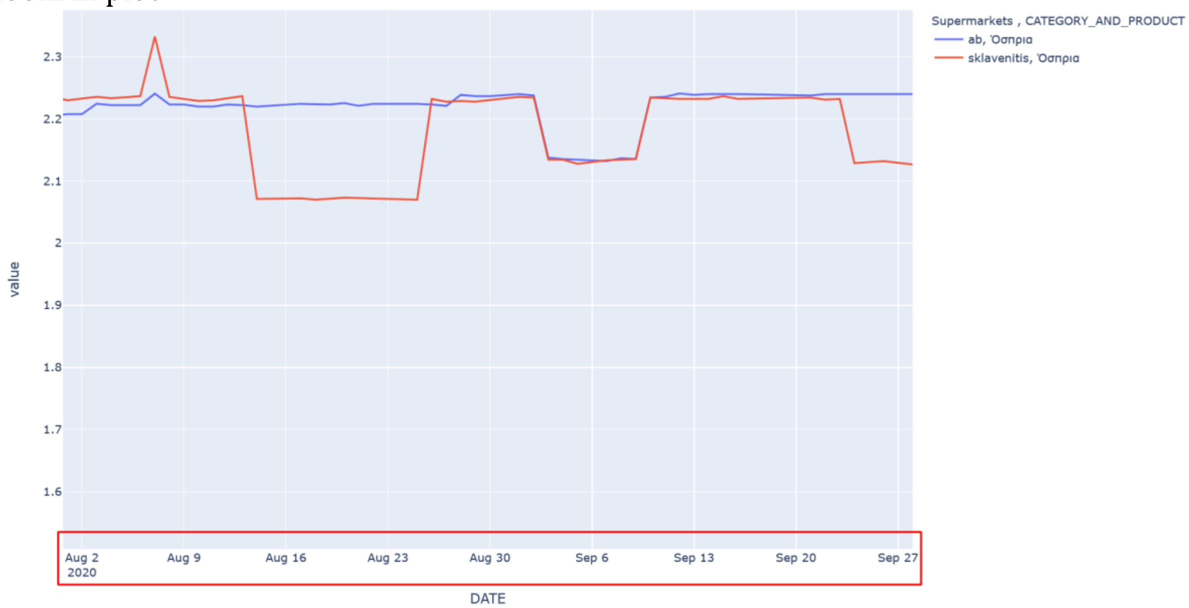


Pan

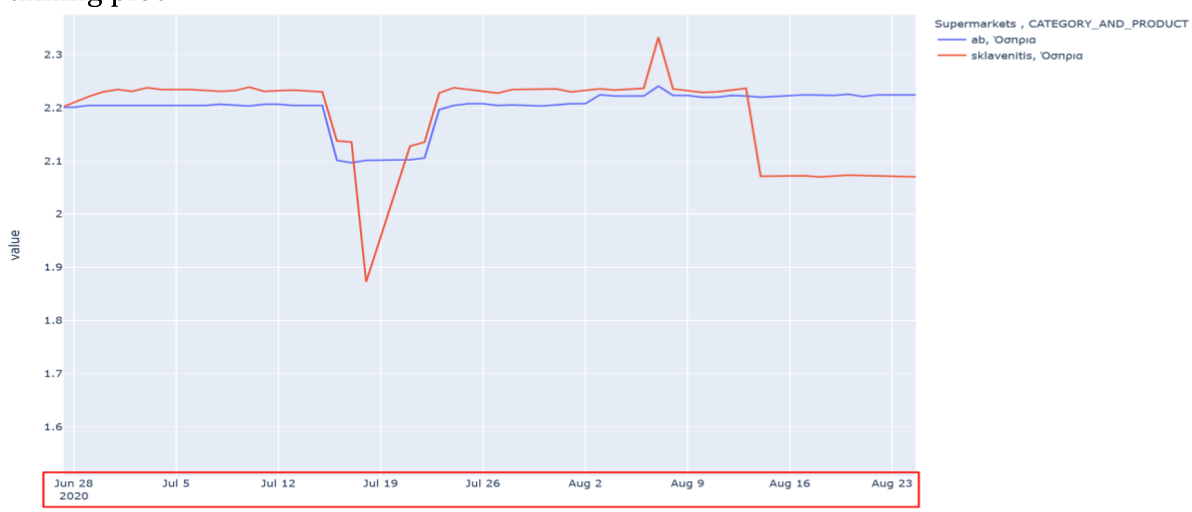
We can pan above the plot by press the pan button and after in plot with to hold left click and drag the mouse inside in plot we can pan the plot



Zoom in plot

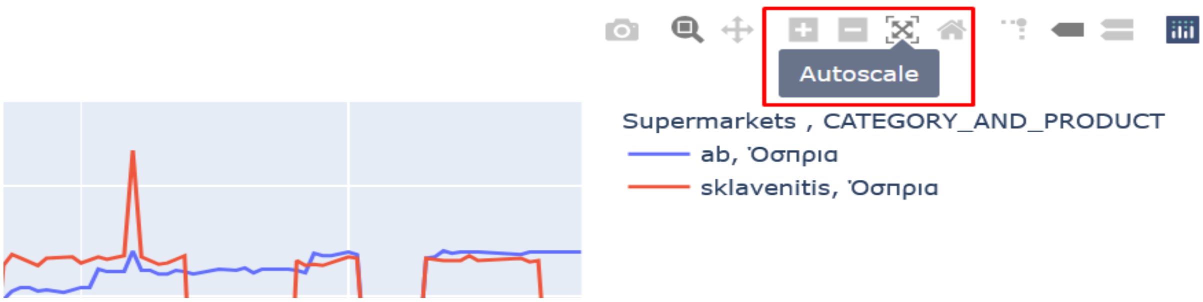


Panning plot



Autoscale / Reset Axis

After zoom and panning if we want to go in the beginning plot we can press the Autoscale button or Reset Axis button.

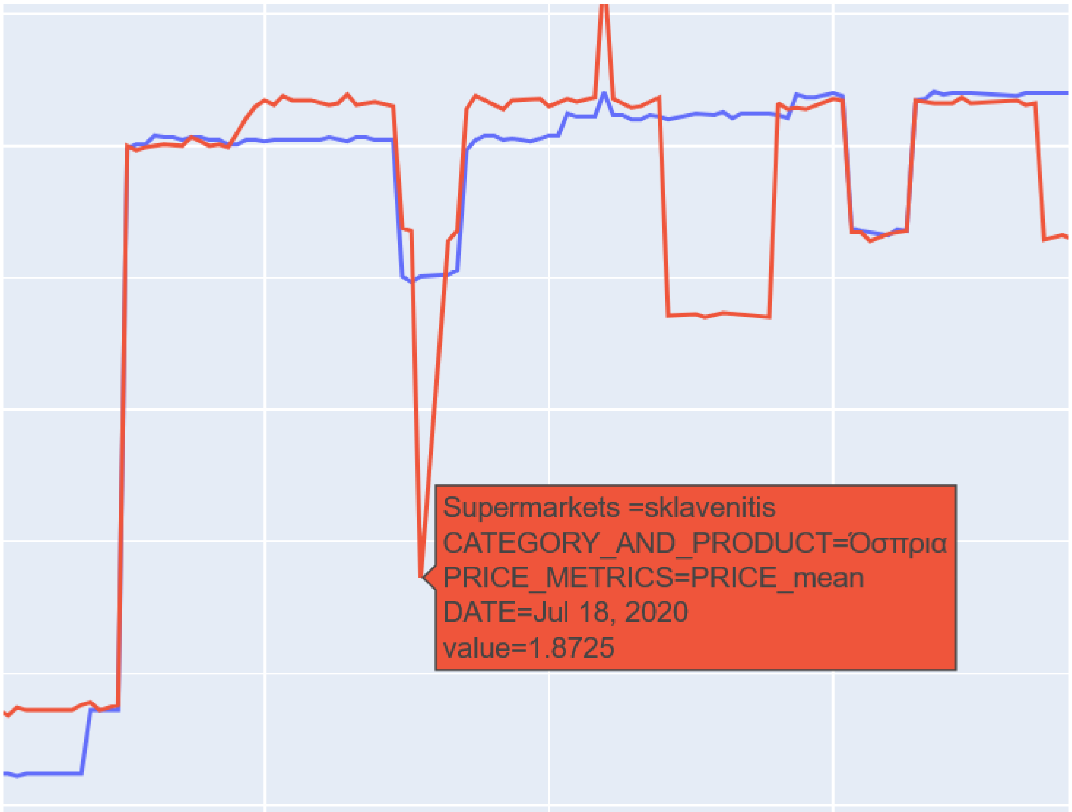


Toggle Spike Lines

By pressing Toggle Spike Lines we can have connected lines in x-axis and y-axis.

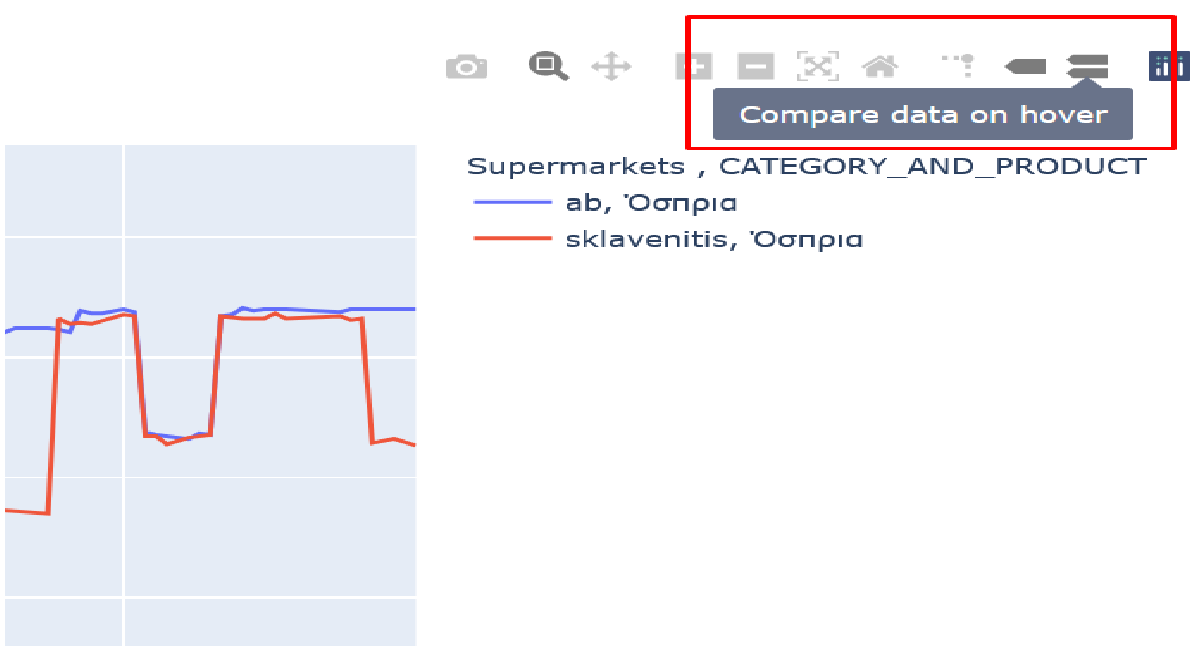
Default Hover

By dragging your mouse in the plot you can see the data of specific point.



Compare Hover

By pressing compare data in hover you can compare data in specific date, now if you drag your mouse in the plot in specific point you can see the data of specific date in all lines.



Comparable plot:

2.3.3. Infrastructure

The application is being deployed as a Flask Server that incorporates the dashboards. The interactive dashboards are created by utilizing the framework of Plotly-Dash that is known for its usability features and scalability.

2.3.3.1. External Data Sources

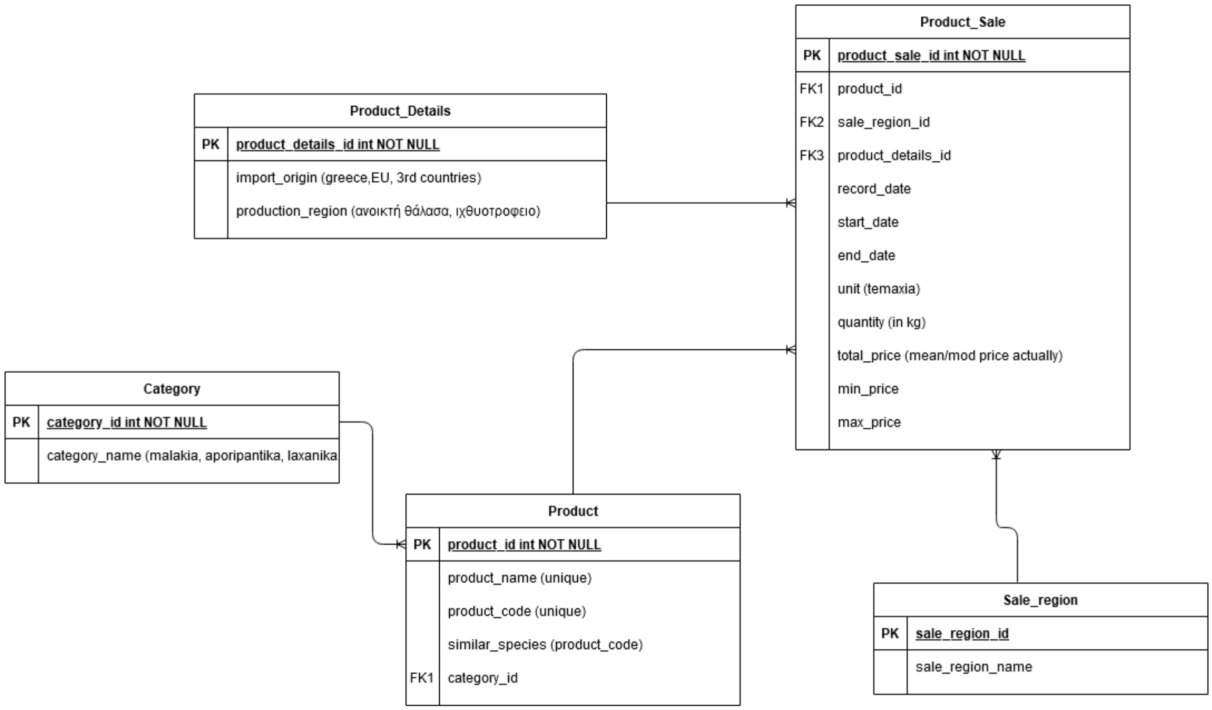
The dashboards rely on multiple external data sources that are integrated in a single Database. We can see a high level description of the process in the diagram below. The process starts by some scheduled tasks that retrieve data from external sources via different methods (sftp, scrapping, api call) and produce a file with the data for the specific time interval. The data are then preprocessed and transformed in order to have the appropriate format to be integrated in the central database.

2.3.3.1.1. Updating Fish Products

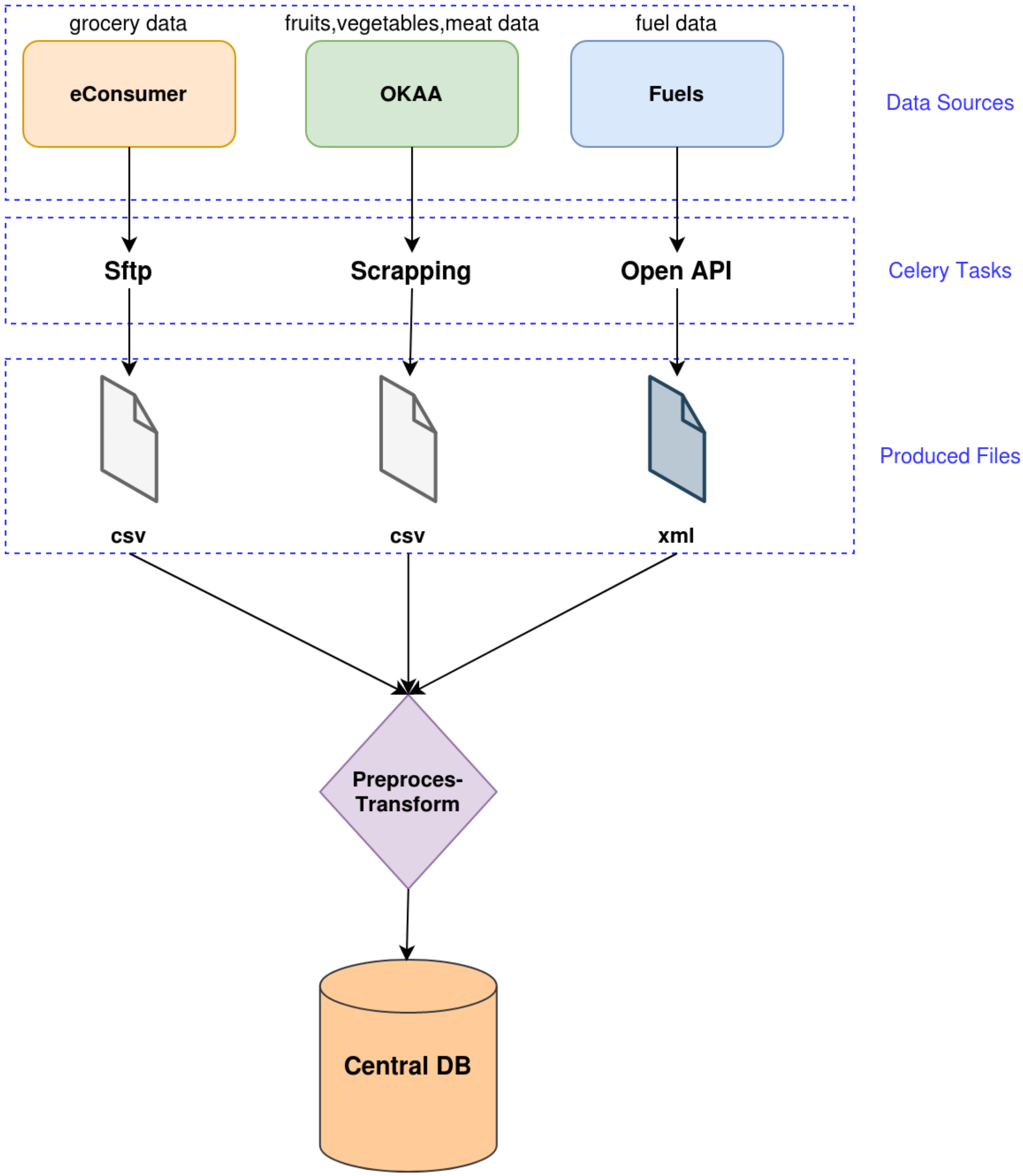
The OKAA (Οργανισμός Κεντρικών Αγορών και Αλιείας) is responsible for monitoring product prices in multiple different sectors that contain fresh products (fish, fruits, vegetables). In the initial implementation of the HCC Intelligence Platform the fruits and vegetables were already integrated. The next step was to integrate the fish products that are being uploaded on a monthly basis via the open data of OKAA. We have created an infrastructure that scraps the data from the site and uploads them in newly created tables in the existing database.
The database tables that are being used are the following:

- fish_products (contains the fish products)
- fish_categories (contains the fish categories)
- fish_product_sale (contains the quantities and prices of a product that is being sold)
- fish_product_details (contains the import and production region of the product)
- fish_sale_region (contains the location that the fish are being sold)

Below we have a diagram depicting the database tables



The fish products are being scrapped from the open data of OKAA using the Beautiful Soup Framework of python. Initially they are in an excel format that is being parched, preprocessed and then uploaded to the corresponding database tables. Other than the initial upload an update function was necessary. The update function checks if we have all the latest files that are being uploaded and downloads them if needed. The update task was scheduled as a Celery task that runs every day at a specific time (18:30) in a Redis server that is created in the inbound hcc server (dias.epant.gr). Finally, a new diagram was created in order to incorporate the fish products. This diagram is an error bar because we wanted to depict all the information that we had available (minimum/maximum/average price).



2.3.3.1.2. Issues

1. The data require further preprocessing after they are retrieved from the Central DB since we have duplicate categories and products. Furthermore some products are misclassified to the wrong category
2. The design of the database makes the queries that need to be executed slow when retrieving for large time intervals

3. Each data source has different availability and issues throughout time. These are depicted in the table below.

Table 3: Data Sources for the HCC Economic Intelligence Platform

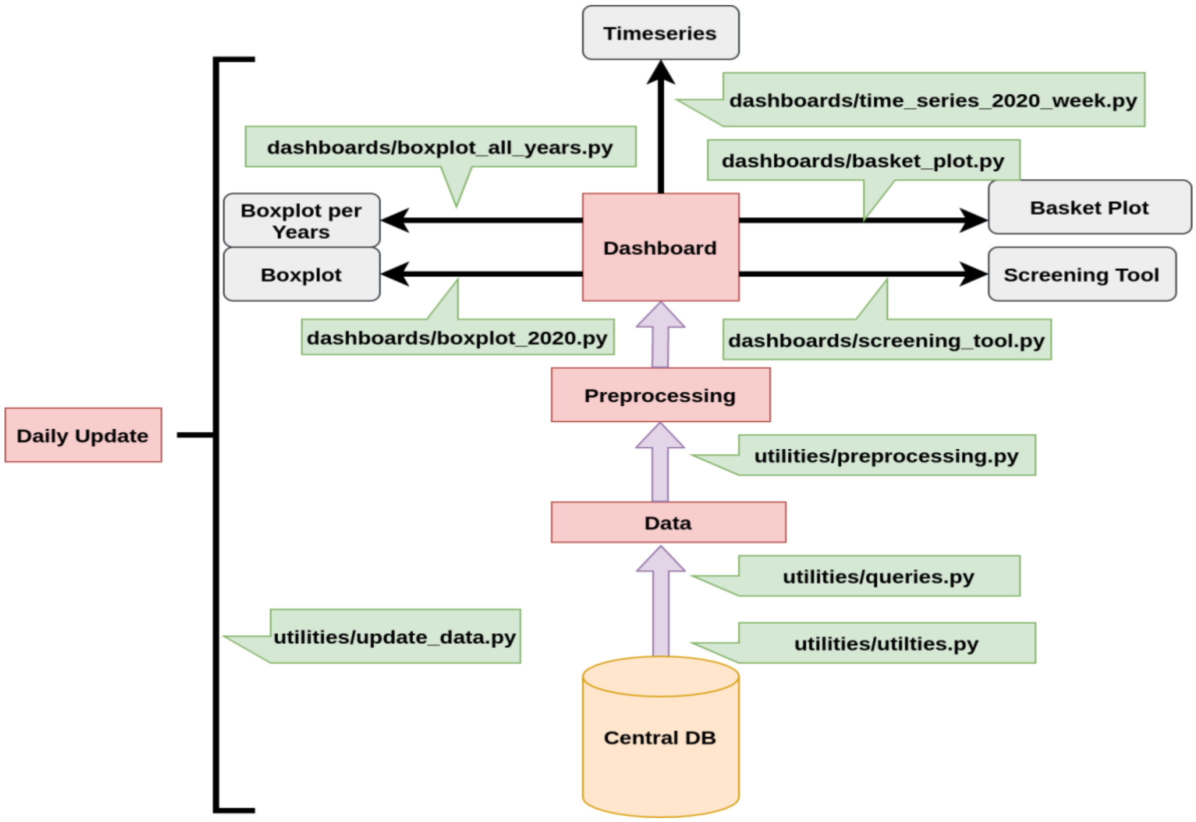
Sources	**Availability**	**Updated**	**Issues**
Supermarket Data (e-consumer)	2014, 2015, 2016, 2020	Yes (Daily)	• The products are not the same from previous years and the year 2020 • The previous years do not have daily data
Meat, Fruits and Vegetables (OKAA)	2017,2018, 2019, 2020	Yes (In Week at least one time)	
Fuels	2015, 2016, 2017, 2018, 2020*	Yes	• For the year 2020 the available data are from 22/04/2020 - 07/05/2020 and then they get updated from 18/09/2020 until today • In most

			cases the fuel station is not available
Fish (OKAA)	2018,2019,2020	Yes (Monthly)	• In some cases the excel file that is being scrapped from the site is not encoded properly and it cannot be retrieved (total 0f 4 cases)

2.3.3.2. Technologies Used

Below are listed the core technologies for the HCC Intelligence Platform:

- Flask
- Plotly Dash
- Python 3.8



In this plot we briefly present the overall procedure including the collection of data from the database till the final plots in Dashboard. Moreover in each step the corresponding .py files are provided including the code for the specific task and all these files are inside the "hcc_app/plotlydash" path in github. Firstly in "utilities/utilities.py" the connection with the database of HCC is made and then the appropriate queries for gathering the data are described in ''utilities/queries.py". After fetching data a preprocessing is made as presented in "utilities/preprocessing.py". Especially, the general process includes the drop of duplicate rows, drop of rows with NaNs and drop of rows with negative price values. In case of products belonging to categories of 'fruits', 'vegetables' and 'meat' further preprocessing is made due to the fact that same products may have slight different descriptions. Moreover, we have set manually what products belong to fruits and vegetables because in different cases the same product could be characterized either as fruit or vegetable. After the finalization of preprocessing, the data can be presented in five different dashboards. The majority of the dashboards also provide the ability to use the deseasonalized price as a metric. We created an autonomous new library for removing the seasonality based on the time basis that is defined by the user. We used data from the years 2020 (since previous years have very sparse data points) and we removed seasonality on a monthly basis. The library calculates monthly indices by dividing the average monthly price of each product by the average yearly price. Then for each product we average the monthly seasonal indices. Then the actual prices of the products are multiplied by the average seasonal indices in order to produce the deseasonalized price. There is also a video tutorial that was provided to us that describes the process (here). This code is included in “utilities/seasonality.py”.

In terms of plots we give the opportunity of creating boxplots, line plots and examining suspicious activity for a product. Specifically, in “dashboards/boxplot_2020.py” there is the code for making boxplots presenting the price or deseasonalize price changes per category or product including the percentiles, median, security threshold and outliers for the supermarkets’ data of 2020, fuels’ data of 2018 and 2020 and fruits’ and vegetables’ data of 2017-2020. Moreover, in “dashboards/boxplot_all_years.py” the code for different boxplots for comparison of prices across years is presented in case of supermarkets’ data of 2014-2016 and 2020, fuels’ data of 2015-2018 and 2020 and fruits’ and vegetables’ data of 2017-2020. Furthermore, the corresponding line plots for different products and categories are created by the code in “dashboards/time_series_2020_week .py” considering mean or median price or the corresponding deseasonalize price.In case of “dashboards/basket_plot.py” the code creates line plots for mean or median price or the corresponding deseasonalize price considering a basket of products together and not only one. Finally, in “dashboards/screening_tool.py” the code for detecting anti-competitive practices for a product is given.

In conclusion wherever the app starts the data are updated automatically and the code for that is shown in “utilities/update_data.py”. Specifically, it is tested if data is up to day and if this is violated then the new data is fetched from the database in order to be updated.

2.4. Case studies: Applying the screening tool and using the HCC Economic Intelligence platform in concrete cases during the COVID-19 pandemic

The above screening tool was implemented in a number of investigations opened by the Hellenic Competition Commission during the first months of the Covid-19 pandemic.

2.4.1. Investigation on health and hospital equipment procurement

The Hellenic Competition Commission (HCC), within the framework of its responsibilities and in order to investigate whether the conditions for initiating an ex-officio investigation for suspected violations of the provisions of Law 3959/2011 (the Greek Competition Act) in public procurement tenders are met, launched an investigation in the markets of a) healthcare materials, b) other appropriate means of individual or collective protection against the spread of coronavirus and c) special hospital equipment for the treatment of coronavirus cases, evaluating supply data before and after the application of the legislative act A΄42/25.2.2020, ar. 19 of Law 4675/2020.

The purpose of this preliminary investigation was to identify those companies which, during the health crisis of COVID-19 in Greece, proceeded in excessive and/or exploitable pricing. This action was deemed necessary following the sudden increase of demand for specific healthcare and medical equipment and the need for immediate supply of certain products departing from the standard public tender processes, which may have led to increased prices deriving from value chain business practices that may fall under the provisions of Law 3959/2011.

The research was based on two data sources: data collected by the HCC from the seven (7) Health Regional Units of the country and data from the open public procurement platform "Diavgeia.gov.gr".

In particular, on 16.4.2020 and subsequently on in 23.4.2020, the HCC sent questionnaires to the Health Regional Units of Greece, requesting information on the supply of healthcare materials (surgical masks, masks FFP2/FFP3, antiseptics, disposable gloves, Tyvec uniforms, eyes protection, protective glasses, protective shields, disinfectant tablets, thermometers, flow meters, etc.) for the period from November 2019 to March 2020, as well as during the months from November 2019 until the emergency response measures to COVID-19.

The data contains information for each public tender with regard to the contracting authority, the product purchased, all the suppliers who submitted bids as well as the winning bidder, the price per unit of product, the type of procurement process (direct supply, informal tender, calls for proposals, etc.), the selection and award criterion and the signature date of the contract. From this data, 12 products were selected, for which there were many observations and the sample was processed, omitting those observations from which data for key variables were missing. The observations used for further analysis from data collection amounted to 808.

Data from DIAVGEIA, the open government database on public expenses data, was collected through the development of algorithms (using Application Programming Interface - API), in three basic steps, as the speed, volume and variety of structure and nature of the information exchanged requires special technology and analytical methods for its conversion into exploitable data for the detection of anti-competitive practices.
In particular the administrative data was semi-automatically collected in three steps.

At the first stage of the processing of the data, potentially relevant contracts were searched through the Diavgeia API using products' keywords (e.g., "ΜΑΣΚΕΣ", "ΓΑΝΤΙΑ", "FFP3"). Next, the metadata of these contracts and the corresponding files were downloaded at a local database in order to be further processed. The contracts' files that were retrieved are in the format of exploitable, semi-structured PDF-files, i.e. they contain unstructured non-uniform information which cannot be easily and readily extracted in exploitable mode for the total of the contracts. It should be noted that during this first stage of analysis, the aim was to export big data on which to test the application and adjustment of tailor made algorithms, in order to render it exploitable for the extraction of relevant data.

At a second stage, that of data pre-processing, the collected results were reviewed and filtered, allowing for the rejection of possibly biased results. This stage, which is what we call feature engineering, aims at the dimensional normalization of the results and also at the gradual improvement and update of the API queries' parameters. Consequently, API queries' parameters were updated to retrieve only the most relevant contracts. Through the several rounds of data cleansing, re-sampling and review, the sample of contracts and other administrative data files decreased from more than 150.000 thousand to 2.584 contracts.

Finally, at the third stage of the analysis and given that Diavgeia API does not allow for collecting unit prices, the algorithm was further elaborated in order to export unit prices from the semi-structured exported big data. More specifically, automatic data extraction methods were applied using Camelot and Tabula software Python packages, in order to identify prices for the relevant products from PDF-files for the sample of 2.584 contracts. Data extraction was successful for 692 contracts (27% of the sample). However, only 109 contracts out of this sample exported from Diavgeia were selected for further analysis as only these records contained unit prices for the products that were represented in the survey (e.g., surgical masks, latex gloves).

Through this exercise, the HCC team managed to set the framework for the next steps of analysis, that is, the study, design and "training" of a self-taught algorithm which does not depend on manual intervention for the repetition of the above steps, using Natural Language Processing and Machine Learning Processes. The aim is to set up a platform where algorithm will be applied on publicly available data in order to trace price outliers which can serve for further investigation according to the provisions of competition law.

The final set of data analyzed includes 917 observations: 808 from the data collected from the Health Regions and 109 from DIAVGEIA platform. The purpose of the analysis is to identify unusually high prices for the products under investigation. The assumption is that within these product groups, there is relatively unobserved variability in product quality hence the analysis can concentrate on prices only. The analysis first proceeds in a simple bivariate set-up looking at unit price in the pre/post crisis periods. Second, the prices are examined in a multivariate set-up also controlling for district, buyer fixed effects, procedure type and purchased quantity.

The simple comparison of pre/post crisis group averages and variances within each product category gives a sufficient insight into general price movements over time. Unsurprisingly, for virtually all product categories with sufficient number of observations, the median unit price increased while unit price variances also skyrocketed (Table 1).

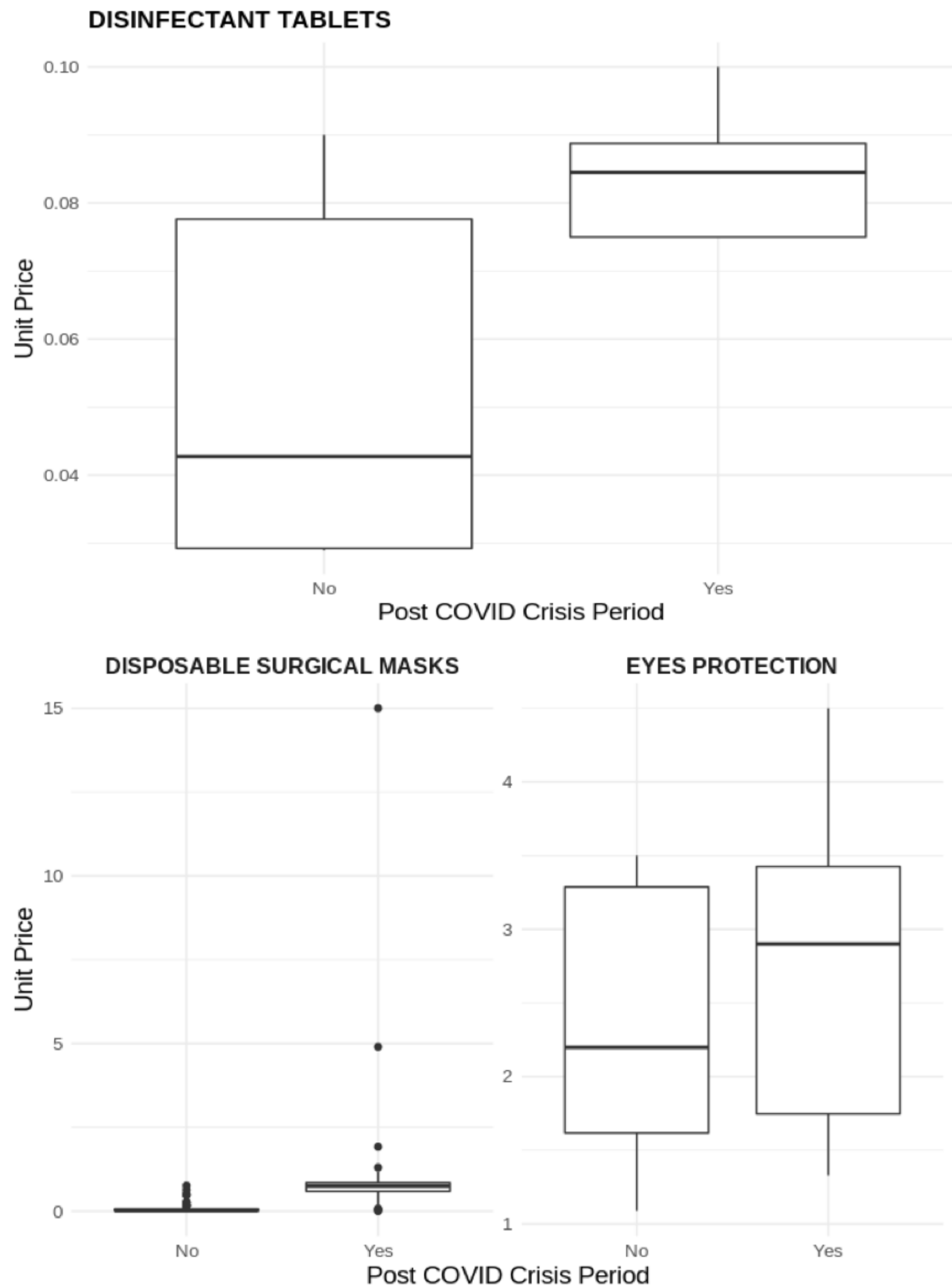
A comparison of average prices and fluctuations before and during the COVID-19 period in each product category provides an overview of general price changes over time. Unsurprisingly, for most of the product categories investigated with a sufficient number of comments, the median price increased, while in most cases the fluctuations also increased (Table 4).

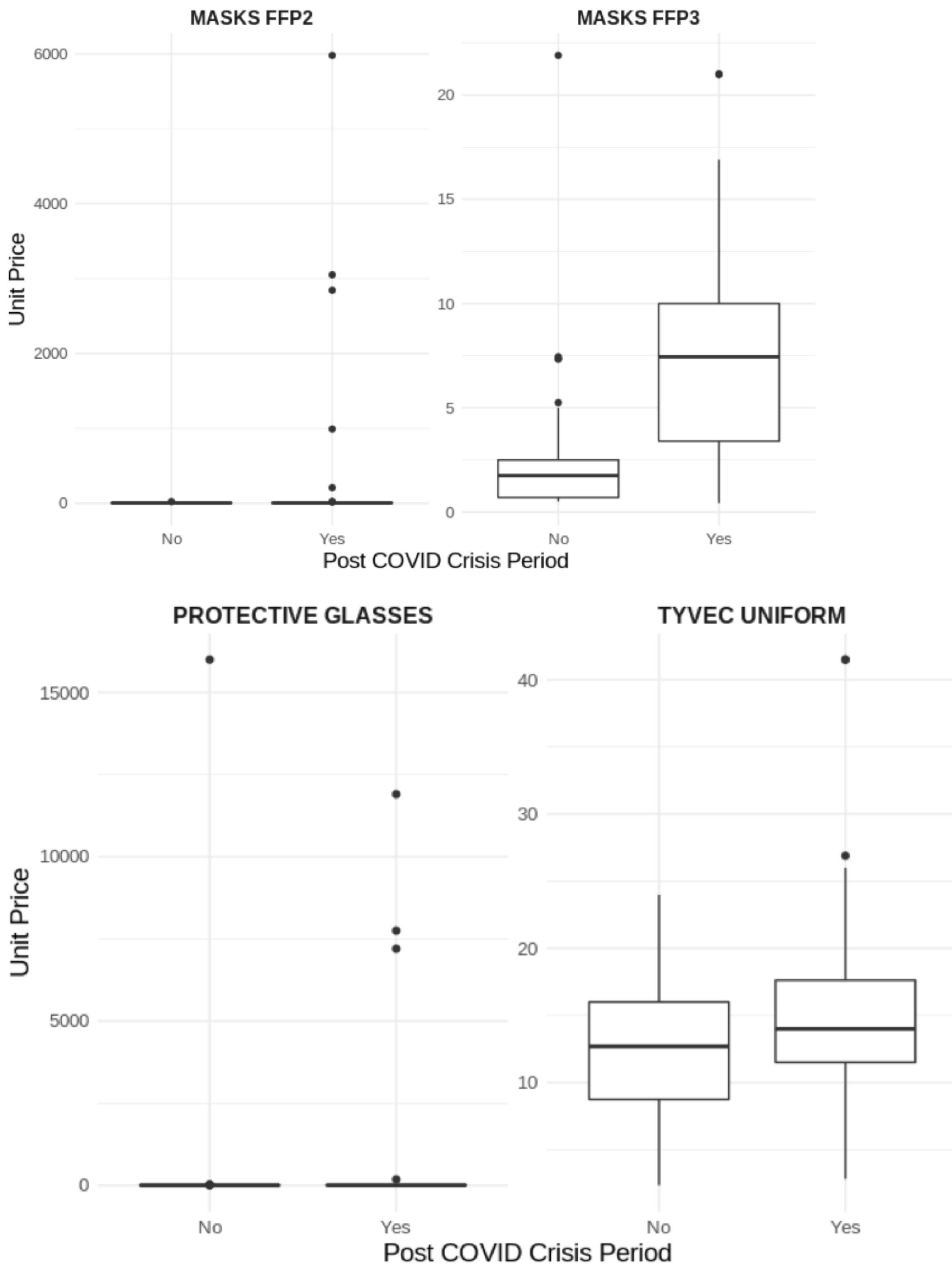
Table 4: Descriptive Statistics for Unit Price Values by Products and Pre/Post COVID Crisis Periods

	Dependent variable:	
	Log Unit Price	
	(1)	(2)
Post COVID Crisis (Yes)	3.148***	3.036***
	(0.180)	(0.230)
Product (Reference Category: Disposable Surgical Masks)		
Eyes Protection	4.487***	4.856***
	(0.388)	(0.672)
Gloves (latex)	-0.123	-0.838*
	(0.188)	(0.463)
Masks FFP2	4.954***	5.135***
	(0.328)	(0.593)
Masks FFP3	4.198***	4.432***
	(0.213)	(0.504)
Other Masks	3.825***	2.177***
	(0.402)	(0.490)
Protective Glasses	4.884***	5.045***
	(0.223)	(0.473)
Tyvec Uniform	6.012***	6.103***
	(0.285)	(0.528)
Post COVID Crisis (Yes):Eyes Protection	-3.058***	-3.218***
	(0.529)	(0.887)
Post Covid Crisis (Yes):Gloves (Latex)	-3.070***	-3.126***
	(0.263)	(0.347)
Post Covid Crisis (Yes):Masks Ffp2	-2.605***	-2.926***
	(0.374)	(0.490)
Post Covid Crisis (Yes):Masks Ffp3	-1.936***	-1.955***
	(0.297)	(0.396)
Post Covid Crisis (Yes):Other Masks	-4.432***	-2.763***
	(0.512)	(0.546)
Post Covid Crisis (Yes):Protective Glasses	-2.549***	-2.648***
	(0.290)	(0.367)
Post Covid Crisis (Yes):Tyvec Uniform	-3.009***	-3.355***
	(0.358)	(0.460)
Constant	-3.997***	-3.225***
	(0.350)	(0.803)
District	Yes	No
Procuring Entity	No	Yes
Procedure Type	Yes	Yes
Observations	749	758
Adjusted R^2	0.817	0.808
Note:	*p<0.1; **p<0.05; ***p<0.01	

The increased variation around the median values is also indicated by box plots (Charts 1-4), in which the dots represent the observed extreme values.

Charts 1-4: Box Plots of Unit Price Values by Products and Pre/Post COVID Crisis Periods





As outlined before, first the process looks at outliers in a simple bivariate setting: pre/post crisis unit prices. For this bivariate outlier identification, means and standard deviations were calculated for each product in the data. The records with unit prices higher than +2 standard deviations from the average price were identified as outliers.

Overall, there are 120 unique suppliers represented in the data. Based on the bivariate identification of outliers, 29 suppliers were selling products 1 standard deviation above the average price of the given product, while for 17 suppliers, the price overturned the mean values by 2 standard deviations. While this is potentially indicative of some sort of unusual behavior, a range of alternative explanations may account for outliers. Hence, we look at potential outliers in a multivariate setting.

The multivariate outlier identification relied on linear regression analysis with the log unit price as the dependent variable, using as independent variables pre/post crisis dummy, product class fixed effects, log quantity purchased, district of the procuring entity, procuring entity fixed effects and procedure type as well as interacted effects between these variables. The observations were considered as highly probable outliers if their residuals were larger compared to other observations.

Below are presented some indicative regressions with significant explanatory power.

Table 5: Interacted OLS regression results

	Dependent variable:	
	Log Unit Price	
	(1)	(2)
Post COVID Crisis (Yes)	3.148***	3.036***
	(0.180)	(0.230)
Product (Reference Category: Disposable Surgical Masks)		
Eyes Protection	4.487***	4.856***
	(0.388)	(0.672)
Gloves (latex)	-0.123	-0.838*
	(0.188)	(0.463)
Masks FFP2	4.954***	5.135***
	(0.328)	(0.593)
Masks FFP3	4.198***	4.432***
	(0.213)	(0.504)
Other Masks	3.825***	2.177***
	(0.402)	(0.490)
Protective Glasses	4.884***	5.045***
	(0.223)	(0.473)
Tyvec Uniform	6.012***	6.103***
	(0.285)	(0.528)
Post COVID Crisis (Yes):Eyes Protection	-3.058***	-3.218***
	(0.529)	(0.887)
Post Covid Crisis (Yes):Gloves (Latex)	-3.070***	-3.126***
	(0.263)	(0.347)
Post Covid Crisis (Yes):Masks Ffp2	-2.605***	-2.926***
	(0.374)	(0.490)
Post Covid Crisis (Yes):Masks Ffp3	-1.936***	-1.955***
	(0.297)	(0.396)
Post Covid Crisis (Yes):Other Masks	-4.432***	-2.763***
	(0.512)	(0.546)
Post Covid Crisis (Yes):Protective Glasses	-2.549***	-2.648***
	(0.290)	(0.367)
Post Covid Crisis (Yes):Tyvec Uniform	-3.009***	-3.355***
	(0.358)	(0.460)
Constant	-3.997***	-3.225***
	(0.350)	(0.803)
District	Yes	No
Procuring Entity	No	Yes
Procedure Type	Yes	Yes
Observations	749	758
Adjusted R^2	0.817	0.808
Note:		*$p<0.1$; **$p<0.05$; ***$p<0.01$

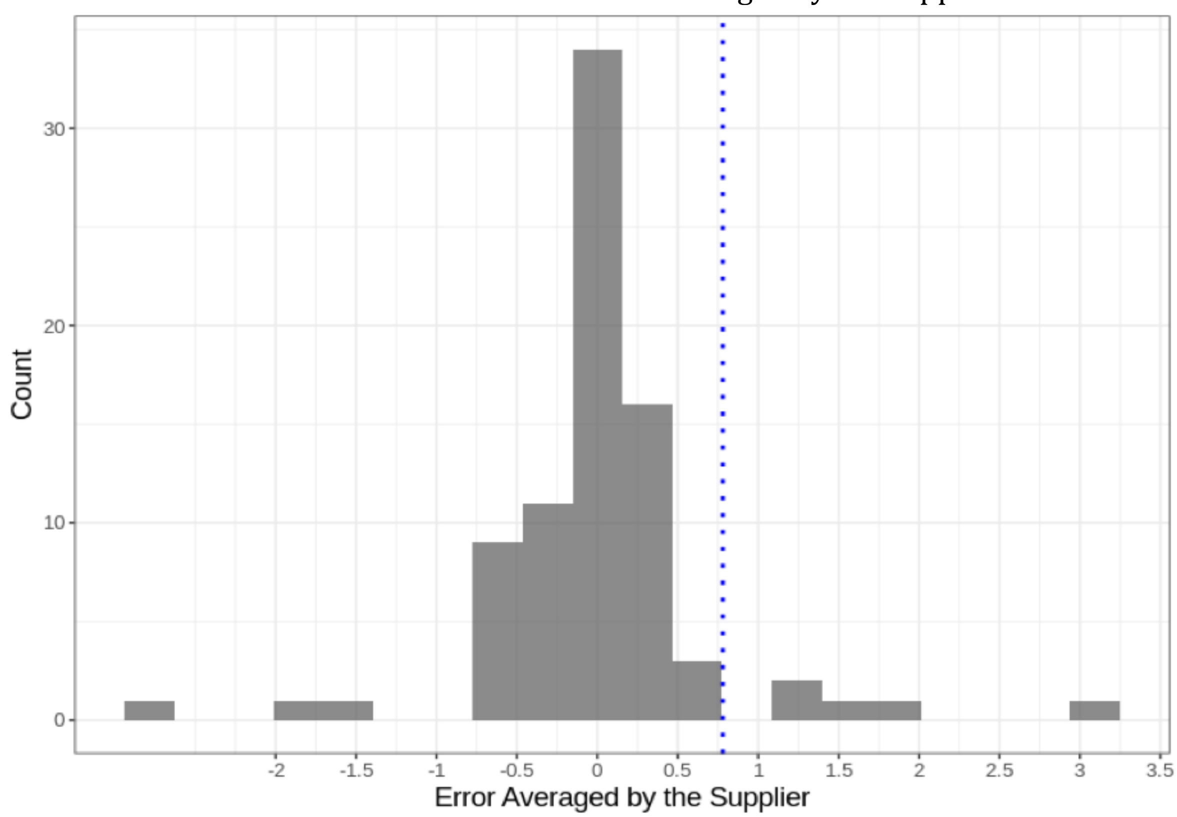
For the regression-based identification of the outliers, the model with highest explanatory power is chosen. Overall, the model with interactions effects fits data better than the others (R^2 = 81%). Thus, the model with interactions (Column 2) was selected to identify outliers based on the error term distribution. In this model, the error term behaves as expected, not suggesting any systematic error in model building, albeit more regression diagnostics could be carried out (Table 6).

Table 6: Descriptive Statistics for the Model's Error Term

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-4.452	-0.402	-0.000	0.000	0.331	5.28

To identify outliers, we averaged the model's error term for the post-crisis period by supplier and plotted the distribution of the calculated values. Chart 5 suggests that the distribution is symmetrical with a few highly probable outliers. The blue dotted line highlights the chosen cut-off point/ threshold (x=0,8) for the identification of the observations that fall outside the pattern. Observations located to the right from the cut-off point are considered to be potential outliers.

Chart 5: Distribution of the Model's Error Term Averaged by the Supplier.



According to the results of multivariate modelling, unit prices offered by five (5) suppliers in the post crisis period can be considered as potential outliers. Two (2) of these suppliers were identified as outliers in the simple bivariate set-up.

The development of algorithms that enable the automated analysis of Big Data derived from publicly available procurement databases provided an important tool for the HCC to complete in timely way its investigation.

2.4.2. Investigation into the effects of COVID-19 pandemic on the markets for basic food commodities

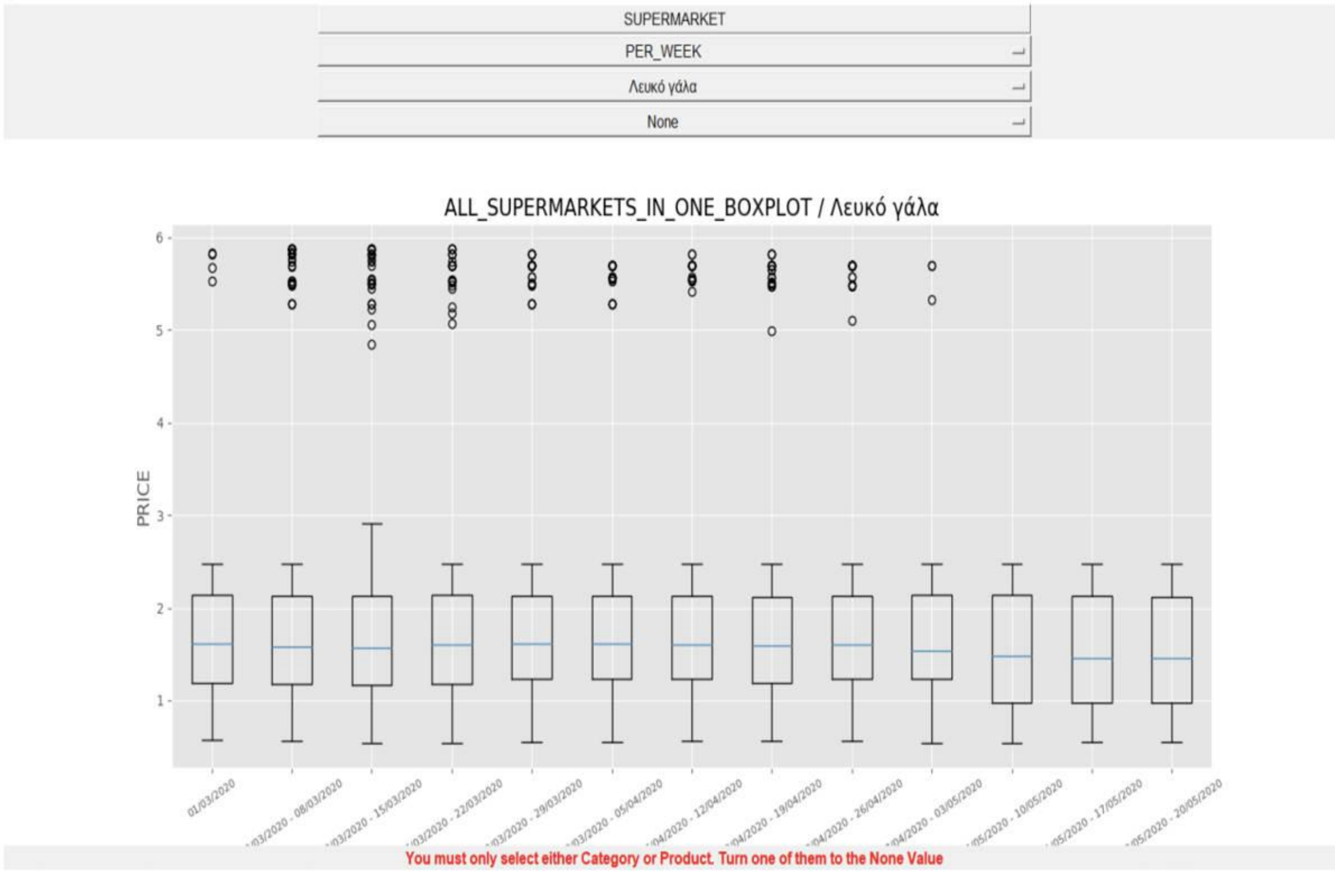
Following relevant media reports, especially during the crucial period of COVID-19 pandemic outbreak, concerns were raised on potential shortages and/or price increases of particular agricultural and food products. The HCC initiated ex officio investigations in the markets and supply chains for milk, cereals and flower.

In this respect, on 15.4.2020, the HCC sent questionnaires, requesting purchase and sales data for the period from February 2020 to April 2020, to undertakings active in the production and marketing of the above products. In addition, the HCC, in order to investigate the entire value chain of the products, with a particular focus on possible effects of the COVID-19 pandemic on consumer prices, carried out, in collaboration with Experts – Professors of Computer Science and Economics– a consumer prices analysis regarding certain basic food commodities of the above categories.

The HCC has at its disposal the appropriate tools enabling it to monitor price development in the sub-categories of its interest, even more systematically. Statistical analyses are now being carried out on multiple categories of basic consumer products, including those mentioned above. Furthermore, the use of time series analysis allows the HCC to observe, by product category, the key parameters emerging over time, such as, for example, price trend, any cyclical or seasonal components, but also random or irregular variations.

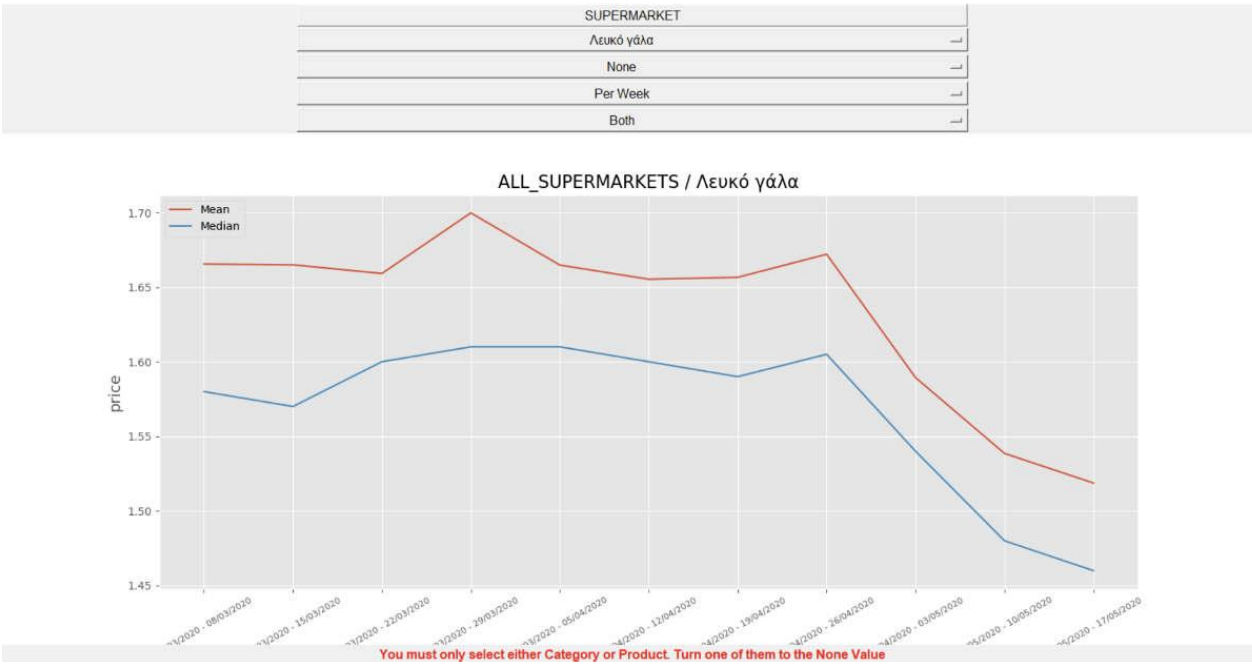
Based on the above tools, and in particular for the white milk category, as shown in the Figure below, it is observed that the median price for all supermarket companies was relatively stable during the Covid-19 pandemic outbreak period in our country until 26.4.2020 (end week), when a decrease thereof is reflected. Furthermore, there is a greater dispersion of white milk prices in relation to their lower levels (i.e. lower than the median price).

Figure 1: White milk median price – all supermarkets, per week (March – May 2020)



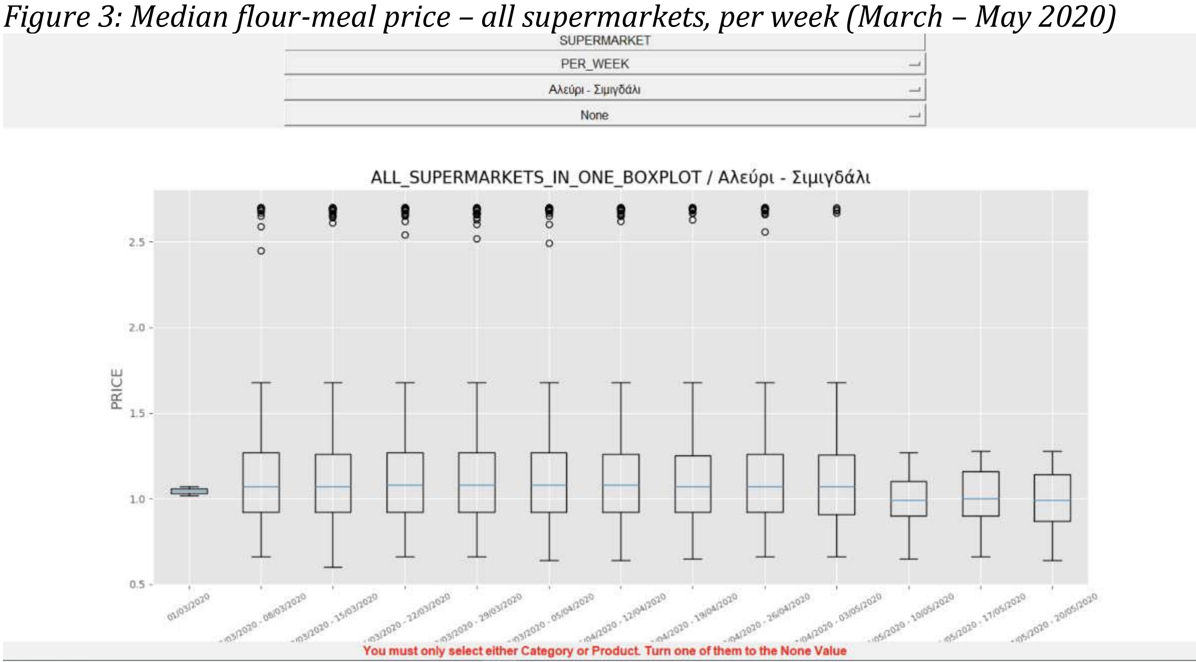
The above observations are also confirmed by the time series analysis[4]. The following Figure shows a slight increase of the white milk median price at the beginning of the movement restriction period, due to the Covid-19 pandemic. This is followed by a relative price stability while, at the end of the movement restriction period, white milk prices declined by 10%.

Figure 2: Time series analysis – Average/median price of white milk in all supermarkets, per week



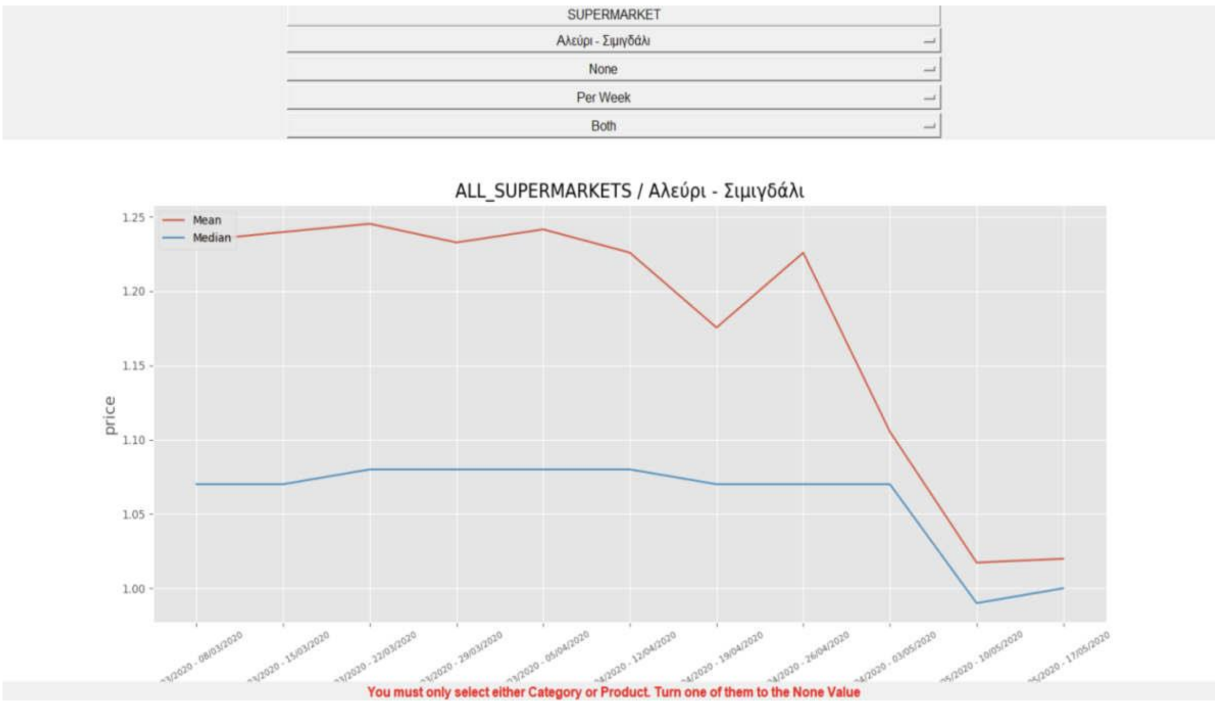
Regarding this category, over time as well as during the whole period of the Covid-19 pandemic outbreak in our country, until 03.05.2020 (end week), stability in the median price of flour-meal is observed, despite the increased demand recorded in the same period. Similarly, both price dispersion and the maximum and minimum prices do not show significant changes during the period under consideration. On the contrary, after the suspension of the restrictions imposed due to the pandemic, there is a decrease in the maximum prices of flours and a slight decrease in their median price.

Figure 3: Median flour-meal price – all supermarkets, per week (March – May 2020)



These conclusions are confirmed by the time series analysis, as shown in the Figure below, which shows that the median price remains almost constant for the entire period 01/3 - 26/4, i.e. both during the restriction period due to the Covid-19 pandemic, as well as during Easter, when demand for these products was high. A drop in the median price is observed in the period after 03.05.2020 in the supermarket channel.

Figure 5: Time series analysis – Average/ median price of flower-meal in all supermarkets, per week



At this stage the analysis was descriptive. The review of the above data showed that there was no significant increase in the median prices of white milk and flour-meal in supermarket chains during the outbreak of the Covid-2019 pandemic (Jan-May 2020) in our country. The explanation for the respective changes, as well as any price increases at other stages of the supply chain will be provided by the HCC at the next stage of the investigation.

2.4.3. In-depth investigation in healthcare materials during the coronavirus health crisis

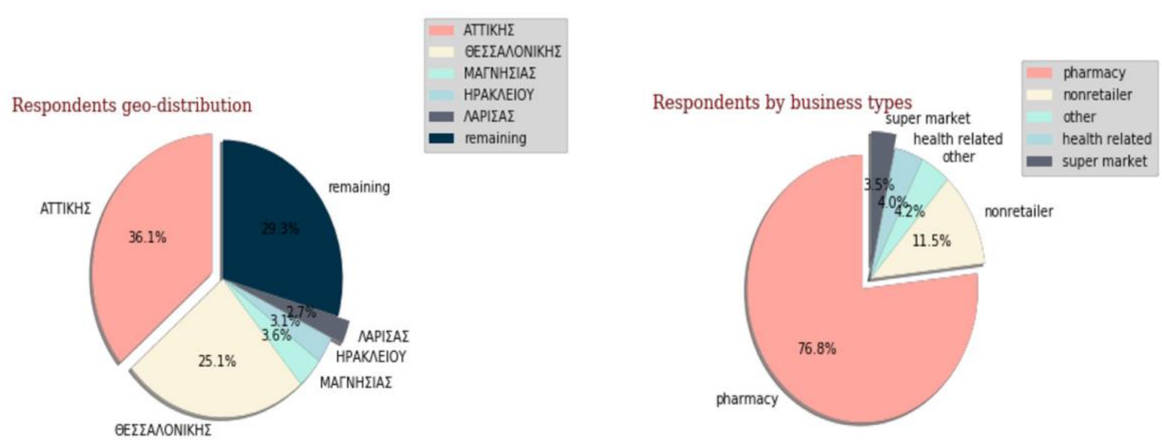
The Hellenic Competition Commission (HCC), acting within its powers, carried out an investigation into the market for healthcare materials. This action was deemed necessary following numerous consumer complaints and press coverage regarding, on the one hand, significant price increases of the products in question at a number of retail outlets, and shortcomings of these products, on the other, which are likely to stem from business practices in the distribution chain that may fall under the provisions of Law 3959/2011.

In this respect, on March, 20th 2020, the HCC sent an online questionnaire, requesting purchase and sales data for the period from November 2019 to March 2020, to 4056 undertakings active in the production, import and marketing of healthcare materials, in particular surgical masks and disposable gloves, as well as other products such as antiseptic wipes and antiseptic solutions.

Sending thousands of questionnaires via an online programme and, then, swiftly categorising and statistically and econometrically analysing the collected data through data analytics tools to decide on further action is an innovative way adopted by the HCC for conducting its investigations (and the first time to date). After the expiry of the deadline for responses, data were extracted from almost 3000 companies that responded to the questionnaire and a multi-member group of scientific experts, composed of economists and econometricians, has carried out their processing and analysis.

Among the respondents to the questionnaire, were many pharmacies because of the existence of a significant number of this category of businesses in Greece (about 10,000 in total) as well as undertakings from all the levels of the distribution chain for the products concerned, namely import, production and wholesale levels, while most of the companies that responded to the investigation are based in the prefectures of Attica and Thessaloniki.

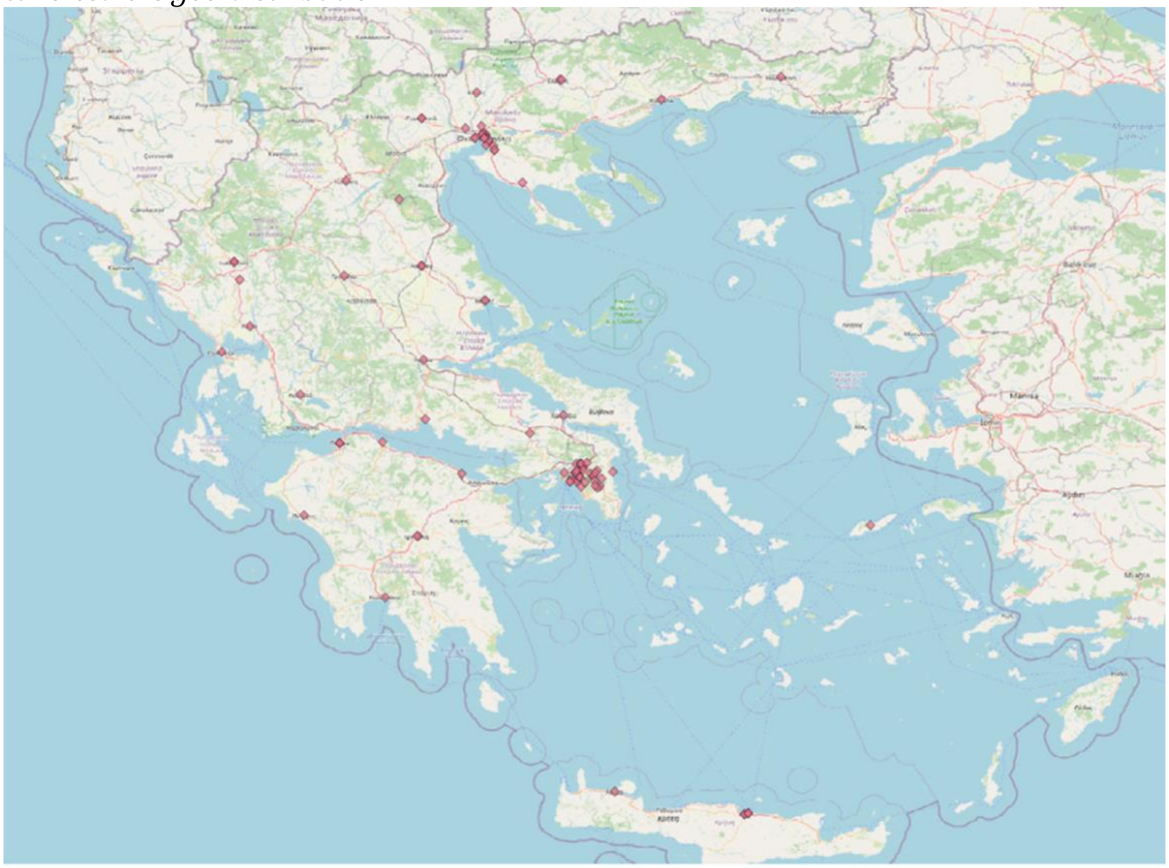
Figure 6: Distribution of undertakings by sector of activity and geographical location



Almost all prefectures are represented in the survey, while the representation of the islands is more sparse, with the majority of comments mainly coming from the larger Cycladic, Dodecanesian and Ionian islands and Crete.

The following map shows the geographical distribution of the registered companies which are active in wholesale distribution (without that necessarily being their sole activity). Apart from their distribution in mainland Greece, particularly in large urban centers, their respective island distribution is sparse and basically observed in Crete, which leads to the main conclusion that the supply of retail outlets in the island areas involves additional transportation costs.

Wholesalers geo-distribution



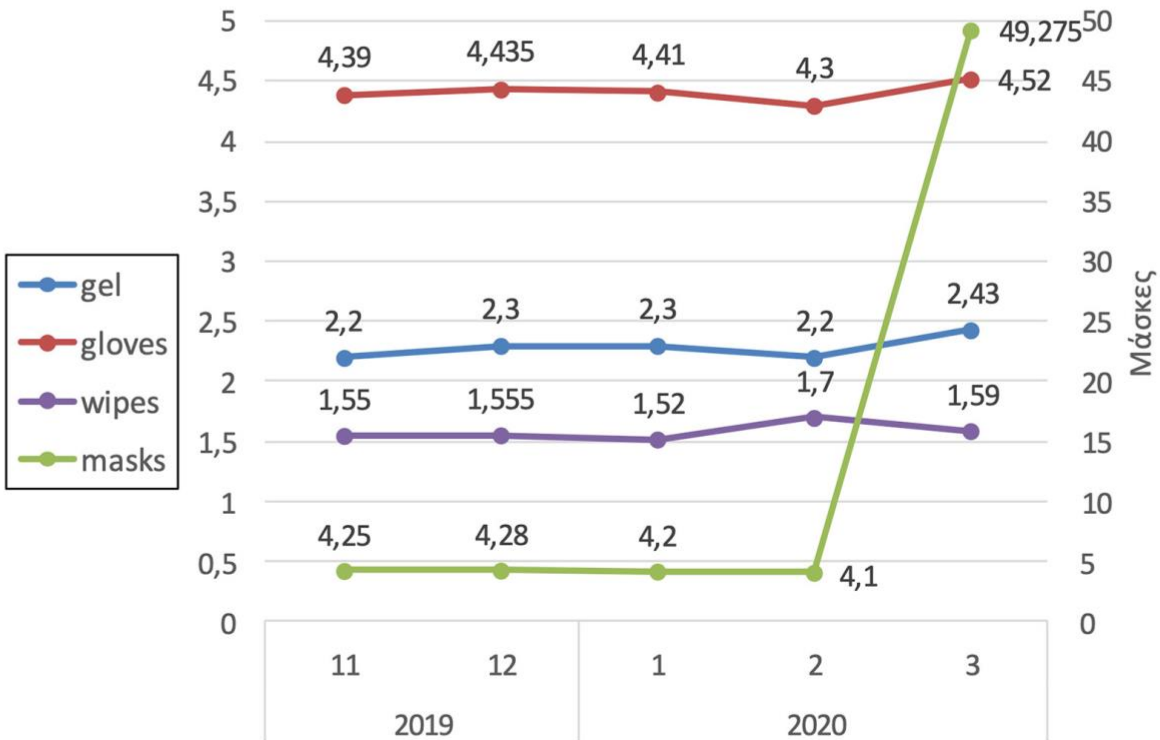
Wholesalers

The investigation revealed that, during the period considered, there seems to be an increase in companies that are active in the retail market for all the healthcare materials and products at issue. The sharp rise in demand for these products has been accompanied by an increase in the number of businesses that are marketing or selling these products, suggesting a healthy market response. On the basis of the sample, the increase in the retail outlets for antiseptic solution and disposable gloves appears to be larger.

On the basis of the median sale prices of all products as reflected regarding all the companies investigated, it seems that in the median sale price a sharp increase was observed especially in the disposable surgical masks from February 2020 onwards. The median price of antiseptic gels and disposable gloves has slightly increased, while a marginal drop in the price of antiseptic wipes was observed.

The sale of these products by more companies seems to have curbed the rise in prices, while the increase in the price of masks is likely to have resulted from stock shortages during the period considered.

Figure 7: Median sale price for all undertakings (Masks on the right axis)



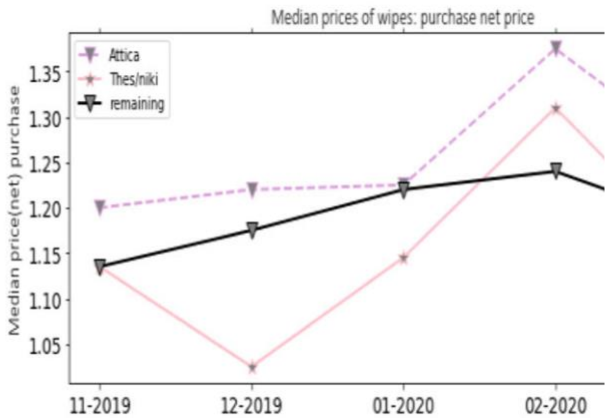
However, no systematic increase in the average and / or median gross profit margin from the sale of the healthcare product concerned during the investigation period has been confirmed. In particular, it was found that no substantial fluctuation has occurred in the median gross profit margin during that period, which was at a similar level for different products.

Comparing the median purchase price in the period from 1.11.2019 to 31.3.2020, between the prefectures of Attica, Thessaloniki and the rest of the territory, the same price behaviour was observed regarding the products concerned. Median purchase and sale prices seem to follow the same pattern in the two major prefectures of the country, with Thessaloniki showing higher prices in the market for disposable gloves, Attica showing higher prices for antiseptic wipes and prices being at approximately the same levels throughout Greece.

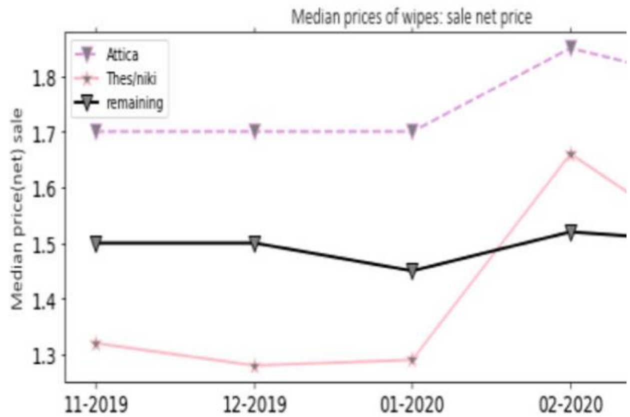
Figure 8: Median purchase and sale price of the products concerned from November 2019 to March 2020 and comparison between the two largest prefectures and the rest of the territory

Antiseptic wipes

Median purchase net price

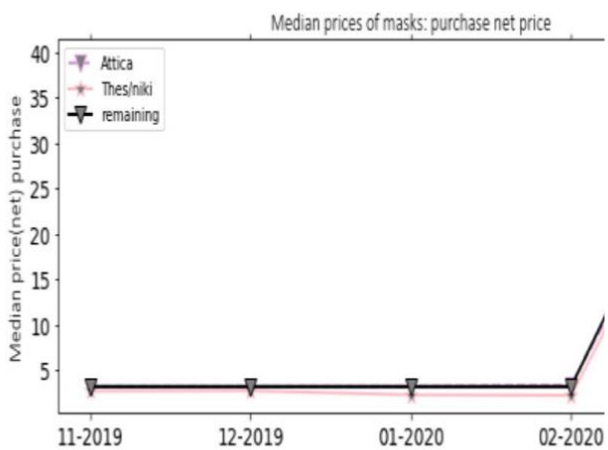


Median sale net price

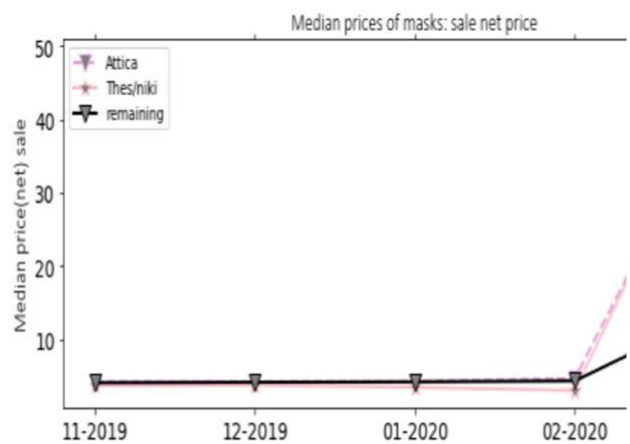


Surgical masks

Median purchase net price

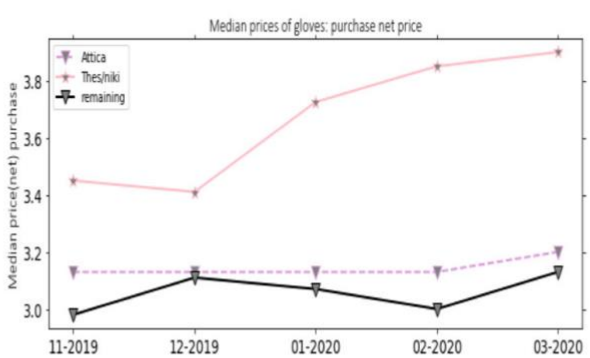


Median sale net price



Disposable gloves

Median purchase net price



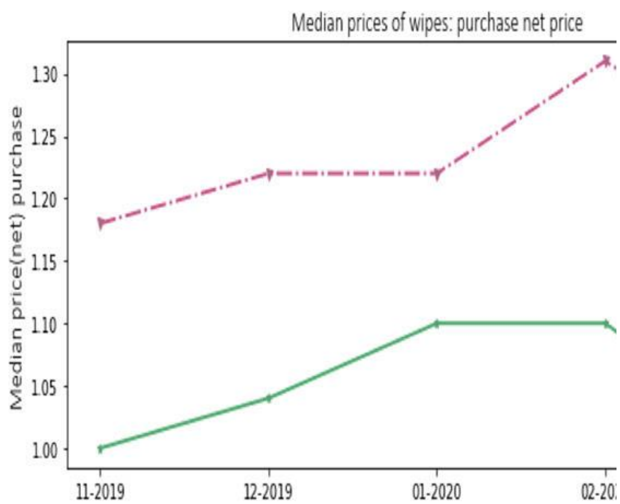
Median sale net price

Furthermore, a similar behavior was observed for the median purchase and sale price of the products under consideration between mainland and island Greece, as well as between urban and non-urban centers. The following figure shows the evolution of prices of antiseptic wipes, masks and disposable gloves in mainland and island Greece. As far as antiseptic wipes and gloves are concerned, it seems that prices are usually lower in the island areas compared to the mainland areas. Interestingly, the median sale price for masks is slightly lower in the island regions after February 2020 compared to the corresponding price in the mainland and in relation to the respective median purchase price.

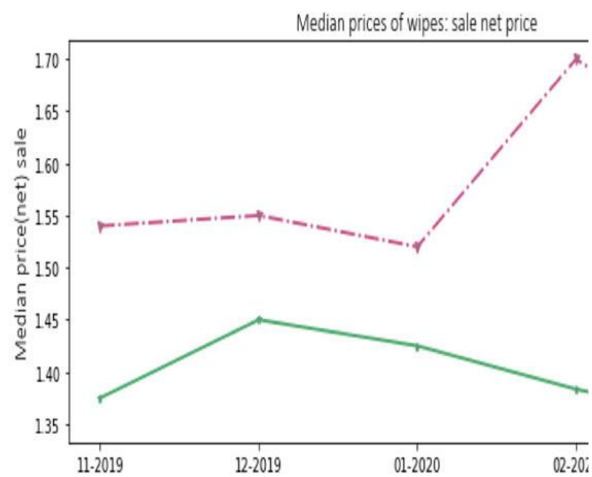
Figure 9: Median purchase and sale price of the products under consideration, from November 2019 to March 2020, and comparison between mainland and island Greece

Antiseptic wipes

Median purchase net price

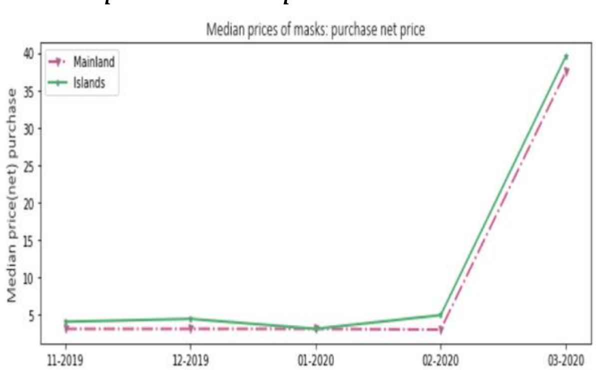


Median sale net price

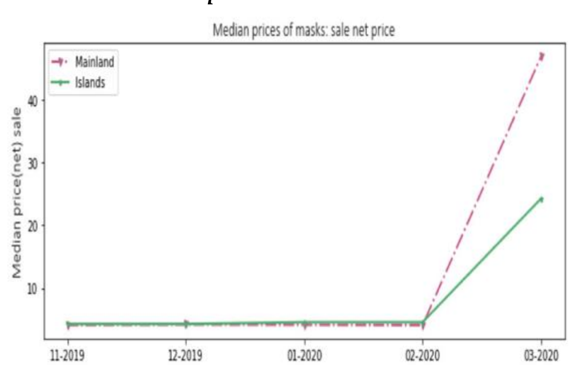


Surgical masks

Median purchase net price

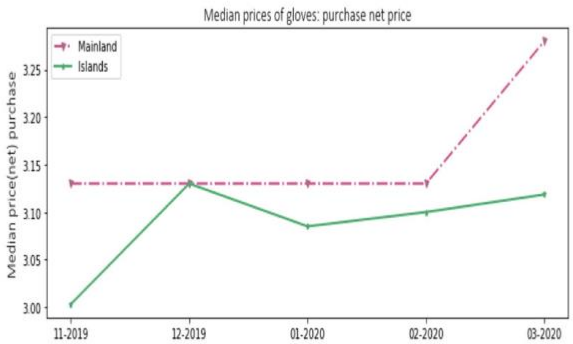


Median sale net price

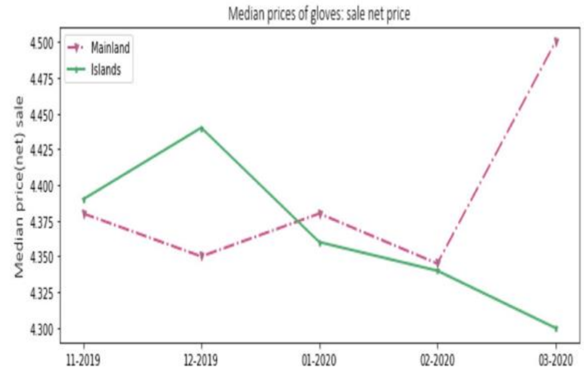


Disposable gloves

Median purchase net price



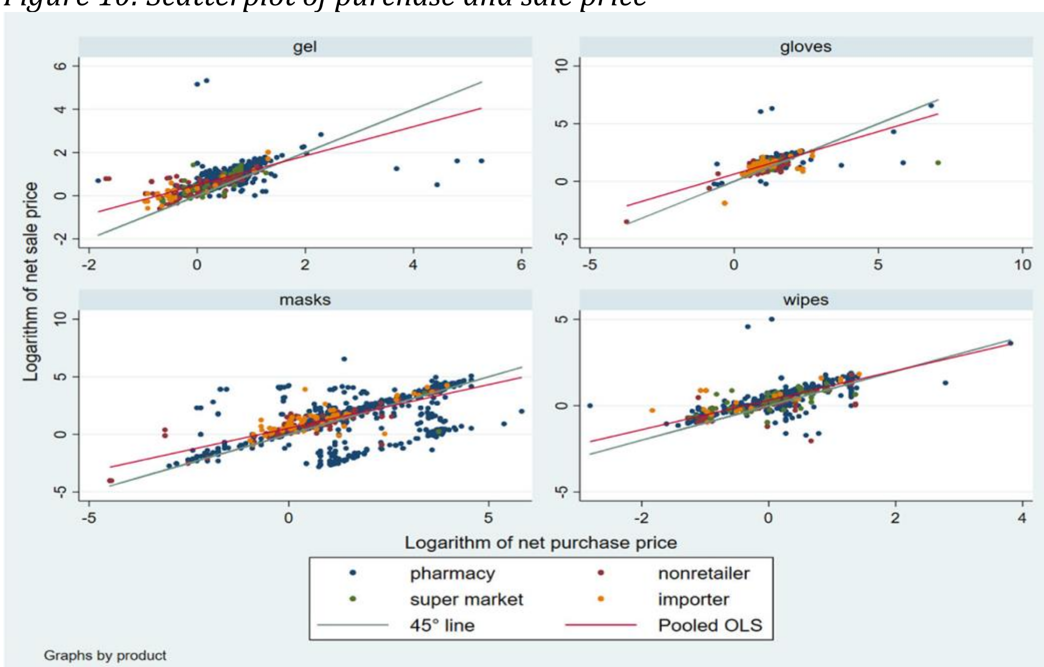
Median sale net price



The following scatter plot shows the logarithms of purchase price (horizontal axis) and sale price (vertical axis), for all months and all undertakings.

- Compared to the 45° line, most observations seem to suggest the existence of a fixed mark-up, while there are also some outliers.
- Several observations are below the 45° line, implying that the sale price is lower than the purchase price. This is probably due to the fact that the purchase price does not always correspond to the products sold in that month, i.e. sales concerned the product stock from previous months. This is particularly evident in masks.

Figure 10: Scatterplot of purchase and sale price



According to the statistical and econometric processing of the available data, the increase in the retail sale price of the healthcare materials considered comes mainly from the pass-through of the increase in the wholesale price. In addition, the study found that the pass-through of the wholesale price increase to antiseptic wipes and disposable gloves was higher in pharmacies than in supermarkets. Regarding masks, the results showed that the undertakings which were also active at another distribution level in addition to retail, i.e. production, imports or wholesale, showed higher prices than those active exclusively in retail.

Examining the pass-through rate of change in the purchase price of masks to the sale price to end consumers, it appears to be higher in March 2020. Furthermore, the greater variation in the price pass-through rate appears in the sale of disposable gloves in February 2020.

Table 7 shows indicatively the findings of an econometric model using panel data on price pass-through to consumers over time.

Table 7: Findings- Interactions with product and business type

Variables	Panel Data
pharmacy_purchase_price	
gel	0.580***
	(0.127)
gloves	0.489***
	(0.188)
masks	0.889***
	(0.017)
wipes	0.764***
	(0.14 1)
supermarket_purchase_price	
gel	0.677***
	(0.099)
gloves	0.523**
	(0.230)
masks	
wipes	0.334*
	(0.180)
health_purchase_price	
gel	0.866***
	(0.061)

gloves	0.202***
	(0.060)
masks	0.655**
	(0.265)
wipes	0.592***
	(0.096)
other_purchase_price	
gel	0.694***
	(0.070)
gloves	0.514**
	(0.200)
masks	0.986***
	(0.008)
wipes	0.221
	(0.156)

Robust standard errors in parentheses
***p<0.01, **p<0.05, *p<0.1

The findings of the above linear regression only for retailers examine the pass-through rate in each product-business type combination. Judging from the confidence intervals resulting at a statistical materiality level of 5%, the ceiling is rather close to 1, which corresponds to a perfectly competitive behaviour. Therefore, where the estimated rate is close to 1, the business cannot absorb an increase in the price and therefore passes it through to consumers. The above table of findings shows that, in pharmacies, the price pass-through rate is high for masks and antiseptic wipes and lower for antiseptic gels and disposable gloves. This may be due to the combined facts that pharmacies specialise in the sale of specific products and, at the same time, they face intense competition from competing companies.

Finally, on the basis of the **purchase outliers analysis** for the products concerned, it was observed that:

- 1% of the highest net purchase prices per month considered concerns companies mainly located in the two larger prefectures of Attica and Thessaloniki and
- 1% of the highest net purchase prices per month considered concerns mainly pharmacies.

Similarly, on the basis of the **sale outliers analysis** for the products concerned, it was observed that:

- 1% of the highest net sale prices per month considered concerns companies mainly located in the two larger prefectures of Attica and Thessaloniki, while the aggregated data per month considered indicate that the majority of companies with the highest sale prices are based in the prefecture of Attica and

- 1% of the highest net sale prices per month considered concerns mainly pharmacies.

The latter data items as well as further data collected by companies active in the wholesale of healthcare materials will be used to identify any cases of abusive pricing by companies that hold a longstanding nationwide and / or temporary local dominance in the markets at issue.

2.5. A radar chart method by FAS

Russian competition authority developed a radar chart method to detect collusion practices[90]. The essence of the method is to analyze multiparametric conditions of firms' appropriate behavior or functioning, which allows forming a familiar figure of the relevant market. The set of parameters is formed based on the case study concerning violation of antitrust rules. For example, before the initial application of the method, parameters were selected after analyzing more than 600 decisions on cartel cases over the past five years. The study of these parameters is intended to answer questions about their value in relevant markets within competitive conditions and whether there are grounds to judge that a deviation from such values may lead to a violation of one of the *per se* prohibitions.

Market parameters		
Number of sellers	Differentiation between participants' market shares	Market shares dynamics
Number of buyers	Barriers	Information on market coordination
Information availability	Products homogeneity	Revenue jumps

Violations
Fixing or maintaining prices (tariffs), discounts, markups (surcharges) and (or) additions to prices
Increasing, reducing or maintaining prices during competitive bidding
Dividing the goods market according to a geographic principle

[90] https://fas.gov.ru/news/29307

Rate of return	Products novelty	Price fluctuations
Concentration level	Market volume dynamics	Price-to-quality ratio

Reducing or terminating production of the goods
Refusing to conclude contracts with particular sellers or buyers

The first task here is to estimate the values of market parameters (based on their combination) so that it will be possible to judge whether all market participants face competitive conditions. The second task is to determine the deviation degree of the parameter values in particular cases to judge antitrust violations. Since deviations of the parameters' values may occur both up and down, comparing a particular case with an ideal model based on the figures area calculation will possibly mislead from the correct position. Thus it is more appropriate to calculate the percentage deviation of the shapes of the figures, which can be carried out as follows:

$$\text{Collusion-risk deviation} = \sum_{i=1}^{n} \frac{|x_i - x'_i|}{x_i},$$

where x_i — the value of the market parameter corresponding to fair market behavior;
x'_i — the value of the same market parameter in the case under authority consideration;
n — total number of market parameters.
For each type of industry, there should be values for the percentage deviations between the figures so that when a certain threshold is reached, the antitrust authority will receive signals about a dangerous distortion of competition.

3. The promise of computational economics and system analysis for competition law enforcement

The research explores the impact these new computational technologies and their increasing use in economics (computational, complex economics) may have on competition law enforcement. The starting point is that the ‘simple economics’ so far used by competition law and policy rely on partial equilibrium thinking grounded on few propositions (e.g. rational choice), reducing heterogeneity by grouping the various elements that compose the system in few broad categories (e.g. the consumer, the firm, or in other words the ‘representative agent’). It also ignores the ‘connective complexity of the economy’ (the net of links that shape the economy, but also their underpinning societal relations, being kept very simple due to the hypotheses of complete information so that each element of the economy can contact and evaluate all others at no cost, the network of connections being irrelevant to the functioning of the system). Unfortunately, using the same tools to understand complex economies and societies fails, because it ignores the variety of adaptive processes at play.

This research aims to (i) provide a succinct theoretical mapping of computational economics and complex economics, (ii) examine their application/use so far in competition law enforcement, (iii) explain how these may be relevant in a new 'polycentric' competition law framework that incorporates values such as privacy, sustainable development and in particular climate change goals, (iv) explore some metrics that may be used for the analysis of such complex systems. The above will be examined in a report, which will also make recommendations for next steps in the development of the research agenda of the project, and eventually some possible case studies.

3.1. Defining complexity

Some definitions of complexity focus on the internal structure of the system rather than the complexity of the behaviour. They qualify a system as complex "when it is composed of many parts that interconnect in intricate ways".[91] That said, an important concept in complexity theory is 'emergence'. Contrary to neoclassical economics in which the behaviour of the system is assumed to reflect the behaviour of its constituent parts, complex economics accepts that there is a disconnect between an individual's localised behaviour and the way in which this aggregates into global behaviour.[92] As a result of this disconnect, the overall emergent behaviour of a complex system is difficult to predict, even when the behaviour of the subsystem is readily predictable. Small changes in inputs and/or parameters may, thus, produce large non-linear changes in behaviour. Markets that are characterised by network effects and various feedback loops, whether they be positive or negative, may tip once a critical threshold has been reached. This should not be considered as a criticism of competition law enforcement given the difficulty of precisely determining the effects of a specific conduct on the competitive process and/or on the interests protected by competition law.

Complex systems are also dynamic. As they learn, evolve and adapt, they generate emergent non-deterministic behaviour that breaks with the assumptions expected under the equilibrium behaviour of simple economics.[93] Complex systems are not populated by homogeneous predictable agents but by a collection of heterogeneous agents (individuals, organisations etc.), the state of whom influences and is influenced by the state of others (for instance, situations of social contagion), and the interactions of whom give rise to global systemic properties that equate to more than the sum of individual behaviour. As the

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[91] J. Sussman, "Collected Views on Complexity in Systems", (2003), MIT Engineering Systems Division Working Paper Series, ESD-WP-2003-01.06, 6, cites the definition of J. Moses, Complexity and Flexibility (Mimeo).

[92] J. Miller and S. Page, *Complex Adaptive Systems* (Princeton University Press, 2007), 50.

[93] For an excellent introduction to the significance of complex economics for public policy, see B. Furtado, P. Sakowski and M. Tóvolli, *Modelling Complex Systems for Public Policies* (IPEA, 2015).

interactions within complex systems are not independent, various feedback loops can enter into the system and affect individual decisions.

This complex economy is characterised by various features. First, is increasing returns to scale and scope. Second is 'feedback loops'. When interactions between agents are not independent, this may fundamentally alter the dynamics of the system. In systems with negative feedback loops, changes get absorbed quickly and the system becomes stable relatively quickly; whereas in a system with positive feedback loops, "changes get amplified leading to instability".[94] Third is 'leverage points', which are "places where the system can be altered or changed"[95]. Fourth is 'tipping points'. These occur "where a system suddenly changes [its] state, based on a small change in a parameter of the system". Fifth is 'path dependence', which means that "the current possibilities of the system are in some sense constrained by the past choices that were made".[96]

The study of complexity also demands different strategies of engagement and new methodologies. As Colaner writes, "instead of trying to find a formal analytical model, with a formal solution for these complex phenomena, complexity theory looks for patterns that develop when non-linear processes are repeated for long periods of time", with the mathematics used being "non-linear dynamics", and the models generally used being "open models with no unique deterministic solution [and as such] many solutions are possible; which one is arrived at depends upon initial conditions and the path the model follows".[97]

This emphasises computation and brings it to the forefront of the economic enquiry simulation approaches that rely less on theory and more "on conjectures and patterns that temporarily fit".[98] In simple economics, models are constructed for the purposes of prediction and are derived from a set of first principles, which often include assumptions as to the abilities and motives of the underlying agents with these being linked through mathematical reasoning and deduction with axioms, the latter being associated with the notion that "social systems tend toward equilibrium states".[99] In contrast, the computational models are used as mapping tools.[100] They provide the foundation for computational experiments and, thus, aim to generate only inductive proof. In these models, "abstractions maintain a close association with the real-world agents of interest" and "uncovering the implications of these abstractions requires a sequential set of computations involving these abstractions".[101] These computational models should enable

[94] *Ibid*, 50.
[95] Ibid.
[96] See the discussion in W. Rand, "Complex Systems: Concepts, Literature, Possibilities and Limitations" in *Modelling Complex Systems for Public Policies* (edited by B. Furtado, P. Sakowski and M. Tóvolli, IPEA, 2015), 37 and 41.
[97] D. Colander, *Complexity and the History of Economic Thought* (Routledge, 2008), 4.
[98] *Ibid*, 6.
[99] J. Miller and S. Page, *Complex Adaptive Systems* (Princeton University Press, 2007), 59.
[100] *Ibid*, 36.
[101] *Ibid*, 65.

the consideration of the complicated preference structures of both the population and its heterogeneity in order to account for their more elaborate set of choices.

One of the tools that is often used to generate these computational models is 'agent-based modelling'. It attempts to depart from the abstraction of the underlying agents in a system by combining all agents into a single simplified and representative agent.[102] Agent-based modelling cannot completely dispense with this step: even if it does not rely on a representative agent, there is some level of abstraction involved in constructing an artificial adaptive agent based on real agents. However, it allows for the direct interaction between these agents (hence the focus on 'adaptive') by using computation. Adaptation can be incorporated through different means, such as employing metaheuristic-inspired, population-based search evolutionary algorithms (e.g. a genetic algorithm) that draw on the process of natural selection and rely on a pool of potential solutions, rather than just one.[103]

These interactions depend on, and determine the boundaries of, the "space" within which these agents are contained, with the space often being endogenous in a system. However, determining the relevant "space" or "field" of interaction cannot be done before fully engaging computationally with the interactions of the agents themselves. Such needs to take into account the possibility of asynchronous activation, with each agent potentially waking up at a different time, processing the information that is currently available to them and, thereby, through its action altering "the information ether" with which other agents are confronted upon activation.[104] Such an approach may cater for situations in which, assuming that the focus is on competitive interactions, there is a potential competitor.

In view of the focus of complex economics on interactions between agents, it models social systems as a network of nodes and ties. These ties act as pipes through which things, such as information, flow. This brings the role of networks as spaces of interaction to the fore and has important implications on the understanding of power relations within systems. For instance, in 'small worlds' networks, in which each agent is first connected to a set of neighbouring agents, information can be transmitted between any two nodes using only a small number of connections and, thereby, allows the generation of 'six degrees of separation'. This shows the crucial role in the operation of the system of only a few

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[102] *Ibid*.

[103] The process involves several steps, beginning with a set of individuals, i.e. the population, with each individual being characterised by a set of parameters (variables or 'genes'). These are then joined into a string to form a solution, i.e. a chromosome. A fitness function measures the ability of an individual to compete with other individuals (how 'fit' an individual is) with each individual being given a fitness score. The selection of the fittest individuals to pass their 'genes' to the next generation depends on their fitness score. The next stage involves crossover, where for each pair of parents to be mated, a crossover point is chosen at random from within the genes. Random new offspring from the crossover are subject to a mutation with a low probability in order to maintain genetic diversity within the population, with the algorithm being terminated if the population has converged, i.e. the offspring produced are not significantly different from the previous generation.

[104] J. Miller and S. Page, *Complex Adaptive Systems* (Princeton University Press, 2007), 97.

intermediate nodes.[105] If, however, a network is solely composed of neighbourhood connections, "information must traverse a large number of connections to get from place to place", which limits the power and/or influence of the intermediary nodes.[106] Hence, the position of an agent in a network may be a source of advantage and power.

The type of connections that link the agents is also a crucial issue. The 'strength of weak ties' theory is a well-known contribution in the field of sociology.[107] Weak ties are surprisingly valuable because they are more likely to be the source of novel information than strong ties. This stems from the hypothesis that if A and B have a strong tie, they are likely to have many acquaintances, i.e. weak ties, in common. Strong ties create transitivity, which, in turn, creates a closed world with redundant ties. Bridges are ties that connect different parts of the network: removing the tie between A and B would mean the shortest path from A to B would be quite long. These are more likely than other ties to be sources of novel, non-redundant information. Weak ties are more likely to be bridges than strong ties.

According to another theory, the 'structural holes' theory, structural holes denote a lack of connection between two nodes that has been bridged by a broker, provide informational benefits and may lead to reward and ,thus, emphasise the power that the broker may draw from his position within the system.[108] This theory does not focus, as the strength of weak ties theory does on the strength of the relationship between two entities, but rather on the lack of a tie between entities (the "chasm") that may become a source of power for the broker. Complex economics allow for these different sources of wisdom, such as economic sociology, network theory, neuro-economics etc., to be integrated into the way in which computational models are constructed. As a result of such, their explanatory power in the context of a complex set of interactions between heterogeneous agents is augmented.

Computational models may also allow for a greater heterogeneity of the agents the interactions of whom will be modelled. For instance, it may allow for the developing of "an ecology of agent types, each relying on different behavioural governing mechanisms".[109] Although as mentioned above, computational models cannot completely dispense with the constitution of representative agents. This enables theorists to construct computation models from the bottom-up, with any abstraction being focussed "over the lower-level individual entities that make up the system".[110] The model also integrates learning and adaptation as a by-product of this direct interaction. As such, it incorporates frameworks for emergence with the model being flexible enough that "new unanticipated features" may naturally arise within the model.[111]

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[105] *Ibid*, 155.
[106] *Ibid*.
[107] M. Granovetter, "The Strength of Weak Ties", (1973) 78(6) *American Journal of Sociology*, 1360.
[108] R. Burt, *Structural Holes: The Social Structure of Competition* (Harvard University Press, 1992).
[109] J. Miller and S. Page, *Complex Adaptive Systems* (Princeton University Press, 2007), 101.
[110] *Ibid*, 66.
[111] *Ibid*, 69.

This contrasts with the top-down modelling of simple economics which "abstracts broadly over the entire behaviour of the system".[112] Even if one managed to acquire "a complete specification of the psychological aspects of behaviour or the probability of interaction" of all the underlying agents, it would still be difficult to fully understand the macro-level implications of their interactions because the models of simple economics do not anticipate emergence.[113]

Emergence does not deny the possibility for an equilibrium state. However, it indicates that this equilibrium state may not be unique and may "depend on various random elements of the model or non-linearities" as a result of the system being in "perpetual motion".[114]

This computational modelling may seek to uncover a simple structure of interactions premised on the behaviour of artificial adaptive agents. Equally, it may seek to uncover a more complicated structure of interactions, which, in the case of computational modelling and the use of simulations, allows for the constitution of "artificial life" or artificial worlds. This latter type of structure would rely on a model of "adapting, communicating and multiple-game playing artificial agents".[115]

One may consider reproducing the digital twin of a network or ecosystem to link the real and digital worlds and using artificial intelligence (henceforth, 'AI') to convert data into actionable insights. The first step would involve various sorts of data being harvested and then leveraging millions of examples of curated data to train deep-learning neural networks. The next step would involve neural networks being used to approximate parts of the computational model. This could potentially be used for evaluating the effectiveness of tailored treatments and for experimenting with various forms of intervention by using advanced simulation to develop more precise prognoses. These tools may enable a better and quicker filtering of the situations in which more elaborate competition law analysis is needed. They may also provide solid evidence upon counterfactuals for competition law investigations can be built.

Some of the theoretical insights and concepts espoused in complex economics have gradually been incorporated into competition economics' scholarship and competition law enforcement. Terms, such as increasing returns, tipping points and leveraging points are widely used by scholars, competition authorities and courts and now form part of the current mainstream approach in competition law and economics.

However, the tools and methodologies of complex economics have neither impacted upon competition law enforcement nor competition law and economics literature. The authors consider that it is time that competition authorities made the effort to engage with these new tools and develop the capabilities required for engaging with computational

[112] *Ibid*.
[113] *Ibid*, 67.
[114] *Ibid*.
[115] *Ibid*.

economics. In view of the large availability of data and the complexity of the issues raised by digital platforms and networks, the digital economy offers plenty of opportunities for which these new methodologies and tools, such as agent-based modelling, computational models, digital twins etc., can be employed. In the authors' view, one of the major impediments to the use of such novel approaches is the rigidity of the 'consumer welfare' standard that has provided the theoretical framework that has underpinned the action of competition authorities over the last few decades. The emphasis put on consumer welfare is very much linked to the simple economics of the 'representative agent' but such does not account for the heterogeneity of agents and the complexity of their preference structures, especially as competition law becomes more "polycentric".[116]

It is quite important to see the COVID-19 pandemic and the resulting economic crisis, as well as the challenges of climate change and sustainable development as an opportunity to develop a new set of tools that would enable competition authorities to assess more accurately more complex interactions and trade-offs (for instance between price and sustainability or privacy), and which would also be appropriate to analyse the digital economy in which large scale data is more readily available. Competition authorities increasingly focus on a broader range of social costs, than price effects, such as impact on environmental sustainability, privacy and other quality dimensions of competition. Hence, we need methodological tools and metrics than enable us to implement competition law in this broader framework.

Of particular interest is the definition of the new 'spaces' of competition, such as business ecosystems, which new computational methods and technologies may assist us in exploring. In view of its focus on interactions between agents, complex economics models social systems as networks of nodes and ties. Complex economics and systems theory allow for different sources of wisdom (e.g. economic sociology, network theory, neuro-economics) to be integrated in the way the computational models are constructed, thus augmenting their explanatory power in the context of a complex set of interactions between heterogeneous agents.

Computational models may also allow for a greater heterogeneity of the agents whose interactions will be modelled. This enables the theorist to construct computation models 'bottom-up' and to integrate learning and adaptation as a byproduct of this direct interaction, thus incorporating frameworks for emergence, the model being flexible enough so that 'new unanticipated features' may naturally arise within the model. This constrasts with the 'top-down' modelling of simple economics. This computational modelling may aim to unveil a simple structure of interactions, abstracted from the behaviour of artificial adaptive agents, or a more complicated structure of interactions, in case the computational modelling and the use of simulations allows for the constitution of 'artificial life' or artificial worlds.

[116] I. Lianos, "Polycentric Competition Law", (2018) *Current Legal Problems*, 161.

Some of the theoretical insights and concepts of complex economics have been gradually incorporated in competition economics' scholarship and some in competition law enforcement. However, the tools and methodologies of complex and computational economics have not yet made any impact on competition law enforcement, but also on competition law and economics literature. We consider that it is time competition authorities make the effort to engage with these new tools, and to develop capabilities for engaging with computational economics. In view of the large availability of data, and the complexity of the issues raised by digital platforms and networks, the digital economy offers plenty of opportunities to try these new methodologies and tools, such as agent-based modelling, computational models, digital twins etc.

The research will explore the promises and pitfalls of using complex economics and computational economics for the assessment of business conduct and markets. An important issue that will also require some further analysis is the way to assess inter-market spillovers and contagion effects. This is particularly important as the recent Covid-19 pandemic has led to a global demand and supply shock that affects financial, product and labour markets Competition authorities need to disentangle the various interdependencies between these markets and explain contagion on the basis of real channels of trade, at least regarding product markets and become more pro-active in their role in deterring anticompetitive activity.

3.2. A new space of competition: business ecosystems

Over the last few years, research has focused on the way firms try to gain advantage not only by competing within a particular sector, but by shaping its very nature, and the architecture that governs its workings. Digital technologies, combined with regulatory change, have enabled the transformation of existing sectors and the emergence of new ones, including social media, search and geolocation-based services, enhanced by advances in mobility. Such orchestrators benefit from their complementors while also using them strategically– not by controlling them, but by enabling them. Orchestrators also come to wield significant power by exploiting the "bottlenecks" that emerge in these new industry architectures. Some of the resulting big winners have been those platform orchestrators who have succeeded in building ecosystems around their platforms. These transformations have led to new asymmetries of power, strengthened by a new breed of expansive actors who wield unusual power across ecosystems. These often include a core (digital) platform orchestrator and a select group of their complementors – for example, app developers, network operators and device manufacturers. Hence, the "field" of competition is not the relevant product market, but an ecosystem of various complementary products. While these dynamics may raise novel competitive concerns, the question of how we should address them remains open to debate.

The concept of ecosystems has gained significant traction as a separate organizational form. In a study by BCG, the use of the term "ecosystem" in annual reports of large companies in the US had grown 13-fold from 2008 to 2017, and there was a clear positive correlation between the use of this term and corporate growth rates (Fuller et al, 2019[117]). Yet, what exactly is meant by the term, even in the management literature, is unclear as authors had idiosyncratic understandings, and metaphorical color may have overweighed analytical rigor (Iansiti & Levien[118], 2004; Moore, 1993[119]; Teece, 2007[120]). The rise of ecosystems is linked to the emergence of business environments marked by modularity in production, co-evolution and decisional complexity as innovation has to be coordinated across complementary contributions across different hierarchies, markets and industries in a synergistic process (Baldwin & Clark[121], 2000; Moore, 2006). More recently, two influential papers have tried to systematize our understanding of ecosystems, and relate them to management literature: Adner (2017)[122] and Jacobides et al (2018)[123] focused on ecosystems as groups of collaborating firms which collectively produce a good, service or solution, and the latter emphasized "groups of firms that must deal with either unique or supermodular complementarities that are non-generic, requiring the creation of a specific structure of relationships and alignment to create value." This focus on "intentional communities" of economic actors who co-evolve their goods and services with aligned visions and "whose individual business activities share in some large measure the fate of the whole community" (Moore, 2006[124]), as well as the emphasis on deliberate, non-generic complementarities programmatically focused around collective value stands in stark contrast with the looser uses of the term on any types of interactions that are, for instance found in industrial districts and clusters (e.g. Beccatini, 2002[125]). Additional reviews of the concept have been offered by Kapoor (2018)[126], Bogers, Sims, and West

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[117] J. Fuller, M.G. Jacobides, M. Reeves, 2019. The myths and realities of business ecosystems, *Sloan Management Review* Digital Article, February.

[118] M. Iansiti, R. Levien. 2004. *The Keystone Advantage: What the New Dynamics of Business Ecosystems Mean for Strategy, Innovation, and Sustainability*. Harvard Business School Press: Boston, MA

[119] J.F. Moore, 1993. Predators and prey: a new ecology of competition. *Harvard Business Review* **71**(3): 75-86.

[120] D.J. Teece 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* **28(**13): 1319-1350

[121] C.Y. Baldwin, K.B. Clark. *Design Rules: The Power of Modularity*. Vol. 1. (MIT Press: Cambridge, MA, 2000).

[122] R. Adner. 2017. Ecosystem as structure: An actionable construct for strategy, *Journal of Management* **43**(1): 39–58.

[123] M.G. Jacobides, C. Cennamo, A. Gawer, Towards a theory of ecosystems, (2018) 39 *Strategic Management Journal* 2255-2276.

[124] J.F. Moore, Business Ecosystems and the View from the Firm, (2006) 51(1) Antitrust Bulletin 31.

[125] G. Becattini, 2002. "About the marshallian industrial district and the theory of the contemporary district. A brief critical reconstruction," Journal of REGIONAL RESEARCH, Asociación Española de Ciencia Regional, issue 1, 9-32.

[126] R. Kapoor. 2018. Ecosystems: broadening the locus of value creation. *Journal of Organization Design* **7**(1): Article 12

(2019)[127], and Baldwin (2020)[128], discussing how ecosystem research relates to other streams in strategy and innovation.

Most strategy literature implicitly or explicitly considers that ecosystems are often based on platforms, which enable the connections between ecosystem actors and possibly end users. As Kapoor (2018) notes[129], "many ecosystems are organized around a central platform-based architecture that serves as a foundation for firms to offer complementary products or services." There are ecosystems that do not require platforms (such as the Michelin PAX tire ecosystem described in Adner, 2013[130]), and there are many platforms which do not engender non-generic complementarities, and as such dependencies, which mean that they do not build ecosystems with participants which are bound together in a way that the relationship becomes symbiotic.

However, platforms and ecosystems cannot be conflated to each other. Platforms may be defined as a new business model, a new social technology, or a new infrastructural formation, or all the three, that replace and rematerialize the process of Walrasian "tatonnement" (Walker, 1987[131]) in decentralised markets with an architecture of intermediation in some persistent form, with the goal of making clusters of transactions and economic relationships stickier. Ecosystems form "spaces" of possible business behaviours which do not necessarily arise from some centralized control but rather autonomously although intentionally from the interactions between the various components of a correlated system, whose components although depending on one another do not necessarily act in the same way (A.F. Siegenfeld & Bar-Yam, 2020[132]). One may distinguish correlated systems from random systems in which each component is independent from each other, such as markets, and coherent systems in which all components exhibit the same behaviour, the typical example being hierarchies. The emphasis here is on a "space" of business opportunity, rather than just a "field" of competitive interaction as the former concept also englobes future domains of business activity that may not exist today, or exist in nascent form, but take their competitive significance through a complex process of financial markets valuation marked by futurity (Lianos, 2019[133]).

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[127] M. Bogers, Sims J., West J. 2019. *What is an ecosystem? Incorporating 25 years of ecosystem research*. Working Paper. DOI: 10.5465/AMBPP.2019.11080abstract

[128] C.Y. Baldwin. 2020. *Design rules, volume 2: How technologies shape organizations, chapter 14, introducing open platforms and ecosystems.* Working paper 19-035, Harvard Business School

[129] R. Kapoor. 2018. Ecosystems: broadening the locus of value creation. *Journal of Organization Design* **7**(1): Article 12, p. 8.

[130] R. Adner *The Wide Lens: What Successful Innovators See that Others Miss*. (Penguin Random House, 2013).

[131] D.A. Walker, 'Walras's Theories of Tatonnement',(1987) 95 Journal of Political Economy, 758–74

[132] A. F. Siegenfeld, Y. Bar-Yam, An Introduction to Complex Systems Science and its Applications, (2020) Complexity arXiv:1912.05088 , 2.

[133] I. Lianos, Competition Law for the Digital Era: A Complex Systems' Perspective (August 30, 2019). Available at SSRN: https://ssrn.com/abstract=3492730 or http://dx.doi.org/10.2139/ssrn.3492730 .

Such ecosystems often compete with other business ecosystems and hierarchies (inter-ecosystem competition), which emphasizes substitutability (Crane, 2019[134]), but as each ecosystem is formed through interactions between independent firms, it is also possible to observe horizontal intra-ecosystem competition (between product ecosystems and specialized firms) (Bourreau, 2020[135]), which can still be explored through the traditional conception of rivalry as substitutability, as well as vertical intra-ecosystem competition (in particular within multi-actor ecosystems as to the highest percentage of the surplus value brought by the ecosystem), which emphasizes relations of complementarity and division of the value captured through joint collaboration in the ecosystem, something that the traditional competition law and economics metrics cannot gauge (Lianos, 2021[136]).

Although business ecosystems may become source of significant distributed innovation and creativity through effective collaboration between ecosystem members, which helps firms sharpen their organizational focus via economies of scale and specialisation (Grundlach, 2006[137]), non-generic complementarities between the various actors could also enable powerful ecosystem orchestrators to exploit locked-in complementors. Such lock-ins can accentuate the inherent challenges that emerge in the context of Multi-Sided Platforms (MSPs) which link different complementors, such as advertisers and visitors to a site, where a zero-price good for the final consumer (such as free storage or email) is subsidized from the fees the platform orchestrator receives from the advertisers. In this case, network and learning effects, which have been scrutinized from a competition vantage point, provide a foundation for our analysis (Lianos et al, 2019[138]).

Furthermore, as the Stigler Report notes, "the increased scale and scope of control has provided modern digital platform owners with increased power over their ecosystems. Today's platforms understand that they can obtain higher margins if they either make all of the necessary complements themselves or position themselves as a mandatory bottleneck between partners and customers" (Stigler Report, 2019)[139]. This moves beyond the conception of ecosystems as it is generally used in the strategy field, and, it refers not to the *multi-actor* ecosystems, but to the *multi-product* ecosystems. Hence, ecosystems do not only denote the "theory of the firm" alternatives to vertical integration or the supply chain arrangements, which has been the focus of the earlier papers on ecosystems (e.g., Adner,

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[134] D. Crane, Ecosystem Competition and the Antitrust Laws, 98 NEB. L. REV. 412 (2019).
[135] M. Bourreau, Some Economics of Digital Ecosystems, DAF/COMP/WD(2020)89.
[136] I. Lianos, Digital Value Chains and Capital Accumulation in 21st Century Digital Capitalism: A Legal Institutionalism Perspective, CLES Research Paper 1/2021.
[137] G.T. Grundlach, Complexity Science and Antitrust?, (2006) 51(1) Antitrust Bulletin 17.
[138] I. Lianos, Competition Law for the Digital Era: A Complex Systems' Perspective (August 30, 2019). Available at SSRN: https://ssrn.com/abstract=3492730 or http://dx.doi.org/10.2139/ssrn.3492730 .
[139] Stigler Committee on Digital Platforms, Final Report, September. https://research.chicagobooth.edu/stigler/media/news/committee-on-digitalplatforms-final-report , at 49.

2017[140]; Jacobides et al, 2018[141]). Beyond these (multi-actor) ecosystems, the concept also encompasses horizontally connected goods and services that are packaged together to offer convenience to the customer. Such *multi-product* ecosystems denote mutually enhancing products or services “that come together to create an attractive solution. […] So, one would often refer to “the Google ecosystem” (including Android, Google Search, Google Docs, Google Drive, Gmail, Google Maps, etc.); or “the Apple ecosystem” (iOS, iPhone, iPad, MacBook, Apple TV, etc.) [...] The ecosystem owner derives their competitive advantage either from the way the products interact, or from how data is combined, which can allow them to lock in end users [… and] exploit multi-product ecosystems by leveraging their existing multi-actor ecosystems.” (Jacobides et al, 2020: 13[142]).

The basis of these ecosystems (illustrated by Figure 11) rests on leveraging both customer inertia (broadening their scope to make them an easier “default” for the final customer, and in enhancing the product offering. It also comes from the fact that ecosystems often create value for the customer—with or without their knowledge—through personalization. Google, for instance, collects browsing history and Android app usage data, granting it hyper-personalized information on each user and their habits. This insight then allows Google to charge advertisers higher fees for highly targeted leads. Facebook draws information from the usage patterns at its main site and its subsidiaries WhatsApp and Instagram, using a device identifier, to customize advertising or content for its users. The challenge here is that often, customers simply go with the recommendations they are offered, which could take advantage of their behavioural predisposition to stick with the default (Thaler, 2015[143]). Beyond the power of orchestrators to appropriate value from their complementors in their ecosystems (defined, as they usually are in the strategy literature, as groups of interacting firms which need to collaborate to offer something of joint value to the customer), there is also the possibility that powerful actors in ecosystem power may also exploit final consumers, either by enabling the ecosystem leader to charge higher prices (in case there is limited inter-ecosystem competition) or to impose conditions that impact on non-price parameters of competition, such as innovation and privacy (Economides & Lianos, 2019[144]).

Figure 11: (Multi-firm) and Multi-Product Ecosystem for Google

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140 R. Adner, Ecosystem as structure: An actionable construct for strategy, (2017) 43(1) *Journal of Management* 39–58.

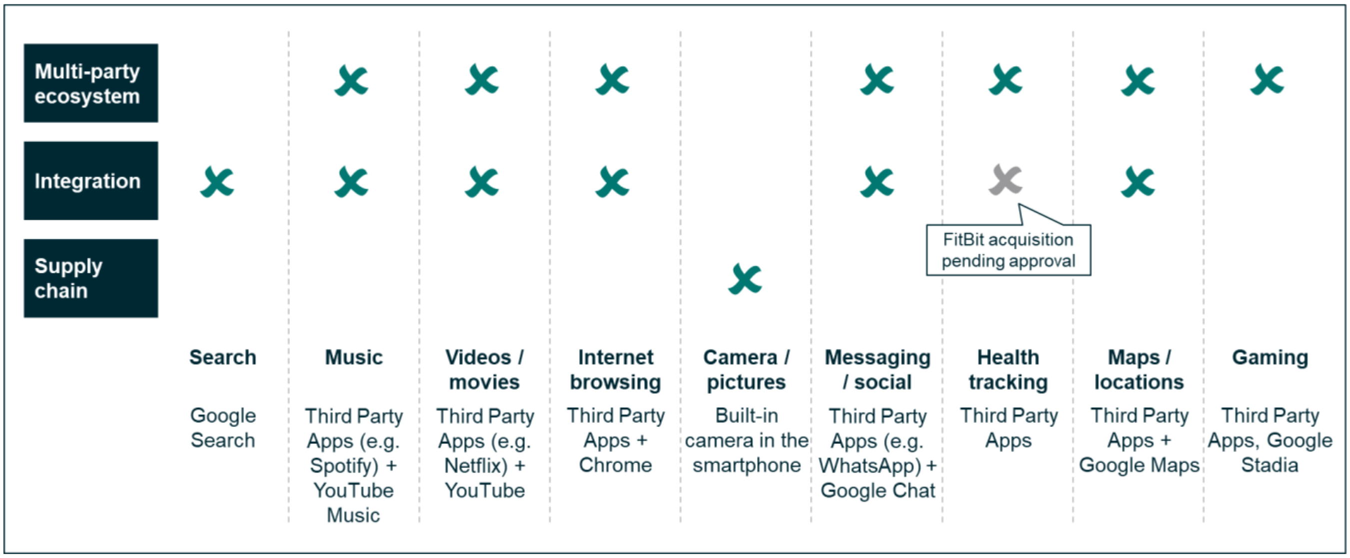
141 M.G. Jacobides, C. Cennamo, A. Gawer, Towards a theory of ecosystems, (2018) 39 *Strategic Management Journal* 2255-2276

142 M.G. Jacobides, C. Cennamo, A. Gawer 2020. *Distinguishing between Platforms and Ecosystems: Complementarities, Value Creation and Coordination Mechanisms*, working paper, on file with the authors.

143 R.H. Thaler, *Misbehaving: The Making of Behavioral Economics*, (New York: WW Norton, 2015).

144 N. Economides & I. Lianos, Restrictions on Privacy and Exploitation in the Digital Economy: A Competition Law Perspective (August 30, 2019). CLES Research Paper Series 5/2019, ISBN: 978-1-910801-29-1, NYU Stern School of Business, Available at SSRN: https://ssrn.com/abstract=3474099 or http://dx.doi.org/10.2139/ssrn.3474099 .

***Google** (& Google Mobile Services)*



Source: Jacobides, Cennamo & Gawer, 2020 (Figure 2a)[145]

Therefore, ecosystems create potential dependencies both to the customers, enhanced by information usage and targeting – with a fine line on where customer convenience ends and customer lock-in and its exploitation begins and because of the ability of ecosystem orchestrators, especially in the presence of a multi-product lock-in, to squeeze their complementors in terms of their multi-actor ecosystems. Furthermore, the interaction between various firms competing with each other in niche markets within the same ecosystem also raises the traditional competition concerns over tacit and explicit collusion, although the collective synergistic properties of the ecosystem would call for a more complex analysis than the one usually applied in such situations.

These issues are particularly visible in the case of Gatekeepers (Alexiades & de Streel)[146]. This is a special case of dominance in ecosystems arising out of "architectural concentration" (Moore, 2006[147]), which is enduring and almost irreversible in the medium term because, for instance, of the control by the dominant actor of the general purpose technology (GPT) (Bresnahan & Trajtenberg, 1995[148]) on which the complementors depend and which is particularly attractive to final consumers. In particular, some orchestrators have extraordinary power as their platforms provide irreplaceable access to

[145] Jacobides MG, Cennamo C, Gawer A. 2020. *Distinguishing between Platforms and Ecosystems: Complementarities, Value Creation and Coordination Mechanisms*, working paper, on file with the authors.
[146] P. Alexiadis & Alexandre de Streel, Designing an EU Intervention Standard for Digital Platforms, EUI Working Paper RSCAS 2020/14).
[147] J.F. Moore, Business Ecosystems and the View from the Firm, (2006) 51(1) Antitrust Bulletin 31.
[148] T. Bresnahan & M. Trajtenberg, General Purpose Technologies: 'Engines of Growth'?,(1995) 65(1) Journal of Econometrics, 83.

consumers who need to engage through their ecosystems, made all the stronger by the difficulty users to multi-home or switch between rival offerings. This underpins the very definition of a gatekeeper, which wields significant potential power, suggesting that they may need to be held to account and to a higher standard, especially if potential complementors are also more readily substitutable, and when the ecosystem leads to network effects, leading complementors to need to multi-home across platforms. Again, this becomes all the more salient when orchestrators engender additional lock-ins by virtue of their scope and becoming a “default” for customers, making it difficult for them to be pushed over. This means that even established players of significant size such as Tinder will find it difficult to resist the push of gatekeepers like Apple, who mediate the relationship between customers and their services: Apple users, locked in their system, are unlikely to use an Android phone as a (multi-home) alternative; sellers of complements such as Apps (e.g., dating Apps) co-exist in a competitive market where they are not hard to substitute; and network effects, enhanced by the set of mutually complementary products and services, make users more likely to stay within the Apple (multi-product) ecosystem. So Tinder, part of Apple’s App multi-party ecosystem, has to accept the terms offered, or risk seriously undermining its appeal by eliminating from its dating site the demographic which uses Apple, that would detract from its own network desirability.

In all, ecosystem orchestrators have changed the nature of economic and technological dependency, and the structure of the industry landscape. They also use new tools to enhance their power. They make strategic use of their APIs (Application Programming Interfaces, which enable external apps to connect), algorithms based on Big Data analytics or contractual restrictions – among other forms of ecosystem “glue” – in order to ensure interconnectivity and interoperability for final consumers. However, the same means also provide them with profitable points of control and the resources to build a strategic competitive advantage. This means they can exploit their users’ willingness-to-pay better than conventional firms in one of two ways. First, if their platform acts as an intermediary, they can better understand the willingness-to-pay of the various sides of their market through data harvesting and personalisation, thus extracting a higher surplus for their “matching”. Second, they can serve as hubs for collusive activity across their ecosystem to set prices or “fix” other important parameters of competition, as this is not necessary for the operation and development of pro-competitive collaboration within the ecosystem. Third, they can increase users’ willingness to pay for the platform itself by adding new functionality and features and inducing complementors to develop products that increase the value of the platform. Fourth, they can extract more surplus value from their ecosystem – for instance, by capturing “value as a portion of the sale of every complementary product or service sold for the platform, including its complements they build themselves” (Cusumano et al, 2019[149]). Finally, they can extract value through the

[149] M. Cusumano, A. Gawer, D.B. Yoffie, The Business of Platforms (Harper-Collins, 2019), 79.

recognition of the anticompetitive potential of their "gatekeeper" role by financial markets and the appreciation of their stocks due to higher expected returns in their future, which raises the market value of the core player within the ecosystem.

Although these problems are now well understood by economic and business literature, there is still difficulty to engage with the reality of the phenomenon ecosystem power and come to legal descriptions and definitions that may enable regulatory authorities to act in this complex reality (Jacobides & Lianos, 2021)[150].

3.3. How the current competition law framework cannot handle the complex economics of ecosystems

Usually, competition law enforcement focuses on the impact some allegedly anticompetitive business conduct may have on a specific relevant market(s), the latter concept serving as the main unit of analysis in order to assess anticompetitive (or procompetitive) effects. The boundaries of the 'relevant market' depend on the existence of cross-price elasticities of demand and supply and the degree to which two products may be substitutable to each other. However, with the emergence of platforms intermediating between various economic activities as well as of more complex business settings, such as multi-product and multi-actors ecosystems, ecosystem strategies, as opposed to standalone product strategies, have become more prominent, in particular in the digital economy, with the result that the relevant market concept does not appear to have the requisite complexity to respond to such new strategies.

First, the relevant market framework fails to fully take into account the complexity of business conduct taking place on a different relevant market than the one dominated by the specific actor. This is usually the case if a specific firm adopts a strategy of leveraging its market power from one relevant market to another. Such strategies may occur in the context of a 'product platform' (Cusumano et al., 2019[151]), involving a number of firms offering a package of complementary products and technologies, which relate to "systems competition" (Katz & Shapiro, 1994, 93[152]). These different "families" of closely related products increase the costs imposed on new entrants. In order to compete, the latter would need to invest in both their core product and complements offering a competing family of products, or to establish some form of co-operation with firms that already produce complements. However, they may face the risk of being subject to exclusionary strategies by a dominant undertaking on a niche relevant market which may choose to make its core product incompatible with other products that have been produced by different firms, thus

[150] M. Jacobides & I. Lianos, Ecosystems and competition law in theory and practice, forth. *Industrial & Corporate Change* (2021).
[151] M. Cusumano, A. Gawer, D.B. Yoffie, The Business of Platforms (Harper-Collins, 2019), 12
[152] M. Katz & C. Shapiro, Systems Competition and Network Effects, (1994) 8(2) Journal of Economic Perspectives 93.

denying innovation and variety to final consumers by "undermining attempts to establish substitute ecosystems based on more advanced technology" (Moore, 2006[153]). It may also seek to subsidise firms that produce complementary products but in doing so it may impose a condition of exclusivity, or it may subsidise its own divisions that sell complementary goods, thus leading to overcharges for final consumers through a softening of competition in the specific ecosystem niche. The total market value of the dominant actor will thus increase, while its competitive position in the various related standalone markets improved by the hurdles it imposes on its rivals.

The issue has been raised in cases where the producer of the original equipment has prevented independent third parties from servicing the equipment or from selling replacement parts. The classic example is a printer manufacturer selling printers at (or below) cost and charging high mark- ups over cost on proprietary printer ink cartridges. This type of "non-structural" market power may be present in aftermarkets, as consumers might be locked in, because of sunk costs and information asymmetry between them and the seller, with regard to a certain primary product, as they often do not consider, when purchasing the primary product, the possibility that they might be exploited by the undertaking in question in the provision of after- sale services or replacement parts. Consumers may also face 'switching costs' when they have already invested in the specific product system. To the extent that these practices may affect the same consumers purchasing both the core and the complementary products, it is possible to identify the effects of such strategies on competition and determine, under a consumer welfare standard which will nevertheless also take into account bounded rationality and informational asymmetries, if the specific conduct harms final consumers. According to the case law, there is a requirement for associative links between the various relevant markets even if these are not vertically related, this is however usually defined quite broadly (Lianos et al, 2019[154]), To the extent that what counts are the welfare effects on the same final consumers, the degree of complexity is such that the competition problem can be solved with the application of the relevant market framework.

Second, the concept of relevant market may face significant challenges in the context of industry or transaction platforms, which increase the degree of complexity. This is archetypical of a complex economy scenario, as the (market) value of the platform increases or decreases, each time there is one additional (or one less) user in view of the network effects and the positive (or negative) feedback loops that result from connecting different *categories* of users (Cusumano et al, 2019[155]). The quality of a specific product, or even that of a family of products is, in this configuration, less important than the value provided by the overall platform or ecosystem to different *categories* of users. Take, for instance, the case of a multi-sided advert-based platform, such as Google, which sells space

[153] J.F. Moore, Business Ecosystems and the View from the Firm, (2006) 51(1) Antitrust Bulletin 31.
[154] I. Lianos, V. Korah & P. Siciliani, Competition Law (OUP, 2019), 901-904.
[155] M. Cusumano, A. Gawer, D.B. Yoffie, The Business of Platforms (Harper-Collins, 2019), 113.

to advertisers on its search page charging a specific price, while it provides free Internet search to consumers to induce them to visit its search page, which may be analyzed as a form of requirement contract bundling digital services with personal data (Economides & Lianos, 2019[156]). This reinforces the positive feedback loop between the Internet search (which is charged at a zero price to consumers) and the data inferences sold by Google to advertisers: free Internet search shifts up the demand for ads sold by Google resulting in higher ads price. In order to be profitable, Google has to balance its ads price with how much it invests in search. Note, however, that Internet search is sold to users and selling ads (to advertisers) in different relevant markets. Despite the significant influence of the user search market on the ads market, the ads and search markets are separate antitrust markets *providing complementary services*.

The analysis of such practice under the traditional consumer welfare standard faces the complication that the end user in one market, the free search services consumer, becomes the productive input in the other side of the market, in where the end users are the advertisers buying data inferences from Google regarding the same consumers. In this context it is possible to analyze anticompetitive effects in the advertising side of the platform, while taking into account the demand shift created in the market for search to users. Alternatively, one may define 'attention markets' (D. Evans, 2017[157]; J.M. Newman, 2019[158]) at the search services side of the platform and focus on the exploitative effects such practice may have on some parameter of competition valued by the end users (e.g. privacy). 'Attention intermediaries' may operate as two-sided platforms providing various forms of intermediation services to different categories of users (app developers, sellers, advertisers and final consumers) (M. Peitz, 2020[159]). Again, in such multi-product platforms, the competitive situation can be assessed from the perspective of a specific category of users with the relevant market framework, but if the effect is different in each side of the platform, any aggregation would face the problem of comparing the welfare of different categories of users and having to make difficult choices as to whether and how the net-effect will be calculated. A competition analysis focusing on consumer welfare will therefore need to decide (i) which relevant market will serve as the main unit of analysis of consumer welfare, or (iii) to balance costs and benefits for the consumers affected in all affected relevant markets. This may prove a rather difficult and resource consuming task, that would also require the consideration of 'out of relevant market' efficiencies which could potentially outweigh consumer harm in another market.

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[156] N. Economides & I. Lianos, Restrictions on Privacy and Exploitation in the Digital Economy: A Competition Law Perspective (August 30, 2019). CLES Research Paper Series 5/2019, ISBN: 978-1-910801-29-1, NYU Stern School of Business, Available at SSRN: https://ssrn.com/abstract=3474099

[157] D. S Evans, The Economics of Attention Markets (October 31, 2017). Available at SSRN: https://ssrn.com/abstract=3044858 .

[158] J.M. Newman, Attention and the Law (July 21, 2019), available at SSRN: https://ssrn.com/abstract=3423487 .

[159] M. Peitz, Economic Policy for Digital Attention Intermediaries (2020). ZEW - Centre for European Economic Research Discussion Paper No. 20-035, Available at SSRN: https://ssrn.com/abstract=3654009 .

Third, an even more complex set of issues arises with multi-actors ecosystems emerging out of joint value creation processes that do not involve complementary products but the development of a hub to which intersect various value chains and which has a specific structure and form. These multi-actors ecosystems group independent economic entities that are active in various economic activities/markets, not necessarily vertically situated to each other, and involve independent undertakings that compete with each other in some market while co-operating in some other (and that may be characterized as in co-opetition with each other). Interestingly, it also covers situations in which the undertakings in question exercise what would appear at first sight as completely unrelated economic activities of conglomerate nature, *but for* the linkage resulting from the existence of the specific hub which sits at the center of this ecosystem and the co-evolution of the various activities of such ecosystem. In contrast to the product system example, in which the associative links between the different relevant markets seem to relate to an input/output production process, the archetypical example being that of two markets vertically related to each other, but also the multi-sided markets example, in which the platform takes advantage and/or structures various indirect feedback loops between categories of users (across different markets), multi-actors ecosystems are essentially value ecosystems, in which various economic activities in co-evolution are moulded together through an elaborate process of financial valuation by capital markets (Lianos & McLean, 2020[160]), on the basis of a "behavioural surplus" generated by the specific ecosystem (Zuboff, 2019[161]).

Furthermore, contrary to the "simple" economics of the relevant market where the behaviour of the system is assumed to reflect the behaviour of its components, the various undertakings producing products found to be substitutable, in multi-actors ecosystems there may be a disconnect between the localised behaviour of an actor in the ecosystem and the way in which this aggregates into global behaviour of the ecosystem itself. Complex systems, such as multi-actors ecosystems, are not populated by homogeneous predictable agents but by a collection of heterogeneous agents (individuals, organisations etc.), the state of whom influences and is influenced by the state of others (e.g. situations of social contagion). Their interactions give therefore rise to global systemic properties that equate to more than the sum of individual behaviour. As the interactions within the multi-actors ecosystem are not independent, various feedback loops, some of which may be situated outside the sub-system of the relevant market, can enter into the system and affect not only the individual decisions of the specific agents but also the overall properties of the ecosystem. Determining the relevant "space" of the interactions of interest for competition law should therefore be done before fully engaging computationally with the interactions of the agents themselves and determining the topography of the ecosystem.

[160] I. Lianos & A. McLean, The Role of Financialisation in Digital Era Competition, CLES Research Paper Series 3/2021.
[161] S. Zuboff, The Age of Surveillance Capitalism: The Fight for a Human Future at the New Frontier of Power (Public Affairs, 2019, 94-96).

Assessing the entire panoply of behavior and power in business ecosystems becomes an impossible task for a regulatory system that only focuses on a specific subset, the relevant market, and a specific dimension of power, that over price. Power may indeed amass at different levels: in spaces of ecosystem competition, in ecosystem leadership and in particular niches within an ecosystem. Power cannot only be defined its usual attributes focusing on the absence of rivalry but should also take into account the positional dimensions of power exercised by ecosystem orchestrators connecting complementary economic activities (Grundlach, 2006[162]; Lianos & Carballa Schmichowski, 2020[163]). Behaviour may also manifest itself at all these different levels. This increasing degree of complexity calls for a regulatory system that would differentially react to the set of (business) behaviours in the specific environment it grapples with (economy). This regulatory response should allow for as much complexity as necessary, not only in order to take into account the whole set of environmental behaviours that correspond to the complex system analysed, but also each subset of the system must have at least as much complexity at all scales as the environmental behaviours corresponding to that subset (Siegenfeld & Bar-Yam, 2020[164]). Designing regulatory institutions and tools for the complex economy of business ecosystems is confronted to different challenges than those to which has been designed to respond the usual approach of the relevant market which explicitly focuses on the average behaviour of a system's components (the firms producing substitutable products) and the deviations of the individual components from this average (e.g. higher prices, lower quality and innovation). This is not an approach that would work in the presence of sufficiently strong correlations between the components of a system, as the ones met in multi-product and multi-actors ecosystems, which give emergence to large-scale behaviours at the ecosystem level.

3.4. New dimensions of ecosystem power

These new developments influence the way public authorities engage with the regulation of economic power in order to pursue various social goals. In the complex digital economy, power may encompass various dimensions beyond that of a simple reduction of output and/or an increase of prices, both of which have been the traditional focus of competition law. The concept of 'market power', employed in competition law, relates to the power over price and output exercised in the context of a relevant market. The traditional relevant market based competition law theoretical framework may face difficulties in considering

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[162] G. T Gundlach, Complexity science and antitrust?, (2006) 51(1) Antitrust Bulletin 17.
[163] I. Lianos & B. Carballa-Schmichowski, Ecosystem and Positional Power: Concept and Metrics, CLES Research paper series 2/2021.
[164] A. F. Siegenfeld, Y. Bar-Yam, An Introduction to Complex Systems Science and its Applications, (2020) Complexity arXiv:1912.05088 .

other facets/dimensions of power that may be particularly relevant in the context of the digital economy.

We discuss the following, going from the easier to the more difficult one, in terms of possibilities of integration in the current theoretical framework:

Bottleneck power: Controlling a bottleneck or a 'chokepoint', i.e. the cutting off of adversaries from flows in a network[165]. Bottleneck power has been a particular concern of competition and regulatory authorities with regard to the digital economy in view of the ability of platforms to adopt strategies, such as exclusive contracts, bundling and/or technical incompatibilities in order to restrict the entry of competitors in relevant markets. Bottleneck power may result from supply-side conditions, such as the control of an essential facility or an input that is necessary for competing producers if they are not to be excluded or marginalised from the market. However, it may equally result from demand-side conditions, such as the propensity of consumers to single-home and, thus, not use more than one platform for the specific functionality.[166] The concept of "bottleneck input" is frequently employed in the context of competition law enforcement[167], or sector-specific competition enhancing regulation[168].

Intermediation power: Recent literature has noted the important role of new 'information intermediaries', i.e. search engines, price comparison platforms, booking portals and trading platforms etc., which collect, sort and rank the information available online and therefore "steer" consumers (Peitz, 2020[169]). However, the ease with, and options through, which consumers can check the quality of the intermediation intermediary itself are limited and the increasing use of information intermediaries had

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[165] H. Farrell and A. Newman, "Weaponised Interdependence: How Global Economic Networks Shape State Coercion", (2019) 44(1) *International Security*, 46.

[166] See the definition of 'bottleneck power' provided by the Committee for the Study of Digital Platforms Market Structure and Antitrust Subcommittee, (2019), Report of Stigler Centre for the Study of the Economy and the State - The University of Chicago Booth School of Business, which defines it as "a situation where consumers primarily single-home and rely upon a single service provider (a "bottleneck"), which makes obtaining access to those consumers for the relevant activity by other service providers prohibitively costly'".

[167] See, for instance, CJEU in Case C- 52/ 09, *Konkurrensverket v TeliaSonera Sverige AB* [2011] ECR I– 527, paras 70-71, If access to the bottleneck input is indispensable for the sale of the retail product, leading to the exclusion of an equally efficient competitor, the anti- competitive effects of margin squeeze are 'probable'. Refusal to deal or margin squeeze in which the dominant undertaking is attempting to exclude a downstream competitor, for instance by refusing to grant access to a bottleneck good which is either used as an input by a potentially competitive downstream industry or when access to the bottleneck is needed in order to reach final consumers (customer foreclosure) give rise to vertical foreclosure. Refusal to deal may, however, be used also as a horizontal foreclosure strategy if the bottleneck is integrated. See also, Commission Decision, , in which the Commission acknowledges that tying the Play Store with the Google Search app, Google is able to establish a bottleneck as Google Search is an important entry point for search queries on mobile devices.

[168] See, Directive 2002/19/EC of the European Parliament and of the Council of 7 March 2002, on access to, and interconnection of, electronic communications networks and associated facilities (Access Directive), [2002] OJ L 108/7, recital 13.

[169] M. Peitz, Economic Policy for Digital Attention Intermediaries (2020). ZEW - Centre for European Economic Research Discussion Paper No. 20-035, Available at SSRN: https://ssrn.com/abstract=3654009 or http://dx.doi.org/10.2139/ssrn.3654009 .

caused sellers of goods and services to become dependent upon consumers accessing and seeing their offers on these intermediaries. In a variety of different contexts, these intermediaries may function as gatekeepers, without necessarily holding a dominant position in a specific relevant market. To deal with this gap, a report for the German Ministry of Economics puts forward the concept of 'intermediation power (Schweitzer et al, 2018[170])'. Usually, intermediation power can be seen as a special form of seller power, namely intermediation power on the market for the supply of intermediation services to suppliers of goods and services. However, this approach does not take into account the dependency of suppliers of goods and services on the intermediation service. Moving beyond its conception as a form of relational power, the report also argues that intermediation power may also exist even if there is no market relation between the intermediation platform and the supplier, as is the case of pure information intermediaries, like specialised search engines that just provide users with aggregated publicly available information.

Superior bargaining power or economic dependence: Concerns over the increasing power of digital platforms have led some competition authorities rely on existing legal rules concerning superior bargaining power or economic dependence. In order to define market power on a relevant market, competition law enforcers usually focus on size and market share. However, one may take a 'game/bargaining theory approach' that will not focus on market shares or the size of the negotiating parties but on the existence of 'threat points', which enable one of the parties to seek its best alternative to a negotiated agreement (henceforth, 'BATNA') even if it does not dispose of a dominant position on a relevant market.[171] A negotiating party with a BATNA has the possibility of resorting to a valid alternative to the negotiation in progress, thus preventing hold-up and negating threats concerning the cessation of negotiations. In conceiving the bargaining model, one may either take a Nash co-operative bargaining solution as the axiomatic starting point,[172] or may resort to a non-co-operative or sequential bargaining model which will attempt to factor in the costs of the delay to agreement and extend this analysis from 'bilateral bargaining' to 'n-person bargaining'.[173] However, in all legal regimes in which abuse of a situation of economic dependence or "relative market power" may be considered as a

[170] H. Schweitzer, J. Haucap, W. Kerber, R. Welker, Modernising the Law on Abuse of Market Power: Report for the Federal Ministry for Economic Affairs and Energy (Germany) (September 17, 2018). Available at SSRN: https://ssrn.com/abstract=3250742 or http://dx.doi.org/10.2139/ssrn.3250742

[171] A. Renda, F. Cafaggi, J. Pelkmans, A. de Brito, F. Mustilli and L. Bebber, "Study on the Legal Framework Covering Business-to-Business Unfair Trading Practices in the Retail Supply Chain", (2014), Final Report DG MARKT/2012/049/E, 25; I. Ayres and B. Nalebuff, "Common Knowledge as a Barrier to Negotiation", (1996) 44 *UCLA Law Review*, 1631.

[172] Most of these studies have relied on this type of model so far.

[173] See J. Sutton, "Non-Cooperative Bargaining Theory: An Introduction", (1986) *LIII Review of Economic Studies*, 709-724; K. Binmore, M. Osborne and A. Rubinstein, "Non-Cooperative Models of Bargaining" (Chapter 7) in *Handbook of Game Theory with Economic Applications* (Elsevier, 1992), 179-225.

competition law infringement[174], the criteria often used for identifying and measuring it relate to the amount of specific investments made for the particular (dyadic) business relation, the amount of one's business done with the other party, the absence of 'outside options' for one of the parties, or the existence of high switching costs. Economic dependence may also be linked to technological dependence, if one of the parties depends on the technology platform of the other for its day to day business.

Panopticon power: The power of specific nodes (actors) does not always result from the dependency of the other nodes of the network in which it forms part, for instance, because of certain individual characteristics of this specific actor but find its source in their strategic position in the network. This strategic position may enable them to extract an information advantage vis-à-vis potential adversaries. "Panopticon power" may emerge in situations in which there is significant (and increasing) learning-by-doing asymmetry between the actor benefitting from this position in the ecosystem: in view of the importance of hubs in a decentralised communications structure, it is possible that "hub nodes can use this influence to obtain information passing through the hubs" (Farell & Newman, 2019: 55[175]). Because of their position in the network, these actors may tap into the information gathering and generating activities of the whole network, which may be well beyond the nodes with which they have direct, or even indirect, relations. Hence, despite the function of such actors as simple intermediaries that provide communication infrastructure, their influence can be quite significant. Panopticon power, thus, results from the position of an actor in an ecosystem, and is not related as such to the existence of some form of economic dependence in the context of a dyadic relation. It is possible that the different actors in a network voluntarily agree to share information through the hub, for instance because they trust it better than a direct communication between them or because it is more convenient to do so. The actor also serves as a hub for a number of other interactions that may provide that specific actor with superior and more complete information regarding the strategies of the other members of the network, including its adversaries if they communicate/interact with some of the nodes that also communicate with the hub.

Positional or architectural power: Competition fights won not only through the use of traditional strategic competitive advantages, such as lower costs, higher quality products etc. Increasingly, firms are engaging with the overall structure, economic and legal, of the industry in which they are active seeking opportunities to frame their architecture in a way that favours their position. This quest for architectural advantage, which, in the context of ecosystems, is particularly important in competitive fights, hints at a different dimension of economic power that is not usually taken into account by the traditional competition law

[174] See, for instance, Germany, Section 20(2) of the German Act Against Restraints of Competition, the Gesetz gegen Wettbewerbsbeschränkungen, (henceforth, the 'GWB'); French Commercial Code (Code de Commerce), Article L 420-2; Italian Law on Industrial Subcontracting (Disciplina della Subfornitura nelle Attività Produttive), No. 192 of 18 July 1998, Article 9; Portuguese Competition Act, Law 19/2012, Article 12..

[175] H. Farrell & A. L. Newman, Weaponized Interdependence: How Global Economic Networks Shape State Coercion, (2019) 44(1) International Security 42, 46.

metrics, that of 'architectural power'. To the extent that this architectural power stems from the central positioning of platforms in ecosystems, it has also been referred to as 'positional power'. This does not necessarily solely relate to the position of an undertaking as an indispensable intermediary, although this may constitute a source of architectural advantage, but relates to the overall position and the centrality of this position of specific platform or undertaking in the industry architecture. In conclusion, being in a position from which one can influence the way in which the industry is organised or structured and the value allocation between the industry (or ecosystem) actors is that which constitutes an 'architectural advantage'.[176] This may prove to be an important source of sustainable abnormal profits and is likely the reason why 'architectural fights'[177] have characterised the evolution of all industries. The competition to become the industry architect plays a crucial role in periods of profound technological transformation, such as the development of new GPTs and/or in periods in which new technologies that confer significant advantages, such as a reduction of costs or an increase in productivity are progressively integrated into the production process employed by a specific industry.[178]

This analytical problem becomes more apparent if we consider that differentiated digital platforms effectively compete in general 'attention markets' (Wu[179], Newman[180]), in which no dominant position can be easily defined. It is conceivable that a platform, despite occupying a central position within an ecosystem, thus effectively determining the competitive conditions that prevail in it, does not satisfy the requirements for a finding of "dominance" on a relevant market to be established.

Hence, there is a clear gap in the existing EU competition law enforcement toolkit in order to preserve competition on the merits (on the basis of product *as well as* ecosystem competition) and to tame entrenched dominant positions that result from positional power and gatekeeper absolute competitive advantage. Furthermore, as technological change matures, it may become more difficult for new entrants to challenge the position of incumbents/ecosystems' gatekeepers, in view of the significant barriers to entry resulting from a combination of network effects, path dependence, learning effects, economies of scope and scale and the emergence of a stable competitive hierarchy as the specific General Purpose Technology (GPT) matures (Bresnahan & Trajtenberg, 1995[181]). This may affect

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[176] M. Jacobides, S. Winter & S. Kassberger, "The Dynamics of Wealth, Profit, and Sustainable Advantage", (2012) 33 *Strategic Management Journal*, 1386..
[177] *Ibid*.
[178] C. Ferguson and C. Morris, "How Architecture Wins Technology Wars", (1993) 71(2) *Harvard Business Review*, 86.
[179] T. Wu, Blind Spot: The Attention Economy and the Law (March 26, 2017). Antitrust Law Journal, Forthcoming, Available at SSRN: https://ssrn.com/abstract=2941094 or http://dx.doi.org/10.2139/ssrn.2941094 .
[180] J.M. Newman, Attention and the Law (July 21, 2019), available at SSRN: https://ssrn.com/abstract=3423487 .
[181] T. Bresnahan & M. Trajtenberg, General Purpose Technologies: 'Engines of Growth'?,(1995) 65(1) Journal of Econometrics, 83.

innovation, productivity and the long-term interests of the consumers, in addition to also producing some other significant social costs (risk for democracy, pluralism in media etc).

However, it is possible to put forward some general guiding principles in order to define dominance in an ecosystem.

The dominant undertaking should have control over an indispensable (not easily replicable for its partners) resource that offers it a significant or absolute competitive advantage in capturing value in the context of the ecosystem, which may include some of the factors listed below (Table 8).

Table 8: Factors providing absolute competitive advantage

Big Data that is of quality, scale and scope that provide this undertaking superior knowledge over consumers' preferences
Algorithms and other technological resources protected by exclusive rights that are essential standards to the industry/industries
Facilities and Infrastructure that are not easily replicable
State conferred exclusive and monopoly rights
Lack of a legally imposed duty to interoperate
Full control over the levers of a platform, including the ability to deny access through APIs

To these factors, it is possible to add others that relate to the superior technological and/or economic capabilities of the dominant undertakings with regard to other members of its ecosystem. The test involves a broad comparative element with the situation of the other members of the ecosystem (see Table 9).

Table 9: Factors providing relative competitive advantage

Higher sunk costs for the partners to the undertaking in view of the asset specificity and the need for them to invest, rather than the specific undertaking in the relation
Higher technological acumen (e.g. algorithms) and portfolio of IP rights
Access to more valuable and voluminous data
Stronger brand value
Intermediary role through control of chokepoints at the intersection of various industries
The fact that a specific undertaking may have a significant financial market capitalization compared to the other members of the ecosystem will also be considered
Significant extent of multi-homing for the complementors in the ecosystem may be a factor denying the finding of a gatekeeping position

Not all undertakings satisfying the above criteria should be considered as having a dominant position in an ecosystem of paramount importance but only those for which potential inter-ecosystem competition is less likely, in view of significant barriers to entry, such as economies of scope, learning effects or low multi-homing. As previously mentioned undertakings may benefit from a safe harbour in view of strong inter-ecosystem competition. For instance, as is provided for in the EU Transfer of Technology Guidelines (European Commission, 2014[182]), the provision may not be infringed where there are four or more independently controlled and non-significantly asymmetrical ecosystems in addition to the one to which participates the specific undertaking, and which may offer an alternative for the complementors at a relatively comparable cost to them.

3.5. New metrics[183]

The development of new concepts, such as ecosystem power require new metrics. These should measure power both at the firm and ecosystem levels.

3.5.1. A metric at a firm level

It is accepted that differential dependency within a value chain can be a source of vertical power. It is common for theories of vertical power belonging to the 'resource dependency' family to recur to network analysis and, in particular, to the notion of centrality to represent a firm's power. The metrics we will propose in this subsection follow this tradition. Building on the indicator of centrality that better translates the notion of resource-based differential dependency (betweenness centrality), we propose a metric that can be used to assess a firm's power within a value chain arising from this source. We will build this indicator in such a manner that, as shown in Part 1, the value retained by each firm of the value chain depends positively on its vertical power. Then we generalize the indicator to the value chain level in order to assess the extension of power differentials within a value chain.

Before starting developing the indicator, let us briefly present how we will represent the problem in terms of network theory. Firms are denoted by nodes (which are graphically represented as circles) and commercial transactions[184] between them (selling/buying a good or service, licensing a patent, etc.) as weighted directed vertices (graphically represented as arrows linking the dots). When firm A sells a good or service to firm B, the arrow goes from firm A to firm B. The weight of the vertices represents the

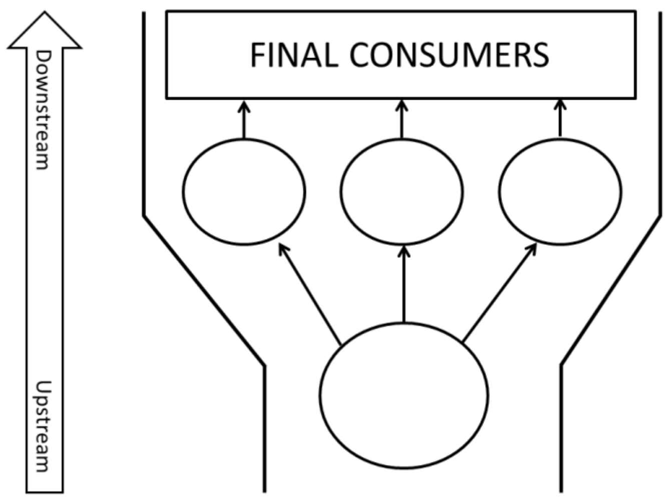
[182] Guidelines on the application of Article 101 of the Treaty on the Functioning of the European Union to technology transfer agreements, [2014] OJ 89/3, para. 157.

[183] This section draws on I. Lianos & B. Carballa-Schmichowski, Ecosystem and Positional Power: Concept and Metrics, CLES Research paper series 2/2021.

[184] For the sake of simplicity and comparability, we assume that all managerial coordination relations are translated in commercial transactions, which is a realistic assumption. For example, if a firm advices another one on the development of a product, it translates into a contract in which a firm sells consulting to the other.

unitary cost for purchaser node B of acquiring a good from selling node A[185]. It is graphically represented as the length of the vertex so that the costlier the input is, the longer the vertex is. Following Zhang (2006)[186], this cost includes both monetary and non-monetary costs such as quality and coordination costs. Nevertheless, contrary to Zhang's model, and following the administered prices/normal cost doctrines, monetary costs are not marginal costs but full costs. Firms' vertical positions in the figure represent the tier in which they participate. The lower part of the spectrum corresponds to more upstream activities (for example, the extraction of primary goods) and the upper side of the spectrum corresponds to more downstream activities such as marketing and retail. Institutional and technical conditionings are represented as a two-dimensioned space (i.e. as lines on a plan) on which firms (nodes) are contained. Figure 12 illustrates this.

Figure 12: A value chain with one upstream supplier



[185] A second dimension defining the weight graphically represented as the thickness of the vertex could be added to account for the firm's market share. In that way, concentration and economies of scale (a negative relation between a vertex thickness and its length) can be added to our framework. Milberg's theory of pricing and profits in a global value chains context [see, W. Milberg & D. Winkler, *Outsourcing Economics: Global Value Chains in Capitalist Development* (CUP, 2013)] can be then thought of as a particular case of an extended version of our thesis that includes market shares. This also goes in line with two of the three variables of economic dependence Baudry and Chassagnon (2012) [B. Baudry & V. Chassagnon, The vertical network organization as a specific governance structure: What are the challenges for incomplete contracts theories and what are the theoretical implications for the boundaries of the (hub-) firm?, (2012) 16(2) Journal of Management and Governance 285] identify within the value chain: "the concentration of exchanges between member firms" and "the respective sizes of subcontractors". The third one, "the importance of the specific assets engaged in the economic relationship" is implicit in our formulation because the more specific an investment firm A did to work for firm B, the more central firm B will be in respect to firm A. For the sake of simplicity, and in order to highlight what we consider to our main original contribution in this chapter, we have decided not to include market shares and sizes, although they are perfectly compatible with our thesis.

[186] X.F. Zhang, Information Uncertainty and Stock Returns, (2006) 61(1) The Journal of Finance 105.

In Figure 12, nodes represent firms and the lines that surround them represent the technical and institutional conditionings affecting the value chain. In this example, the combination of technical and institutional conditionings leaves room for only one firm to exist downstream in the supply chains that can be formed. An example of this can be railway transportation in many European countries, where high fixed costs of having deployed already-existing networks (technical conditioning) and the decision of antitrust agencies to have competition on infrastructure (institutional conditioning) created a monopoly upstream. Technological progress that reduces the high fixed cost of deploying a network or a change in antitrust policy to create competition through infrastructure can be represented by a loosening in the lines that surround the upstream node (firm), opening the possibility to the existence of more firms upstream. Then, changes in any of these two conditionings affect the number of firms in each tier, the scope of their possible vertical integration and the possibility of relating to each other[187]. In terms of Jacobides, Knudsen and Augier (2006)[188], the latter are the "technical" and "legal and regulatory authority" determinants of industry architectures[189].

If a central firm was to leave the value chain, the value loss for the latter would be greater than if a non-central easy-to-replace firm left (Crook & Combs, 2007[190]). Because "a node [firm] with high betweenness centrality has a great capacity to facilitate or constrain interactions between other nodes [firms] (Freeman, 1979[191]) (Kim, Choi, Yan, & Dooley, 2011)[192]", its removal affects the network more than the removal of a node (firm) with a low betweenness centrality. This means that central firms are those on which the whole value chain depends more to function because they perform tasks that are more necessary to assure the overall coordination of the value chain. This is the ultimate reason of its resource-based vertical power based on differential dependency. This form of market power is vertical in that it is exerted from suppliers to buyers or vicecersa, and it is 'fully' vertical in that it affects the whole value chain and not only the upstream or downstream tiers directly linked to the firm exerting it. Therefore, we will speak hereafter of "fully vertical market power".

As network theory shows, a node's (firm's) centrality, in turn, is a property of the topology of the network (value chain). If we wanted to establish which node is the most

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[187] Let us note that barriers to entry and rent-earning resources can be represented by shaping the contouring lines that would benefit one node over other horizontally competing nodes in, for example, placing it vertically 'closer' to suppliers and/or more far away from clients than other competing nodes (i.e. by making it able to charge more and purchase for less than competing firms).

[188] M.G. Jacobides, T. Knudsen & M. Augier, Benefiting from innovation: Value creation, value appropriation and the role of industry architectures, (2006) 35 Research Policy 1200.

[189] The authors also consider path-dependency as a third factors that shapes industry architectures.

[190] T.R. Crook & J.G. Combs, Sources and consequences of bargaining power in supply chains, (2007) 25 Journal of Operations Management 546.

[191] L.C. Freeman, Centrality in Social Networks: Conceptual Clarification (1979) 1 Social Networks 215.

[192] Y. Kim, T. Choi, T. Yan, K. Dooley, Structural investigation of supply networks: A social network analysis approach, (2011) 29(3) Journal of Operations Management 194.

central in a network, there would be many ways to do so. Network theory offers different centrality measures that translate different concepts of centrality. The one that is pertinent to us, as we anticipated a few line ago, is betweenness centrality, which is a measure of the share of total shortest paths in a network that pass through a node (a firm) in a network (value chain). A shortest path is defined as the minimum number of vertices that have to be transited to go from point A to point B. Because in our representation of value chains all the vertices have to be transited (i.e. all the intra-value chain transactions have to be done for the final product to be sold), all paths are shortest paths. Then, if we notate a node as N_x where x identifies a particular node in the network, its betwenness centrality can be calculated using Equation 1.

Equation 1: Formula of betwenness centrality of node X

$$\mathrm{BC}\ (\mathrm{N_x}) = \frac{\text{Number of paths passing through } \mathrm{N_x}}{\text{Number of paths in the network}}$$

Where BC stands for “betweenness centrality” and N_x for “node X”.

Since vertices represent a firm buying something to another to continue with the production process of the value chain, the bigger the share of shortest paths that pass through firm X relative to other firms in the network, the more essential that firm’s contribution to the production of the final product is to the value chain relative to others. This is the case because each shortest path represents a production process that has been carried on by other firm(s) and requires firm X’s intervention for the final product to be produced. In other words, a firm’s betweenness centrality relative to other firms’ (‘relative centrality’ hereafter) translates its differential dependency within the value chain. Hence, our metric of vertical power has to be able to give us two different values for two firms that belong to different value chains and have the same betwenness centrality but different relative centralities. Equation 2 provides an indicator that meets this requirement.

Equation 2: Resource-based vertical market power based on differential dependency for a node x

$$\mathrm{SSBC}(\mathrm{N_x}) = \frac{\mathrm{SBC}\ (\mathrm{N_x})}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{SBC}\ (\mathrm{N_i})}$$

Where “SSBC” (Share of square betweenness centrality), SBC stands for “square betweenness centrality” and Nx for “node x”.

In other words, Equation 2 poses that the level of a firm's resource-based vertical market power based on differential dependency can be measured as its share of the sum of the square betweenness centralities of each node (firm) of the value chain.

Let us illustrate the use of the indicator with an example represented in Figure 13.

Figure 13: Two non-competing value chains with two tiers and different numbers of upstream suppliers

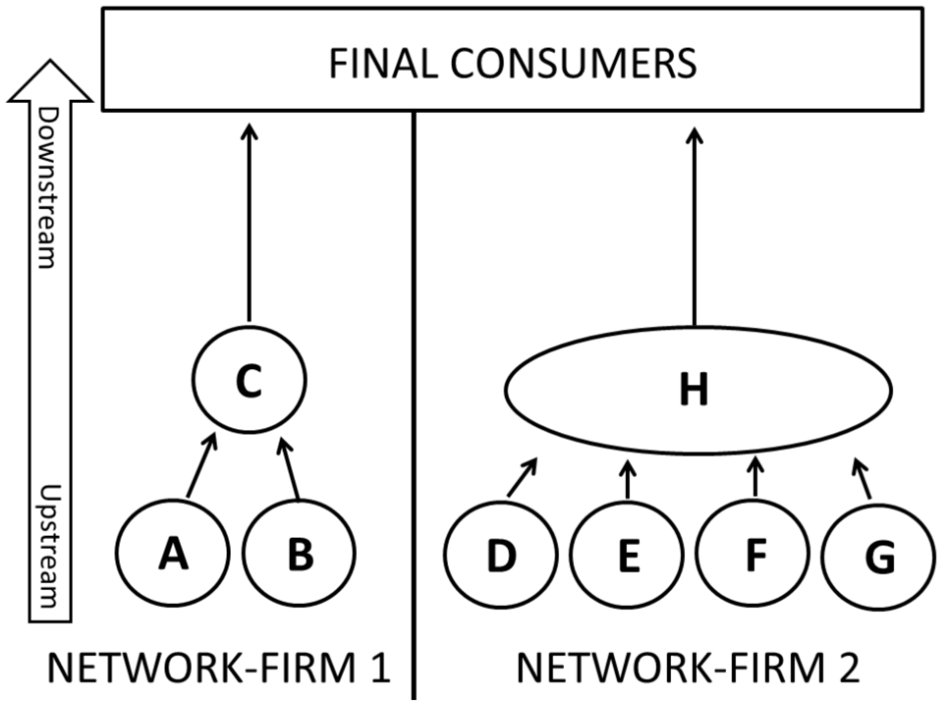

Figure 13 shows two non-competing value chains with two tiers each, one upstream and one downstream. In both, there is a single firm at the downstream level. The line between the two can be interpreted as an institutional and/or technical barrier to entry that makes non-viable for any firm to switch to the other value chain. For example, the two value chains could produce the same final good but be located in different continents, with transportation costs and tariffs making it non-profitable to compete with or to switch to the other value chain. For the sake of simplicity, we will assume that they both sell at the same price per unit, which is 1 even though horizontal price competition is not acting because of the existence of barriers to entry. Graphically, because the lengths of arrows represent absolute per unit prices, this translates into the arrow going towards final consumers having the same length in both value chains. In Value chain 1, there are two upstream firms while in Value chain 2 there are four. In the first value chain, there are two shortest paths from upstream suppliers to final consumers, while in the second one there are four.

Table 10: Betweenness centrality, price and value retained for firms in two competing supplying chains for Figure X

FIRM	VALUE CHAIN	TIER	BETWEENNESS CENTRALITY	SQUARE BETWEENNESS CENTRALITY	SHARE OF SQUARE BETWEENNESS CENTRALITY (LEVEL OF VERTICAL POWER)
A	1	Upstream	0.5	0.25	0.17
B	1	Upstream	0.5	0.25	0.17
C	1	Downstream	1	1	0.67
D	2	Upstream	0.25	0.06	0.05
E	2	Upstream	0.25	0.06	0.05
F	2	Upstream	0.25	0.06	0.05
G	2	Upstream	0.25	0.06	0.05
H	2	Downstream	1	1	0.80

Since in both value chains the downstream firms (C and H) are necessary in all the steps of the production process (each of them is the only retailer of its supply chain, for example), their betweenness centrality is 1. On the contrary, suppliers are less central in the second value chain, where each is needed in one out of four processes (making the betweenness centrality of each of them equal to 0.25), while in the first value chain each is needed in half of the processes, which is why suppliers A and B have a centrality of 0.5 each. If we used each node's betwenness centrality as a direct measure of their fully vertical market power, we should conclude that since both downstream firms (C and H) have the same betweenness centrality, they should both retain the same share of the value created in their respective value chains. Nevertheless, as we said above, a firm's fully vertical market power within its value chain depends on its differential dependency (which is translated by its betweenness centrality in the value chain) relative to others firms'. In our example, this means that a firm like firm C that has a betweenness centrality of 1 (i.e. an unavoidable firm in the production process of its value chain) but deals with two firms that have a centrality of 0.5 each (half of firm C's centrality) has less fully vertical market power than a firm like H that has also a centrality of 1 but deals with four firms that have a betweenness centrality of 0.25 each (a quarter of firm H's centrality). In other words, given that firm H is more central relative to the other firms in its value chain than firm C, firm H has more fully vertical market power than firm C. A way of representing this relationship arithmetically is to calculate a firm's fully vertical market power as a share of all firms of its network's fully square betwennness centralities added, as shown in Table 10. For example, firm A has a square betweenness centrality of 0.25 (0.5 to the square). The sum of all firms' square centralities in value chain number 1 is 1.5 (0.25 + 0.25 + 1), which makes firm A's level of vertical power equal to 0.17 (0.25/1.5). Using this formula, we find that although firm H has the same betweenness centrality as firm C, since it has a higher relative centrality, its level of vertical power (0.8) is higher than C's (0.67).

3.5.2. A metric at an ecosystem or value chain level

We have just shown how the square betweenness centrality of a firm can be used as a metric of resource-based vertical power based on differential dependency. However, because this metric is firm centric, it does not tell us what is the level of vertical power differentials within a value chain, or broader ecosystem, a piece of information that could be useful to do a more aggregated analysis of power, especially from an antitrust perspective. Consequently, with this indicator we cannot say if there is more power concentration in a certain value chain, or ecosystem, than in another one. Therefore, in this subsection we will adapt this metric to overcome these difficulties.

Given that each firm's level of vertical power corresponds to its share of the sum of the square betweenness centralities of all of the firms (nodes) of its value chain, a simple way of assessing the level of power imbalances within a value chain, or ecosystem, would be to calculate the standard deviation of this indicator. However, the level of standard deviation is only interpretable for a given variable. Then, in order to be able to compare the level of vertical power imbalances between several value chains, we will use instead the coefficient variation. Then, our indicator to assess the level of power imbalances within a value chain is given by Equation 3.

Equation 3: Value chain level resource-based vertical market power imbalances based on differential dependency for a node x

$$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n} SSBC_i^2 - \overline{SSBC}^2}}{\overline{SSBC}}$$

Where SSBC stands for "share of square betweenness centrality" calculated as given by Equation 2.

Then, the higher the indicator in Equation 3 is, the more imbalanced power is in the value chain, or ecosystem. This indicator would then be analogous to HHI. While the latter measures the level of market power in a market resulting from market concentration, the indicator in Equation 3 measures the level of market power in a value chain resulting from resource-based vertical power based on differential dependency.

3.5.3. A metric of panopticon power

We have previously explained that one of the positional sources of economic power, "panopticon power"[193], is based on an actor being able to benefit from its position in a network or ecosystem to gather valuable information that gives it a competitive advantage. This advantage is more relevant when there is significant and growing learning-by-doing asymmetry between the actor benefitting from this position in the network and the other nodes in the network. In this subsection we will develop a metric of this type of power. In order to do so, we shall start by defining more precisely what makes information valuable and, hence, a source of competitive advantage.

Information or data[194] is valuable because of what it allows to do. Benyayer and Chignard[195] summarize what data allows to do in four verbs: describe, explain, predict and prescribe. Nevertheless, not any kind of data is valuable. In order for a dataset to allow for proper descriptions, explanations, predictions and prescriptions it needs to have certain properties, namely volume, quality and scope[196]. It is important to notice that each of these three properties have a different ponderation in making the data valuable depending on the use intended. The value of data is therefore contextual to its use[197].

Volume refers to the number of observations of the dataset. The above-mentioned valuable uses of data (describing, explaining, predicting and prescribing) rely on extracting insightful patterns using statistical techniques. As the results of the latter are more precise and robust as the dataset increases in volume, the more data there is the more solid the conclusions that can be drawn from it are. The quality of data refers to the characteristics of a dataset that make it easier to extract meaningful information from it. It is difficult to list all the properties that constitute quality. In order to illustrate the multidimensional nature the term 'quality' acquires to qualify data, we will retain the following categories of quality employed by Floridi[198]: accuracy, objectivity, accessibility, security, relevancy, timeliness, interpretability and understandability. It is important to stress that he meaning of quality is contextual to the use intended of the data. This implies that any metric of the quality of a dataset requires a qualitative assessment of the importance of the different

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[193] H. Farrell & A. L. Newman, Weaponized Interdependence: How Global Economic Networks Shape State Coercion, (2019) 44(1) International Security 42, 46.
[194] For the purposes of developing an indicator of panopticon power, in this subsection we will use the terms "information" and "data" as synonyms as we will use the e-commerce sector as an example.
[195] Chignard, S., & Benyayer, L. D. (2015). *Datanomics. Les nouveaux business models des données*. FYP editions.
[196] Carballa Smichowski, B. (2018). The value of data: an analysis of closed-urban-data-based and open-data-based business models. Science Po's Cities and Digital Technologies Chair Working Paper 2018-01.
[197] OECD. (2015). Data-Driven Innovation: Big Data for Growth and Well-Being. OECD Publishing
[198] Floridi, L. (2014). Big Data and information quality. In *The philosophy of information quality* (pp. 303-315). Springer, Cham.

dimensions of quality for a specific use. The scope of data refers to two related yet distinct properties. One is the fact that a dataset can be easily linked to others. The other property that constitutes the scope of data is what Mayer-Schönberger and Cukier[199] call "option value of data": how many different domains a single dataset can provide information about. Datasets that can create links between seemingly unrelated domains are valuable as they enrich the comprehension of a phenomenon (description and explanation), and hence the possibilities of acting (predicting and prescribing) on it in the 'right' way.

Having briefly introduced the three properties that make data valuable, let us turn now to developing an indicator of panopticon power that takes them into account. In doing so, we will only include volume and quality as dimensions. This is due to the fact that the value coming from the scope of a dataset is purely contextual to the use and the characteristics of its holder. Hence, developing an indicator that takes into account would be difficult and of little replicability across cases. However, a qualitative assessment of the scope of data can be very important in antitrust, notably in data mergers, as the Apple/Shazam[200] and Facebook/WhatsApp merger[201] cases have shown.

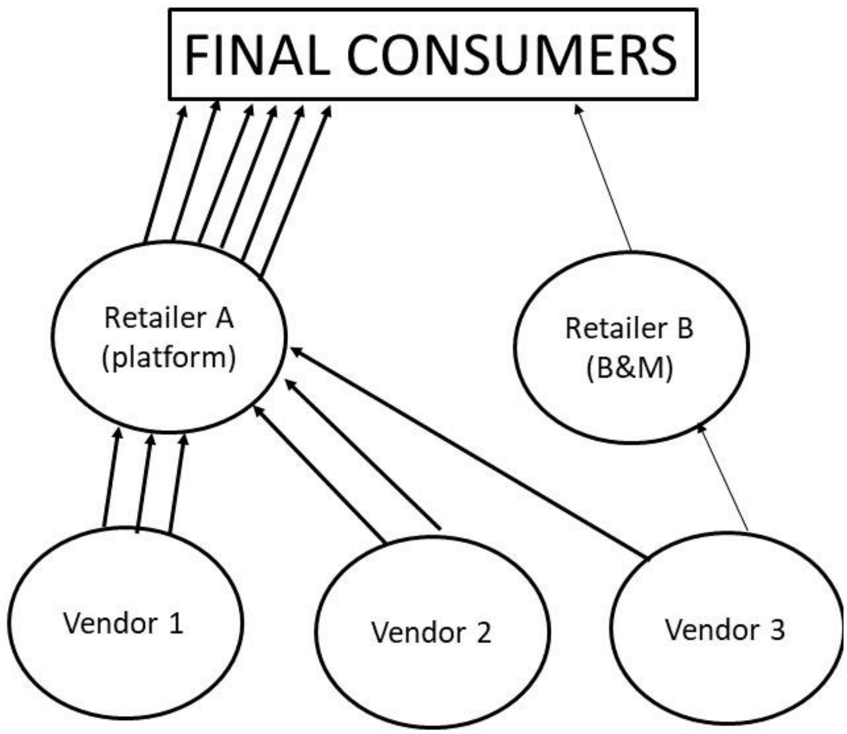
In order to develop the indicator, we will use the example of two competing retailers. Retailer A is a digital e-commerce platform and retailer B is a brick-and-mortar store. For the sake of simplicity, let us assume that they only compete on one product. They both act as intermediaries between three vendors and final consumers. The commercial transactions involving valuable data transfers between these agents are described in the following figure.

Figure 14: Panopticon power visualisation

[199] Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.

[200] *Apple/ Shazam* (Case M.8788) Commission Decision (11 November 2018), available at http:// ec.europa. eu/ competition/ mergers/ cases/ decisions/ m8788_ 1279_ 3.pdf

[201] Case No. M.7217 –Facebook/WhatsApp, Commission's decision of 3 October 2014, sections 5.1, 5.2 and 5.3, available at: https://ec.europa.eu/competition/mergers/cases/decisions/m7217_20141003_20310_3962132_EN.pdf



The network is a multilayer network in which each of the three layers represents a tier of the value chain: producers/vendors, retailers and final consumption. Firms are denoted by nodes (which are graphically represented as circles) and commercial transaction between them (selling/buying a good or service) as weighted directed vertices (graphically represented as arrows linking the dots). When firm A sells a good or service to firm B, the arrow goes from firm A to firm B. For every arrow (sell) going from a vendor to a retailer there is a corresponding arrow (sell) from the retailer to final consumers, as we only represent sells having taken place. The weight of the vertices represents the quality of the information embedded in the sell. Only retailers collect information from consumers and vendors. In our example we assume that retailer A obtains more information from the vendors it buys from and from the final consumers it resells to than retailer B because the former is an online platform while the latter is a brick-and-mortar store. Indeed, being an online platform gives retailer A the possibility of siphoning more data through the use of cookies that track consumer behaviour, the necessary identification of individual buyers, etc. It even gives it the possibility to gather valuable consumer behaviour data when consumers do not buy. Indeed, online retailers like Amazon track "what shoppers are searching for but cannot find, as well as which products they repeatedly return to, what they keep in their shopping basket, and what their mouse hovers over on the screen"[202].

[202] Khan, L. M. (2016). Amazon's antitrust paradox. *Yale LJ*, *126*, 710, p. 782.

Online platforms can also gather data on vendors that brick-and-mortar retailers cannot such as vendors' response to consumers' inquiries, returns, the notation of their products, etc.

Algebraically, the network described in Figure 14 can be represented by and adjacency matrix A_{ij} coding the data-embedding links between the nodes (sells). The Q_{ij} matrix represents the weight of each link, which in turn translates the quality of the information they embed. The values of this matrix range from 0 (worst possible level of quality) to 1 (best possible level of quality). In order to calculate the values of this matrix, a qualitative assessment of the importance of the different dimensions of quality (timeliness, relevancy, interpretability, etc.) in the specific use of selling the product as a retailer has to be made first. Then, each of this dimension can be given a score ranging from 0 to 1. The quality of the data of each sell would then be a weighted average of each dimension's score in which the weight of the score translates the relevancy of each dimension to assess the quality of the data in the given context.

We can now define indicators of the value of data arising from volume ('$ValV_i$') and quality ('$ValQ_i$') for a given node i in a network with n nodes out of which m nodes are information gatherers (retailers in our example).

$$ValV_i = \sum_{\mathrm{j}=1}^{m} \frac{A_{ij}}{n-m}$$

In other words, the value of the data gathered by retailer i that is attributable to volume s measured as its degree centrality regardless of the direction of the vertices, as retailers gather information from vendors and final consumers. The denominator is divided by n-m (all the nodes except retailers) as retailers cannot extract information from other retailers or themselves.

Similarly, we have:

$$ValQ_i = \sum^{m} \frac{Q_{ij}}{n-m}$$

In other words, the value of the data gathered by retailer i that is attributable to quality is calculated as the sum of the quality score from each transaction divided by the number of nodes out of which it could extract information.

In order to obtain a metric of panopticon power from the metrics of value of data, we divide the numerators of $ValV_i$ and $ValQ_i$ by the total volume-related and quality-related value of the data gather by all the data gatherers (retailers in our example) of the network respectively. In this manner, we obtain the shares of volume-related ($SValV_i$) and quality-related ($SValQ_i$) data value.

$$SValV_i = \frac{\sum_{j=1}^{m} A_{ij}}{\sum_1^m \sum_{j=1}^{m} A_{ij}}$$

$$SValQ_i = \frac{\sum^m Q_{ij}}{\sum_1^m \sum^m Q_{ij}}$$

Given the context-dependent relative importance of volume (β^V) and quality (β^Q) in constituting the value of the data, the share of the value of data captured by a firm i attributable to both quality and volume ($SValVQ_i$) is equal to:

$SValVQ_i = \beta^V . SValV_i + \beta^Q . SValQ_i$

Where $\beta^V + \beta^Q = 1$

Finally, we can recur to the methodology of the HHI index to build a Panopticon HHI index which is equal to:

$$PANOPTICON - HHI = \sum_{i=1}^{m} \mathrm{SValVQi}^2$$

Then, a certain threshold of the PANOPTICON-HHI index can be established to consider that there is considerable concentration in valuable data gathering in a market, which would be an indicator of possible panopticon power. The analysis of this type of power could be then complemented with a qualitative analysis of the scope-related value of the data taken into account.

4. Conclusion

The development and use of new computational techniques in competition law enforcement will have important implications to the theory and practice of competition law, to a certain extent similar to those generated by the turn to a more economic approach and the systematic use of economics in competition law a couple of decades ago. We are at the beginning of a new antitrust revolution that will bring similar reforms to the institutional design of competition authorities than those undertaken with regard to the use of economic analysis, including an adaptation of evidence rules and procedure to this new reality. The emergence of computational competition law and economics is linked to different factors, such as the prevalence of the digital economy, which enables the harvesting of immense volumes of data about all dimensions of economic activity and consumer behaviour, the development of data analytics and algorithms that enable competition authorities to monitor real time market activity, the creation of screening tools that assist competition authorities in making more accurate predictions, and finally the development of a deeper understanding of economic activity as part of a larger complex economy, in which the linear dynamics of neoclassical price theory may not prove adequate. The report reviewed these developments by systematically exploring the use of screening tools and algorithms in competition law enforcement, the adaptation of the institutional arrangements and procedural requirements in order to implement these new computational technologies, the rethinking of the law of evidence. It also offered a number of examples regarding the use of such tools in practice in a number of jurisdictions, focusing, in particular, on the important experience accumulated so far in the Hellenic Competition Commission with the use of advanced data science approaches in its enforcement activity. The Report presents the HCC Economic Intelligence Platform and explains how data science and data scientists were employed in a number of competition law investigations. The use of computational techniques, that is, advanced numerical methods for complex models and in order to analyse complex fact patterns, ad computational economics may not only provide new investigative and data analysis capabilities to competition authorities but may also enable them to develop new concepts and metrics of economic power that may be used to guide competition law enforcement. The Report offers concrete examples by focusing on different dimensions of economic power developed in the context of the digital economy.

Annex: Table 2: Computational capabilities in competition authorities

OECD/BRICS Countries	Chief Technology officer (CTO), Chief Data Scientist (CDS), or Chief Innovation Officer (CINO)	Data science Unit - Digital Unit Or - Forensic Unit	Data Scientists
Australia		The Australian Competition and Consumer Commission (ACCC)[203],[204] has established a Legal and Economic Division, delivering expert legal, economic and data analysis support across all the activities of the AER and ACCC. The Division consists of the Legal Group, the Economic Group and the Strategic Data Analysis Unit (including data governance and management functions). The Strategic Data Analysis Unit provides expert quantitative advice and support to line areas of the agency. The unit members are working	

[203] ACCC and AER Corporate Plan, 2020-2021, https://www.accc.gov.au/system/files/20-28RPT%2520ACCC%2520and%2520AER%2520Corporate%2520Plan%25202020-21_D05.pdf (p.16, 36)
[204] Speech of Mr Rod Sims, Chair, Gilbert & Tobin seminar, 26 November 2018 https://www.accc.gov.au/speech/gilbert-tobin-seminar-the-data-economy

		in basic research and issues where the use of complex data and analysis required. The Unit also supports the context analysis and the identification of data sources. The Division also leads the data governance function that is becoming a significant part of the way the authority operates. Data generation plays a very important role in the economy. To address the challenges this poses, ACCA is investing in data by strengthening its data governance processes, improving how it stores and accesses data across teams, as well as strengthening staff capability. In addition the Strategic Data Analysis Unit assists the Agency in analysing data and algorithms across a range of investigations, which concern both the competition and consumer areas. The unit played a crucial role in the Trivago case.	
Austria		The Austrian Federal	

		Competition Authority[205] has established an IT Forensics Unit, which concerns IT-Forensics, and data collection.	
Belgium	No	No	No
Canada	In July 2019, a Chief Digital Enforcement Officer has been hired by the Competition Bureau of Canada[206]. The officer supports the Bureau to monitor the digital landscape, as well as identify and evaluate new investigative techniques. The Chief Digital Enforcement Officer will provide advice on a wide variety of issues, including tools and skills development, in order to boost the Bureau's investigations in the digital economy. Moreover, the Bureau uses a wide range of technological tools for cartel detections.		
Chile	No	No	No
Columbia	No	No	No
Czech Republic		The Office for the Protection of Competition of Czech Republic has established an IT Unit. The Head of the IT Unit	

[205]Federal Competition Authority website, Organization of the Authority https://www.bwb.gv.at/en/federal_competition_authority/organisation/

[206]Competition Bureau Performance Measurement & Statistics Report 2019-20, https://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/04508.html

Message from the Commissioner, 25 July 2019, https://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/04480.html

Ibid, Matthew Boswell in his November 2017 speech, https://www.canada.ca/en/competition-bureau/news/2017/11/bid-rigging_detectionandpreventionensuringacompetitiveandinnovat.html

		could be considered as CTO, as he works closely with other units during dawn raids and in particular investigations. The IT Unit provides equipment for data processing and technical support to the investigators. Within the Office, the Chief Economist could have similar competences as CDS or CINO. His unit analyses, case by case, problematic competition issues.	
Denmark			The Danish competition authority has integrated data scientists in their investigation and cartel division, as well as in their market analysis and economics division and in our digital platforms division. The authority has developed its own software solutions, using Python as developing tool. For picture categorization the authority is mainly using ready-made software.
Estonia	No	No	No
Finland		A new ICT and digital unit were established as of May 2020 in	

		order to strengthen their capacity to meet new digitalisation challenges. The office is headed by a chief technology officer (CTO), who has a background in antitrust enforcement. This digital unit collaborates with other units of the authority, as well as with its Forensic IT functions, which is part of the cartel enforcement Unit.	
France		In January 2020, the French Competition Authority created a digital economy unit. This specialised unit will report directly to the General Rapporteur (the head of investigations at the French NCA) and will be tasked with developing in-depth expertise in all digital areas. The unit will be composed of a head of unit, an economist, a data scientist, a software engineer and a lawyer. The digital economy unit will take part in the Autorité's discussions and sector-specific inquiries on	

		new issues related to the development of digital technology, in line with those already carried out on big data, online advertising and algorithms. The team will also be responsible for developing new digital investigation tools, based in particular on algorithmic technology, big data and artificial intelligence. The new service will also provide support to the Autorité's investigation and inspection units that are handling cases with a significant digital dimension (mergers involving actors from the digital sector, breaches of competition law committed by digital means, problems with referencing, ranking bias or collusion through the use of algorithms). Finally, the digital economy unit will work in close cooperation with industry regulators, relevant government departments and other	

		competition authorities at European and international level to develop convergent and standardised methods of analysis and intervention. It will also be responsible for developing discussions with the academic community and research institutions specialising in digital subjects.	
Germany		In 2009 the German Competition Authority[207] has set up a Unit specialising on IT forensics[208], which assists the decision divisions in collecting and analysing IT data e.g. in conducting online surveys in major proceedings and seizing and evaluating IT data in cartel detections. The Unit is also responsible for developing further the forensic expertise in	

[207]Bundeskartellamt Annual Report 2019, https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Jahresbericht/Jahresbericht_2019.pdf?__blob=publicationFile&v=3 (p.12)
Organisation Chart of the Bundeskartellamt, 1 January 2021, https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/OrganizationalChart/Organisation%20Chart.pdf?__blob=publicationFile&v=46

[208] It is mentioned as "Information Technology Unit" in the New Organisation Chart of the Bundeskartellamt.

		this area. Moreover the new "Digital Economy" unit cooperates with IT Unit. (*It is mentioned as Information Technology Unit in the New Organisation Chart of the Bundeskartellamt)	
Greece		The Hellenic Competition Commission has also established as of October 2020 a forensic IT unit, which is headed by an economist and cooperates with a number data scientists, who are acting as external experts for the authority.	The IT Unit works closely with a number data scientists, who are acting as external experts for the authority. Moreover, the Commission is at the process of setting up an expandable Big Data Management Infrastructure Platform/dash-board, tailor made for the authority by an external contractor where real-time public data from different sources (Price Observatory of Supermarkets, fuel prices, vegetables and fruits prices, public procurement data, etc.) will be automatically uploaded. A screening-tool program, mainly for cartels and excessive pricing, is also being designed, based on a theoretical framework

			which sets the data parameters needed for cartel detection primarily, and which could also apply in bid-rigging markets. All the above will be placed on the platform in an integrated way and we plan to have completed the first phase of this project by the end of July. At the same time the Commission has appointed experts to design a program, drawing raw data from unstructured information available in the internet in pdf formats, as well as in other formats and extract it in csv files form. It will be gradually concluded possibly by mid next year. This data will be mainly used for cartel-detection but will also offer an integrated data analytics environment with various tools/apps on the basis of bespoke programmes and /or available off the shelf software tools to visualise and analyse data. In addition, the Commission has

			employed contractors to develop an integrated data template and dashboards as well as bespoke software programs for the needs of the Authority.
Hungary		The Hungarian Competition Authority[209] has included in its organizational structure an IT and Document Management section.	
Iceland	No	No	No
Ireland	No	No	No
Israel	No	No	No
Italy		The Italian Competition Authority[210] has established an IT Operations and Forensic IT Office.	
Japan[211]	The Japan Fair Trade Commission[212] has included in its organizational structure the position of a Counselor for Cybersecurity and Information Technology Management.		
Korea	No	No	No
Latvia	No	No	No
Lithuania	No	No	No

[209] The Organisational Structure of the Hungarian Competition Authority, https://www.gvh.hu/en/gvh/legal_status_of_the_gvh/organigram
[210] Italian Competition Authority, IT Operations and Forensic IT Office, https://en.agcm.it/en/about-us/organization/detail?id=32a1c931-ec76-4340-8691-0150005f74a9
[211] https://www.jftc.go.jp/en/about_jftc/index_files/200929.pdf (Organisation Chart)
[212] Organisation Chart of the Japan Fair Trade Commission, https://www.jftc.go.jp/en/about_jftc/index_files/200929.pdf

Luxemburg	No	No	No
Mexico		In March 2020, the Mexican Federal Economic Competition Commission (COFECE)[213] issued a press release, announcing the establishment of a Digital Markets Unit within its institutional structure with the purpose of advancing in the comprehension of the digitization of the Mexican economy to execute the powers bestowed upon it by the LFCE with greater effectiveness.	
Netherlands	The Dutch ACM has also appointed a Chief Data Officer with experience in cognitive science and artificial intelligence. The Chief Data officer is responsible for the DataHub, which groups 15~20 data engineers and data scientists, who are working in projects with and for all departments within ACM and also contribute to the development of the data strategy of the ACM.		
New Zealand	No	No	No

[213]COFECE's press release, Digital Strategy, 30 March 2020, https://www.cofece.mx/wp-content/uploads/2020/03/COFECE-013-2020-DIGITAL-STRATEGY-Vf.pdf
COFECE Digital Strategy, March 2020, https://www.cofece.mx/wp-content/uploads/2020/03/EstrategiaDigital_ENG_V10.pdf (p.15)

Norway	No	No	No
Poland [214]		The office of Competition and Consumer Protection in Poland has established an office of IT and security which is responsible for planning and implementing tasks related to the maintenance and development of IT systems of the Office and ensuring property protection.	
Portugal			The Portuguese competition authority includes a number of data scientists in their forensic IT team.
Slovak Republic	No	No	No
Slovenia	No	No	No
Spain		The Spanish competition authority (CNMC)[215] has a Systems and Information and Communication Technologies unit, specialised in computer	

[214] https://www.uokik.gov.pl/departments.php#faq4136
[215] Cani Fernandez interview in 27.09.2020 at https://www.competitionpolicyinternational.com/cpi-talks-with-cani-fernandez/ see also "Spain: Competition Authority", Lexology, 8 July 2020 https://www.lexology.com/library/detail.aspx?g=b909538a-4ef5-4933-9e21-909fb77727b2 and OECD "LATIN AMERICAN AND CARIBBEAN COMPETITION FORUM – Session I: Digital Evidence Gathering in Cartel Investigations", Contribution from Spain, 28–29 September 2020, http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/LACF(2020)5&docLanguage=En paras. 4-10 and 33-35.

		technologies, which provides support to all the units of the CNMC and which is responsible for the implementation of and permanent support for all technological infrastructure. Furthermore, in 2018 the CNMC created the Economic Intelligence Unit (EIU) with full time staff dedicated to the ex-officio detection of anticompetitive practices and a particular focus on the detection of cartels, especially in the field of public procurement. This unit, which is located in the Competition Directorate, is equipped with qualified staff and specific resources to promote the ex-officio detection of collusive behaviour, in particular of cartels affecting public contracts. The staff of this unit specialises in quantitative techniques, forensic analysis, open-source intelligence (OSINT) and cartel	

		investigation and is responsible for the development of statistical tools and screening techniques to identify collusive patterns in the data. The type of analysis carried out depends on the data to be studied in each specific case. This means that while the use of relatively simple screens is sufficient in some cases, in others more complex statistical and econometric techniques, network analysis and machine learning methods, both supervised and unsupervised, are beginning to be applied. In some areas, where the availability of data is not so evident, case detection is much more limited. To address this, techniques such as web scraping or text mining can be used to increase data availability. The development and application of these techniques is carried out by the Competition Authority itself and	

		specifically within the Economic Intelligence Unit. Statistical software, such as R, Python, SPSS, and Stata, are used to apply the above techniques. As inspection procedures have developed, gathering evidence on cartels during company inspections using various forensic analysis tools (off-the-shelf or developed inhouse by the CNMC's forensic IT experts) has become particularly important. These software applications are developed in close cooperation with competition inspectors, who are in charge of investigating cases. Among the tools used is the Nuix software platform, which enables analysis of multiple databases and offers a high-speed indexing engine. This software allows the use of various clustering algorithms and other machine learning techniques. Additionally, it offers	

		the option of social network analysis, which can improve information filtering.	
Sweden		The Swedish Competition Authority (SCA)[216] has a Communications and IT Unit which is responsible for external and internal communications, publications and press. The unit is also responsible for the Authority's overall management function of external tip-offs and enquiries and for the IT-support in the organisation. Moreover, SCA has set up a project group who is currently analysing the possibilities for the SCA to use AI in its investigations. So far, the main areas of potential use concern situations where the SCA needs to process and analyse obtained data using machine learning and text analysis. The Authority is in the early stages of developing a ML-tool aiming at organising a	

[216] Organization Chart of Swedish Competition Authority https://www.konkurrensverket.se/en/omossmeny/about-us/organisation/

		large number of documents based on their content. Such a tool would make it possible for a case team to quickly get an overview of the casefile following an inspection where a lot of digital material has been collected.	
Switzerland	No	No	No
Turkey		TCA[217] has recently empowered its already existing Strategy Development Department to catch up with the new developments in digital markets. Considering the huge effects of competition law infringements through big data and algorithms, traditional applications and approaches are predicted to be insufficient in dealing with the new problems in this field. In that regard, TCA redesigned the responsibilities of its Strategy Development Department, with the aim of ensuring to act proactively. The new	

[217] OECD, ''Consumer data rights and competition – Note by Turkey'' https://one.oecd.org/document/DAF/COMP/WD(2020)55/en/pdf paras.7-9

		tasks of Strategy Development Department include assisting case handlers, providing opinions for investigations, providing support for competition probes relating to the digital economy, conducting trainings in relation to digital market-related matters, exchanging information and experience with national and international institutions, raising awareness regarding impacts of the digital economy and algorithm usage on both markets and consumers, contributing to the development of public policies in this regard by communicating with the relevant ministries, institutions and organisations[218] [219].	

[218] TCA's Press Release dated 30.01.2020. Available only in Turkish at: https://www.rekabet.gov.tr/tr/Guncel/rekabetkurumu-dijitallesme-ve-rekabet-p-874d77d25943ea118119005056b1ce21

[219] TCA's press release dated 08.05.2020. Available only in Turkish at: https://www.rekabet.gov.tr/tr/Guncel/rekabetkurulu-dijital-ekonomiyi-mercek--61aedbe40a91ea11811a00505694b4c6. See also https://www.mondaq.com/turkey/antitrust-eu-competition-/934258/turkish-competition-authority-designates-its-strategy-unit-for-digital-markets and https://www.kinstellar.com/insights/detail/1129/turkish-competition-authority-designates-its-strategy-unit-for-digital-markets

United Kingdom		In order to efficiently respond to the challenges and opportunities that digital platforms pose to the society, the Competition and Markets Authority (CMA) started setting up its new Data, Technology and Analytics (DaTA) unit aiming to ensure that CMA stays ahead, using the latest in data engineering, machine learning and artificial intelligence techniques. DaTA Unit was also in the priority focus areas of the general "Digital Markets Strategy" that CMA has launched[220]. The unit has in view to pioneer the use of these techniques internally aiming to increase the effectiveness of CMA while enabling it to understand how firms are using data, what their machine learning	

[220] CMA launches Digital Markets Strategy https://www.gov.uk/government/news/cma-launches-digital-markets-strategy and assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/814150/cma_digital_markets_strategy.pdf
See also
https://www.bakermckenzie.com/en/insight/publications/2019/07/cma-launches-digital-markets-strategy

		(ML) and AI algorithms are doing, the consequences of these algorithms and, ultimately, what actions authorities need to take. More specifically, CMA's DaTA Unit[221] has built a cutting-edge analytics platform in AWS using a bespoke implementation of JupyterHub. This enables the storage, processing and analysis of big and complex data speedily and flexibly. On top of this infrastructure, they have implemented an Agile operating model. The implementation of the above are already bringing insights into CMA by developing machine learning tools to identify possible breaches of consumer law on digital platforms and applying the latest natural language processing techniques to sift and review 100,000s of internal documents from companies, which	

[221] "The CMA DaTA unit – we're growing!", Stefan Hunt, 28 May 2019 https://competitionandmarkets.blog.gov.uk/2019/05/28/the-cma-data-unit-were-growing/

		we receive in the context of our cases.. In this context, the DaTA unit is growing in the key capabilities areas of Data Engineering and Data Science Innovation & Intelligence. In particular, the Director of Data Science will have a prominent role as the most senior data scientist in the CMA. Among his responsibilities would be to oversee the development of algorithmic auditing capabilities, intelligence on technological developments in the markets and original research. The data scientists coordinated by the Director will lead a machine learning team with 2 functions, to use machine learning to improve what the CMA does and, importantly, to develop an analytical toolkit to understand how companies are using algorithms and when authorities should	

		intervene. Additionally, the Head of Data Engineering will lead the engineering team, which will support the CMA in understanding the kinds of data used by the companies it investigates, what firms do with that data and how to obtain and wrangle that data. Recent types of data include clickstream data from websites, Instagram posts, large email caches and more. They will also help develop the CMA's thinking about the critical issues of data privacy, data access and the regulation of data. The Lead Technical Expert will be the team's 'Tech Guru', taking responsibility for maintaining a broad understanding of the latest machine learning and AI techniques used in commercial organisations. The Lead Technical Expert will use their knowledge and insight to help the CMA use	

		these techniques and become a thought leader on the use of algorithms, including on issues such as algorithmic fairness, transparency and explainability[222]. In parallel, it is advisable to report on a new Digital Markets Taskforce in connection with the creation of an upcoming Digital Market Unit embedded within the CMA. In March 2020, the CMA was asked to lead a Digital Markets Taskforce[223], working closely with the Office of Communications (Ofcom) and the Information Commissioner's Office (ICO), to provide advice to the government on the design and implementation of a pro-competition regime for digital markets. The government was clear	

[222] "CMA's new DaTA unit: exciting opportunities for data scientists", Stefan Hunt, 24 October 2018 https://competitionandmarkets.blog.gov.uk/2018/10/24/cmas-new-data-unit-exciting-opportunities-for-data-scientists/

[223] A new pro-competition regime for digital markets Advice of the Digital Markets Taskforce, par.1, https://assets.publishing.service.gov.uk/media/5fce7567e90e07562f98286c/Digital_Taskforce_-_Advice_--.pdf

		when commissioning this work that it should complement and build on the outputs of the Furman Review[224], as well as drawing evidence from the CMA's market study into online platforms and digital advertising. The Digital Markets Taskforce will be informing a new Digital Markets[225] Unit which will be set up within the CMA. The new unit will begin to operate in April 2021 while working closely with regulators including Ofcom and the ICO in order to introduce and enforce a new code to govern the behavior of platforms. In addition, the Digital Markets Unit could be given powers to suspend, block and reverse decisions of tech giants, order them to take certain actions to	

[224] Report of the Digital Competition Expert Panel "Unlocking digital competition", Furman Review https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/785547/unlocking_digital_competition_furman_review_web.pdf

[225] New competition regime for tech giants to give consumers more choice and control over their data, and ensure businesses are fairly treated, https://www.gov.uk/government/news/new-competition-regime-for-tech-giants-to-give-consumers-more-choice-and-control-over-their-data-and-ensure-businesses-are-fairly-treated

		achieve compliance with the code, and impose financial penalties for non-compliance.	
United States		The Federal Trade Commission has also proceeded to the appointment of a specific division. The primary focus of the Technology Enforcement Division (TED) [226] [227] is to identify and investigate anticompetitive conduct (including consummated mergers) in markets in which digital technology is an important dimension of competition, such as online platforms, digital advertising, social networking, software, operating systems, and streaming services. The TED will leverage its existing expertise	

[226] Inside the Bureau of Competition August 2020, p.21 https://www.ftc.gov/system/files/attachments/inside-bureau-competition/inside_the_bureau_of_competition_updated_august_2020.pdf see also FTC Tehnology Enforcement Division and press release attached https://www.ftc.gov/news-events/press-releases/2019/02/ftcs-bureau-competition-launches-task-force-monitor-technology

[227] Also for TED in PREPARED STATEMENT OF THE FEDERAL TRADE COMMISSION: OVERSIGHT OF THE FEDERAL TRADE COMMISSION Before the COMMITTEE ON COMMERCE, SCIENCE, AND TRANSPORTATION UNITED STATES SENATE WASHINGTON DC in August 2020, p.34 https://www.ftc.gov/system/files/documents/public_statements/1578963/p180101testimonyftcoversight20200805.pdf

		and work with other Commission staff, including technologists, to develop a deep understanding of some unique features of complex, dynamic digital markets[228].	
Brazil		The Competition Authority of Brazil (Cade) established the creation of an Intelligence Unit. The Intelligence Unit is formed by senior case handlers and civil servants recruited in institutions responsible for criminal investigations. In this sense, the Intelligence Unit – by promoting training programs for planning and	In 2014, Competition Authority of Brazil (Cade) contracted external consultants with specialized knowledge in Statistics, IT, and data mining for the development of analytical tools.

[228] In February 2019, the FTC created a task force entirely dedicated to address competition issues in the technology industry. The task force has since been converted into a permanent Bureau of Competition division called the Technology Enforcement Division (TED). In July 2019, Facebook disclosed that it was being investigated by the FTC, which the FTC subsequently confirmed was part of the TED's antitrust probe of multiple large technology firms classified as "multi-sided platforms." Several major media outlets have reported that Amazon is also a main focus of the FTC's ongoing investigation. In January 2020, FTC Chairman Joseph Simons revealed that the FTC was nearing a decision on whether it will bring a related enforcement action.While the TED was continuing its investigation, the FTC's Deputy Director, Daniel Francis, discussed the creation of the FTC's first new enforcement division in nearly twenty years during a panel discussion on September 12, 2019, titled, "Big Tech and Antitrust: What Lies Ahead." Mr. Francis explained that the TED was created to address the unique issues that big-tech firms present to antitrust enforcement in the United States, including the ever-evolving nature of digital platforms. Mr. Francis made clear that while the FTC is highly attuned to these issues, it will continue to pursue traditional, evidence-based cases to develop its enforcement response to digital platforms. https://www.winston.com/en/competition-corner/doj-and-ftc-lock-in-on-big-tech-firms-but-t-mobilesprint-merger-opinion-provides-a-potential-compelling-antitrust-defense.html

		conduction of interviews and hearings, the use of analysis softwares, investigating and mapping, among others – acts in the consolidation of knowledge in the field of investigation, identifying among the various complaints received by Cade those that could give rise to effective investigations of violations to the economic order. The use of active techniques for cartel detection works as an additional element in the system of incentives of reactive tools. In other words, the consolidation of screening tools – via opening of administrative proceedings and eventual condemnations in the administrative sphere – will certainly work as an additional incentive for companies and individuals to apply for leniency, to propose Cease and Desist Agreements (TCC in its acronym in	

		Portuguese), and to file complaints with Cade.[229]	
Russia		In 2018[230] , Andrey Tsarikovskiy, Deputy Head of Federal Antimonopoly Service of the Russian Federation (FAS), had reached a conclusion that it was necessary to establish a special team to investigate cases on cartels and other anticompetitive agreements in the digital field. The Anti-Cartel Department would form a special unit to deal with digital investigations. This special Unit is probably the "Division for Digital Investigations" which belongs to the Anti-cartel Department[231], however no further information from FAS is released. It is noticed, also, that the "Big Digital Cat" web service belongs to the	

[229]OECD, "LATIN AMERICAN AND CARIBBEAN COMPETITION FORUM Session III: Promoting effective competition in public procurement -- Contribution from Brazil --" , 12-13 April 2016 http://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF%2FCOMP%2FLACF(2016)19&docLanguage=En&fbclid=IwAR3g7tbnfvfqIBaWDOzVkNSGr7kvKCDBFuYFmnt0yRgouqVKmqPOTET3gaA, para.8-22.

[230] FAS press release: FAS creates a new web-service: "Big Digital Cat", 22/10/2018 http://en.fas.gov.ru/press-center/news/detail.html?id=53478

[231] Structure of FAS, https://en.fas.gov.ru/about/structure/

		same Department.	
India	No	No	No
South Africa		The Competition Commission of South Africa has implemented a service dedicated to Information Technology (IT). The aim of this service is to understand the problems and needs of the Commission as the basis for determining how IT can be used to bring about improvements for the business, leading to improved business processes, improved information systems, new or improved computer applications and knowledge sharing[232][233]. However there is a will of digital transformation in Competition Commission of South Africa in order to boost its ability to detect, examine digital cartels. In order to realize these outcomes, the Authority would	

[232] Competition Commission's website http://www.compcom.co.za/information-and-system/
[233] "CompCom takes aim at 'digital markets", online article https://za.newschant.com/technology/compcom-takes-aim-at-digital-markets/

		develop applicable instruments for detecting digital cartels and assessing the results of agreements amongst rivals, build and employees a cartel forensic lab as well as develop tips for establishing the fee’s jurisdiction in instances of digital collusion that have an impact in South Africa.	
DG Comp	No	No	No