



Algorithms and Competition

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Executive Summary

I. Introduction

There is little doubt that digitalisation is revolutionising many sectors of our economies. Algorithms are among the most important technological drivers of this process and enable firms to be more innovative and efficient. Nevertheless, debate has arisen on whether and to what extent algorithms might have detrimental effects on the competitive functioning of markets, especially by facilitating collusive practices.

This joint study by the *Autorité de la concurrence* and the *Bundeskartellamt* addresses the potential competitive risks associated with the use of algorithms. It elaborates on the concept of algorithm as well as on different types and fields of application (II.) and subsequently focusses on algorithms and collusion (III.). After that, the study discusses practical challenges when investigating algorithms (IV.) and concludes with a tentative outlook for the tasks of competition authorities deriving from the study (V.).

II. Algorithms – notion, types and fields of application

In principle, any kind of software consists of one or more algorithm(s). However, in the context of the study, the focus is on algorithms which entail potential economic consequences and, more specifically, potential impacts on competition. Such cases can relate to algorithms performing a wide variety of tasks. Thus, it can be helpful to categorise algorithms in several ways, by the task they perform, by the input parameters that they use or by the involved learning method.

In particular, the paper discusses algorithms used for dynamic price setting. These algorithms may adapt prices to the company's own cost, capacity, or demand situation but also to competitors' prices, which can be monitored using yet another algorithm. Furthermore, the paper takes into account peculiarities of self-learning algorithms, which might derive their parameters with a high degree of automation from a potentially dynamic set of training data.

Issues concerning the interpretability of algorithms are also addressed. In this regard, one can broadly distinguish algorithms which are basically interpretable for humans, in particular allowing to identify the strategy and actions that result from using the algorithm via the code or a description of the algorithm, from algorithms whose behaviour is hardly interpretable for humans. The study refers to the former as "descriptive" algorithms and to the latter as "black-box" algorithms.

III. Algorithms and collusion

With a particular focus on pricing algorithms, the study explores potential detrimental effects of such algorithms on competition and the different ways in which they may affect strategic interactions between companies, potentially leading to horizontal collusion.

First, the economic principles behind horizontal collusion are analysed, including considerations on algorithms' potential impact on both the stability and the emergence of collusion (A.). Second, the use of pricing algorithms is discussed considering three scenarios, elaborating on the situations that they cover as well as their potential competition law implications (B.).

The paper also discusses interdependencies between algorithms and the market power of the companies using them. In particular, these interdependencies can lead to additional market entry barriers.

A. Economic principles of horizontal collusion

Although economic research has addressed horizontal collusion from various perspectives, with partly varying definitions, collusion can be described as a situation in which firms employ reward-punishment schemes for rewarding competitors as they abide by a supra-competitive outcome and punishing them when they depart from it.

Both economic research and case practice have identified several factors that can influence the stability of collusion, such as the number of companies on a market, the existence of entry barriers, the interaction frequency, and the degree of market transparency for different market participants. Algorithms could affect some of these factors and thus potentially have an impact on the stability of collusion. Considering the potential effects, the study finds that the actual impact of the use of algorithms on the stability of collusion in markets is *a priori* uncertain and depends on the respective market characteristics.

The paper also discusses the emergence of collusion, in particular by considering how companies might coordinate on a specific equilibrium without human communication. The study in particular reaches the preliminary conclusion that theoretical findings on the emergence of collusion can provide only limited practical insights into which kinds of algorithms are more prone to facilitate the emergence of tacit collusion.

B. Use of algorithms in different scenarios

The paper considers three scenarios. The legal assessment of the scenarios notably takes into account the fact that Art. 101 TFEU and the corresponding domestic provisions only prohibit agreements and concerted practices. In other words, a violation of competition law necessitates some kind of communication between the companies concerned. Conversely, companies have the right to adapt their behaviour intelligently to the existing or anticipated conduct of their competitors.

1. Algorithms as supporters or facilitators of “traditional” anticompetitive practices

The first scenario covers situations in which a “traditional” anticompetitive practice resulting from prior contact between humans already exists. The algorithm thus only comes into play in a second step to support or facilitate the implementation, monitoring, enforcement or concealment of the respective anticompetitive practice.

Besides supporting or facilitating horizontal collusion, algorithms could also be used in the context of vertical agreements or concerted practices. For example, algorithms could be used to detect deviations from a fixed or minimum resale price or to allow a retaliation by manufacturers against retailers not complying with a given price recommendation.

The study points out that the involvement of an algorithm in such a scenario does not raise specific competition law issues, as a prior agreement or concerted practice can be established, which in general may be assessed under Art. 101 TFEU. Nevertheless, although the existence of an

infringement might be found without further consideration of the algorithm, developing a case-specific understanding of the algorithm might still be advisable, for example as it could allow an assessment of potential counteracting efficiencies as well as reinforced negative effects of the anticompetitive practice.

2. Algorithm-driven collusion between competitors involving a third party

In the second scenario, a third party, e.g. an external consultant or software developer, provides the same algorithm or somehow coordinated algorithms to competitors. The particularity of these situations is that there is no direct communication or contact between the competitors, but a certain degree of alignment could nevertheless arise from the actions of the third party.

Generally, one could distinguish between alignment at the level of the algorithm (code level) and alignment at the level of the input factors (data level). Alignment at code level could arise when a third party not only provides algorithms with a shared purpose, for example the calculation of prices, but also using a similar (or related) implemented methodology. A specific form of alignment at code level would be the complete delegation of strategic decisions to a common third party who takes these decisions using an algorithm. Alignment at data level could involve the competitors using the algorithm as a means for an information exchange or a software supplier causing an alignment of input data by relying on a common data pool between competitors.

So far, there is only very limited algorithm-specific case law. Due to the variety of potential situations covered within this scenario, an assessment will always depend on the specificities of each case. Given the ECJ jurisprudence (VM Remonts¹, Eturas²), one of the central questions in this scenario is whether the competitors are aware of the third party's anticompetitive acts, or could at least reasonably have foreseen them.

Potential competition concerns in such situations could, *inter alia*, depend on the content of the algorithmic alignment. For example, an alignment of prices or price parameters at code level will likely constitute a restriction of competition by object. As for an alignment at data level, the established principles for information exchange apply.

In all of these cases, market coverage might be relevant both for the assessment of competitive concerns as well as for authorities exercising their discretion on whether to initiate an investigation.

3. Collusion induced by the parallel use of individual algorithms

The algorithms covered by this third scenario are unilaterally designed and implemented, i.e. each company uses a distinct pricing algorithm. There is no prior or ongoing communication or contact between the respective companies' human representatives. Still, the fact that several or even all competitors rely on pricing algorithms might facilitate an alignment of their market behaviour, resulting from a mere interaction of computers.

Beyond algorithms reaching tacit collusion, the question arises of whether algorithms could engage in behaviour that resembles explicit forms of collusion. However, so far, there has been significant uncertainty on the nature of potential "algorithmic communication", which is most

¹ ECJ, VM Remonts v Konkurences padome, Judgment of 21.07.16, Case C-542/14.

² ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba, Judgment of 21.01.16, Case C-74/14.

often discussed in the context of self-learning “black-box” algorithms. A specific form of “algorithmic communication” could be signalling practices, i.e. situations in which algorithms indicate to competitors that they are about to change a relevant parameter of competition, such as the price, in a certain way.

In addition to the theoretical considerations on the emergence and stability of collusion discussed in the previous section, there is a growing body of research considering the plausibility of algorithmic collusion by analysing concrete technical implementations of algorithms in specific, mostly experimental, settings. In other words, two or more pricing algorithms are tested in research laboratories of universities by making them interact in an experimental setting that mimics a competitive environment. In many of the experiments, the results show that some degree of collusion can be achieved. Against this background, the paper discusses the assumptions taken in experimental settings as well as their relation to real-world markets. The paper concludes that it currently remains an open question whether an alignment of pricing algorithms could likely arise “by chance” in settings that correspond to real market conditions.

Assessing this scenario from a legal point of view, the study first turns to the distinction between coordination and mere parallel behaviour. In light of the uncertainties concerning potential shapes of “algorithmic communication”, the paper points out that it seems to be too early to clearly delineate which potential types of interaction constitute illegal behaviour. Moreover, the paper recalls that under the current case law, Art. 101 TFEU does not prohibit conscious parallel behaviour. Thus, situations in which an algorithm merely unilaterally observes, analyses, and reacts to the publicly observable behaviour of the competitors’ algorithms might have to be categorised as intelligent adaptations to the market rather than coordination.

Another legal issue in this scenario concerns the question of the extent to which the behaviour of a self-learning algorithm can be attributed to a company. Some authors have suggested treating algorithmic behaviour as one would consider a company’s employees’ actions. Consequently, companies could be held liable simply for introducing and using an algorithm that engages in anti-competitive behaviour. Others suggest accountability of a company for the behaviour of its algorithm(s) if a reasonable standard of care and foreseeability is breached.

The paper concludes that the standards for assessing a company’s responsibility for collusive algorithmic behaviour may vary to some extent between these two approaches. It seems clear, however, that companies need to think about how they could ensure antitrust compliance when using pricing algorithms.

IV. Practical challenges when investigating algorithms

The study also addresses practical challenges when investigating algorithms by first describing potential types of evidence that might be used to establish a competition law infringement and subsequently outlining ways to obtain and analyse relevant information.

Among potential types of evidence, a distinction can be made between relevant information associated with the role of the algorithm and its context on the one hand, and the functioning of the algorithm on the other hand. For example, as regards the role of the algorithm and its context, information on the objective of the algorithm, its implementation and changes over time could be relevant. Furthermore, authorities might consider information on the input data used by the

algorithm. Finally, it could be helpful to gather information on the output and the decision-making process connected with the algorithm.

Once an authority has initiated an investigation, it can build on its established investigative powers, such as information requests, inspections and interviews, to obtain the necessary information. Depending on the case at hand, information could also be acquired by requesting internal documentation.

A more in-depth analysis of the algorithm may yield additional evidence, in particular revealing additional facts associated with the functioning of the algorithm. For such an analysis, different investigative approaches could be envisioned, *inter alia* an analysis of (relevant parts of) the source code in connection with information on the respective environment and interfaces, a comparison of real (past) input/output couples, a simulation of the algorithmic behaviour on generated inputs or a comparison of the algorithm to other (more easily interpretable) algorithms and methods.

V. Concluding remarks

The study concludes that in the situations considered so far, the contemporary legal framework, in particular Art. 101 TFEU and its accompanying jurisprudence, allows competition authorities to address possible competitive concerns. In fact, competition authorities already have dealt with a certain spectrum of cases involving algorithms, which have not raised specific legal difficulties.

As regards the scholarly debate whether Art. 101 TFEU needs to be understood more broadly, and inasmuch as some authors call for a broader interpretation of Art. 101 TFEU, the paper recalls that it is yet unclear which types of cases competition authorities will face in the future; consequently it is not possible yet to predict whether there is a need to reconsider the current legal regime and the methodological toolkit and, if so, in which way.

As digital markets keep evolving, authorities should continue expanding their expertise on algorithms, in an exchange with each other as well as by interacting with businesses, academics and other regulatory bodies. Such an effort is in line with the more general tendency of authorities to devote more resources to the challenges posed by the ongoing digitalisation.

Table of contents

I.	Introduction.....	1
II.	Algorithms – notion, types and fields of application.....	3
A.	Typology of algorithms by the task they perform.....	4
1.	Algorithms used for monitoring and data collection.....	4
2.	Pricing algorithms.....	4
3.	Personalization based on consumers’ data.....	6
4.	Ranking algorithms.....	6
5.	Further fields of application.....	7
B.	Typology of algorithms by input parameters.....	8
C.	Additional ways to classify algorithms.....	9
1.	Distinction by method of learning.....	9
2.	Distinction by degree of interpretability of the algorithm and its behaviour.....	11
3.	Distinction by developer of the algorithm.....	13
III.	Algorithms and collusion.....	15
A.	Economic principles of horizontal collusion.....	15
1.	Algorithms in the implementation phase of collusion: focus on the stability of collusion.....	17
2.	Algorithms in the initiation phase of collusion: focus on the emergence of collusion.....	19
B.	Use of algorithms in different scenarios.....	26
1.	Algorithms as supporters or facilitators of “traditional” anticompetitive practices.....	27
a)	Potential situations covered by this scenario.....	27
b)	Potential competition law aspects.....	29
2.	Algorithm-driven collusion between competitors involving a third party.....	31
a)	Competitors knowingly use the same or somehow coordinated third party algorithms.....	32
aa)	Potential situations covered by this scenario.....	33
aaa)	Alignment at code level.....	33
bbb)	Alignment at data level.....	33
bb)	Potential competition law aspects.....	34
aaa)	Concertation via a third party.....	35
bbb)	Potential competition concerns.....	38
b)	Competitors unknowingly use the same or somehow coordinated third party algorithm.....	41
3.	Collusion induced by the (parallel) use of individual algorithms.....	42

a)	Potential situations covered by this scenario.....	42
b)	Debate on the plausibility/likelihood of purely algorithmic collusion.....	45
aa)	Transparency of the market and degree of common knowledge between competitors.....	46
bb)	Time horizon.....	46
cc)	Stability of the competitive environment.....	47
dd)	Degrees of freedom and complexity of the algorithm.....	48
ee)	Initialization, exploration strategy and learning rate.....	49
ff)	Symmetry/similarity in terms of algorithms and companies.....	50
gg)	Interim conclusion.....	50
c)	Potential competition law aspects.....	52
aa)	Distinction between coordination and mere parallel behaviour.....	52
bb)	Accountability of undertakings for parallel behaviour caused by algorithms.....	56
IV.	Practical challenges when investigating algorithms.....	61
A.	Potentially relevant evidence for inferring an infringement.....	61
1.	Role of the algorithm and its context.....	62
a)	Objective, implementation and changes over time.....	62
b)	Inputs.....	63
c)	Output and decision-making.....	64
2.	Functioning of the algorithm.....	64
B.	Ways to obtain and analyse relevant information.....	65
1.	Obtaining information.....	65
2.	Analysing the algorithm.....	67
a)	General considerations when analysing algorithms.....	68
b)	Potential analytical approaches.....	70
aa)	Analysing the code.....	70
bb)	Comparing real past inputs/outputs couples.....	70
cc)	Testing (simulating) the behaviour of an algorithm on predefined inputs.....	71
aaa)	Confronting the algorithm with simulated queries in a real-world context.....	71
bbb)	Implementing a replication of the algorithm in a controlled setting (“sandboxing”).....	72
dd)	Comparing the algorithm to other (more easily interpretable) algorithms/methods.....	72
V.	Concluding remarks.....	75

Boxes

Algorithms and market power	22
Vertical agreements or concerted practices	30
Delegation of strategic decisions to a third party that takes these decisions using an algorithm	40
Collusion facilitated by simple undercutting or “price-matching” algorithms?.....	43
Screening for collusion	65
Peculiarities in fine proceedings.....	67

Abbreviations

ADLC.....	Autorité de la concurrence
Art.....	Article(s)
BKartA.....	Bundeskartellamt
CMA.....	Competition & Markets Authority, United Kingdom
Commission.....	European Commission
cf.....	confer
ECJ.....	European Court of Justice
e.g.....	exempli gratia
et seq.	et sequens/sequentia
EU.....	European Union
fn.	footnote(s)
GWB.....	Gesetz gegen Wettbewerbsbeschränkungen (German Competition Act)
GC.....	General Court (European Union)
ML.....	machine learning
OWiG.....	Gesetz über Ordnungswidrigkeiten (German Act on Regulatory Offences)
p(p).	page(s)
StPO.....	Strafprozessordnung (German Code of Criminal Procedure)
TFEU.....	Treaty on the Functioning of the European Union

I. Introduction

There is little doubt that digitalisation is revolutionising many sectors of our economies. Understanding the associated transformation of markets – caused for example by the rise of digital platforms – is of paramount importance for competition authorities. And even though digitalisation may concern different aspects of an economy, there appears to be a consensus that big data as well as algorithms are among its most important driving technological forces. The French *Autorité de la concurrence* (ADLC) and the German *Bundeskartellamt* (BKartA) have previously examined the key issues and parameters that may need to be considered when assessing the interplay between data, market power and competition law.³ Following up on these primarily data-related considerations, the study at hand further analyses algorithms and their effects on competition.

It should be stressed that algorithms enable firms to innovate. Their widespread use in more and more business contexts unleashes significant potentials *inter alia* for new business models, improved quality of products and services as well as lower prices. Picking just a few examples, search algorithms are capable of learning from past search queries, thus improving the relevance of subsequent results; matching algorithms underlie new business ideas, for instance in the sharing economy; ranking algorithms may reduce search costs and assist consumers in purchasing decisions; and personalization algorithms can be used to align recommendations with consumers' specific interests and needs. Importantly, on the supply side, such potentials not only benefit established players, but also allow innovation driven by disrupting start-ups. At the same time, these potentials provide new opportunities also for the demand side, both in business-to-business and business-to-consumer contexts. And as algorithms are becoming progressively more sophisticated, for example due to reliance on artificial intelligence methods, the potential associated with their use has not been exhausted yet.

While acknowledging such opportunities, it has been debated in recent years whether and to what extent algorithms might also have detrimental effects on the competitive functioning of markets under certain circumstances. Among other things, this debate relates to the issue of algorithms potentially increasing the risk of collusion between companies and revolves in particular around pricing algorithms, as they are relevant in e-commerce and may become more widespread also in other areas. This study intends to address, among others, such competitive risks. However, its scope does not extend to providing universal or definitive legal or economic classifications. As cases involving algorithms might differ in important nuances, the competent authorities will have to decide each case on its own merits, taking into account its respective peculiarities.

Keeping in mind the positive effects of algorithms on the economy, this study's assessment of potentially associated competitive risks will start by elaborating on the concept of algorithm as well as different types and fields of application (II).⁴ The subsequent section focusses on

³ ADLC/BKartA, Competition Law and Data, 2016 (<https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.html>).

⁴ Pp. 3 et seq.

algorithms and collusion (III.);⁵ it features a brief summary of the economic principles behind horizontal collusion and discusses potential situations in which algorithms could potentially raise competition concerns. After that, practical challenges when investigating algorithms are discussed (IV.).⁶ The paper concludes with a tentative outlook for the tasks of competition authorities deriving from the study (V.).⁷

⁵ Pp. 15 et seq.

⁶ Pp. 61 et seq.

⁷ Pp. 75 et seq.

II. Algorithms – notion, types and fields of application

There seems to be no clear consensus on a definition of the term algorithm.⁸ It can have a wide meaning, not linked to a specific software, source code or a particular programming language, but referring to a standardized or systemized procedure. A possible definition of the term that reflects this wide meaning could be ‘a sequence of simple and/or well-defined operations that should be performed in an exact order to carry out a certain task or class of tasks or to solve a certain problem or class of problems’.⁹ In that wide interpretation, algorithms are sometimes compared¹⁰ to cooking recipes that could indeed be depicted in such a formal way, the inputs being the ingredients, the elementary operations any simple cooking operations and the output the desired meal. However, others emphasize that an algorithm needs to be general in the sense that it does not only solve one single problem but a class of similar but distinct problems, achieving some degree of abstraction in the procedure.¹¹ The term “algorithm” could thus refer both to a standardized or automated method to solve a certain class of problems and to the practical application of this “universal” method, coded in a particular programming language or related to a particular recipe.¹² For instance, an algorithm could refer to the written division method taught to pupils at school but also to the implementation of this very method in a programming language.

Although the general term does not explicitly relate to mere *computational* sequences to be carried out by computers, the focus of this study is limited to such *digital* algorithms. Restricted to computer science, an algorithm could then also be seen as “any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as output”, i.e. “a sequence of computational steps that transform the input into the output”.¹³ This

⁸ The term *algorithm* derives from the name of the ninth century Persian scientist *Al-Khwarizmi*, who wrote a very influential book – “*Kitab al jabr wa 'l-muqabala*” or “*rules of restoring and equating*”, from which stems the word “algebra” – proposing a systematic study to compute the solutions of some problems, laying down basic algebraic principles. His treatise was later translated into Latin, where some translators used “*Algoritmi*” as a Latinized version of the scientist’s name. See for instance, *Knuth*, *The Art of Computer Programming. Volume 1. Fundamental Algorithms*, 3rd edn., 1997, pp. 1 et seq.

⁹ See *Knuth*, *The Art of Computer Programming. Volume 1. Fundamental Algorithms*, 3rd edn., 1997, pp. 1 et seq. or *Cormen/Leiserson/Rivest/Stein*, *Introduction to Algorithms*, 3rd edn., 2009 pp. 5 et seq. for other possible definitions. The French public report on open data of court rulings (rapport “Cadiet”) includes the following definition of algorithms: “*Finished sequence of rules and operations enabling to obtain a result from inputs provided. This sequence can be the object of an automated execution process. Some algorithms, called self-learning, see their behavior evolve over time according to the data provided.*”, *Cadiet*, *L’open data des décisions de justice*, 2018, p. 14.

¹⁰ See for instance *OECD*, *Algorithms and Collusion*, 2017, p. 8 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>); *Lindsay/McCarthy*, *Do we need to prevent pricing algorithms cooking up markets?*, *European Competition Law Review* 2017, pp. 533 et seq.

¹¹ Cf. e.g. *Garey/Johnson*, *Computers and Intractability: A Guide to the Theory of NP-Completeness*, 1979, p. 4.

¹² See also *OECD*, *Algorithms and Collusion*, 2017, pp. 8 et seq. (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

¹³ *Cormen/Leiserson/Rivest/Stein*, *Introduction to Algorithms*, 3rd edn., 2009, p. 5.

interpretation also includes artificial intelligence methods, although these are hardly comparable to a sequence tailored to solve (only) a very specific problem or to a cooking recipe.

In principle, any kind of software consists of one or more algorithms. Similarly, each calculation step taken by any type of computer relates to one or several algorithms. Therefore, algorithms may not necessarily have significant economic consequences and by far not all of them are of competitive relevance. In order to structure and focus the further discussion on algorithms that are of competitive relevance, it seems helpful to categorise them. In particular, algorithms potentially differ regarding the task they perform, i.e. the output they produce (part A.), the type of inputs they use (part B.) or the methods they rely on (part C.). As algorithms can potentially differ in other dimensions, the following distinctions are not exhaustive.

A. Typology of algorithms by the task they perform

Algorithms may perform typical tasks which can be found in multiple sectors and market levels.

1. Algorithms used for monitoring and data collection

Algorithms can facilitate the collection of various data, for instance related to general market dynamics, to competitors (for instance via the use of scraping algorithms¹⁴) or to buyer behaviour or preferences¹⁵. For example, according to the e-commerce sector inquiry that the *European Commission* (hereafter: *Commission*) conducted between June 2015 and March 2016, a significant fraction of online retailers monitored prices set by other sellers with such algorithms.¹⁶ Such monitoring activities seem natural in the context of e-commerce. Moreover, the amount of information on offline offers that is available online appears to be increasing as well, also driven by the rise of multi-channel strategies comprising online and offline channels.

2. Pricing algorithms

Algorithms can also be used for the purpose of dynamic pricing,¹⁷ in particular based on a company's *own* cost, capacity, or demand situation. For example, companies active in the airline industry have used automated yield management for several decades now.¹⁸ While yield management tools can increase company revenues – partly due to optimized pricing – they can

¹⁴ Scraping is a method for crawling web sites and automatically extracting structured data on it. For instance Scrapy (<https://scrapy.org/>) is a Python open source package to scrape data from websites.

¹⁵ See for instance *ADLC*, Opinion no. 18-A-03 of 06.03.18 on data processing in the online advertising sector (<https://www.autoritedelaconcurrence.fr/fr/avis/portant-sur-lexploitation-des-donnees-dans-le-secteur-de-la-publicite-sur-internet>), for a discussion on the number and sophistication of algorithms dedicated to personal data gathering for publicity purposes.

¹⁶ The inquiry found that “53 % of the respondent retailers track the online prices of competitors, out of which 67 % use automatic software programmes for that purpose”, cf. *Commission*, Commission Staff Working Document – Final report on the E-commerce Sector Inquiry, 10.05.17, para. 149 (http://ec.europa.eu/competition/antitrust/sector_inquiry_swd_en.pdf).

¹⁷ For the OECD, “dynamic pricing involves adjusting prices to changes in demand and supply, often in real time, not implying any kind of discrimination between consumers”. OECD, Personalised Pricing in the Digital Era, 2018, p. 9 ([https://one.oecd.org/document/DAF/COMP\(2018\)13/en/pdf](https://one.oecd.org/document/DAF/COMP(2018)13/en/pdf)).

¹⁸ In particular, American Airlines implemented an automated overbooking process as soon as 1968, see for instance *Smith/Leimkuhler/Darrow*, Yield Management at American Airlines, Interfaces 1992, pp. 8 et seq.

also help to manage and allocate inventories or production assets, thereby contributing to a more efficient use of resources. Although many airlines use such tools, this does not necessarily imply that their pricing is fully automated.¹⁹

Algorithms may also be used for price setting or adaptation based on *other* available offers. For instance, online sellers use (re)pricing tools to monitor prices set by other sellers and adapt their own prices following certain predefined rules. In the context of the e-commerce sector inquiry mentioned above, the *Commission* found that “[t]he majority of those retailers that use software to track prices subsequently adjust their own prices to those of their competitors (78 %).” Note, however, that 87 % of the respondent retailers stated that they did not apply “[d]ynamic/personalized pricing, in the sense of setting prices based on tracking the online behavior of individual customers”, while only 2 % explicitly stated that they used such pricing.²⁰ A research paper on algorithmic pricing of third-party sellers on Amazon Marketplace²¹ devised a method to detect dynamic pricing and applied it to analyse the behaviour of sellers regarding best-selling products. Although based on data from 2014 and 2015, the paper found that a significant number of the sellers of those products were using algorithmic repricing strategies based on the prices of their competitors.²²

In addition, algorithms can also be used for setting prices for goods sold in brick-and-mortar stores, potentially with a view to prices set by both offline and online competitors. Moreover, electronic shelf labels used in stores can facilitate dynamic pricing based on the stores’ respective own cost, capacity or demand situations as well as pricing based on other available offers.²³

Although algorithmic pricing might be used in almost every sector, some applications or markets seem to be discussed more often than others. For example, some studies refer to petrol stations’ use of pricing algorithms.²⁴ However, even when focussing on a single industry, there seems to be a very mixed picture concerning the effects of increased availability of both information and

¹⁹ Cf. *BKartA*, Press release of 29.05.18, Case B9-175/17, (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2018/29_05_2018_Lufthansa.html) regarding Lufthansa’s price increases on some German domestic routes.

²⁰ *Commission*, Commission Staff Working Document – Final report on the E-commerce Sector Inquiry, 10.05.17, paras. 149, 152, 602 et seq. (http://ec.europa.eu/competition/antitrust/sector_inquiry_swd_en.pdf).

²¹ *Chen/Mislove/Wilson*, An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace, Proceedings of the 25th International Conference on World Wide Web 2016, pp. 1339 et seq.

²² The estimated number of sellers depends on details of the methodology used to identify those who use algorithmic repricing. *Chen/Mislove/Wilson* utilized the number of price changes in a certain period as a filter criterion. Applying what they call “a conservative threshold”, they find that more than 500 sellers (2,4% of all sellers in their dataset) used algorithmic pricing.

²³ Cf. e.g. *Pieters*, Albert Heijn to combat food waste with “dynamic discounts”, *NL Times*, 21.05.19 (<https://nltimes.nl/2019/05/21/albert-heijn-combat-food-waste-dynamic-discounts>) and *XPlace*, xplace completes switch to electronic shelf labels at Media Markt and Saturn, Press release of 22.02.2017, (<https://www.xplace-group.com/en/press-release-biggest-esl-project-for-media-saturn>).

²⁴ Cf. e.g. *OECD*, Algorithmic Collusion – Note by A. Ezrachi & M. E. Stucke, 2017 (<https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/WD%282017%2925&docLanguage=En>), who in particular argue that posting petrol prices online promoted tacit collusion; however, there are also different findings, cf. e.g. *Haucap/Heimeshoff/Kehder/Odenkirchen/Thorwarth*, Auswirkungen der Markttransparenzstelle für Kraftstoffe, Wirtschaftsdienst 2017, pp. 721 et seq.

pricing solutions, ranging from competition becoming fiercer to concerns about an increased risk of collusion.²⁵

3. Personalization based on consumers' data

Thanks to various targeting technologies and forecasting models used in combination with consumer data, algorithms can contribute to the personalization of products and services, in particular ads. One classic example of such use of algorithms are product suggestions based on personal interests and past purchases of the individual used in many e-commerce sites.²⁶

Beyond such personalized suggestions, debate has also arisen on the possible use of personalized pricing strategies or, more generally, algorithm-based price discrimination.²⁷ Such pricing practices can be distinguished from dynamic pricing as the latter refers to price variation over time, whereas price discrimination predominantly refers to charging different (groups of) customers different prices at a single point in time. As will be discussed below, such price discrimination between customers can have various and ambiguous effects on competition and consumer welfare.²⁸

4. Ranking algorithms

Algorithms can also be used for ranking purposes. Many services include filtering or ranking algorithms that either create a certain shortlist as a selection of a larger set of items or sort a number of items according to predetermined criteria. Areas of application include comparison websites – e.g. in the area of travel, insurance, financial services, telecommunications and

²⁵ For a general economic discussion, cf. part III.A, pp. 15 et seq., *vide infra*. For the debate centered around petrol stations and the increased availability of price information, cf. e.g. *Bundesministerium für Wirtschaft und Energie*, Bericht über die Ergebnisse der Arbeit der Markttransparenzstelle für Kraftstoffe und die hieraus gewonnenen Erfahrungen, Bundestagsdrucksache 19/3693, in particular pp. 21 et seq.

²⁶ See for instance *Linden/Smith/York*, Amazon.com recommendations: Item-to-item collaborative filtering, IEEE Internet computing 2003, pp. 76 et seq.

²⁷ See for instance *Borgesius/Poort*, Online price discrimination and EU data privacy law, Journal of consumer policy 2017, pp. 347 et seq.; *Reinartz/Haucap/Wiegand/Hunold*, Preisdifferenzierung und -dispersion im Handel, Ausgewählte Schriften der IFH-Förderer 2017; *Office of Fair Trading*, Personalised Pricing – Increasing Transparency to Improve Trust, 2013 (https://webarchive.nationalarchives.gov.uk/20140402165101/http://oft.gov.uk/shared_oft/markets-work/personalised-pricing/oft1489.pdf); *CMA*, Energy Market Investigation – Final report, 2016 (<https://assets.publishing.service.gov.uk/media/5773de34e5274a0da3000113/final-report-energy-market-investigation.pdf>); *CMA*, Pricing algorithms – Economic working paper on the use of algorithms to facilitate collusion and personalized pricing, 2018 (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf); *OECD*, Algorithms and Collusion, 2017, pp. 1 et seq. (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

²⁸ In particular, see the box on algorithms and market power on pp. 61 et seq.

energy²⁹ – as well as e-commerce platforms³⁰, app stores³¹ and search engines³². Ranking algorithms are sometimes also called “relevancy algorithms”.³³ Furthermore, such algorithms are also a central element of many social media services that include “news feed” functionalities, which require a ranking of all posts that might be shown to the respective user.³⁴ By matching the ranked items to a user’s needs or preferences, ranking algorithms can decrease search costs and hence increase welfare.³⁵

5. Further fields of application

Another field of application of algorithms are *matching functionalities*. For instance, online dating platforms use algorithms to connect personal profiles to each other by calculating matching scores.³⁶ Other examples of services massively relying on matching algorithms include dynamic ridesharing where passengers’ ride requests and drivers’ ride offers need to be matched on short notice.³⁷

Many modern *auctioning mechanisms* also use complex algorithms. For example, in the context of online advertising, auctioning mechanisms were established to award advertising slots to advertisers as early as the late 1990s. Nowadays, companies offering online advertising services, including search engines such as Google, often use elaborate automated real-time mechanisms to auction off and allocate advertising space to advertisers.³⁸

Algorithms are also used by online *price tracking services* which monitor product offers and allow consumers to receive alerts when prices drop, supporting them in their decision on when and where to buy. Such services are often offered by online comparison websites. In a similar vein, the German Market Transparency Unit for Fuels receives price data from mineral oil companies and

²⁹ See for instance the *BKartA*, Press release of 11.04.19 (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2019/11_04_2_019_Vergleichsportale.html) regarding the sector inquiry on comparison websites.

³⁰ Cf. e.g. Feedvisor’s “Buy Box Bible” on ranking in the context of the Amazon buy box (<https://feedvisor.com/resources/industry-news/2018-buy-box-bible/>).

³¹ Cf. e.g. *Nicas/Collins*, How Apple’s Apps Topped Rivals in the App Store It Controls, New York Times 2019 (<https://www.nytimes.com/interactive/2019/09/09/technology/apple-app-store-competition.html>).

³² *Langville/Meyer*, Google’s PageRank and beyond: The science of search engine rankings, 2011.

³³ *Commission*, Decision of 27.06.17 (Google Search (Shopping)), Case AT.39740, para. 286.

³⁴ Cf. e.g. *Constine*, How Instagram’s algorithm works, Techcrunch 01.06.18 (<https://techcrunch.com/2018/06/01/how-instagram-feed-works/>).

³⁵ *Ursu*, The power of rankings: Quantifying the effect of rankings on online consumer search and purchase decisions, *Marketing Science* 2018, pp. 530 et seq.

³⁶ *BKartA*, Decision of 22.10.15, Case B6-57/15.

³⁷ See for instance *Schreieck/Safetli/Siddiqui/Pflügler/Wiesche/Krcmar*, A matching algorithm for dynamic ridesharing, *Transportation Research Procedia* 2016, pp. 272 et seq. and *Chen/Mislove/Wilson*, Peeking beneath the hood of Uber, in: *ACM*, Proceedings of the 2015 Internet Measurement Conference 2015, pp. 495 et seq.

³⁸ *Edelman/Ostrovsky/Schwarz*, Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords, *American economic review* 2007, pp. 242 et seq.; *ADLC*, Opinion no. 18-A-03 of 06.03.18 on data processing in the online advertising sector (<https://www.autoritedelaconurrence.fr/fr/avis/portant-sur-lexploitation-des-donnees-dans-le-secteur-de-la-publicite-sur-internet>); *BKartA*, Online advertising, Series of papers on “Competition and Consumer Protection in the Digital Economy”, 2018 (https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Schriftenreihe_Digitales_III.pdf?blob=publicationFile&v=5).

petrol station operators and passes these on to private consumer information service providers. These providers in turn inform the consumer, e.g. via the internet, a smartphone or navigation system.³⁹

Further demand-side applications include *automated switching services*, e.g. in the energy sector.⁴⁰ Some authors also discuss a certain shift of decision-making processes from human consumers to algorithms that comes along with the use of “digital butlers” such as Apple’s Siri, Google Assistant and Amazon’s Alexa or of “algorithmic consumers”.⁴¹ Similar to the above example of apps listing petrol prices and providing recommendations on when to refuel, algorithms can help consumers compare a large number of offers. Extending on that, they could, at least in theory, automatically accept the best offer, on behalf of the consumer, thus saving the consumer some time.

Further applications include tools used in B2B contexts such as automated stock-keeping and order management based on past sales and current inventories.

B. Typology of algorithms by input parameters

As discussed above, algorithms can be seen as standardized methods to transform inputs into outputs.⁴² The previous typology focused on the task performed by algorithms, i.e. the type of outputs they produce. In the following, the focus is on the type of input parameters given to the algorithms to perform the desired task.⁴³

Many of the algorithms that will be considered in this study are designed to collect or exploit large data sets. The analysis of the impact of these algorithms is thus linked to the type and the content of the data they rely on. In this regard, analysing the impact of the increased algorithm use on competition shares some common aspects with the analysis of the effects of big data on competition as carried out in the previous study of the French and German competition authorities.⁴⁴ However, some algorithms, such as simple pricing algorithms that periodically

³⁹ Cf. *BKartA*, Webpage presentation of the Market Transparency Unit for Fuels, (https://www.bundeskartellamt.de/EN/Economicsectors/MineralOil/MTU-Fuels/mtufuels_node.html).

⁴⁰ Examples include <https://flipper.community/>, <https://www.esave.de>, <https://www.switchup.de>, <https://www.wechselpilot.com>, <https://www.wechselstrom.de>.

⁴¹ *Gal/Elkin-Koren*, Algorithmic consumers, *Harvard Journal of Law and Technology* 2017, pp. 309 et seq. (314, 336). The authors define algorithmic consumers as algorithms that “*could automatically identify a need, search for an optimal purchase, and execute the transaction. In the pet food example, a specialized algorithm would collect data from the pet and its food bag to determine whether it is time to replenish the supply and could also consider the actual nutritional needs of the particular pet*”.

⁴² See the definition of algorithms presented in the introduction of part II, p. 3, *vide supra*.

⁴³ Of course, both typologies are closely related as certain tasks can only be performed if a certain type of input is available. Likewise, the quality or accuracy of the output (i.e. of the task which is performed) can depend heavily on the characteristics of the inputs, such as the volume and types of data and whether they are structured or not. See *ADLC/BKartA*, *Competition Law and Data*, 2016, pp. 4-11 (<https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.html>).

⁴⁴ *ADLC/BKartA*, *Competition Law and Data*, 2016 (<https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.html>).

monitor the price of a certain competitor and eventually adapt the corresponding price of the algorithm user, might rely on relatively few data points.⁴⁵

Apart from the number of data points on which they rely, algorithms can also differ in the number of input parameters, ranging from one to thousands. In addition, the number of variables is to some extent related to the granularity, i.e. the level of detail of the data. High granularity can also refer to the time dimension, in particular if information is collected for short time intervals, coming along with frequent updating of inputs.

Another technical dimension according to which inputs could be classified is by their data types, e.g. including only numerical inputs in tabular form (e.g., prices observed in the market) or also less structured ones such as textual inputs (e.g., a description of goods on offer) or image data (e.g. a photo of the item). This, in turn, also impacts how the data can be stored, as certain types of data bases or data storages are either more or less appropriate for unstructured data.

Moreover, the content of inputs might differ. For example, a company might consider mainly information that refers to its own situation such as cost of production, inventory or current orders. In contrast to that, it could also gather additional data on competitors (e.g. prices, estimated inventories) or customers. In either case, it can also be of interest whether this data is freely or publicly available and whether it covers more recent (potentially real-time) or historical information.

C. Additional ways to classify algorithms

Algorithms can also be classified according to their method of learning (1.), their degree of interpretability (2.) as well as their respective developer (3.).

1. Distinction by method of learning

Part of the concern expressed by the antitrust community about the increased use of algorithms relates to their alleged ability to learn and adapt their behaviour independently of human intervention and will.⁴⁶

In that respect, one can broadly distinguish between two types of algorithms. On the one hand, there are *self-learning algorithms* (sometimes also simply called “learning” or “machine-learning” (ML) algorithms). Those are algorithms that derive their parameters of conduct with a high degree of automation from a – potentially dynamic – set of training data. In principle, such algorithms are capable of improving their performance on the class of tasks that they are supposed to solve with growing experience.⁴⁷ On the other hand, there are “*fixed*” *algorithms*, with human-chosen parameters (possibly via statistical methods) that do not (semi-)automatically change over time

⁴⁵ Also cf. the box on simple undercutting or “price-matching” algorithms on p. 43.

⁴⁶ See for instance *Ezrachi/Stucke*, Sustainable and Unchallenged Algorithmic Tacit Collusion, 2018 (<https://ssrn.com/abstract=3282235>), or *Ezrachi/Stucke*, Virtual Competition, 2016, but also contributions such as *Schwalbe*, Algorithms, Machine Learning, and Collusion, *Journal of Competition Law & Economics* 2018, pp. 568 et seq. or *Lewis/Rickyard*, Automatic harm to competition? Pricing algorithms and co-ordination, 2018, that question the actual relevance of such concerns to some degree.

⁴⁷ Cf. e.g. the characterization of “learning” in *Mitchell*, *Machine Learning*, McGraw-Hill Higher Education, 1997, p. 2.

in response to new information. In this context, “change” refers to the parametrization of the implemented principles and not to a variation in outputs due to a change in inputs. For a pricing algorithm, for instance, a variation in outputs due to a change in inputs would refer to a price adaption, e.g. following a price change by a monitored competitor but leaving the underlying pricing mechanism unchanged. In contrast, learning would refer to a change in the implemented pricing scheme or formula.

Generally, machine learning can be understood as a subfield of artificial intelligence, which is a broader branch of research at the intersection of computer science, philosophy, neuro-science, statistics and robotics.⁴⁸

Within the field of ML algorithms, different distinctions can be made, for instance based on the objective of the learning algorithm, the frequency of learning, and the method of learning. Three main types of learning are traditionally distinguished: supervised learning, unsupervised learning and reinforcement learning.

Supervised learning allows identifying relations between inputs and outputs by analysing a set of given, typically labelled, input-output-pairs.⁴⁹ Applications include categorization tasks, for instance identifying whether an e-mail is likely to be spam, after having derived characteristic properties of spam e-mails from a data set of e-mails containing a manually added spam/no spam label. Hence, an e-mail will be labelled spam because, for example, it contains certain keywords or has been sent by a certain type of address. Companies might also use such types of algorithms for example to identify the influence of factors such as weather, season, or current events on the observed demand for a given product, e.g. by performing regression tasks using a data set containing these four variables.

Unsupervised learning consists of the analysis of patterns or commonalities (and, as a consequence, anomalies) in data. For instance, given a set of data on consumer characteristics and behaviour, unsupervised learning will allow to identify groups of customers that are alike in many characteristics. Such a classification could then be used in an attempt to better target ads or to adapt the price or offer to the characteristics of the consumer. In this case, in contrast to supervised learning, the training data does not contain information (e.g. “labels”) about the consumer’s response to ads or pricing or consumer categories. Hence, no direct link between their characteristics and the efficacy of targeted ads or pricing discounts can be inferred.

Reinforcement learning relies mostly on a return from experimentation. In this framework, an algorithmic agent learns how to choose from a set of possible actions, given their current state in an only partially known environment. Typically, reinforcement learning algorithms do this by computing an expected reward associated to each possible couple of state and action and then choosing optimal actions accordingly. The trade-off between “exploitation”, i.e. choosing the action that maximizes its expected reward given the current knowledge of the environment, and

⁴⁸ Cf. *OECD, Algorithms and Collusion*, 2017, pp. 8 et seq. (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

⁴⁹ This type of learning trains on a dataset that presents both raw data and their “label”, i.e. the corresponding category or type to which the data belongs.

“exploration”, i.e. choosing an action at random to improve the knowledge of its environment, is at the core of reinforcement learning. An example of the use of such algorithms is AlphaGo Zero, a successful software that plays Go developed by Google’s DeepMind.⁵⁰ After being taught the rules of the game, the software was entirely trained by playing with itself, hence using reinforcement learning. A particular class of reinforcement learning are Q-learning algorithms which choose their actions only based on observed rewards from prior actions, not supported by a model of the environment.⁵¹ These are often used in studies investigating the capacity of algorithms to collude without human intervention.⁵²

The frequency of learning, i.e. the frequency of automatic changes to the parameters of the algorithm, can vary from a purely initial training to continuous learning. In the case of purely initial training, the algorithm will derive parameters from the training data only once and afterwards the parameters will no longer be modified. In the case of continuous training, the parameters will be dynamic and change over time. For instance, reinforcement learning algorithms are one example of a complex form of continuous learning.

2. Distinction by degree of interpretability of the algorithm and its behaviour

A further distinction may be made according to the degree of interpretability of algorithms. Roughly speaking, algorithms can be divided into two groups:

On the one hand, there are algorithms whose implemented principles are basically interpretable for humans. In particular, one can identify the strategy and the actions that result from using the algorithm via the code of the algorithm, albeit in some cases only with considerable effort. There are several terms or labels to describe this group. While the terminology slightly differs, the underlying classification seems similar. In particular, such algorithms can be called “adaptive”⁵³, “white-box”⁵⁴, “heuristic”, “static” or “analytical”⁵⁵. In the following, the study will refer to all of them by the term *descriptive*. A descriptive algorithm typically has at least partly predefined ways to observe the “state” of the world, often including the competitive environment, as for example

⁵⁰ See for instance *Silver/Hassabis*, AlphaGo Zero: Starting from scratch, Deep Mind Blog, 18.10.17 (<https://deepmind.com/blog/article/alphago-zero-starting-scratch>).

⁵¹ To present Q-learning algorithms, *Calvano/Calzolari/Denicò/Pastorello* for instance state that “*Q-learning tools tackle the problem of finding an optimal policy in Markov Decision Problems or problems alike. A Markov Decision Problem is a formal framework that allows the analysis of repeated decision making in dynamic stochastic environments. To be concrete, consider the problem of a price setting firm in oligopoly. Every period, the firm i) observes relevant information such as the price charged by its rivals in previous periods or the state of demand, ii) sets its own price and iii) collects the resulting profits. The firm’s problem is that of finding the pricing policy that maximizes the present value of its profits. A policy is a mapping from what it observes, the “state”, to its control variable, the price. The Q-Learning algorithm is a tool designed to “crack” this decision problem through a process of experimentation. Experimenting allows to learn the policy that maximizes long-run profits*”. *Calvano/Calzolari/Denicò/Pastorello*, Algorithmic Pricing: What Implications for Competition Policy?, Review of Industrial Organization 2018, pp. 1 et seq.

⁵² Cf. part III.B.3.b), pp. 45 et seq., *vide infra*.

⁵³ Cf. *Calvano/Calzolari/Denicò/Pastorello*, Algorithmic Pricing: What Implications for Competition Policy?, Review of Industrial Organization 2018, pp. 1 et seq.

⁵⁴ Cf. *Gesellschaft für Informatik*, Technische und rechtliche Betrachtungen algorithmischer Entscheidungsverfahren, 2018 (http://www.svr-verbraucherfragen.de/wp-content/uploads/GI_Studie_Algorithmenregulierung.pdf).

⁵⁵ Cf. for the last three terms *Oxera*, When algorithms set prices: winners and losers, Discussion paper 2017.

competitors' prices. It then analyses this state, possibly using more or less sophisticated statistical and analytical methods, and potentially also including some learning elements. In the context of price setting, this step might include finding the lowest price currently offered by a competitor. Finally, it applies certain predefined rules to determine its reaction, for example by matching the lowest price.

However, complexity⁵⁶ of the algorithms may vary within this group. In particular, some algorithms might be less easy to "read" than the price matching variant sketched before, at least without access to the code. For example, providing a more sophisticated example of a descriptive algorithm, some authors discuss "first-generation pricing algorithms" or "estimation-optimization" algorithms.⁵⁷ This type of algorithms selects a price based on a two-step approach: an estimation step and an optimization step. The estimation module typically estimates market demand while the optimization module "*chooses the optimal price given the demand estimate and observed past behavior of rivals*".⁵⁸

On the other hand, there are algorithms whose behaviour is hardly interpretable even with access to their code. In the following, the study will refer to them as *black-box* algorithms. Such algorithms might involve advanced learning methods and therefore may process a wider range of capabilities. Although there might be approaches to investigate (and maybe also supervise) the resulting behaviour as well as to extract the predefined goal of the algorithm,⁵⁹ the strategy that results from using such an algorithm often cannot be fully identified just from its code. While it might still be possible to determine which objective the algorithm is supposed to achieve, it can be much more complicated to analyse the means the algorithm uses to meet this objective. Of course, the extent of such difficulties varies on a case-by-case basis.⁶⁰ A specific methodological example associated with black-box algorithms are deep learning algorithms which rely on a so called "network of neurons". To some extent, such a neural network mimics the architecture of the human brain. It consists of nodes or "neurons" that are typically arranged in layers and connected to each other. The exact architecture of a neural network varies considerably according to the area of application. The inputs enter at the input layer and get subsequently modified by each layer of the neural network until they reach the output layer. The transformation is defined not only by the overall architecture of the neural network, but also by a large set of weights or parameters determining the transformation in each node, which are usually learned from training

⁵⁶ The use of the term 'complexity' throughout the paper typically does not correspond to the use of the same term in computer science. Here, it refers to algorithmic sophistication or its range of possible behaviours.

⁵⁷ Cf. *Calvano/Calzolari/Denicolò/Pastorello*, Algorithmic Pricing: What Implications for Competition Policy?, Review of Industrial Organization 2018, pp. 1 et seq.; *Harrington*, Developing Competition Law for Collusion by Autonomous Artificial Agents, Journal of Competition Law & Economics 2018, pp. 331 et seq.; *Calvano/Calzolari/Denicolò/Pastorello* distinguish "adaptive" pricing algorithms, a term that refers to the framework analysed by *Milgrom/Roberts* (1990), and "learning" pricing algorithms.

⁵⁸ Cf. *Calvano/Calzolari/Denicolò/Pastorello*, Algorithmic Pricing: What Implications for Competition Policy?, Review of Industrial Organization 2018, pp. 1 et seq.; see also *Shakya/Chin/Owusu*, An AI-based System for Pricing Diverse Products and Services, Knowledge-based systems 2010, pp. 357 et seq.

⁵⁹ Cf. part IV, pp. 61 et seq., *vide infra*.

⁶⁰ In particular, in contrast to the previous example, the estimation and optimization steps as described in the previous case are typically integrated.

data.⁶¹ The more layers the network relies on, the more weights or parameters there will be to estimate: the performance of this type of learning algorithm might rely significantly on the volume of the set of training data. As opposed to other methods of learning algorithms, which rely on a simpler model of the link between the inputs and the outputs, this type of algorithmic behaviour will often not be easily interpretable.

In the specific context of automated pricing, more “autonomous” models translate to algorithms not explicitly defining a particular pricing strategy. Typical examples of black-box learning-algorithms for automated pricing include, in line with the above examples, Q-learning (a specific version of reinforcement learning) algorithms or deep-learning algorithms (sometimes also called “second-generation pricing algorithms”⁶²). Using these methods does not necessitate building an explicit model of the behaviour of the market before developing a strategy to respond to it. Instead they can rely on an exploration-exploitation mechanism.⁶³

However, as there are many different aspects of algorithms that render them more or less accessible to human understanding and interpretation, there is no obvious or comprehensive way to rank algorithms in terms of their accessibility to human understanding.

3. Distinction by developer of the algorithm

Another distinction can be made according to the identity of the developer of the algorithm. In particular, an algorithm can be designed internally by the companies who intend to use it or it can be designed and/or coded by an external software developer who might sell a similar algorithm to multiple actors within one and the same market. Section III.B.2, below, discusses some of the competition issues that could ensue when a third party provides the same algorithm or somehow coordinated algorithms to competing companies.

⁶¹ Other parameters, called hyperparameters, are not learned and need to be set by the data scientist. They can influence greatly the performance of the algorithm which thus depends heavily on the skill and experience of the data scientist.

⁶² Cf. *Calvano/Calzolari/Denicò/Pastorello*, Algorithmic Pricing: What Implications for Competition Policy?, Review of Industrial Organization 2018, pp. 1 et seq.; *Harrington*, Developing Competition Law for Collusion by Autonomous Artificial Agents, Journal of Competition Law & Economics 2018, pp. 331 et seq.

⁶³ See part II.C.1, pp. 9 et seq., *vide supra*, for more details on the exploration-exploitation mechanism.

Summary of “Algorithms – notion, types and fields of application”

An algorithm can be understood as ‘a sequence of simple and/or well-defined operations that should be performed in an exact order to carry out a certain task or class of tasks or to solve a certain problem or class of problems’.

Notwithstanding this wide definition, the study focuses on digital algorithms that may entail economic consequences and, more specifically, potential impacts on competition. In particular, the study discusses algorithms used for dynamic price setting, e.g. based on a company’s own cost, capacity, or demand situation as well as other available offers.

Several possible categorisations are discussed. Besides by the task they perform, algorithms can, for instance, be categorised by the input parameters that they use or the involved learning method.

Issues concerning the interpretability of algorithms are also addressed. The study notably distinguishes “descriptive” algorithms, which are basically interpretable for humans, from “black-box” algorithms, whose behaviour is hardly interpretable for humans.

III. Algorithms and collusion

Algorithms provide a plethora of beneficial opportunities for the economy and society. For example, as indicated above, they can facilitate innovative services, allow for the personalization of products and services, support the optimization of inventories and/or reduce search costs.

They may nevertheless have detrimental effects on competition, too. In the following section, the study explores some of those adverse effects with a particular focus on pricing algorithms and the different ways such algorithms may affect strategic interactions between companies, ultimately leading to horizontal collusion.

The section starts by summarizing the economic principles behind horizontal collusion (A.). Subsequently, the use of pricing algorithms in three scenarios as well as potential competition law implications will be discussed (B.).

A. Economic principles of horizontal collusion

Economic research has addressed horizontal collusion from various perspectives, ranging from theoretical oligopoly models over the “*theory of learning in games*”⁶⁴ and evolutionary game theory⁶⁵ to experimental studies.⁶⁶

Economists mostly study collusion in dynamic game settings, often with an infinite (or uncertain) time horizon, in which companies take into account long-run profits in their decisions. They seek to identify the possible equilibria⁶⁷ in such games, with various definitions of what possible strategies might be, what equilibrium concept is used and which knowledge each player possesses on the setting and on the behaviour of the other players.

In many of these game-theoretic settings, there are multiple equilibria. The corresponding outcomes may range from competitive price levels or so-called “myopic” outcomes⁶⁸ to monopolistic price levels. In principle, each equilibrium other than the myopic competitive outcome could potentially be considered a “collusive” outcome.

However, observing a supra-competitive price set by a player or a company might not be enough to characterize collusion. In particular, a supra-competitive price set by only one company will not increase its profit. As *Harrington*⁶⁹ emphasizes,

“[c]ollusion is often misperceived to be supra-competitive prices but that is actually the result of collusion. Collusion is about a firm causing rival firms to set supra-competitive prices. More

⁶⁴ Cf. e.g. *Fudenberg/Levine*, *The Theory of Learning in Games*, 1998.

⁶⁵ Cf. e.g. *Maynard Smith*, *Evolution and the Theory of Games*, 1982.

⁶⁶ See also part III.B.3.b), pp. 45 et seq., *vide infra*.

⁶⁷ An equilibrium is a stable combination of strategies, i.e., no player has an interest in choosing another strategy given the strategies chosen by the other players.

⁶⁸ Competitive “myopic” outcomes are outcomes that will result from a setting in which companies ignore that they interact repeatedly or do not take into account their future income.

⁶⁹ *Harrington*, *Developing Competition Law for Collusion by Autonomous Agents*, working paper, The Wharton School, University of Pennsylvania 2017.

specifically, collusion is when firms use strategies that embody a reward-punishment scheme which rewards a firm for abiding by the supra-competitive outcome and punishes it for departing from it”.

The emphasis is thus on the stability of collusion, which can be tested by observing the reaction of companies to a rival setting a lower price and the incentives resulting from it: will the rival be punished for doing so? Does this punishment effectively deter deviation, in the sense that the outcome for deviant companies will be less profitable than maintaining supra-competitive prices? In principle, collusion can be sustainable if and only if companies put sufficient weight on future profits relative to present profits.⁷⁰

Yet, in focusing on collusion stability, the mechanism and the likelihood for collusion to emerge are not addressed. However, several questions on the emergence of collusion arise, for example whether stable collusive equilibria will be achieved in practice and if so, after how much time; furthermore, in cases of multiple possible equilibria, whether companies will manage to coordinate on one of the equilibria.

In relation to these issues, some authors⁷¹ identified two broad issues conditioning the existence of collusion in a given market:

- the *initiation* of collusion, i.e., the agreement or convergence of companies on the conditions of collusion, such as the price level, the available mechanisms to monitor the collusion and deter deviation, etc.
- the *implementation* of collusion, i.e., “*managing the ongoing operation of the collusive structures*”, including effective punishment of a deviant company, adjusting to changes in the demand, etc.

In particular, several experimental studies,⁷² but also a number of theoretical models⁷³ have addressed the impact of communication (in particular modelled by players’ ability to communicate e.g. on the type of strategy they intend to follow) on collusion. Communication between companies can considerably increase the chances for collusion to be achieved as it can help solving the coordination problem of which of the potential equilibria to “choose” during the initiation phase. However, communication can also have a positive effect on the stability of collusion during the implementation phase, for instance by helping participants understand why certain actions, potentially (seemingly) diverging from the collusive strategies, have been chosen at a given point in time, or to adjust to changing market conditions.

⁷⁰ Cf. *Ivaldi/Jullien/Rey/Seabright/Tirole*, The Economics of Tacit Collusion, Final report for DG Competition, March 2003, p. 8.

⁷¹ Cf. e.g. *Green/Marshall/Marx*, Tacit collusion in oligopoly, in: *Blair/Sokol*, Oxford Handbook on International Antitrust Economics, Vol. 2, 2015, pp. 464 et seq.

⁷² Cf. e.g. *Fonseca/Normann*, Explicit vs. tacit collusion – The impact of communication in oligopoly experiments, *European Economic Review* 2012, pp. 1759-1772; *Haan/Schoonbeek/Winkel*, Experimental Results on Collusion, in: *Hinlopen/Norman* (eds.), Experiments and Competition Policy, 2009, pp. 9-33.

⁷³ Cf. e.g. *Awaya/Krishna*, On Communication and Collusion, *American Economic Review* 2015, pp. 285-315.

From an economic point of view, tacit collusion can be defined as collusion that does not involve any communication, neither in the initiation nor the implementation stage. In contrast, explicit collusion generally relies on some form of communication in at least one of the stages, and, therefore, might sometimes be easier or more likely to achieve and/or maintain than tacit collusion.

Part 1 below analyses the impact of algorithms on the stability of collusion, focussing on the implementation phase. Afterwards, part 2 deals with the impact of algorithms on the emergence of collusion, i.e. during the initiation phase.

1. Algorithms in the implementation phase of collusion: focus on the stability of collusion

Both economic theory and case law have identified economic factors likely to facilitate or impair the stability of collusion. These factors include: a low number of companies on a market, high barriers to entry, high frequency of interactions between competitors, high market transparency for the companies and low market transparency for the consumers, low asymmetry between companies, few innovations etc.⁷⁴ Correspondingly, markets that exhibit such features are more prone than others to experience long-lasting collusion if such a collusion effectively emerges.

The development and use of algorithms, and in particular of pricing and monitoring/scraping algorithms, could affect these factors that in turn will affect the stability of collusion, and thus have an impact on the overall risk of collusion, regardless of whether collusion is explicit or tacit. The table below presents an overview over selected parameters, their potential effects on the stability of collusion and the respective impacts of algorithms which are illustrated in the following. However, both this overview and the following explanations are not meant to be conclusive, and therefore cannot predetermine the assessment of (changes in) the risk of collusion in a specific situation.

⁷⁴ For a review of these factors, see *Ivaldi/Jullien/Rey/Seabright/Tirole*, The Economics of Tacit Collusion, Final report for DG Competition, March 2003. Such factors susceptible to facilitate collusion are generally analysed when considering the competitive impact of exchanges of past information. See for instance *Commission*, Decision of 17.02.92, Case 92/157/EEC, paras. 35 to 52.

Parameter (market characteristic)	Potential effect of an increase in this parameter on the stability of collusion	Impact of algorithms on the stability of collusion <i>via</i> this parameter
Number of companies	Decreasing	Positive
Barriers to entry	Increasing	Ambiguous, depending on the market
Frequency of interactions	Increasing	Positive
Market transparency for companies	Increasing	Positive
Market transparency for consumers	Ambiguous, depending on the market	Ambiguous, depending on the market
Asymmetry between companies	Decreasing	Ambiguous, depending on the market
Product differentiation	Decreasing	Ambiguous, depending on the market
Innovation	Decreasing	Negative or ambiguous, depending on the market

Table: Effects of various market characteristics on stability of collusion and resulting impact of algorithms on collusion stability⁷⁵

The impact of a higher *number of companies* is usually to make collusion less sustainable, due to higher costs of coordination and to greater profit gains in case of deviations. Yet, algorithms can reduce coordination costs e.g. by facilitating the processing of information needed to implement coordination, thereby increasing the stability of collusion.

Entry barriers are usually said to increase the stability of collusion by allowing participants to increase their prices without triggering entry. Algorithms can have an ambiguous effect on the stability of collusion as entry barriers can be either decreased (e.g. more effective pricing strategies can be devised thanks to algorithms) or increased (e.g. the data needed to implement an algorithm can increase entry barriers).

The *frequency of interactions* is often said to facilitate collusion by making punishments of deviations more rapid. Algorithms could further increase the frequency of interactions and thus increase the stability of collusion, in particular by making price adjustments faster and/or less costly.

Market transparency for companies facilitates the detection of deviations and thus can increase the stability of collusion. By allowing a greater gathering and processing of information, monitoring algorithms collecting these data could thus foster collusion.

In competitive markets, *market transparency for consumers*, i.e., consumers' ability to compare market offers, is often said to have a pro-competitive effect. Consequently, an increase in market transparency (e.g. caused by a reduction in search costs) can lead to competition becoming

⁷⁵ See also OECD, Algorithms and Collusion, 2017 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

fiercer.⁷⁶ However, when focusing on the stability of collusion, this pro-competitive impact of market transparency via the demand side can overall have an ambiguous effect: on the one hand, transparency increases the profits ensuing from deviations (making collusion less stable due to increased incentives to undercut competitors); on the other hand, transparency also increases the loss generated by punishments (making collusion more stable). Therefore, the increase in market transparency entailed by algorithms used by consumers can either increase or decrease the stability of collusion, depending on the specific market circumstances.

Asymmetries between companies as well as *product differentiation* can make punishments of deviating companies more difficult to enact, in particular for less close competitors. Another issue is that collusive prices may also have to be differentiated if products and/or firms are differentiated, making the detection of unilateral deviations from a collusive regime more difficult. Hence, the stability of collusion is reduced in such settings. The use of algorithms is ambiguous in this regard. On the one hand, it can increase asymmetries between companies by making their products and processes more differentiated. On the other hand, it might foster coordination by enabling companies to analyse and react to competitors' prices for a diverse range of differentiated products more efficiently and in more sophisticated ways, potentially using more complex pricing strategies adapted to a higher degree of differentiation. Concerning the stability of such a regime, algorithms might aid (asymmetric) companies in separating competitors' price adjustments taking place within a collusive regime from deviations from this regime, thus increasing its stability.

Finally, *innovation* increases asymmetries between companies and makes the environment less stable, thus inducing companies to privilege short-term profits (i.e., deviations) over long-term benefits (i.e., cooperation). By generally fostering innovation, algorithms may thus decrease the stability of collusion regarding this particular aspect.

Algorithms might thus increase the stability of collusion in specific sectors although there might also be countervailing effects. Consequently, the actual impact of the use of algorithms on the stability of collusion in a given market is *a priori* uncertain and depends on the market characteristics. Moreover, making collusion potentially more stable is not necessarily sufficient to generate collusion in the first place.

2. Algorithms in the initiation phase of collusion: focus on the emergence of collusion

In contrast to the questions relative to the stability of collusion, the initiation stage of collusion has been less studied in economics. As *Ivaldi/Jullien/Rey/Seabright/Tirole*⁷⁷ note, "*while economic theory provides many insights on the nature of collusive conducts, it says little on how a particular industry will or will not coordinate on a collusive equilibrium, and on which one*". However, two

⁷⁶ Cf. e.g. *Stahl*, *Oligopolistic Pricing with Sequential Consumer Search*, *American Economic Review* 1989, pp. 700 et seq.

⁷⁷ *Ivaldi/Jullien/Rey/Seabright/Tirole*, *The Economics of Tacit Collusion*, Final report for DG Competition, March 2003.

broad approaches have been adopted to study the initiation phase of collusion without communication between companies, a theoretical approach and an experimental one.⁷⁸

Most theoretical studies of how collusion can emerge without communication fall within the theoretical framework of dynamic games presented above. It consists in analysing whether rational companies playing a specific game, with various definitions of what “rational” means, eventually converge to a specific equilibrium.⁷⁹

A possible explanation of how companies might coordinate on a specific equilibrium without communication is the existence of a “focal point”. Such a point is a “natural” collusive equilibrium, identified as such by each company and/or featuring a natural tendency to be adopted by rational players. For instance, focal points can result from a cognitive bias common to all company managers, like choosing a round number, or setting a price in reference to the price of another similar good, such as a national brand for private label products. Intuitively, these situations may seem less likely to emerge without human intervention. Also, focal points can result from the existence of a reference company in the market – often the market leader – acknowledged as such by all companies. In that scenario, the behaviour of the reference company is observed and followed by other companies.⁸⁰ Intuitively, in this type of scenario, algorithms could help initiate and maintain collusion by facilitating the monitoring of competitors’ prices and the automation of the response to these prices. If such monitoring is costly (for instance, monitoring different companies might require adjustments of the scraping method to the different websites), market players would monitor only a few (or no) other players than the market leader, leading to a natural coordination consisting in adapting to its behaviour. In such settings, algorithms may not be decisive in fostering the emergence of collusion, in particular as humans could also foster coordination.

However, most of the times, the market may not exhibit any focal point sufficiently natural to be elicited as a natural strategy for each competitor: most economic environments are complex and display several possible ways to collude, none of which may offer a sufficiently high probability of being chosen by each competitor. In these settings, as in the *Ezrachi/Stucke*⁸¹ scenario of “*tacit collusion on steroids – the predictable agent*”, algorithms could then be seen as “super-humans” in the sense that they could better analyse the complex trade-offs that need to be dealt with when

⁷⁸ See also part III.B.3.b), pp. 45 et seq., *vide infra*, for this latter approach. Note that the impact of algorithms on the initiation phase of collusion is not restricted to tacit collusion, as algorithms could also facilitate communication or help curtaining communication to initiate collusion (see part III.B.1, pp. 27 et seq., *vide infra*).

⁷⁹ For more details and a literature review, see *Green/Marshall/Marx*, Tacit collusion in oligopoly, in: *Blair/Sokol*, Oxford Handbook on International Antitrust Economics, Vol. 2, 2015, pp. 464 et seq. However, beyond classical game theoretical models, the field of “algorithmic game theory” chooses another approach, typically taking on certain assumptions on bounded rationality of players and applying alternative equilibrium/solution concepts, cf. e.g. *Nisan/Roughgarden/Tardos/Vazirani* (eds.), *Algorithmic Game Theory*, 2007.

⁸⁰ *Byrne/de Roos*, Learning to coordinate: A study in retail gasoline, *American Economic Review* 2019, pp. 591 et seq., provide an example of such a coordination among companies initiated by the market leader in the retail gasoline market in Perth, Australia.

⁸¹ *Ezrachi/Stucke*, Virtual Competition, 2016, pp. 56 et seq.

deciding whether and how to collude tacitly.⁸² Specifically, in most real life situations, a company only observes its individual demand and (in the best case) the offers and prices of its competitors. Depending on the characteristics of the market, the behaviour of its competitors or of the customers could be difficult to interpret. For instance, a company could fail to understand a collusive “proposal”. The use of pricing algorithms could facilitate the initiation phase of collusion if it helps to overcome difficulties in analysing the behaviour of other players through potentially superior capabilities to deal with the complexity.

Finally, beyond classical dynamic game frameworks, evolutionary game theory could contribute to analysing the behaviour of some pricing algorithms, in particular reinforcement learning algorithms (see part II.C.1).⁸³ In particular, it provides a theoretical framework to analyse another possible explanation of the emergence of collusion without communication, that is “convergence by chance” to a collusive equilibrium. Indeed, learning algorithms explore all the possible actions and thus can – under certain conditions, and after many interactions – stumble on a stable collusive equilibrium.

However, these theoretical explanations of the emergence of collusion give little practical insights into which kinds of algorithms are more prone to facilitate the emergence of tacit collusion. Neither do they provide an extensive answer to the question of whether algorithms significantly enhance the emergence of collusion under realistic market conditions. Yet, a growing body of research explicitly analyses the emergence (and in parts, the stability) of collusion via concrete technical implementations of algorithms in specific experimental settings. This research is considered in part III.B.3.b), below.⁸⁴

⁸² Also cf. *Green/Marshall/Marx*, Tacit collusion in oligopoly, in: *Blair/Sokol*, Oxford Handbook on International Antitrust Economics, Vol. 2, 2015, pp. 464 et seq. (481 et seq.), for a further discussion of the idea of “higher-order knowledge” and of “arriving at collusion by reasoning”.

⁸³ See for instance *Bloembergen/Tuyls/Hennes/Kaisers*, Evolutionary Dynamics of Multi-Agent Learning: A Survey, *Journal of Artificial Intelligence Research* 2015, pp. 659 et seq.; *Sabourian/Juang*, Evolutionary Game Theory: Why Equilibrium and Which Equilibrium, *Foundations of the Formal Sciences V: Infinite Games*, College Publications 2007; *Hanaki/Sethi/Erev/Peterhansl*, Learning strategies. *Journal of Economic Behavior & Organization* 2005, pp. 523 et seq.; *Maynard Smith*, *Evolution and the Theory of Games*, 1982.

⁸⁴ Pp. 45 et seq.

Algorithms and market power

Beyond the facilitation of horizontal collusion, there might also be interdependencies between algorithms and the market power of the companies that make use of them. In particular, this can lead to additional barriers to market entry. Moreover, various types of abusive behaviour linked to algorithms can be considered, at least from a prospective viewpoint.

(Access to) Algorithms as a factor of market power

As already indicated in part II, algorithms can support businesses in a variety of ways and thus can potentially provide competitive advantages. Against this background, the access to and the use of algorithms constitutes a potential factor contributing to market power. For example, in the Google Shopping case the *Commission* investigated barriers to entry and expansion in markets for general search services. The *Commission* highlighted that “*the establishment of a fully-fledged general search engine requires significant investments in terms of time and resources*”, in particular with regard to the “*initial costs associated with the development of algorithms*”; such investments could in particular relate to research and development, equipment as well as personnel.⁸⁵ The importance of algorithms has also been acknowledged during the 9th amendment of the German Competition Act in 2017. In this context, the memorandum accompanying the legislative proposal considered a company’s capability for analysing and processing data, i.e. the access to and use of algorithms, as potentially relevant for possible competitive advantages.⁸⁶

At the same time, certain aspects of algorithms might no longer have the same impact on market power as they probably have had in earlier years. First, companies are possibly not as dependent on developing algorithms in-house anymore, as more and more third-party services are capable of substituting bespoke business applications. For example, pricing algorithms are readily available even for small online retailers.⁸⁷ Also, machine-learning frameworks have reduced the complexity of implementing AI and thus have lowered the associated entry barrier for benefitting from this more advanced technology. Finally, the availability of cloud computing has reduced scalability issues as well as financial risks that experimenting with computationally intensive algorithms previously entailed.

It should be noted that the market power associated with algorithms could also be intrinsically linked to the access to data which the algorithm is supposed to analyse or process. The Google Shopping decision mentioned above illustrates such interplay as the *Commission* concluded that for a general search engine to compete viably, “*it needs to receive a certain volume of queries*”, both to detect changes in user behaviour as well as to “*improve the relevance of its results*”.⁸⁸ In a similar vein, the 9th amendment to the German Competition Act from 2017 explicitly names “*access to data relevant for competition*” as one of the factors to consider when assessing market power.⁸⁹ It

⁸⁵ Cf. *Commission*, Decision of 27.06.17 (Google Search (Shopping)), Case AT.39740, para. 185 and paras. 286 et seq.

⁸⁶ Bundestagsdrucksache 18/10207, p. 51 in the context of § 18(3a) GWB: “*Relevant für mögliche Wettbewerbsvorteile können aber auch die Fähigkeiten und Möglichkeiten eines Unternehmens zur Datenauswertung bzw. -verarbeitung sein*”.

⁸⁷ Regarding the prevalence of pricing algorithms, cf. part II.A.2, pp. 4 et seq., *vide supra*.

⁸⁸ *Commission*, Decision of 27.06.17 (Google Search (Shopping)), Case AT.39740, paras. 287 et seq.

⁸⁹ § 18(3a) GWB.

should be kept in mind, however, that – as discussed in more detail in the previous work by the *ADLC/BKartA* on competition law and data⁹⁰ – the relevance of data for competitive advantages might depend on which scale, scope and/or availability of data is in fact necessary. Concerning the availability aspect, the lack of rivalry regarding data as well as the existence of data brokers might further mitigate corresponding entry barriers.

Taken together, the questions of whether relevant barriers to entry and expansion exist in connection with algorithms and of whether (access to/knowledge about) algorithms contribute(s) to market power have to be addressed on a case-by-case basis and in consideration of all relevant circumstances.

Besides algorithms potentially contributing to market power, abusive behaviour might involve algorithms in several ways:

Refusal to supply access/information relating to algorithms

In line with the relevance of algorithms for market power, a company's refusal to supply a competitor with information relating to its algorithms could potentially constitute an exclusionary abuse. According to established case law, such a finding could require a determination that information relating to the algorithm is indispensable to someone wishing to compete and that a refusal to grant access would lead to the elimination of effective competition.⁹¹ For example, in the 2004 Microsoft case, the *Commission* concluded that Microsoft had achieved a dominant position in the work group server operating system market.⁹² It had abused said position by refusing to provide a competing operating system vendor with information enabling them to design their system for seamless integration in Microsoft's group server system: The *Commission* held that the interoperability disclosures in question were indispensable even though certain limited open industry standards, limited options for reverse-engineering and limited protocol licensing programs existed.⁹³

Abusive behaviour involving pricing algorithms

One particular concern might be pricing algorithms potentially contributing to an abusive practice,⁹⁴ which might for instance fall into the category of excessive pricing or unfair terms and conditions. Excessive pricing might require an examination of whether the undertaking "*has made use of the opportunities arising out of its dominant position in such a way as to reap trading benefits which it would not have reaped if there had been normal and sufficiently effective competition*".⁹⁵ A suspicion of excessive pricing involving an algorithm can be exemplified by the initial observations in the 2018 German Lufthansa case. A preliminary investigation was initiated by the

⁹⁰ *ADLC/BKartA*, Competition Law and Data, 2016, pp. 25 et seq. (<https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.html>).

⁹¹ Cf. *Whish/Bailey*, Competition Law, 9th edn., 2018, pp. 716, 818 et seq.

⁹² *Commission*, Decision of 24.03.04 (Microsoft), Case COMP/C-3/37.792, para. 541.

⁹³ *Commission*, Decision of 24.03.04 (Microsoft), Case COMP/C-3/37.792, paras. 666 et seq.

⁹⁴ Beyond cases of dominance of a single company, anticompetitive conduct, in particular a collusive market outcome, might also be addressed under Art. 102 TFEU when the respective parties are jointly dominant, although proving the relevant facts might pose considerable difficulties in practice, cf. *Monopolies Commission*, XXII. Biennial Report 2018, para 217.

⁹⁵ *ECJ*, *United Brands v Commission*, Judgement of 14.02.78, Case C-27/76, para. 249.

BKartA after a competitor's insolvency resulted in Lufthansa holding a monopoly position for a few months on certain domestic routes, and subsequently increasing its ticket prices on average by 25-30%.⁹⁶ At some point, Lufthansa had alluded to there not being a manual change to its pricing scheme, the pricing algorithm instead 'merely' reacting to a change in demand;⁹⁷ in the end, however, the question of whether the price increases were actually the result of an algorithm or instead of human intervention was of no significance for the proceedings.⁹⁸

Additionally, concerns might also be raised by algorithms performing individual pricing/price discrimination, e.g. selling or purchasing "*different units of a good or service at prices not directly corresponding to differences in the cost of supplying them*"⁹⁹. Algorithms could, by their essence, facilitate such behaviour as they allow companies to process and analyse large(r) amounts of customer data, thus enabling more precise price targeting or other forms of discrimination/differentiation.¹⁰⁰ The overall effect of such price discrimination between consumers is unclear, i.e. depending on the characteristics of the case at hand.¹⁰¹ In particular, counteracting effects on consumer welfare can occur, e.g. some consumers might be better off under price discrimination, while others might be worse off. Many theoretical models assume that price discrimination requires at least a certain degree of market power. However, price discrimination could also reflect and/or reinforce competition by allowing companies to offer lower prices to customers with a strong preference for another product.¹⁰² Thus a careful analysis of the case at hand will be necessary to determine whether the personalization of algorithmic pricing could be an element of a relevant form of abusive behaviour.¹⁰³

Finally, individual pricing decisions themselves could potentially constitute an infringement of Art. 102 TFEU: the provision explicitly prohibits "*applying dissimilar conditions to equivalent transactions with other trading partners, thereby placing them at a competitive disadvantage*".¹⁰⁴ In this context, it should be kept in mind that a finding of a competitive disadvantage requires an

⁹⁶ BKartA, Press release of 29.05.18 (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2018/29_05_2018_Lufthansa.html).

⁹⁷ Cf. Busse, Bundeskartellamt rügt Lufthansa, Süddeutsche Zeitung, 28.12.17 (<https://www.sueddeutsche.de/wirtschaft/nach-air-berlin-pleite-bundeskartellamt-ruegt-lufthansa-1.3806188>).

⁹⁸ BKartA, Press release of 29.05.18 (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2018/29_05_2018_Lufthansa.html); also see fn. 270, *vide infra*.

⁹⁹ Whish/Bailey, Competition Law, 9th edn., 2018, p. 777, considering price discrimination.

¹⁰⁰ OECD, Price Discrimination. Background note by the Secretariat, 13.10.16, para. 144.

¹⁰¹ Cf. e.g. Locher, Verschiedene Preise für gleiche Produkte? Personalisierte Preise und Scoring aus ökonomischer Sicht, Zeitschrift für Wettbewerbsrecht 2018, pp. 292 et seq.

¹⁰² See for instance ADLC/BKartA, Competition Law and Data, 2016, pp. 21-22 (<https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Berichte/Big%20Data%20Papier.html>).

¹⁰³ Cf. Salaschek/Serafimova, Preissetzungsalgorithmen im Lichte von Art. 102 AEUV, WuW 2019, pp. 118 et seq. (119 et seq.). Concerning the (limited) use of personalized pricing in practice, also cf. fn. 27, *vide supra*.

¹⁰⁴ Art. 102(2)(c) TFEU. It is, however, not entirely clear whether that provision also applies to final consumers and/or whether Art. 102(1) TFEU would be applicable in such situations (cf. Langen/Bunte-Bulst, Kartellrecht. Band 2, Art. 102 TFEU para. 214). Domestic law might differ in this regard, too.

examination of all the relevant circumstances.¹⁰⁵ Additionally, such a discrimination could still be objectively justified.

Abusive behaviour involving other types of algorithms

Abusive behaviour might also be facilitated by algorithms used for other purposes than pricing. For example, ranking algorithms could feature a ranking bias by preferring a company's own services to the competitors' detriment.¹⁰⁶ Situations of self-preferencing can again be exemplified by the Google Shopping case, in which the *Commission* stated that the "*more favourable positioning and display, in Google's general search results pages, of Google's own comparison shopping service compared to competing comparison shopping services*" constituted an abusive conduct.¹⁰⁷ More specifically, the decision explains how certain dedicated algorithms reduced the ranking of some competing comparison shopping services in Google's search results pages and therefore affected their visibility in Google's general search result pages. Besides, the *Commission* explained that Google's service was not subject to these dedicated algorithms that reduced the rankings in Google's general search pages.

Moreover, a ranking algorithm might potentially be involved in abusive behaviour when a company uses the algorithm for exerting pressure on other companies, e.g. by threatening a de-ranking of suppliers/customers in order to induce them to engage in certain anticompetitive conduct.¹⁰⁸ Such conduct was dealt with by ADLC in a 2018 decision in which a website creation intermediation company, Interactive Lab, complained of discriminatory and exclusionary practices, constitutive of an abuse of a dominant position, which were allegedly implemented by Google in its AdWords service. Google was accused of manipulating the results of AdWords' auction system in order to maximise the number of customers and revenues of its service and consequently to exclude Interactive Lab from the intermediation market for the creation of websites on which it operates. This case was rejected by ADLC due to a lack of evidence.¹⁰⁹

¹⁰⁵ *ECJ*, Judgment of 19.04.18 (MEO), Case C-525/16, para. 37.

¹⁰⁶ Cf. *Schweitzer/Haucap/Kerber*, *Modernisierung der Missbrauchsaufsicht für marktmächtige Unternehmen*, 2018, p. 97 (https://www.bmwi.de/Redaktion/DE/Publikationen/Wirtschaft/modernisierung-der-missbrauchsaufsicht-fuer-marktmaechtige-unternehmen.pdf?__blob=publicationFile&v=14); *Crémer/de Montjoye/Schweitzer*, *Competition policy for the digital era*, 2019, pp. 66 et seq. (<http://ec.europa.eu/competition/publications/reports/kd0419345enn.pdf>).

Such self-preferencing could also manifest itself in an indirect way, for instance if ranking takes place by certain criteria which the company's own products are more likely to meet. In this context, proving a (unjustified) bias could potentially be more demanding, in particular if a complex algorithm has been used.

¹⁰⁷ *Commission*, Decision of 27.06.17 (Google Search (Shopping)), Case AT.39740, para. 341 and accompanying headline.

¹⁰⁸ Also cf. § 21(2) GWB. Under such circumstances, the fact that a de-ranking could be implemented indirectly by ranking by certain seemingly 'objective' criteria should again be kept in mind.

¹⁰⁹ *ADLC*, Decision 18-D-13 of 20.07.2018 (<https://www.autoritedelaconurrence.fr/fr/decision/relative-des-pratiques-mises-en-oeuvre-par-google-dans-le-secteur-de-la-publicite-en-ligne>) regarding practices implemented by Google in the sector of online advertising.

Summary of “Economic principles of horizontal collusion”

With a particular focus on pricing algorithms, the study explores potential detrimental effects of such algorithms on competition and the different ways in which they may affect strategic interactions between companies, potentially leading to horizontal collusion.

Both economic research and case practice have identified several factors that can influence the stability of collusion, such as the number of companies on a market, the existence of entry barriers, the interaction frequency, and the degree of market transparency for different market participants. Algorithms could affect some of these factors and thus potentially have an impact on the stability of collusion, but the actual effect of the use of algorithms on the stability of collusion in markets is *a priori* uncertain and depends on the respective market characteristics.

The study also discusses the emergence of collusion, in particular by considering how companies might coordinate on a specific equilibrium without human communication. The study in particular arrives at the preliminary conclusion that theoretical findings on the emergence of collusion can provide only limited practical insights into which kinds of algorithms are more prone to facilitate the emergence of tacit collusion.

Finally, the paper also discusses interdependencies between algorithms and the market power of the companies using them. In particular, these interdependencies can lead to additional market entry barriers.

B. Use of algorithms in different scenarios

For the purpose of illustration, this section will present three different scenarios. However, this should not be understood as a definitive categorization as the scenarios might overlap and their delineation could sometimes be difficult or blurred in practice.

Firstly, there are situations in which there are “traditional” anticompetitive practices resulting from prior contact between human beings (i.e. explicit collusion between competitors or any other type of practice, e.g. vertical agreements). The algorithm only comes into play in a second step as a supporter or as a facilitator in the course of the implementation of anticompetitive practices (1.).

Secondly, situations might exist in which competitors use the same or somehow coordinated algorithms provided by a third party (e.g. an external developer of the algorithm) and this leads to a horizontal alignment of their market behaviour (2.). The particularity of these cases is that there is no direct communication or contact between the competitors. A central legal question is therefore whether the horizontal alignment via the third party constitutes a cartel. Another issue in this scenario is under which circumstances the third party can also be held liable for an ascertained collusion.

Thirdly, there could be collusive effects induced by the (parallel) use of individual algorithms absent any prior contact between human representatives of the respective companies (3.) A central legal question in this scenario is whether the encountered interaction of algorithms constitutes a cartel (in particular, a concerted practice) or legal parallel behaviour. Where

algorithms are autonomous in the sense that they receive only very limited instructions by human beings (i.e. where it is difficult to attribute the collusion to human behaviour), a further question is under which circumstances collusion induced by the use of such algorithms leads to liability of the respective company.

1. Algorithms as supporters or facilitators of “traditional” anticompetitive practices

This section focusses on a scenario in which a “traditional” anticompetitive practice resulting from (prior) contact between humans can be established, i.e. an explicit collusion between competitors exists. The algorithm only comes into play in a second step to support or facilitate e.g. the implementation, monitoring, enforcement or concealment of the respective anticompetitive practice. Some authors have called this a “messenger” scenario.¹¹⁰

The first subsection will describe the potential situations covered by this scenario (a) before the potentially relevant competition law aspects are discussed (b).

a) Potential situations covered by this scenario

The scenario of explicit collusion supported or facilitated by an algorithm may cover a wide variety of different situations. As the following examples will demonstrate, the purpose to be served by the algorithm could elucidate the details of the parties’ prior agreement or concerted practice:

When it comes to the support or facilitation of horizontal agreements or concerted practices, algorithms could be used to implement collusive prices or support market segmentation. An illustrative example is the CMA’s decision in its case on the online sales of posters and frames.¹¹¹ The CMA found that two companies, Trod and GBE, participated in an agreement and/or concerted practice that they would not undercut each other on prices for certain licensed sport and entertainment posters and frames sold only by the two of them on the Amazon UK Marketplace. Both Trod and GBE used (different, presumably “off-the-shelf”) pricing software of third party providers to implement this arrangement. Another example is a recent case by the British regulator of the energy sector, Ofgem. Ofgem found that two energy suppliers had an agreement preventing them from actively targeting each other’s customers.¹¹² A common algorithm was used to share customer meter point details between the competitors, with the algorithm blocking the recruitment of each other’s customers in accordance with the agreement.

¹¹⁰ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review (5) 2017, pp. 1175 et seq. (1782): “[...] humans agree to the cartel and use their computer to assist in implementing, monitoring, and policing the cartel”. See also *BRICS Competition Law and Policy Centre*, Digital Era Competition, 2019, pp. 1 et seq. (632): “Algorithms may be used as a tool to implement explicit collusion”.

¹¹¹ *CMA*, Decision of 12.08.16, Case 50223.

¹¹² *Ofgem*, Decision of 26.07.19 (https://www.ofgem.gov.uk/system/files/docs/2019/07/decision_on_economy_energy_-_e_gas_and_electricity_-_dyball_associates_infringement_of_chapter_i_ca98_doorstep_sales_redacted_decision_document_26_july_2019.pdf).

Furthermore, an algorithm could monitor competitors' prices and/or automatically punish a deviation from the price previously coordinated upon. As outlined above,¹¹³ the increase in transparency and frequency of adjustments potentially caused by an algorithm might strengthen the cartel stability. Furthermore, this monitoring effect can be at work in vertical agreements.¹¹⁴ A horizontal collusion could also be supported or facilitated by an exchange of algorithms (or of the principles implemented therein) between competitors. Such an exchange could raise concerns comparable to an agreement on or to an exchange of pricing formulas, tariff schemes, etc.¹¹⁵

Similarly, an information exchange between competitors might be supported or facilitated by an algorithm. An algorithm could facilitate such an exchange by making it more simple, rapid and direct.¹¹⁶

A particular way of supporting a collusion could consist in using an algorithm for curtaining such collusion. In this context, algorithms could potentially feign effective competition by hiding anticompetitive behaviour. For example, algorithms could be developed to implement different prices when there is no (or very low) demand. In a similar vein, they could be used to generate price heterogeneity and/or instability every once in a while, while maintaining the collusive pricing conduct in general. One specific situation could also be bid-rigging, in which competitors in the context of competitive tendering procedures agree on submitting pre-calculated bids.¹¹⁷ Furthermore, algorithms could be used to conceal communication activities, e.g. by allowing for encrypted messaging.¹¹⁸

¹¹³ Cf. part III.A, pp. 15 et seq., *vide supra*.

¹¹⁴ See the box below on p. 30.

¹¹⁵ For an example on joint calculation of price recommendations, cf. the German cartel case in the area of wholesale of sanitary, heating and air-conditioning products (*BKartA*, Decision of 21.02.18, Case B5-139/12). For another example on the exchange of pricing principles, cf. the German industry battery case (*BKartA*, Decision of 31.03.17/26.06.17, Case B11-13/13), which concerned a commonly applied alloy surcharge. Similarly, the German eyeglass lenses case (*BKartA*, Decision of 28.05.10, Case B12-11/08) concerned parallel pricing after a disclosure of company-specific price calculation formulas in the realm of a "pricing structure working group".

¹¹⁶ Cf. *GC*, *Tate & Lyle et al. v Commission*, Judgment of 12.07.01, Joined Cases T-202/98, T-204/98 and T-207/98, para. 60; *GC*, *Fresh Del Monte Produce v Commission*, Judgment of 14.03.13, Case T-587/08, para. 369.

¹¹⁷ Cf. e.g. *BKartA*, *Wie erkennt man unzulässige Submissionsabsprachen?*, 19.08.15 (<https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Broschueren/Submissionsabsprachen.htm>); *ADLC*, Decision of 21.03.06, Case n°06-D-07, concerning practices in the public works sector in the Île-de-France area (<https://www.autoritedelaconurrence.fr/fr/decision/relative-des-pratiques-mises-en-oeuvre-dans-le-secteur-des-travaux-publics-dans-la-region>).

¹¹⁸ Attempts to conceal communication activities have already been observed before, cf. e.g. *BKartA*, Case summary of 29.07.11, Case B12-12/10 (<https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Kartellverbot/2011/B12-12-10.html>) or *BKartA*, Press release of 23.07.13 (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2013/23_07_2013_Schienen.html?nn=3591568). However, the use of technical means might have increased over time, cf. e.g. *US Department of Justice*, Press release of 07.08.17 (<https://www.justice.gov/opa/pr/e-commerce-company-and-top-executive-agree-plead-guilty-price-fixing-conspiracy-customized>) or *Squires*, Canadian Company Custom-Made Encrypted Phones for Cartels, *Insight Crime*, 14.03.18 (<https://www.insightcrime.org/news/brief/canadian-company-custom-made-encrypted-phones-cartels-authorities/>).

b) Potential competition law aspects

Art. 101(1) TFEU (and its national counterparts) prohibits, *inter alia*, all agreements between undertakings and concerted practices which may affect trade between Member States and which have as their object or effect the prevention, restriction or distortion of competition within the internal market. As an agreement requires the “*existence of a concurrence of wills*”¹¹⁹ between undertakings and a concerted practice necessitates a coordination represented by certain “*direct or indirect contact*”¹²⁰, a violation of competition law presupposes some kind of communication between the undertakings concerned.

Art. 101 TFEU thus requires each undertaking to determine its policy on the market independently.¹²¹ Conversely, this requirement does not deprive companies of the right to adapt themselves intelligently to the existing or anticipated conduct of their competitors.¹²² In other words, mere parallel behaviour without any kind of agreement or contact between competing companies, i.e. implicit or tacit collusion, does not constitute an infringement of Art. 101 TFEU. Moreover, in specific cases, an agreement or concerted practice can be deemed legal in light of the potential specific efficiencies associated with it, depending on whether the requirements of Art. 101(3) TFEU are met.

The scenario outlined in this section does not in principle raise specific competition law issues regarding the involvement of an algorithm as a prior agreement or concerted practice exists which in general may be assessed under Art. 101 TFEU without requiring further analysis of the algorithm.

However, there may be cases where considering the algorithm may be helpful in the context of assessing a potential infringement of Art. 101 TFEU.¹²³ Even where an infringement can be established without reference to the algorithm, it might still be useful to develop a case-specific understanding of the role which algorithms play in the respective case. On the one hand, there might be a need to assess potential (counteracting) efficiencies associated with the algorithm,¹²⁴ while on the other hand the use of an algorithm could reinforce negative effects of an ascertained anticompetitive practice. Analysing the algorithm and its role may also help in the assessment of the sophistication and intentionality of the collusive scheme.

The CMA’s poster decision¹²⁵ introduced above illustrates such considerations: The CMA found that the agreement and/or concerted practice between Trod and GBE of not undercutting each other on prices constituted a by-object infringement of national competition law. To prove the case, the CMA mainly relied on evidence not directly related to the algorithms, such as e-mail

¹¹⁹ *GC*, Bayer v Commission, Judgment of 26.10.00, Case T-41/96, para. 69.

¹²⁰ *ECJ*, Suiker Unie v Commission, Judgment of 16.12.75, Joined cases 40 to 48, 50, 54 to 56, 111, 113 and 114-73, paras. 173, 174.

¹²¹ *ECJ*, Suiker Unie v Commission, Judgment of 16.12.75, Joined cases 40 to 48, 50, 54 to 56, 111, 113 and 114-73, para. 173; *ECJ*, Züchner v Bayerische Vereinsbank AG, Judgment of 14.07.81, Case 172/80, para. 13.

¹²² *ECJ*, Züchner v Bayerische Vereinsbank AG, Judgment of 14.07.81, Case 172/80, para. 14.

¹²³ Concerning practical challenges when investigating algorithms, cf. part IV, pp. 61 et seq., *vide infra*.

¹²⁴ Cf. for example the Luxembourgian Webtaxi case mentioned in the box on “Delegation of strategic decisions to a third party that takes these decisions using an algorithm”, pp. 40 et seq., *vide infra*.

¹²⁵ *CMA*, Decision of 12.08.16, Case 50223.

correspondence. However, the CMA also investigated, to a certain degree, the use of the respective pricing software. In this regard, the CMA first noted that the

*"[...] repricing software used by the Parties to implement the Infringing Agreement is normally used by online sellers to compete with other online sellers by automatically adjusting the prices of their products in response to the live prices of competitors' products. However, in the present case the repricing software was configured by the Parties to restrict price competition between them in order to give effect to the Infringing Agreement".*¹²⁶

The findings concerning the algorithm were, in particular, relevant when assessing the seriousness of the infringement in the context of the penalty calculation. In this context, the CMA *inter alia* accounted for

*"[...] the fact that automated repricing software was used to implement the Infringement, thereby making 'cheating' on the cartel arrangement more difficult".*¹²⁷

Vertical agreements or concerted practices

Besides supporting or facilitating horizontal collusion, algorithms could also be used in the context of vertical agreements or concerted practices. The *Commission* has already identified at least three potential implications for vertical cases:¹²⁸

Algorithms could be used to detect deviations from a fixed or minimum resale price, thus making the fixed or minimum resale price more effective. Furthermore and regarding price recommendations, an increased price transparency through algorithmic monitoring could allow for a retaliation by manufacturers against retailers not complying with the recommendation.¹²⁹ The latter could have a chilling effect as it might *"limit the incentives of retailers to deviate from such pricing recommendations in the first place"* and in the end could turn *"that 'recommended' price into a fixed resale price"*.¹³⁰ Finally, an agreement by a manufacturer on a minimum resale price vis-à-vis one retailer could *"spread high prices"* to other retailers not engaged in the agreement if those other retailers use algorithms matching the price of the first retailer.¹³¹

Such situations can be exemplified by the four decisions concerning consumer electronics manufacturers issued by the *Commission*.¹³² In these decisions it was determined that manufacturers used monitoring algorithms to track online resale prices. The algorithms were

¹²⁶ CMA, Decision of 12.08.16, Case 50223, para. 5.47.

¹²⁷ CMA, Decision of 12.08.16, Case 50223, para. 6.23 c. In this case, the CMA accounted for the fact that software was used when deciding on the starting point for the calculation of the penalty, but not within the subsequent adjustment steps.

¹²⁸ Cf. OECD, Algorithms and Collusion – Note from the European Union, 14.06.17 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

¹²⁹ Commission, Commission Staff Working Document – Final report on the E-commerce Sector Inquiry, 10.05.17, para. 577 (http://ec.europa.eu/competition/antitrust/sector_inquiry_swd_en.pdf).

¹³⁰ OECD, Algorithms and Collusion – Note from the European Union, 14.06.17, pp. 4-5 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

¹³¹ OECD, Algorithms and Collusion – Note from the European Union, 14.06.17, p. 5 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

¹³² Commission, Decision of 24.07.18, Cases AT.40181, AT.40182, AT.40465, AT.40469; for another recent example see also CMA, Decision of 01.08.19, Case 50565-2, paras. 3.97 et seq.

used to detect and quickly intervene with online retailers offering low prices. On a horizontal level, there was a widespread use of pricing algorithms in the industry, and thus even limited vertical interventions regarding low pricing online retailers had a broader impact on overall online prices.

2. Algorithm-driven collusion between competitors involving a third party

This section covers situations in which a third party provides the same algorithm or somehow coordinated algorithms to competitors. The particularity of these situations is that there is no direct communication or contact between the competitors. A certain degree of alignment in the use of algorithms arises nevertheless due to the third party providing similar services to competitors. The third party could, for example, be an external consultant advising several companies in the same line of business on the design and use of algorithms, or a developer supplying competitors with implementations of similar software solutions. In the following, particular emphasis is put on pricing algorithms which seem to already be used by a significant number of online retailers.¹³³

Many authors classify the situations considered here as a “hub and spoke” scenario.¹³⁴ However, there might be slight differences between the scope of such a scenario and the definition used in this paper. *Ezrachi/Stucke*¹³⁵ for example characterize the “hub and spoke” scenario by the fact that “*competitors use the same (or a single) algorithm to determine the market price or react to market changes*”.¹³⁶ These authors therefore refer to the use of largely identical algorithms. However, as negative effects do not necessarily depend on whether competitors use the same, common or very similar algorithm(s), but on whether strategic (pricing) principles are somehow coordinated or aligned, it seems appropriate to widen the scope of the definition and include the case where algorithms are used that differ from each other while driving a collusive outcome.

In its study on pricing algorithms, the CMA considers that the “hub and spoke” scenario is likely to present the most immediate risk¹³⁷ for competition. Indeed, even a straight-forward use of the same pricing algorithm can lead to similar pricing decisions when the algorithm reacts in similar ways to external events, such as changes in input costs or demand.¹³⁸ This does not even require

¹³³ Cf. e.g. *Commission*, Commission Staff Working Document – Final report on the E-commerce Sector Inquiry, 10.05.17 (http://ec.europa.eu/competition/antitrust/sector_inquiry_swd_en.pdf).

¹³⁴ According to the OECD, “[h]ub-and-spoke arrangements can be characterised as any number of vertical exchanges or agreements between economic actors at one level of the supply chain (the spokes), and a common trading partner on another level of the chain (the hub), leading to an indirect exchange of information and some form of collusion between the spokes.” OECD, Roundtable on Hub-and-Spoke Arrangements, 17.10.19, p. 5 ([https://one.oecd.org/document/DAF/COMP\(2019\)14/en/pdf](https://one.oecd.org/document/DAF/COMP(2019)14/en/pdf)).

¹³⁵ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1787 et seq.).

¹³⁶ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1787).

¹³⁷ CMA, Pricing algorithms, 2018, para. 5.35 (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf).

¹³⁸ CMA, Pricing algorithms, 2018, para. 5.17 (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf).

that competitors know about their respective use of similar algorithms. However, if this awareness is given, companies could exploit this knowledge actively:

“[...] if the competitors are aware or able to infer that they are using the same or similar pricing algorithms, firms would be better able to predict their competitors’ responses to price changes, and this might help firms to better interpret the logic or intention behind competitors’ price setting behaviour.”¹³⁹

The third parties’ incentives to engage in such behaviour may vary. In particular, developers might program and offer “off-the-shelf” solutions on their own initiative. Once such a solution is ready for the market, developers are likely to have an incentive to sell it to as many companies as possible. Depending on the respective solution, buyers might be companies that are active in similar industries, potentially competing in one and the same market, but also companies that are active in several different lines of business. However, developers (or external consultants) might also be hired by a specific company, potentially developing a bespoke solution. If the third party serves competing clients and particularly if its remuneration is proportional to the revenue it provides to the companies or if the renewal of its contract depends on its performance, this actor might have an interest in generating collusion between its clients. In this case, it might be more profitable to aim at a coordinated outcome. Thus, this is a step beyond cases where third parties provide algorithmic solutions that in principle follow a unilateral logic, i.e. apply a certain predefined pricing scheme and/or aim at maximization of individual (short-run) profits, without taking advantage of the fact that several competing companies are served.

In the following, two settings are distinguished:

The first setting concerns situations in which at least two competitors¹⁴⁰ know that they use the same or somehow coordinated algorithms provided by a third party (a). A particular situation in this setting relates to competing sellers or service providers delegating certain strategic decisions such as pricing to a third party that then takes these decisions using an algorithm.

The second setting likewise presumes that at least two competing companies use the same or somehow coordinated third party algorithm(s). However, in contrast to the first setting, the respective companies (all or all but one of them) do not know that they use the same or somehow coordinated algorithmic solutions (b).

a) Competitors knowingly use the same or somehow coordinated third party algorithms

In this setting a third party, for example a consultant or an external algorithm developer, provides the same or somehow coordinated algorithms to companies that are aware of this interplay. For instance, this might happen if a common developer or consultant develops pricing algorithms or

¹³⁹ CMA, Pricing algorithms, 2018, para. 5.17 (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf).

¹⁴⁰ In situations in which only one company and the software provider are aware that the same software is used by multiple companies, competitors that are neither aware of anticompetitive acts nor could have reasonably foreseen them cannot be held liable.

pricing strategies for multiple competitors and mentions competitors that have been served as references.¹⁴¹

The section will first describe potential situations covered by this scenario (aa) before discussing potential legal implications (bb).

aa) Potential situations covered by this scenario

Alignment of algorithmic decision-making could arise in different ways. Generally, one could distinguish between alignment at the level of the algorithm (code level) and alignment at the level of the input factors (data level). Of course, both types of alignment may coincide. This seems also to correspond with the line of thought by authors who argue that reliance on the same data pool ("*hub-and spoke structures [...] at the input level (data)*") might intensify the effects of the alignment of behaviour which results from reliance on a common algorithm.¹⁴²

aaa) Alignment at code level

Alignment at code level could arise when a third party not only provides algorithms with a shared purpose, for example the calculation of prices, but also a similar (or related) implemented methodology.

The degree of similarity between the provided algorithms may vary. In the most far-reaching case, algorithms can be completely identical. Their use might even systematically lead to identical prices. In a weaker form, algorithms would be at least to some degree individualized for the respective customer. However, alignment might also arise due to commonalities in the underlying business logic. This might be the case even when these commonalities are limited to certain economic factors of price setting, as seen for example in the adaption of discounts in the Eturas case¹⁴³. In this case, travel agencies were all using the same online booking system provided by Eturas, which limited the discount rates that could be applied to clients. An alignment might occur even if the software merely suggests prices but does not provide automated price setting.

A specific form of alignment at code level would be the complete delegation of strategic decisions to a common third party that takes these decisions using an algorithm. This particular case is discussed in the box below.¹⁴⁴

bbb) Alignment at data level

Alignment could also occur at data level. There can be significant differences regarding the form and extent of such an alignment:

¹⁴¹ Cf. e.g. *Bergin/Frost*, Software and stealth: how carmakers hike spare part prices, Reuters, 03.06.18 (<https://www.reuters.com/article/us-autos-software-pricing-insight/software-and-stealth-how-carmakers-hike-spare-parts-prices-idUSKCN11Z07L>).

¹⁴² *OECD*, Algorithmic Collusion – Note by A. Ezrachi & M. E. Stucke, 2017, para. 32 (<https://www.oecd.org/officialdocuments/publicdisplaydocumentpdf/?cote=DAF/COMP/WD%282017%2925&docLanguage=En>).

¹⁴³ The study will introduce and discuss the Eturas case in the context of potential legal implications, see Part III.B.2.a)bb), pp. 34 et seq., *vide infra*.

¹⁴⁴ Cf. p. 40, *vide infra*.

In one of the most far-reaching cases, a common or somehow coordinated algorithm could provide the means for an information exchange amongst competitors. For example, in the Spanish cigarette case that has been decided recently by the CNMC the authority found that tobacco companies actively used a feature on a distributor's software platform to grant other tobacco companies access to their respective aggregated sales figures.¹⁴⁵

Rather than facilitating an information exchange where competitors directly access sensitive data themselves, a software supplier might also use a shared pool of such data to pursue the goal of maximizing joint profits by executing a single, common algorithm.

However, even if the algorithms provided by a third party software supplier calculate prices separately for each customer (i.e. computationally aiming at maximizing individual, not joint profits), the software supplier might still use other clients' confidential data to calibrate the algorithms. In this case, the supplier would use a common pool of training data including non-public data by multiple competitors. While non-public data would not be shared explicitly in its original form with competitors, in absence of appropriate safeguards on the part of the third party, patterns in a competitor's non-public data could still be picked up by a machine learning model and thus further align the companies' pricing and the future learning and adaption of the pricing algorithm. This might happen only initially, for example by adapting pre-trained models (whose parameters were derived from competitors' data) to new customers, but also repeatedly over time.

It is also conceivable that a software supplier could rely on a specific interface to a public data source or a specific commercial supplier of data to gather relevant input for the supplier's pricing software. This reliance conceivably increases the likelihood that the supplier makes use of this single data source in price computations for several competitors. The use of the software might thus establish an alignment in (parts of the) input data amongst competitors. These competitors might otherwise have relied on different sources, possibly importing somewhat different data, e.g. in terms of completeness, precision of measurement, calculation of aggregate values, data quality, timing of updates, granularity and/or other factors.

bb) Potential competition law aspects

So far, there is few algorithm-specific case law in relation to the situations described above. Also, it is not possible to predict which types of cases might come up in the future. While the following section will discuss potential competition law aspects applicable to the scenario, it is important to keep in mind that due to the variety of situations within this scenario, an assessment under Art. 101 TFEU will always depend on the specificities of each case.

In the literature, algorithmic collusion via a third party is often related to the established "hub and spoke" doctrine. It should be noted, however, that in legal practice this doctrine sometimes addresses quite specific cases, in which the third party's role is limited to passing on information

¹⁴⁵ CNMC, Press release of 12.04.19 (<https://www.cnmc.es/en/node/374435>). It has to be noted, however, that if there is an underlying concertation amongst the competitors, this situation might rather fall within the first scenario (i.e. algorithms as supporters or facilitators of "traditional" anticompetitive practices).

from one supplier to the other.¹⁴⁶ However, in the scenarios of algorithmic collusion the third party might be more active by developing (and potentially also calibrating) the algorithm actually used when taking a strategic decision. Consequently, such practices could disregard Art. 101 TFEU, even if they are not strictly linked to the “hub and spoke” doctrine. However, it still can be acknowledged that from a broader perspective the setting of a communication via a third party is similar in both situations.

A legal assessment of the situations covered by this scenario has to account for the fact that no direct horizontal contact among competitors exists, but only direct vertical contacts between each competitor and the third party (aaa). The potential competition concerns caused by such indirect contact depend on the algorithmic alignment observed in the case at hand (bbb).

aaa) Concertation via a third party

According to established European case law and practice, horizontal agreements and concerted practices can be the result of a mere indirect contact between competitors via a third party. In its Horizontal Guidelines, the *Commission* explicitly notes that an information exchange can take place indirectly through a common agency or a third party.¹⁴⁷ Furthermore, the ECJ has held as early as in 1975 that EU law strictly prohibits any contact – whether direct or indirect – between competitors, the object or effect of which is either to influence the market behaviour of an actual or potential competitor or to disclose to such a competitor one’s own future market behaviour.¹⁴⁸ The fact that such contact can take place indirectly by acts of a third party has also been clarified in more recent case law:

The ECJ found in the VM Remonts case that an undertaking may be held liable for a concerted practice on account of the (anticompetitive) acts of an external service provider that it hired if one of the following conditions is met:¹⁴⁹

¹⁴⁶ In this context, British authorities have pursued several cases with a “hub & spoke” reasoning (*Competition Appeal Tribunal*, Case N° 2005/1071, 1074 and 1623, *Argos Limited and Littlewoods Limited v Office of Fair Trading and JJB Sports Plc v Office of Fair Trading* [2006] EWCA Civ 1318 (‘Replica Football Kit’ et ‘Toys and Games’); Case No 1188/1/1/11, *Tesco Stores Ltd, Tesco Holdings Ltd and Tesco plc v Office of Fair Trading* [2012] CAT 31 (‘Dairy’)). These cases all involve a conspiracy between retailers and their suppliers. In these cases a retailer (A) discloses to its supplier (B) his future pricing intentions. B passes this information on to another retailer (C) who uses this information in determining its own pricing intentions. The circumstances are such that A may be taken to have intended or did in fact foresee that B would pass that information on to retailer (C). C may be taken to have known the circumstances in which the information was disclosed by A to B or that C in fact appreciated that the information was passed to it with A’s concurrence. The case is all the stronger where there is reciprocity. In the pure “hub & spoke” situation the third party (B) is thus a medium that passes on information from one competitor to the other (and possibly vice versa). In this context see also *Whish/Bailey*, *Competition Law*, 9th edn., 2018, pp. 353 et seq. and *Reyntjens/Yasar*, *Not all cartell facilitators are the same*, *European Competition Law Review* 2019, pp. 423 et seq. (430 et seq.).

¹⁴⁷ *Commission*, *Horizontal Guidelines*, para. 55. See also the cases *inter alia* involving a third party listed by *BRICS Working Group on Digital Economy*, *BRICS in the digital economy*, 2019, pp. 1 et seq. (45 et seq.).

¹⁴⁸ *ECJ*, *Suiker Unie v Commission*, Judgment of 16.12.75, Joined cases 40 to 48, 50, 54 to 56, 111, 113 and 114-73, para. 174.

¹⁴⁹ *ECJ*, *VM Remonts v Konkurences padome*, Judgment of 21.07.16, Case C-542/14, para. 27 et seq.

- the service provider was acting under the direction or control of the undertaking concerned (under these circumstances an anti-competitive conduct of an external service provider could be attributed to the undertaking which directs or controls it); or
- that undertaking was aware of the anti-competitive objectives pursued by its competitor(s) and the service provider and intended to contribute to them by its own conduct; or
- that undertaking could reasonably have foreseen the anti-competitive acts of its competitors and the service provider and was prepared to accept the risk which they entailed.

Leaving aside the case described in the first bullet, in which the conduct of the third party could be attributed to the company directing or controlling it, one of the central questions in this scenario thus is whether the competitors are aware that they are relying on the same anticompetitively acting service provider and using the same or somehow coordinated algorithms or could at least reasonably have foreseen it.

The same awareness requirement was relevant in the Eturas case¹⁵⁰, which deals with indirect contact amongst competitors. In fact, the Eturas case is one of the cases concerning a coordination via an algorithm provided by a third party. The case concerned travel agencies that were all using the same online booking system provided by Eturas, the holder of exclusive rights to, and administrator of, the E-TURAS booking system.¹⁵¹ Through the booking system Eturas imposed a technical restriction on the discount rates the travel agencies could offer to clients, causing discount rates in excess of 3% to be automatically reduced to 3% by the system.¹⁵² Eturas posted a message informing its users about this change.

The ECJ found that a concertation between the travel agencies within the meaning of Art. 101 TFEU could only be found if the travel agencies were aware of Eturas' message. In other words, "*the mere existence of a technical restriction implemented in the system*" would be insufficient for inferring a participation in a concertation.¹⁵³ While the assessment of evidence and the standard of proof are governed by national law,¹⁵⁴ the ECJ held that the presumption of innocence in primary law does not preclude a domestic court from presuming awareness of a message from the date of its dispatch in light of further objective and consistent indicia.¹⁵⁵ The resulting presumption must be, however, rebuttable by an undertaking proving e.g. that it did not

¹⁵⁰ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14.

¹⁵¹ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 6 et seq.

¹⁵² *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 12.

¹⁵³ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 45.

¹⁵⁴ The national rules must, however, be in line with the principles of equivalence and effectiveness (*ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 34).

¹⁵⁵ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 40.

receive the message.¹⁵⁶ In France, the Paris Court of appeal has adopted a similar approach in a case where the participation of a company in a concertation was only founded on the fact that it had received sensitive information from competitors by email that it had neither requested nor accepted. The Court of appeal considered, in the case in question, that the mere reception of an email is insufficient for inferring a participation in a concertation, even when companies have not publicly distanced themselves from the content of the message.¹⁵⁷

In addition to a coordination, a concerted practice further requires that the coordination has caused parallel market conduct. In the *Eturas* decision, the ECJ held that if a travel agency was aware of the content of the message, it may be presumed to have participated in the concertation.¹⁵⁸ However, the ECJ also considered that a travel agency may rebut this presumption by proving that it publicly distanced itself from that practice or reported it to the administrative authorities.¹⁵⁹ It also held that other evidence may be adduced with a view to rebutting the presumption, such as - for example in the *Eturas* case - evidence of a systematic application of a discount exceeding the cap in question.¹⁶⁰ In this context it should be noted that when assessing an alleged rebuttal of a presumption of causal market conduct, an authority might have to consider that on the one hand, deviations might undermine coordination while on the other hand, the presence of the algorithm and its suggestions might still reduce strategic uncertainty.

When applying the awareness criterion, a particular question may concern contractual arrangements existing between the company and the third party. Such arrangements could specifically prohibit the third party from using the company's data for other than the contractual purposes, from disclosing that data to other companies, and/or even from providing consulting or software developing services to competitors. It would depend on the peculiarities of the case at hand whether one could deem a breach of such a contractual clause by the third party to be foreseeable for the company within the meaning of the ECJ's jurisprudence.

Finally, if an algorithmic collusion involves a third party, this third party might also be liable under Art. 101 TFEU. The ECJ has already clarified that cartel facilitators can be held liable irrespective of whether they operated in the same market in which the anti-competitive behaviour took place.¹⁶¹ More recently, ADLC has also issued a decision about a facilitator.¹⁶² In this case, the GIE Notimo (Economic Interest Group), a network of 21 notaries, in anticipation of the end of the regulated tariff, secretly elaborated a single "tariff grid" for notaries of the network, with the aim of impeding the application of the law providing for the free setting of his service rate by each notary. The professional order (the chamber of notaries), by making its secretariat available to

¹⁵⁶ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 41.

¹⁵⁷ *Paris Court of Appeal*, Decision of 18.07.18, Case n° 16/01270, p. 55.

¹⁵⁸ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 44.

¹⁵⁹ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 46.

¹⁶⁰ *ECJ, Eturas et al. v Lietuvos Respublikos konkurencijos taryba*, Judgment of 21.01.16, Case C-74/14, para. 49.

¹⁶¹ *ECJ, AC-Treuhand v Commission*, Judgment of 22.10.15, Case C-194/14 P.

¹⁶² *ADLC*, Decision 19-D-12 of 24.06.2019 (<https://www.autoritedelaconurrence.fr/fr/decision/relative-des-pratiques-mises-en-oeuvre-par-des-notaires-dans-le-secteur-de-la-negociation>) regarding practices implemented by notaries in the sector of estate negotiation.

the GIE Notimo, facilitated the agreement: e-mails, faxes and letters relating to the terms of implementation of the agreement were sent to members of the network from the addresses of the chamber.

bbb) Potential competition concerns

As described, same or somehow coordinated third party algorithms can lead to an alignment of algorithmic decision-making at different levels. Also, the extent to which an alignment can be observed can differ significantly. It will depend on the particularities of each case whether the use of a third party algorithm constitutes an agreement or concerted practice restricting competition by object or by effect.

The cases discussed in this scenario mainly concern pricing algorithms. The potential alignment described above relates in particular to prices, price parameters and data relevant in the context of price setting, i.e. a peculiarly sensitive aspect of competition. Concertation as to prices or price parameters is often considered to be harmful to the proper functioning of normal competition by its very nature. It will likely constitute a restriction of competition by object. At the same time, authorities might enjoy a margin of discretion to set priorities in their enforcement activities, thus potentially assessing the extent of an agreement restricting competition (by object or by effect) by a number of factors. These factors include, in particular, the content of the agreement or concerted practice and the objective aims pursued by it. The competitive concerns also depend on the market context in which a concertation takes place. In the cases of third party algorithms a relevant aspect in this respect can be market coverage.

The use of third party algorithms by competitors could in particular constitute a restriction of competition when there is an alignment of prices or pricing parameters at code level.¹⁶³ Cases where identical algorithms are used by competitors and possibly even uniform prices set by the algorithm might amount to price fixing. Where algorithms are only partly identical and commonalities are limited to certain economic factors of price setting, this might – depending on the facts of each case – still have the potential to reduce strategic uncertainty amongst competitors. Such an alignment might, by its very nature, reduce the decision-making independency of the competitors using coordinated third party algorithms. As seen in the Eturas case, even coordination limited to a single pricing parameter (here: a discount) can be sufficient to establish an infringement of Art. 101 TFEU.¹⁶⁴ Depending on the case, even algorithms that only suggest prices but do not provide automated price setting, might have the potential to reduce strategic uncertainty amongst competitors and thus might constitute a restriction of competition.

Where the use of the same or somehow coordinated third party algorithms involves an alignment at data level, the established assessment principles for information exchange apply.¹⁶⁵ Whether

¹⁶³ Concerning the distinction between alignment at code and at data level, cf. part III.B.2.a)aa), pp. 33 et seq., *vide supra*.

¹⁶⁴ Also cf. *BKartA*, Press release of 03.07.09 (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2009/03_07_2009_Silostellgebuehr.html) concerning an agreement in the mortar sector to charge a set-up fee for erecting dry mortar silos in addition to the costs for the mortar.

¹⁶⁵ For the general principles on information exchange see *Commission*, Horizontal Guidelines, 2011, paras. 55 et seq.

an information exchange constitutes an infringement of Art. 101 TFEU always depends on the particularities of the individual case. The type of information and the specific market conditions play a particular role in this respect.¹⁶⁶ Regarding the type of information in particular the exchange of sensitive information that reduces strategic uncertainty in the market may raise concerns. For example, where the algorithm relies on competitors' data relating to prices (for example future or actual prices or discounts), production costs, quantities, turnovers or capacities, this might raise competition concerns.¹⁶⁷ Other factors to be taken into account when assessing an information exchange include the age or currentness of the data, the extent to which the data is individualised or whether the data is public or not.

The way the data is used in the context of the algorithm may also play a role. Where the third party algorithm facilitates a direct information exchange amongst competitors, this could be treated as any other (offline) information exchange amongst competitors. However, similar concerns might also surface when information is not directly exchanged amongst competitors, but "only" used as an input for algorithmic pricing (e.g. an algorithm which is based on a shared data pool of sensitive real-time data). And even where the third party provides algorithms that calculate prices separately for each competitor, competition concerns might be brought up when the third party uses a common pool of training data including non-public data by multiple competitors. In this context, the CMA has stated that

*"[t]here could still be competition concerns if there was an exchange of historic, competitively sensitive, non-public information during the development (i.e. the 'training' phase) of the algorithm, even if no such data were further supplied during the 'live' phase of the algorithm being used to recommend/set prices."*¹⁶⁸

Furthermore, even the exchange of publicly available information (or information easily accessible via scraping software) can involve a restriction of competition, if the modalities of the exchange enable the undertakings to become aware of that information more simply, rapidly and directly.¹⁶⁹ Thus, it might suffice that the software provided by a third party facilitates the gathering, processing and evaluation of publicly available information to constitute an anticompetitive information exchange.

¹⁶⁶ Cf. e.g. *BKartA*, Press release of 07.12.17 (https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2017/07_12_2017_Zement_Plattform.html?nn=3591568) on planned launch of cement trading platform; *BKartA*, Case summary of 27.03.18, Case B5-1/18-001 (https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Kartellverbot/2018/B5-1_18-001.html) on planned launch of an electronic trading platform for steel products (XOM Metals), and *BKartA*, Case summary of 26.09.11, Case B2-118/10 (<https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Kartellverbot/2011/B2-118-10.html>) concerning the design of market information systems for the procurement of raw milk.

¹⁶⁷ Also cf. part II.B, pp. 8 et seq., *vide supra*.

¹⁶⁸ *CMA*, Pricing algorithms, 2018, p. 27, fn. 35 (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf).

¹⁶⁹ Cf. *GC*, *Tate & Lyle et al. v Commission*, Judgment of 12.07.01, Joined Cases T-202/98, T-204/98 and T-207/98, para. 60; *GC*, *Fresh Del Monte Produce v Commission*, Judgment of 14.03.13, Case T-587/08, para. 369.

In addition to the content of the algorithmic alignment, market coverage might also play a role in the assessment. There can be significant differences as to the extent the companies involved in the algorithmic alignment cover the market. On the one hand, cases could be envisioned in which only a few marginal competitors use the same or somehow coordinated algorithms, e.g. a few small retailers using the same standardized pricing software. On the other hand, situations could exist in which all or a large part of competitors in an oligopolistic market use aligned algorithms. An information exchange could be more likely to restrict competition when the companies involved in the exchange cover a sufficiently large part of the relevant market.¹⁷⁰ Otherwise, the competitors that are not participating in the information exchange could potentially constrain any anti-competitive behaviour of the companies involved. There may thus be cases of algorithmic alignment which due to their negligible market coverage do not constitute a restriction of competition. However, what would constitute a sufficient market coverage cannot be defined in the abstract and will depend on the specific facts of each case. In any case, where there is no by object restriction of competition and the market coverage is below the relevant thresholds of the *Commission's* De Minimis Notice or its equivalent national counterparts, an appreciable restriction usually can be excluded. Finally, as already mentioned above, market coverage might also be an aspect to be taken into account when an authority decides (not) to take up a case within its discretionary power.

Delegation of strategic decisions to a third party that takes these decisions using an algorithm

There may also be situations in which competitors knowingly delegate strategic decisions (such as pricing) to a third party that then takes these decisions using an algorithm.¹⁷¹ For example, a consultancy or a provider of “software as a service” could act as an agent for e.g. retailers entrusting this agent with dynamic price setting for the respective retailers’ online shops or an online marketplace. In such a case, the agent might use an algorithm (irrespective of its type and complexity) that automatically sets or adapts the respective prices using interfaces of online shops or marketplaces.

Furthermore, the third party could be a provider of additional services, while at the same time taking decisions on parameters of the interaction that it mediates between the competitors and their demand side. In this case, the latter decisions might have a certain connection to the further services that the third party provides.¹⁷² For example, such a third party could operate a platform that offers matching of supply and demand – as in the case of dynamic ridesharing, where platforms such as Uber act as intermediaries between drivers and passengers. In such situations, concerns that arise due to competitors relying on one and the same third party could be particularly pronounced since delegation might imply a *continuous* exchange between each competitor and the common third party. Moreover, concerns might reach far beyond the exchange

¹⁷⁰ In the context of an information exchange having restrictive effects on competition cf. *Commission*, Horizontal Guidelines, paras. 87 et seq.

¹⁷¹ Cf. *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1788): they refer to Uber as well as a “third-party pricing strategist”.

¹⁷² Cf. e.g. *Monopolies Commission*, XXII. Biennial Report 2018, paras. 192-194; for a more detailed discussion, cf. e.g. *Chen/Mislove/Wilson*, Peeking Beneath the Hood of Uber, 2015 (https://www.ftc.gov/es/system/files/documents/public_comments/2015/09/00011-97592.pdf); *Anderson/Huffman*, The Sharing Economy Meets the Sherman Act, Columbia Business Law Review 2017, pp. 859 et seq.

of specific information as both expectations and intentions about future developments of the respective market as well as strategies are built on the part of the common third party.

Depending on the particular case, such situations might raise specific questions, e.g. on the relationship between and the roles of the respective competitors and the third party. In particular in the sharing economy it might not always be clear (i) whether the respective “competitors” are undertakings and (ii) whether transactions would take place at all in absence of a common third party (platform).¹⁷³

Furthermore, if reliance on a common agent (or underlying agreements) were deemed to be anticompetitive and potentially violating competition law in a specific case, it might still be justifiable, in particular if it is inseparably connected with and indispensable for the provision of other services featuring counterbalancing benefits/efficiencies.¹⁷⁴ In this context, details of the delegated strategic decisions might need to be considered, in particular whether the decisions need to be binding. For example, it might not be clear how far positive effects would be mitigated if competing principals could deviate from prices set by the common agent by negotiating or offering individual rebates.

b) Competitors unknowingly use the same or somehow coordinated third party algorithm

Companies could also use algorithms developed by a third party without being aware that their competitors are relying on the same third party (in the sense of not knowing and not being able to reasonably foresee it).¹⁷⁵

As in the previous section, the use of such algorithms may not be neutral for competition. It could equally lead to an alignment of competitors’ behaviour at code level or at data level. As explained above, in order to establish an infringement by the competitors themselves, they must be at least aware of the third party’s anticompetitive acts or could have at least reasonably foreseen them. Where this is not the case, the conduct may be apprehended as a legal parallel behaviour on the part of the competitors.

One might, however, contest the likelihood of these situations in the first place. In particular, independent third parties often submit themselves to codes of conduct that require them to

¹⁷³ *Competition Commission of India*, Order of 06.11.18, Case No. 37 of 2018, paras. 20-22; *Commission*, A European agenda for the collaborative economy, Communication of 02.06.16 (<https://ec.europa.eu/docsroom/documents/16881/attachments/2/translations/en/renditions/pdf>). For a further analysis of the delegation of strategic (pricing) decisions, cf. e.g.

Foros/Kind/Shaffer, Apple’s agency model and the role of most-favored-nation clauses, *RAND Journal of Economics* 2017, pp. 673 et seq.; *Bonanno/Vickers*, Vertical Separation, *Journal of Industrial Economics* 1988, pp. 257 et seq.; *Bernheim/Whinston*, Common Agency, *Econometrica* 1986, pp. 923 et seq.

¹⁷⁴ *Monopolies Commission*, XXII. Biennial Report 2018, paras. 258-261; *Conseil de la concurrence*, Decision of 07.06.18, Case No. 2018-FO-01 (<https://concurrence.public.lu/fr/decisions/ententes/2018/decision-2018-fo-01.html>).

¹⁷⁵ Regarding a situation in which only one competitor and the third party are aware of the common use of the algorithm, see fn. 140, *vide supra*.

disclose to their client if they might find themselves in a conflict of interest, e.g. when they advise competitors.

From the perspective of competition law, such hypothetical situations may have detrimental effects to competition anyhow. There have been suggestions to discuss a change of the legal framework in a way that would expressly cover the liability of third party providers of algorithms in such cases.¹⁷⁶

3. Collusion induced by the (parallel) use of individual algorithms

This section focusses on collusion induced by the parallel use of individual algorithms in absence of any prior or ongoing communication or contact between the respective companies' human representatives. The hypothesis in the situations covered by this category is that an alignment might result from a mere interaction of computers. The discussion on this scenario is mainly hypothetical as so far there seems to be no case practice, and the relevance of this scenario is yet to be confirmed.¹⁷⁷

The following first subsection illustrates potential situations which might evolve within this scenario (a). The second subsection deals with the debate on the plausibility and likelihood of purely algorithmic collusion (b). Finally, the third subsection concerns legal aspects of the specific scenario under discussion here (c).

a) Potential situations covered by this scenario

The algorithms covered by this scenario are unilaterally designed and implemented, i.e. each company uses a distinct pricing algorithm. In that scenario, there is no prior or ongoing communication or contact between the respective companies' human representatives. Still, the fact that several or even all competitors rely on pricing algorithms might facilitate an alignment of their market behaviour.

While the situations have in common that collusion might be a potential outcome, the complexity of algorithms used may vary. As explained above,¹⁷⁸ one can roughly distinguish between descriptive and black-box algorithms. When an algorithm is descriptive, it is possible to identify the strategy and the actions that result from using the algorithm via the code of the algorithm. In contrast, black-box algorithms are much less interpretable. The strategy that results from using such an algorithm often cannot be fully identified just from its code. More "autonomous" models translate to algorithms not explicitly defining a particular pricing strategy. In particular, using such methods does not necessitate building an explicit model of the behaviour of the market before developing a strategy to respond to it.

¹⁷⁶ *Monopolies Commission*, XXII. Biennial Report 2018, paras. 269 et seq. In this report, one option contemplated (but not specifically recommended) is to structure the responsibility in such a way that liability does not depend on the behaviour of the users of the algorithm as before, but exclusively on the behaviour of the IT service provider itself.

¹⁷⁷ Also cf. *Schwalbe*, Algorithms, Machine Learning, and Collusion, *Journal of Competition Law & Economics* 2018, pp. 568 et seq. (596): "To date, there has been no case, legal or otherwise, in which autonomous algorithms have learned to coordinate their price-setting behavior to maximize joint profits and thereby collude tacitly".

¹⁷⁸ Cf. part II.C.2, pp. 11 et seq., *vide supra*.

In a similar vein, *Ezrachi/Stucke*¹⁷⁹ distinguish between a “predictable agent” and a “digital eye” scenario. They characterize their “predictable agent” scenario by stating that “*humans unilaterally design the machine to deliver predictable outcomes and react in a given way to changing market conditions*”.¹⁸⁰ Their “digital eye” scenario covers situations where the computer is set a target such as profit maximisation and the algorithm then operates autonomously to achieve the target. Here, “*tacit coordination – when executed – is not the fruit of explicit human design but rather the outcome of evolution, self-learning, and independent machine execution*”.¹⁸¹

Little is known so far on how a collusive outcome is reached in the scenarios discussed here. As the *OECD* states with regard to self-learning algorithms: “*It is still not clear how machine learning algorithms may actually reach a collusive outcome*”.¹⁸² In particular it is not clear whether algorithms would manage to coordinate strategic behaviour tacitly, or whether this would rather be based on some kind of “communication of algorithms”.

The recent debate largely focuses on collusion induced by unilateral behaviour of algorithms. Although there might be countervailing effects, it is often assumed that because algorithms allow for a greater market transparency and faster reactions to market changes, they might lead to tacit collusion without the need for further communication.¹⁸³ For example, the two above-mentioned scenarios considered by *Ezrachi/Stucke* focus on unilateral behaviour of algorithms resulting in conscious parallelism.¹⁸⁴

Collusion facilitated by simple undercutting or “price-matching” algorithms?

While the economic debate on collusion often focuses on dynamic games with a potentially infinite or long time horizon, incentives to maintain supra-competitive prices might also evolve in less forward-looking scenarios, without considering an infinite time horizon.

In particular, simple undercutting or “price-matching” algorithms can provide such incentives, at least if they adjust prices in the same direction as (monitored) competitors do. Indeed, once a company learned about its competitor’s algorithm immediately reacting to a price reduction by reducing its own price (possibly to the same extent), it could anticipate that price reductions do not pay off in terms of a demand shift, leaving prices unchanged (possibly at a supra-competitive level).¹⁸⁵ These incentives might be quite similar to effects identified by the considerable

¹⁷⁹ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq.

¹⁸⁰ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1783).

¹⁸¹ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1795).

¹⁸² *OECD*, Algorithms and Collusion, 2017, p. 31 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

¹⁸³ See part III.A, pp. 15 et seq., *vide supra*, for a more detailed discussion.

¹⁸⁴ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1783, 1795).

¹⁸⁵ In a partly similar manner, *Ezrachi/Stucke* explain that one variant of their “predictable agent” scenario might be characterized by each rival’s response being a best response, but not motivated by retaliation or deterrence nor intended to sustain an agreed-upon market outcome, cf. *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1790).

literature on so called “price relationship agreements”, in particular “across-sellers agreements” like low-price guarantees, price-matching or price-beating guarantees or meet-or-release clauses under which a seller guarantees customers not to offer conditions worse than those offered by competitors.¹⁸⁶

Beyond algorithms reaching tacit collusion, the question arises whether algorithms could engage in behaviour more similar to explicit forms of collusion. The *Commission* considers such a scenario by posing the question “*whether pricing algorithms could, without explicit instructions to do so, engage in explicit collusion with each other*”.¹⁸⁷ Similarly, *Schwalbe* points out that

*“[...] the question arises whether algorithms are able to communicate with each other or whether different algorithms might even be able to learn to communicate without being explicitly programmed, that is, without a common communication protocol.”*¹⁸⁸

However, so far little is known about the actual real-world use of advanced techniques for pricing purposes. In particular, it remains to be seen if and how pricing algorithms can arrive at some kind of communication. This uncertainty is partly caused by the fact that the exact nature of potential “algorithmic communication” cannot be anticipated. For example, it is not clear yet whether algorithms could open up a “private channel” more or less autonomously to exchange sensitive information and/or indicate their current or future strategy to each other. Most often, the possibility of such or similar spontaneous complex interactions is raised in the context of artificial intelligence black-box algorithms. According to *Schwalbe*

*“[...] considering the rapid progress in research on AI, it cannot be ruled out that algorithms may learn to communicate and thereby increase the likelihood of algorithmic collusion”.*¹⁸⁹

In this context, a specific form of communication could be signalling practices, i.e. situations in which algorithms indicate to competitors an intent to change a relevant parameter of competition such as the price.¹⁹⁰ As the *OECD* points out,

“[a]lgorithms might reduce or even entirely eliminate the cost of signalling, by enabling companies to automatically set very fast iterative actions that cannot be exploited by consumers, but which can still be read by rivals possessing good analytical algorithms. [...] For

¹⁸⁶ Cf. *Schwalbe*, Algorithms, Machine Learning, and Collusion, *Journal of Competition Law & Economics* 2018, pp. 568 et seq. (574). For a review of the literature on price relationship agreements, see for instance *Aguzzoni/Buccirosi/Ciari/Corts/Tognoni/Spagnolo/Vitale/Zampa/di Giò*, Can ‘fair’ prices be unfair? A review of price relationship agreements, study by LEAR for OFT, (<http://www.learlab.com/wp-content/uploads/2016/04/Can-%E2%80%98Fair%E2%80%99-Prices-Be-Unfair-A-Review-of-Price-Relationship-Agreements.pdf>).

¹⁸⁷ *OECD*, Algorithms and Collusion – Note from the European Union, 14.06.17, para. 28 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)); *Käseberg/von Kalben*, Herausforderungen der Künstlichen Intelligenz für die Wettbewerbspolitik, *Wirtschaft und Wettbewerb* 2018, pp. 2 et seq. (4).

¹⁸⁸ *Schwalbe*, Algorithms, Machine Learning, and Collusion, *Journal of Competition Law & Economics* 2018, pp. 568 et seq. (594).

¹⁸⁹ *Schwalbe*, Algorithms, Machine Learning, and Collusion, *Journal of Competition Law & Economics* 2018, pp. 568 et seq. (596).

¹⁹⁰ *OECD*, Algorithms and Collusion – Note from the European Union, 14.06.17, para. 27 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

instance, firms may program snapshot price changes during the middle of the night, which won't have any impact on sales but may be identified as a signal by rivals' algorithms."¹⁹¹

b) Debate on the plausibility/likelihood of purely algorithmic collusion

As discussed above, theoretical economic research has identified several parameters that affect the stability and/or establishment of collusion and has also elaborated on potential impacts of the use of algorithms on these parameters.¹⁹²

At the same time, there is a growing body of research considering the plausibility of algorithmic collusion by analysing concrete technical implementations of algorithms in specific, mostly experimental, settings. In other words, pricing algorithms are tested in research laboratories of universities by making them interact in an experimental setting that mimics a competitive environment.

Most of these implementations apply algorithms that could be classified as black-box algorithms. More precisely, the papers considered below often rely on Q-learning algorithms, a specific type of reinforcement learning algorithms. As stated above, reinforcement learning algorithms are designed to maximize the present value of a flow of rewards in a repeated choice setting. In order to do so, these algorithm must arbitrate, for every action they perform, between "exploration" (choosing a random action to improve current knowledge of the environment – "learning phase"), and "exploitation" (choosing the action that will maximise the present value of future flows given the algorithm's current knowledge of the environment). In Q-learning algorithms, a few settings have to be made during the initialization phase, as for instance the choice of an exploration strategy, which determines the balance between "exploration" and "exploitation", and the choice of the learning rate, which constitutes the weight assigned to new information relative to old information. The algorithm may also be provided with an initial knowledge on the payoffs associated with each possible state of the game. *Calvano/Calzolari/Denicolo/Pastorello* explain their choice to rely on Q-learning algorithms by notably pointing out their popularity among computer scientists as well as their simplicity, including the fact that the few parameters they rely on can easily be interpreted in economic terms.¹⁹³

In many instances, those experiments, aiming to simulate competition between companies that rely on pricing algorithms, have led to a certain degree of cooperation¹⁹⁴ between the simulated players. In other words, in these rather basic experiments, evidence of collusion between algorithms is likely to be found. As will be seen however, these experiments also rely on certain strong assumptions so that their results may not be straightforwardly transposed to real-world settings. Below (aa-gg), these assumptions and whether they could constitute obstacles to the

¹⁹¹ OECD, Algorithms and Collusion, 2017, p. 30 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

¹⁹² Cf. part III.A, pp. 15 et seq., *vide supra*.

¹⁹³ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

¹⁹⁴ For example, studies report the number of steps needed for algorithms to converge to supra-competitive outcomes, the fraction of simulations that led to supra-competitive outcomes and/or the level of supra-competitive prices or profits enabled by the algorithms, often as a percentage of the supra-competitive prices or profits that a perfectly collusive scheme (monopoly) would entail.

emergence of algorithmic collusion in a real-world setting will be discussed in particular by reviewing results of some recent and more sophisticated experimental studies.

aa) Transparency of the market and degree of common knowledge between competitors

Many of the experimental settings leading to algorithmic collusion require a certain degree of common knowledge. This common knowledge can concern demand conditions, for instance, but in many of the experimental studies on algorithmic collusion,¹⁹⁵ it also concerns competitors' prices. As argued e.g. by *Tesauro/Kephart*¹⁹⁶, some of these assumptions may not be realistic in all settings.¹⁹⁷

bb) Time horizon

Even if a collusive outcome can be reached solely through the (inter)actions of algorithms, its emergence will in many cases require a significant number of preceding interactions in order to yield a sufficiently large amount of data to allow the training of the algorithm (i.e. sufficient "exploration"). For instance, while in *Tesauro/Kephart*¹⁹⁸, convergence towards a collusive equilibrium may in some instances be observed after only 200 interactions, in *Calvano/Calzolari/Denicolo/Pastorello*, collusion is attained, on average, after 70.000 steps of repeated interaction.¹⁹⁹ The number of steps required to attain collusion may notably depend on the types of algorithms used as well as on the simplifying assumptions made to model the interactions in the market. For instance, *Klein* shows that the speed of convergence decreases as the number of discrete prices the algorithms may use increases.²⁰⁰ It is thus likely that the number

¹⁹⁵ See for instance *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, Autonomous Agents and Multi-Agent Systems 2002, pp. 289 et seq.; *Waltman/Kaymak*, Q-learning agents in a Cournot oligopoly model, Journal of Economic Dynamics and Control 2008, pp. 3275 et seq.; *Calvano/Calzolari/Denicolo/Pastorello*, Algorithmic pricing and Collusion: What Implications for Competition Policy, Review of Industrial Organization 2018, pp. 1 et seq.; *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>); *Klein*, Autonomous Algorithmic Collusion: Q-learning Under Sequential Pricing, Amsterdam Law School Research Paper 2019; and *Crandall/Oudah/Tennom/Ishowo-Oloko/Abdallah/Bonnefon/Cebrian/Shariff/Goodrich/Rahwan*, Cooperating with machines, Nature Communications Vol. 9 2018; all of them assume full knowledge on the current state of the market and opponents' price and some on past actions. See *Leibo/Zambaldi/Lanctot/Marecki/Graepel*, Multi-agent reinforcement learning in sequential social dilemmas, AAMAS '17 Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems 2017, pp. 464 et seq. for a generalization of these models to an incomplete information setting.

¹⁹⁶ *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, Autonomous Agents and Multi-Agent Systems, 2002, pp. 303 et seq.

¹⁹⁷ See also *Green/Marshall/Marx*, Tacit collusion in oligopoly, in: *Blair/Sokol*, Oxford Handbook of International Antitrust Economics Vol. 2, 2015, pp. 464 et seq. (481), who in particular consider "common knowledge, and mutual knowledge about other players' mental states (e.g., intentions, beliefs)". They refer to it as "higher-order knowledge", which they think might be unrealistic to achieve without a certain form of communication between companies.

¹⁹⁸ *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, Autonomous Agents and Multi-Agent Systems, 2002, pp. 297 et seq.

¹⁹⁹ *Calvano/Calzolari/Denicolo/Pastorello*, Algorithmic pricing and Collusion: What Implications for Competition Policy, 2018, pp. 1 et seq. (11) (https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3209781).

²⁰⁰ *Klein*, Autonomous Algorithmic Collusion: Q-learning Under Sequential Pricing, Amsterdam Law School Research Paper, 2019.

of steps needed to attain collusion would be higher in real-life markets, where, for instance, prices are not set as a limited number of discrete values.

A large number of interactions before collusion is attained may not be prohibitive if, for instance, these interactions only occur in a laboratory: in that setting, no real losses may be associated with the exploration strategies implemented by the algorithms.²⁰¹ However, such virtual settings are unlikely to be used by companies. First, sandbox testing of competing pricing algorithms may amount to a direct communication between companies and thus may not be legal. Second, in its learning phase, the algorithm may not only need the competitors' prices but also some data about the level of demand and how it reacts to the implemented prices. Furthermore, some time may be needed in order to observe these demand reactions.

Hence, during this (potentially long) learning/training phase, profits might be significantly lower than before the adoption of the pricing algorithm in question. It is therefore questionable whether the company will tolerate these possible losses sufficiently long to allow the learning phase to conclude and thus whether the company will be willing to engage in such practices in the first place.²⁰²

cc) Stability of the competitive environment

The experimental settings used to assess the plausibility and impact of algorithmic collusion so far typically assume a stable market environment. Yet, in most real-world settings, the competitive environment will from time to time undergo changes. Particularly frequent or significant changes might destabilize the interaction of algorithms.

Examples of factors that can contribute to the deviation from a stable or stationary setting include entries of new players, (stochastic) demand shocks or changes in other conditions not resulting from competitors' behaviour. Instability can also arise through the adoption or adaptation of algorithms themselves: As a newly adopted or revised algorithm will influence the respective company's behaviour, frequent revisions will tend to inhibit algorithmic collusion.²⁰³

There are several ways in which algorithmic decision-making might react when confronted with market-instability.²⁰⁴ The effects of these different options on the likelihood that a (collusive)

²⁰¹ See for instance *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>). The authors argue that “[i]n practice, the issue of the slowness of learning is addressed by training the algorithms off the job, that is, before putting them to work”.

²⁰² Note that some empirical results indicate that in certain instances the interplay of algorithms might converge to a collusive state even if not all of the actors have long-term preferences, cf. *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, *Autonomous Agents and Multi-Agent Systems* 2002, pp. 289 et seq. (297).

²⁰³ Cf. *Salcedo*, Pricing Algorithms, *Essays in economic theory*, Thesis, The Pennsylvania State University 2016, pp. 37 et seq. (48), where the frequency of revisions is set arbitrarily low in order to derive the collusion outcome.

²⁰⁴ In many cases, algorithms will not explicitly recognize non-stationarities and thus, simply put, ignore them. In other cases, the algorithm can be instructed to discount information from the past by assigning higher relevance to recent data. Other more advanced concepts for dealing with non-stationarities (for example those introduced in *Hernandez-Leal/Kaisers/Baarslag/Munoz de Cote*, A Survey of Learning in Multiagent Environments: Dealing with Non-Stationarity, 2017, pp. 1 et seq.,

equilibrium will be reached might vary and are a subject of ongoing research. For instance, in their recent paper, *Calvano/Calzolari/Denicolo/Pastorello* on the one hand illustrate that the introduction of stochastic demand shocks only slightly decreases the extent of collusive behaviour. On the other hand, random entry and exit of one company induces a significant decrease in supra-competitive profits, which may result both from the effect of increasing the number of players from two to three as well as from the uncertainty created by the variable market structure.²⁰⁵

dd) Degrees of freedom and complexity of the algorithm

Degrees of freedom are conceptually linked to the range and diversity in possible behaviours the algorithm could adopt. Although there might be both complex algorithms with a small number of degrees of freedom and relatively simple algorithms allowing a large number of degrees of freedom²⁰⁶, an increase in degrees of freedom tends to come along with a higher complexity.

A larger number of degrees of freedom in the technical sense can generate a larger number of degrees of freedom in the economic sense. For instance, whereas a simpler algorithm might only adapt the price of a single product at certain given points in time, models with higher flexibility can determine a wide range of parameters of a broader product policy. For example, models with higher flexibility may allow more sophisticated strategies such as unrestricted pricing for multiple products or strategic decisions in multiple dimensions such as quantity, quality and variety. Conversely, some models considering the behaviour of pricing algorithms put strong restrictions on the set of actions that can be decided, for instance allowing only for two price levels, one “high” and one “low”.²⁰⁷ In this case, there are much fewer possible combinations of possible values for inputs (past and current prices) and outputs (future prices) than in models allowing more flexibility in pricing.

The effect of broadening the scope for possible behaviour of an algorithm on the likelihood of collusion currently seems ambivalent. On the one hand, a greater flexibility of the algorithm seems to facilitate cooperation in some instances.²⁰⁸ On the other hand, the need to learn values for a

<https://www.researchgate.net/publication/318785642> *A Survey of Learning in Multiagent Environments Dealing with Non-Stationarity*) fall outside the scope of this short overview.

²⁰⁵ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²⁰⁶ An example for the latter would be a simple linear regression with a large number of independent input variables, consequently allowing a reaction to a significant range of (measurable) changes in the economic environment. Conversely, more complex algorithms such as neural networks, that are often associated with a large number of parameters, might limit the number of inputs in some cases, for example to avoid overfitting on small data sets.

²⁰⁷ Cf. e.g. *Calvano/Calzolari/Denicolo/Pastorello*, Algorithmic pricing and Collusion: What Implications for Competition Policy, 2018, pp. 1 et seq.

(https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3209781). A more recent paper by the same authors considers a wider scope of price values, see *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²⁰⁸ See for example *Leibo/Zambaldi/Lanctot/Marecki/Graepel*, Multi-agent reinforcement learning in sequential social dilemmas, AAMAS '17 Proceedings of the 16th Conference on Autonomous Agents and MultiAgent Systems 2017, pp. 464 et seq. (<https://dl.acm.org/citation.cfm?id=3091194>), where deeper networks seem to cooperate more often than shallow ones in games where cooperative strategies are harder to learn.

(possibly unnecessarily) large number of parameters might slow down learning and require a larger set of training data. In several papers it is speculated that increasing the number of possibilities to approach a more realistic model would increase the computational burden and the time needed for competing algorithms to converge.²⁰⁹ For instance, as mentioned above, *Klein* shows that the speed of convergence decreases as the number of discrete prices which the algorithms may use increases. This result matches that of *Calvano/Calzolari/Denicolo/Pastorello*²¹⁰ who show that, when holding the number of iterations constant, a finer discretization of feasible prices reduces supra-competitive profits. This loss in profits is attributed to the increased exploration needed to achieve a given level of learning. The authors also explore the effects of other sources of complexity for the algorithms (e.g. increased number of players, stochastic demand²¹¹ or variable market structure), which all individually lead to a reduction in supra-competitive profits, albeit of different magnitudes.

However, it would seem that the reductions in supra-competitive profits generated by a wider set of algorithms' choices are generally small.²¹² Yet, a real-life market environment is likely to encompass several sources of complexity simultaneously. Their joint effect on the likelihood of collusion remains an open question for future economic research.

ee) Initialization, exploration strategy and learning rate

Machine learning algorithms, in particular reinforcement learning methods, typically need to be provided with an initialization determining their behaviour at the very beginning of the learning phase. This can be solved in several ways, for example by prescribing initial random exploratory behaviour²¹³ or by providing a perhaps more natural starting point as for example a certain equilibrium²¹⁴. In a real-life setting, the quality of the initialization of the algorithm is likely to depend both on the companies' knowledge of the environment as well as on the know-how of the developer to correctly transcribe this knowledge into the parameters of the algorithm.

Although the importance of the initialization on further progress in learning has not been fully understood yet, some studies show that this initialization may have an influence both on the likelihood of collusive behaviour as well as on the relative profits of the companies.

²⁰⁹ See for instance *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, Autonomous Agents and Multi-Agent Systems, 2002.

²¹⁰ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²¹¹ The term "stochastic demand" refers to a situation in which demand for a good or service evolves "randomly" over time. The introduction of stochastic demand is meant to mimic real-life conditions of markets in which demand is likely to vary in time.

²¹² For instance, *Calvano/Calzolari/Denicolo/Pastorello* show that increasing the number of discrete prices that the algorithms can set from 15 to 100 only decreases the supra-competitive profits of the firms from 85% to 70% of what these supra-competitive profits would be under full collusion.

²¹³ *Crandall/Oudah/Tennom/Ishowo-Oloko/Abdallah/Bonnefon/Cebrian/Shariff/Goodrich/Rahwan*, Cooperating with machines, Nature Communications Vol. 9 2018, Supplementary Notes, pp. 1 et seq. (25).

²¹⁴ Cf. e.g. *Calvano/Calzolari/Denicolo/Pastorello*, Algorithmic pricing and Collusion: What Implications for Competition Policy, 2018, pp. 1 et seq. (12).

Some research supports the view that certain initializations might, for example, create a so-called optimistic learning bias and could lead to a preference of high-risk-strategies with potentially higher rewards, which can aid in minimizing the likelihood of arriving at myopic strategies.²¹⁵

Furthermore, in particular *Waltman/Kaymak*²¹⁶ show that the choice of the exploration strategy (i.e., the balance between “exploration” and “exploitation”) and of the learning rate (i.e., the weight assigned to new information relative to old information) has a complex influence on the likelihood of collusion. For example, decreasing the value of the learning rate may increase the likelihood of cooperation for a given exploration strategy but have the opposite effect when another exploration strategy is used. *Calvano/Calzolari/Denicolo/Pastorello*²¹⁷ further show that when assigning different learning rates to the two competing algorithms of a given experiment, the distribution of profits between the two competing companies changes, with one company increasing its profits relative to the other.

ff) Symmetry/similarity in terms of algorithms and companies

So far, most experiments consider so-called self-play, i.e., all agents using the same algorithm.²¹⁸ Moreover, often these algorithms are initialised with the same parameter values (e.g. similar learning rates) while agents (i.e., companies) are symmetric.

Yet, as regards the symmetry of companies, *Calvano/Calzolari/Denicolo/Pastorello*²¹⁹ consider the case of competition between asymmetric companies, with one company benefiting from a certain relative cost advantage. This asymmetry reduces the supra-competitive profits, although only to a limited extent. As regards the differences in terms of algorithms and initialization and in contrast to merely varying learning rates in *Calvano/Calzolari/Denicolo/Pastorello* mentioned just above, *Crandall et al.*²²⁰ consider a variety of algorithms playing against each other on a selection of two-player repeated stochastic games. They show that some algorithms consistently achieve higher degrees of cooperation than others. In particular, Q-learning algorithms, on which most of the experimental research considered above rely, may not be the best suited class of algorithms to reach a collusive outcome.

gg) Interim conclusion

While many experiments on algorithmic pricing show that some degree of collusion can be achieved, whether these results will transpose to a real-world setting seems uncertain at present.

²¹⁵ *Crandall/Goodrich*, Learning to Compete, Coordinate, and Cooperate in Repeated Games Using Reinforcement Learning, Machine Learning 2011, pp. 281-314 (288, 291).

²¹⁶ *Waltman/Kaymak*, A Theoretical Analysis of Cooperative Behavior in Multi-agent Q-learning, ERIM Report Services Research in Management, 2006.

²¹⁷ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²¹⁸ *Schwalbe*, Algorithms, Machine Learning, and Collusion, Journal of Competition Law & Economics 2018, pp. 568 et seq. (591).

²¹⁹ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²²⁰ See *Crandall/Oudah/Tennom/Ishowo-Oloko/Abdallah/Bonnefon/Cebrian/Shariff/Goodrich/Rahwan*, Cooperating with Machines, Nature Communications, Vol. 9, 2018 (<https://www.nature.com/articles/s41467-017-02597-8>).

Indeed, experiments on algorithmic collusion rely on strong assumptions on the economic environment. For instance, these settings may consider only two players, no risk of entry, a stable demand and/or discrete prices. However, in particular some recent results by *Calvano/Calzolari/Denicolo/Pastorello*²²¹ show that relaxing these assumptions individually may not decrease the risk of collusion to a great extent. Nevertheless, the joint effect of these assumptions on the results of current experiments is yet to be explored. Furthermore, the environment's complexity and instability may be greater than envisioned in their paper.

Also, even if collusion were attained in a real-world setting, experiments show that a significant number of iterations is required. During these initial iterations companies might expect profit losses, which they may deem unacceptable and may lead to a refusal to experiment with algorithmic pricing. Moreover, the number of iterations required may depend on the complexity of the environment. Hence, the number of iterations needed to attain collusion in the experimental studies may constitute a lower bound, thus further decreasing companies' willingness to engage in such practices. Further factors may be the quality of the initialization of the algorithms, the learning rate and the exploration strategy. Initializing the algorithm requires information on the economic environment as well as know-how from the developer. The quality of the initialization is likely to be only observable *ex-post*, therefore further reducing the companies' willingness to engage in algorithmic pricing. Yet, some results seem to indicate that the algorithms traditionally used in experiments on collusion are not necessarily the ones that allow for the highest degree of cooperation. In particular, other forms of algorithms may enable faster cooperation while relying less on the quality of their initialization.

Finally, even when assuming an algorithm which may achieve collusion in experiments replicating a realistic economic environment, almost all the games considered in these experiments postulate perfect and symmetric information at zero-cost and zero-delay. *Tesauro/Kephart* argue that these assumptions are unrealistic since "*the expected consumer demand for a given price pair [might not be] instantaneous, deterministic and fully known to both players*" and "*agents may not know the details of other agents' profit function, and indeed an agent may not know its own profit function, to the extent that buyer behaviour is unpredictable*".²²² With the exception of one extension considered by *Calvano/Calzolari/Denicolo/Pastorello*²²³, which includes stochastic demand, the effects of introducing uncertainty to the market also remains an open question for future research.

Despite the findings of several experimental studies that collusion can in principle be achieved, there is a significant number of researchers and practitioners who oppose the hypothesis that algorithms could plausibly establish coordinated behaviour by themselves in real markets.²²⁴ Such doubts are partially validated by some of the authors of the experimental studies not only mentioning certain limitations of their studies, but explicitly noting themselves that their studies

²²¹ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²²² *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, Autonomous Agents and Multi-Agent Systems 2002, pp. 289 et seq. (303).

²²³ *Calvano/Calzolari/Denicolo/Pastorello*, Artificial Intelligence, Algorithmic Pricing and Collusion, 2019 (<https://ssrn.com/abstract=3304991>).

²²⁴ *Kühn/Tadelis*, The (D)anger Behind Algorithmic Pricing, 2017 (mimeo); *Schwalbe*, Algorithms, Machine Learning, and Collusion, Journal of Competition Law & Economics 2018, pp. 568 et seq.

rely on unrealistic assumptions.²²⁵ Furthermore, some authors also oppose the idea that algorithmic capabilities to establish or stabilize collusion could exceed human capabilities.²²⁶

In essence, there are a number of different aspects which may play a role in the assessment of whether algorithmic collusion is plausible. Although there is an increasing body of research analysing algorithmic interaction, the relevance of the empirical studies has to be judged with an eye on their specific experimental setting, on the associated costs of algorithmic pricing, especially when the algorithm has to learn about the market, and the possible reluctance of companies to use certain kinds of algorithms. Overall, it currently seems to remain an open question whether an alignment of two or more pricing algorithms can likely arise “by chance” in settings that correspond to real market conditions.

c) Potential competition law aspects

As discussed before, it is not yet clear how and to what extent the parallel use of algorithms can lead to collusive outcomes when there is no prior or ongoing communication or contact between the respective companies’ human representatives. As there is no case practice yet, it is not possible at this stage to provide an extensive picture of the legal issues which might come up.

However, there are two aspects which are already broadly discussed in the current debate. First, there is the question of under which circumstances a collusive outcome via the parallel use of algorithms results from coordination rather than mere parallel behaviour (aa). Second, as the alignment of competitive behaviour results from mere interaction of computers, the extent to which a coordination caused by an algorithm can be attributed to an undertaking will be discussed (bb).

aa) Distinction between coordination and mere parallel behaviour

Competition law distinguishes between illegal explicit collusion and legal parallel behaviour.²²⁷ Art. 101 TFEU reflects this distinction by addressing agreements and concerted practices only. An agreement usually “*centres around the existence of a concurrence of will*”²²⁸. It requires some kind of communication and a sense of mutual commitment. A concerted practice involves a form of coordination between undertakings, which, without having been taken to the stage of concluding a formal agreement, have knowingly substituted practical cooperation for the risks of competition.²²⁹ A coordination can be constituted by direct or indirect contact between companies, the object or effect thereof is either to influence the conduct on the market of an actual

²²⁵ *Tesauro/Kephart*, Pricing in Agent Economies Using Multi-Agent Q-Learning, Autonomous Agents and Multi-Agent Systems 2002, pp. 289 et seq. (303).

²²⁶ Cf. e.g. *Ezrachi/Stucke*, Virtual Competition, 2016, pp. 56 et seq.

²²⁷ Cf. the first paragraphs of part III.B.1.b), p. 29, *vide supra*.

²²⁸ *GC, Bayer v Commission*, Judgment of 26.10.00, Case T-41/96, para. 69. Note that the parties need to somehow express their common will to act on the market in a certain way. This can also be done via a series of acts or continuous conduct if the various actions form part of an ‘overall plan’ which distorts competition (*ECJ, Nederlandse Federatieve Vereniging voor de Groothandel op Elektrotechnisch Gebied v Commission*, Judgment of 21.09.06, Case C-105/04 P, para. 110).

²²⁹ *ECJ, Suiker Unie v Commission*, Judgment of 16.12.75, Joined cases 40 to 48, 50, 54 to 56, 111, 113 and 114-73, para. 26.

or potential competitor or to disclose to such a competitor future intended conduct.²³⁰ Vice versa, Art. 101 TFEU does not prohibit what is regularly referred to as (mere) conscious parallel behaviour, i.e. situations in which each economic operator determines independently the policy which it intends to adopt on the common market.²³¹ Art. 101 TFEU does “*not deprive economic operators of the right to adapt themselves intelligently to the existing and anticipated conduct of their competitors*”.²³²

Accordingly, in the scenario at hand, algorithmic market behaviour resulting in a collusive outcome only falls within the scope of Art. 101 TFEU if there is direct or indirect contact between the algorithms, i.e. some sort of “algorithmic communication” as opposed to mere unilateral parallel behaviour. As seen above, it cannot be ruled out that algorithms might achieve such a sense of “algorithmic communication”, for example via a private channel to exchange sensitive information and/or indicate their current or future strategy to each other. Generally speaking, if practices are illegal when implemented “offline”, equivalent practices will be illegal when implemented “online”.²³³ For example, if black-box algorithms found a way to exchange sensitive information, the requirement of a communication would clearly be met.

However, it is yet unknown whether “algorithmic communication” is a realistic scenario²³⁴ and, if it is, in what shape it might come up. It is thus too early to further develop which type of algorithmic interaction might constitute an “algorithmic communication”. In any case, there needs to be an element of interaction which goes beyond unilaterally exploring the competitor’s pricing behaviour and adapting to it.

As algorithms allow for more rapid and sophisticated interaction compared to human interaction, it cannot be excluded that algorithms could develop other, more complex or subtle forms of interactions. The *Commission* has pointed out that there might be “*more creative and novel types of interactions*”²³⁵ which could in certain situations be characterized as “algorithmic communication”.

A particular issue in this respect is how far specific forms of algorithmic interactions could be addressed by the concept of signalling. Signalling describes situations of potential explicit collusion in which companies publicly announce an intent to change a relevant parameter of competition, e.g. their respective price. According to the Horizontal Guidelines, unilateral announcements that are “*genuinely public*” generally do not constitute a concerted practice.²³⁶

²³⁰ *ECJ*, *Suiker Unie v Commission*, Judgment of 16.12.75, Joined cases 40 to 48, 50, 54 to 56, 111, 113 and 114-73, paras. 173, 174.

²³¹ *ECJ*, *T-Mobile et al. v Raad van bestuur van de Nederlandse Mededingingsautoriteit*, Judgment of 04.06.09, Case C-8/08, para. 32.

²³² *ECJ*, *Suiker Unie v Commission*, Judgment of 16.12.75, Joined cases 40 to 48, 50, 54 to 56, 111, 113 and 114-73, para. 174.

²³³ *OECD*, *Algorithms and Collusion – Note from the European Union*, 14.06.17, para. 27 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

²³⁴ Cf. part III.B.3.b), pp. 45 et seq., *vide supra*.

²³⁵ *OECD*, *Algorithms and Collusion – Note from the European Union*, 14.06.17, para. 33 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

²³⁶ *Commission*, *Horizontal Guidelines*, para. 63. However, when signalling (or, more generally, information exchange) happens ‘in the public domain’, but the costs involved in collecting the

However, a concerted practice cannot be precluded in situations “*where such an announcement is followed by public announcements by competitors*”.²³⁷

As described above, algorithms might reduce the cost of signalling. While algorithms could be limited to a supporting role, allowing for the transmission and/or reception or monitoring of signals, they might also facilitate and accelerate (previously) human signalling practices. Furthermore, self-learning algorithms could even develop signalling capabilities as a special form of “communicative” skills.

In the offline-world, there have been few cases concerning signalling so far, with most of them focusing on explicit public announcements of intended future pricing. At the European level,²³⁸ the ECJ in the Imperial Chemical case held that by announcing prices in advance the undertakings eliminated “*all uncertainty between them as to their future conduct*”.²³⁹ In the more recent Container (Line) Shipping commitment decision, the *Commission* expressed the preliminary view that the regular early public announcements of intended future price increases by container liner shipping undertakings constituted a concerted practice and a by-object restriction.²⁴⁰ The practice in question “*may have had the objective of communicating pricing intentions to competitors rather than informing customers about price developments*”.²⁴¹ In this context, signalling might enable competitors to “test” a potential implementation of price increases without a risk of losing market share or triggering a price war,²⁴² strengthening the chance that price increases are supported by competitors and, hence, aligning the level and timing of price increases.²⁴³

respective information deter other companies and customers from doing so, this is not to be regarded as ‘genuinely public’ (*Commission*, Horizontal Guidelines, para. 92).

²³⁷ *Commission*, Decision of 07.07.16 (Container Shipping), Case AT.39850, para. 45; see also *Commission*, Horizontal Guidelines, para. 63.

²³⁸ There have also been some national cases dealing with related anticompetitive practices. It is, however, questionable whether these cases always satisfy the requirement of a ‘genuinely public’ announcement. In its sector inquiry into the cement and ready-mix concrete sector, the *BKartA* found that there is a widespread practice, at least in the cement sector, to send out generic price increase letters. In these letters the companies announced price increases to all customers, but the information was usually also received by their competitors. The *BKartA* expressed concerns about this practice and informed the companies involved about its preliminary legal assessment after the report was published (*BKartA*, Case summary of 14.02.18 (https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Kartellverbot/2018/B1-240_17.html)). Similarly, building on its market investigation, the *CMA* published an order which “sets out that suppliers of cement and cementitious products in Great Britain (GB) will be prohibited from sending generic price announcement letters to their customers.” (*CMA*, News story of 22.01.16 (<https://www.gov.uk/government/news/cma-publishes-final-cement-price-announcement-order>)). The *ACM* also dealt with announcements in the area of telecommunications. The announcements in question were made in the public domain about intended market behaviour, which harmed consumers and had not been finally decided on within the respective companies. The *ACM* issued a commitment decision eliminating the identified anticompetitive risks, but leaving open whether there was a violation of the Dutch Competition Act (*ACM*, Decision of 07.01.14 (<https://www.acm.nl/en/publications/publication/14326/Commitment-decision-regarding-mobile-operators>)).

²³⁹ *ECJ*, Imperial Chemical Industries Ltd. v Commission, Judgment of 14.07.72, Case 48/69, para. 101.

²⁴⁰ *Commission*, Decision of 07.07.16 (Container Shipping), Case AT.39850, paras. 45 et seq.

²⁴¹ *Commission*, Decision of 07.07.16 (Container Shipping), Case AT.39850, para. 52.

²⁴² *Commission*, Decision of 07.07.16 (Container Shipping), Case AT.39850, para. 37.

²⁴³ *Commission*, Decision of 07.07.16 (Container Shipping), Case AT.39850, para. 38.

There is yet no case involving algorithms in which the existing criteria were applied. However, it can already be foreseen that there are specific features of algorithmic interaction which might need to be considered when assessing algorithmic behaviour under the concept of signalling:

This, *inter alia*, concerns the earliness of announcements. In the decided cases, announcements took place well in advance and one of the potentially decisive criteria when assessing announcement practices has been whether “*announcements may give competitors insight into each other's future [p]rices while not being useful for customers since they are not booking yet*”²⁴⁴. As the use of algorithms might increase the overall pace of competitive interactions, the scale for determining the required time between announcement and potential implementation might differ. For example, an announcement could take place just a few hours in advance as opposed to several weeks in previous cases.

It could also occur that instead of explicitly announcing an intended price-increase, signalling takes place “implicitly”, e.g. by actually changing competitive parameters in the form sketched by the *OECD* (e.g. “*snapshot price changes during the middle of the night*”)²⁴⁵. Here, it might be challenging to distinguish between algorithmic experimentation (in the course of “exploration”) and algorithmic signalling. Explorative experiments might happen “in the middle of the night” as the assumption could be that observed reaction patterns would be similar at other times of the day. However, timing experiments “in the middle of the night” could also potentially make an objective of coordination between competitors more likely than it serving a legitimate goal of informing and/or attracting customers. It would depend on the facts of the specific case whether any of these situations would constitute a concerted practice or rather an intelligent market exploration.

Finally, it is conceivable that even more subtle indications are used, e.g. messages that convey the respective signals in a masked way.²⁴⁶ Such coded messages could be seen as a form of “algorithmic communication” and thus raise Art. 101 TFEU concerns.²⁴⁷

²⁴⁴ *Commission*, Decision of 07.07.16 (Container Shipping), Case AT.39850, para. 80.

²⁴⁵ *OECD*, Algorithms and Collusion, 2017, p. 30 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

²⁴⁶ This can be illustrated by an example frequently cited in economic literature on auction theory (but not related to algorithms) concerning spectrum auctions in the US. Some bidders engaged in so called “code bidding”, using the last digits of actual bids to coordinate with other bidders on (geographical) allocation (cf. for example *Cramton/Schwartz*, Collusive Bidding: Lessons from the FCC Spectrum Auctions, *Journal of Regulatory Economics* 2000, pp. 229 et seq.). Another example, partly related to algorithms, is the US airline tariff publishing company (“ATPCO”) case (<https://www.justice.gov/atr/case-document/file/483626/download>): Airline companies sent fare information to ATPCO as a central clearinghouse for distribution of fare change information. The DOJ had concerns that airlines had detailed conversations and negotiations on prices through ATPCO. In fact airlines used first ticket dates to signal (timing and level of) intended future price increases. Furthermore, fare code numbers and ticket date footnotes have been utilized as signalling/communication devices (for more details, see *Borenstein*, Case 9. Rapid Price Communication and Coordination, in: *Kwoka/White*, The antitrust revolution: economics, competition, and policy, 4th edn. 2004, pp. 233 et seq.).

²⁴⁷ *OECD*, Algorithms and Collusion – Note from the European Union, 14.06.17, para. 27 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

Overall, the question of whether algorithmic interaction constitutes a coordination within the ECJ's definition of concerted practices under Art. 101 TFEU is manifold and largely depends on the specific situation. It is clear, however, that under the current case law Art. 101 TFEU does not prohibit conscious parallel behaviour. Accordingly, where an algorithm merely unilaterally observes, analyses and reacts to the publicly observable behaviour of the competitors' algorithms, this might usually have to be considered as an intelligent adaptation to the market rather than a coordination. For example, through repeated interactions two companies' pricing algorithms could come to "decode" each other, thus allowing each one to better anticipate the other's reaction.

In view of the features of algorithms potentially facilitating collusion, some recognize the possibility that more cases of mere parallel behaviour arise which cannot be covered by the current case law of Art. 101 TFEU. The *OECD* sees the risk that algorithms "*expand the grey area between unlawful explicit collusion and lawful tacit collusion*".²⁴⁸ It points out that "*algorithms may enable firms to replace explicit collusion with tacit co-ordination*".²⁴⁹

Against this background, some have raised the question of whether the current understanding that mere parallel behaviour does not fall into the scope of Art. 101 TFEU needs to be reconsidered.²⁵⁰ It is also discussed whether the concept of coordination should be interpreted more broadly. However, as discussed before, the effects of algorithms on collusion still need further assessment. It is yet to be seen whether (legal) parallel behaviour will increase in the future and thus seems too early to think about an expanded application of Art. 101 TFEU at this stage.²⁵¹

bb) Accountability of undertakings for parallel behaviour caused by algorithms

The standard for distinguishing legal and illegal behaviour relies on whether that collusive outcome can be attributed to a meeting of the minds in case of an agreement or to a "*mental consensus whereby practical cooperation is knowingly substituted for competition*"²⁵² in case of a concerted practice. In other words, both normative concepts require to some extent the ascertainment of the respective undertaking's will. For the present scenario, in which the parallel use of individual algorithms supposedly induced a collusive outcome, this raises the question under what circumstances an undertaking's accountability for the behaviour of its algorithms can be assumed under competition law.²⁵³

²⁴⁸ *OECD*, Algorithms and Collusion, 2017, p. 25 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

²⁴⁹ *OECD*, Algorithms and Collusion, 2017, p. 25 (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

²⁵⁰ Cf. e.g. *OECD*, Algorithms and Collusion, 2017, pp. 36 et seq. (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>).

²⁵¹ Cf. also part V, pp. 75 et seq., *vide infra*.

²⁵² *Whish/Bailey*, Competition Law, 9th edn., 2018, p. 116 (original emphasis).

²⁵³ Similarly to the question of accountability, domestic law (such as § 81 GWB in Germany) could necessitate investigating whether individuals acted intentionally/negligently even if the authority contemplates fining the undertaking only (cf. §§ 30, 130 OWiG in German law). When assessing whether an individual acted at least negligently, an authority will have to decide whether the competition law violation was foreseeable.

In the case of descriptive algorithms, this seems to be a trivial question. Inasmuch as an algorithm pursues a predefined strategy, i.e. operates in a specific way directly based on human instructions, the undertakings will usually be responsible for the algorithmic behaviour. However, in case of autonomously acting black-box algorithms, which are only provided with abstract and/or very limited instructions by their operators, this question will be of higher relevance. For example, *Ezrachi/Stucke* argued in connection with their “digital eye” scenario that

*“[...] algorithm developers are not necessarily motivated to achieve tacit collusion; nor could they predict when, how long, and how likely it is that the industry-wide use of algorithms would yield tacit collusion. Nor is there any intent or attempt by the developers and user of the algorithm to facilitate conscious parallelism. The firm “merely” relies on AI.”*²⁵⁴

While it is yet unclear whether black-box algorithms could engage in coordination, there seems to be a general reluctance to deny a company’s responsibility merely because the technology it uses is based on AI. As EU Commissioner *Vestager* has emphasised

*“[...] companies can’t escape responsibility for collusion by hiding behind a computer program. [...] And businesses also need to know that when they decide to use an automated system, they will be held responsible for what it does. So they had better know how that system works.”*²⁵⁵

However, there has been no case practice yet in which such responsibility issues were addressed. In legal academia different standards for assessing an undertaking’s responsibility for collusive algorithmic behaviour have been outlined:

Some suggest accountability of an undertaking for the behaviour of its algorithm(s) if a reasonable standard of care and foreseeability is breached.²⁵⁶ It is argued that extending legal responsibility even to algorithmic behaviours which could be completely unforeseeable and beyond any experience or expert opinion could potentially discourage undertakings from using particular algorithms.²⁵⁷ By the (initial) use of algorithms undertakings shall be regarded as participants in a concerted practice only if they could have foreseen it. To establish that, a close review of the relevant algorithm in particular with a view to the programming, available safeguards, its reward structure, and the scope of its activities is considered necessary.²⁵⁸ In justifying their view, *Janka/Uhsler* and *Salaschek/Serafimova* refer not only to standards in (German) criminal law, but also to the ECJ’s decisions in *AC-Treuhand* and *VM Remonts*²⁵⁹, thus drawing parallels to an

²⁵⁴ *Ezrachi/Stucke*, *Artificial Intelligence & Collusion*, *University of Illinois Law Review* 2017, pp. 1775 et seq. (1795).

²⁵⁵ *Vestager*, *Speech at the Bundeskartellamt 18th Conference on Competition*, Berlin, 16.03.17 (see transcript at https://ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/bundeskartellamt-18th-conference-competition-berlin-16-march-2017_en).

²⁵⁶ *Janka/Uhsler*, *Antitrust 4.0*, *European Competition Law Review* 2018, pp. 112 et seq. (121); *Salaschek/Serafimova*, *Preissetzungsalgorithmen im Lichte von Art. 101 AEUV, Wirtschaft und Wettbewerb* 2018, pp. 8 et seq. (15 et seq.).

²⁵⁷ *Janka/Uhsler*, *Antitrust 4.0*, *European Competition Law Review* 2018, pp. 112 et seq. (121).

²⁵⁸ *Ezrachi/Stucke*, *Artificial Intelligence & Collusion*, *University of Illinois Law Review* 2017, pp. 1775 et seq. (1801).

²⁵⁹ See part III.B.2.a)bb)aaa), pp. 34 et seq., *vide supra*.

undertaking's accountability for acts of an independent third party.²⁶⁰ *Ezrachi/Stucke* further contemplate limiting an undertaking's accountability for the behaviour of its algorithm. They suggest that only if an undertaking omitted a necessary intervention after becoming aware of a coordinated behaviour, it could potentially infringe the prohibition of Art. 101 TFEU.²⁶¹

According to another approach, algorithmic behaviour could be treated similarly to an undertaking's employees' actions.²⁶² According to established case law of the ECJ, for an undertaking to be held accountable and hence liable for the actions of its employee

*"[...] it is not necessary for there to have been action by, or even knowledge on the part of, the partners or principal managers of the undertaking concerned; action by a person who is authorized to act on behalf of the undertaking suffices."*²⁶³

It is worth noting that in the context of an anticompetitive agreement, being "authorized" does not mean that the employee or representative of the undertaking who took part in an anticompetitive meeting had been given authority to that specific effect. Indeed, as underlined by the ECJ,

*"[...] participation in agreements that are prohibited by the FEU Treaty is more often than not clandestine and is not governed by any formal rules. It is rarely the case that an undertaking's representative attends a meeting with a mandate to commit an infringement."*²⁶⁴

Consequently, if one were to apply this standard to cases involving algorithmic behaviour, an undertaking could be held liable simply for introducing and using²⁶⁵ an algorithm if that algorithm is authorized to take decisions regarding certain market behaviour, e.g. pricing. Distinguishing between different degrees of autonomy, i.e. between descriptive and black-box algorithms, would not be necessary within this concept: As even a significant degree of autonomy enjoyed by an employee does not preclude attributing his or her actions to the undertaking, an algorithmic

²⁶⁰ *Janka/Uhsler*, Antitrust 4.0, European Competition Law Review 2018, pp. 112 et seq. (121 et seq.); *Salaschek/Serafimova*, Preissetzungsalgorithmen im Lichte von Art. 101 AEUV, Wirtschaft und Wettbewerb 2018, pp. 8 et seq. (15, fn. 76.).

²⁶¹ *Ezrachi/Stucke*, Artificial Intelligence & Collusion, University of Illinois Law Review 2017, pp. 1775 et seq. (1804).

²⁶² Cf. *Dohrn/Huck*, Der Algorithmus als „Kartellgehilfe“?, Der Betrieb 2018, pp. 173 et seq. (178 et seq.); *Wolf*, Algorithmengestützte Preissetzung im Online-Einzelhandel als abgestimmte Verhaltensweise, Neue Zeitschrift für Kartellrecht 2019, pp. 2 et seq. (6 et seq.). See also *OECD*, Algorithms and Collusion – Note from the European Union, 14.06.17, para. 38 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

²⁶³ *ECJ*, *Musique Diffusion française and Others v Commission*, Judgment of 07.06.83, Joined Cases 100/80 to 103/80, para. 97; see also *ECJ*, *Protimonopolný úrad Slovenskej republiky v Slovenská sporiteľna*, Judgment of 07.02.13, Case C-68/12, para. 25. Similarly, the General Court judged that “[t]he presence of an employee or other representatives at anti-competitive meetings is a factual element that enables the Commission to find an undertaking liable for an infringement of Article 81 EC. According to the case-law, the Commission’s power to impose a sanction on an undertaking where it has committed an infringement presumes only the unlawful action of a person who is generally authorised to act on behalf of the undertaking.” (*GC*, *H&R ChemPharma GmbH v Commission*, Judgment of 12.12.14, Case T-551/08, para. 73).

²⁶⁴ *ECJ*, *Protimonopolný úrad Slovenskej republiky v Slovenská sporiteľna*, Judgment of 07.02.13, Case C-68/12, para 26.

²⁶⁵ It should be noted that by referencing such human representatives' actions this approach does not appear to deny that algorithms are incapable of forming a will on their own (cf. *Harrington*, Developing Competition Law for Collusion by Autonomous Artificial Agents, *Journal of Competition Law & Economics* 2018, pp. 331 et seq. (347 et seq.)).

behaviour would similarly be attributed even if the undertaking was not aware of its anticompetitive implications. Continuing the analogy, as actions by an undertaking's employees are exempted from attribution only in the rare cases in which the employees acted without any authorization, using an algorithm would similarly allow an undertaking to escape liability only under exceptionally atypical circumstances. Such an approach would foster legal consistency by subjecting undertakings to the same rules regardless of whether they delegate decision-making to employees or algorithms. Moreover, it is more in line with the way competition authorities want to encourage companies to take precautions if they want to promote "compliance by design"²⁶⁶. It is also consistent with the idea that practices illegal when implemented offline, equivalently will be illegal when implemented online,²⁶⁷ in the spirit of a "technological neutrality" principle.

All in all, the standards for assessing an undertaking's responsibility for collusive algorithmic behaviour may vary to some extent between these two approaches. It seems to be clear, however, that companies need to think about how they could ensure antitrust compliance when they use pricing algorithms, in particular to adhere to what EU Commissioner *Vestager* has called "*compliance by design*"²⁶⁸ in this context.

²⁶⁶ Also cf. *Vestager*, Speech at the Bundeskartellamt 18th Conference on Competition, Berlin, 16.03.17 (see transcript at https://ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/bundeskartellamt-18th-conference-competition-berlin-16-march-2017_en).

²⁶⁷ Cf. *OECD*, Algorithms and Collusion – Note from the European Union, 14.06.17, para. 27 ([https://one.oecd.org/document/DAF/COMP/WD\(2017\)12/en/pdf](https://one.oecd.org/document/DAF/COMP/WD(2017)12/en/pdf)).

²⁶⁸ *Vestager*, Speech at the Bundeskartellamt 18th Conference on Competition, Berlin, 16.03.17 (see transcript at https://ec.europa.eu/commission/commissioners/2014-2019/vestager/announcements/bundeskartellamt-18th-conference-competition-berlin-16-march-2017_en).

Summary of “Use of algorithms in different scenarios”

For the purpose of illustration, the paper considers three scenarios. A range of situations that may fall within each of these scenarios is presented. Moreover, potentially relevant competition law aspects are discussed.

The first scenario covers situations in which a “traditional” anticompetitive practice resulting from prior contact between humans already exists. The algorithm thus only comes into play in a second step to support or facilitate the implementation, monitoring, enforcement or concealment of the respective anticompetitive practice. The involvement of an algorithm in such a scenario does not raise specific competition law issues, as a prior agreement or concerted practice can be established, which in general may be assessed under Art. 101 TFEU. Nevertheless, although the existence of an infringement might be found without further consideration of the algorithm, developing a case-specific understanding of the algorithm might still be advisable, for example as it could allow an assessment of potential counteracting efficiencies as well as reinforced negative effects of the anticompetitive practice.

In the second scenario, a third party, e.g. an external consultant or software developer, provides the same algorithm or somehow coordinated algorithms to competitors. The particularity of these situations is that there is no direct communication or contact between the competitors, but a certain degree of alignment could nevertheless arise from the actions of the third party. Given the ECJ jurisprudence (VM Remonts, Eturas), one of the central questions in this scenario is whether the competitors are aware of the third party’s anticompetitive acts, or could at least reasonably have foreseen it.

In the third scenario, algorithms are unilaterally designed and implemented, i.e. each company uses a distinct pricing algorithm. There is no prior or ongoing communication or contact between the respective undertakings’ human representatives. Still, the fact that several or even all competitors rely on pricing algorithms might facilitate an alignment of their market behaviour, resulting from a mere interaction of computers. There is a growing body of research considering the plausibility of algorithmic collusion by analysing concrete technical implementations of algorithms in specific, mostly experimental, settings. However, it currently remains an open question whether an alignment of pricing algorithms could likely arise “by chance” in settings that correspond to real market conditions. Assessing the third scenario from a legal point of view, the study turns to the distinction between coordination and mere parallel behaviour. The paper recalls that under the current case law, Art. 101 TFEU does not prohibit conscious parallel behaviour. Thus situations in which an algorithm merely unilaterally observes, analyses, and reacts to the publicly observable behaviour of the competitors’ algorithms might have to be categorised as intelligent adaptations to the market rather than coordination. Another legal issue in this scenario concerns the question of the extent to which the behaviour of a self-learning algorithm can be attributed to a company.

IV. Practical challenges when investigating algorithms

As seen in the previous sections, competition authorities may face algorithms in a wide range of cases. There may be cases where investigating the inner workings of the algorithm itself is not a necessity from the point of view of the investigation. This might apply in particular in the first scenario of part III in which an algorithm facilitates a “traditional” cartel. For illustration, in a French case concerning bid-rigging, it was established that a software facilitated the preparation of cover bids by automatically generating their price lists based on the price list of the bid designed to win the call for tenders, but it was not necessary to investigate the algorithm in detail as documents seized during the inquiry were sufficient to establish the existence of cover bids.²⁶⁹ Similarly, in a preliminary investigation of airline prices by the BKartA the question whether price increases were the result of a pricing algorithm or human intervention was raised, but in the end it was of no significance for the examination and its outcome.²⁷⁰ However, in other cases, an authority may opt to include the algorithm in its investigation, though the extent of such investigation may vary significantly.

So far, there are only a few cases involving the analysis of the inner workings of algorithms and there is no indication yet as to which types of cases the competition authorities will face in the future. Accordingly, it is not yet possible to predict whether there is a need for competition authorities to adapt their toolkit, and if so, how. The following overview is thus mostly anticipatory and does not prejudge how competition authorities would investigate future cases.

In the following, the study will summarize potential types of evidence for inferring a competition law infringement (A.). The section proceeds by outlining ways to obtain and analyse relevant information (B.). Given the main subject of the previous section, a certain focus is put on infringements of Art. 101 TFEU, although most (methodological) considerations might also apply more broadly.

A. Potentially relevant evidence for inferring an infringement

Concerning the burden and standard of proof, cases involving algorithms do not raise novel issues per se. In principle the authority asserting an infringement bears the burden of proof (cf. e.g. Art. 2 Reg. 1/2003 concerning Art. 101, 102 TFEU). Which specific facts will be investigated depends on

²⁶⁹ ADLC, Decision of 21.03.06, Case n°06-D-07 concerning practices in the public works sector in the Île-de-France area (<https://www.autoritedelaconurrence.fr/fr/decision/relative-des-pratiques-mises-en-oeuvre-dans-le-secteur-des-travaux-publics-dans-la-region>).

²⁷⁰ BKartA, Case summary of 29.05.18, Case B9-175/17 (<https://www.bundeskartellamt.de/SharedDocs/Entscheidung/EN/Fallberichte/Missbrauchsaufsicht/2018/B9-175-17.html>). While the BKartA stated that the use of an algorithm for pricing will certainly not relieve a company of its responsibility, the investigations in this case revealed that airlines had specified the framework data and set the parameters for dynamic price adjustment separately for each flight. They had also actively managed changes to these framework data and had entered unanticipated events manually. In its decision not to initiate proceedings, the BKartA also considered that price increases had not lasted long and that they were to be expected even in an intact competitive situation, as there had been a significant decline in capacity due to Air Berlin's insolvency.

the case at hand and there will be differences even amongst cases belonging to the same scenario as outlined in part III.

This section provides a non-exhaustive overview on information which may potentially be relevant, in particular when inferring an infringement of Art. 101 TFEU in cases involving algorithms. Depending on the case, the listed information might provide direct evidence or constitute circumstantial evidence in the context of a cumulative assessment of evidence. A distinction can be made between potentially relevant information associated with the role of the algorithm and its context on the one hand (1.) and the functioning of the algorithm on the other hand (2.).

While the section focuses on evidence for inferring an infringement, the information suggested in this section might also be relevant in cases in which an authority could prove an infringement without reference to the algorithm. For example, in the Poster case mentioned above, the CMA primarily relied on e-mail conversations between the parties to prove an agreement,²⁷¹ but it took the algorithm into account when calculating the penalty.²⁷²

1. Role of the algorithm and its context

At the onset of an investigation, it might be helpful for the investigating authority to understand the role of the algorithm in both its business and its technical context. This will allow the authority to assess the relevance of the algorithm for the pursued infringement and will thus help to structure the further investigation. Depending on the case, information on the role of the algorithm and its business and/or technical context may serve as (circumstantial) evidence for inferring that the normative requirements *inter alia* of Art. 101 TFEU are met.

The following non-exhaustive aspects may help elucidate the role of the algorithm and its context: First, information on the objective of the algorithm, its implementation and changes over times could be relevant (a). Furthermore, an authority could investigate information on the input data used by the algorithm (b). Finally, information on the output and the decision-making process connected with the algorithm might be helpful (c).

a) Objective, implementation and changes over time

In order to obtain an understanding of the objective of the use of a particular algorithm, its implementation and changes over time, information on the following facts may be of use:

- reason and incentive for initial implementation of the algorithm;
- time of first implementation of the algorithm (or a similar version of it);
- business processes supported by the algorithm and a description of the type of business decision it was designed to aid and/or used to aid;
- role and identity of the person currently or in the past responsible for suggesting, providing and/or developing the algorithm or specific parts thereof;

²⁷¹ CMA, Decision of 12.08.16, Case 50223, para. 5.18.

²⁷² CMA, Decision of 12.08.16, Case 50223, para. 6.23.

- in case of software developed and/or executed by a third party: information on contractual terms and information on whether multiple competitors rely on the same third party;
- existence of subsequent major changes or revisions and, if applicable, their number, the time of their implementation and the underlying motivation;
- tests and debugging reports made by the company using the algorithm or by the developer of the algorithm along with information about the test protocol.

Such information might be relevant for assessing different normative requirements. First, such facts may be especially useful to understand a potential coordination (e.g. at code level by parallel adaptations²⁷³) and whether a restriction by object can be assumed. The information might also be useful when investigating whether the behaviour of an algorithm can be attributed to an undertaking. Furthermore, the (temporal, substantive, and/or spatial) scope of a suspected infringement could potentially be clarified by considering such facts. Finally, when imposing a fine, the information might allow for inferring awareness of an anti-competitive effect and thus intent or negligence.

b) Inputs

The role of the algorithm can be further clarified by considering information on the inputs it has processed. In this context, investigations might aim at gathering information in particular on

- data sources and the process of collecting the data;
- actual raw inputs and, if applicable, transformations applied to these before the inputs are submitted to the algorithm;
- whether manual adjustments to the inputs occurred;
- automated calibration and related parameters;²⁷⁴
- the existence of a manual calibration process, where applicable, in particular the role and identity of the person currently or in the past responsible for calibration; in addition, information on the underlying business logic as well as the sources of information used for determining parameters.

Again such information might be relevant for several normative requirements.²⁷⁵ The inputs and parameters that have been used by the algorithm could in particular be in the focus when a coordination at data level is suspected. Additionally, depending on the case at hand, what kind of

²⁷³ Cf. part III.B.2.a)aa)aaa), pp. 33 et seq., *vide supra*.

²⁷⁴ Often certain parameters relevant to the behaviour of the algorithm will be derived from a set of data (so-called “training data”) containing, for example, historical information about demand for a product, own prices, competitors’ prices or other data on the economic environment. In such cases, information on the process of selecting training data might be of interest, including the kind of information it contains (for example: a competitor’s pricing data), or the historical time span from which the data originates.

²⁷⁵ Identifying the person responsible for the inputs could also turn out relevant for fining proceedings in German law, cf. box on p. 67, *vide infra*.

inputs were provided to the algorithm might be of relevance when assessing whether there is a restriction by object.

c) Output and decision-making

Furthermore, information on the outputs of an algorithm and the decision-making process may be of relevance. Information gathering may in particular include:

- a description of the structure and the content of the output;
- information on whether and to what extent the algorithm merely provides support for human decision-making or if the results of its computation automatically impact price changes or other competition parameters, along with, where applicable, information on the frequency of manual adjustments of the output.

Within the required normative assessment, information on the output could be especially helpful when assessing a potential coordination. For example in the context of a pricing algorithm, information on the output could potentially be relevant for finding a collusion. Information on the output might also play a role when assessing whether a potential infringement can be attributed to the undertaking, in particular whether the algorithmic behaviour was intended and/or foreseeable.

2. Functioning of the algorithm

Depending on the case the investigating authority may also want to have a thorough understanding of the functioning of an algorithm. Information gathering may in particular include facts concerning the following aspects:

- basic design principles of the algorithm, such as methodology and, where applicable, implemented objective functions or constraints;
- actions that have by design or in practice been triggered conditional on monitored external events, e.g. price changes triggered by changes in competitors' prices (or other competition parameters);
- communication that has taken place via algorithms;
- existence of components potentially used for (or capable of) active curtaining of potential anticompetitive practices;
- similarity of algorithms used by different competitors.

Within the normative assessment, such information might in particular be relevant when investigating a potential coordination (e.g. at code level). These elements might also be taken into account when assessing whether there is a by-object restriction of competition.

B. Ways to obtain and analyse relevant information

When an authority decides to have a closer look at an algorithm in an investigation, it needs to determine the ways to obtain the relevant information on the algorithm and possibly also ways to further analyse the algorithm. However, even before opening an investigation, at the stage of considering initiating proceedings, information on algorithms and their behaviour might become relevant. When deciding whether to open proceedings, an authority may take into account different elements leading to the possibility of a competition law infringement. In this regard, traditional ways, e.g. complaints, leniency applications etc., will most likely stay relevant in cases involving algorithms. However, a particular tool that might be more widely used, in the context of algorithmic collusion, is screening methods:

Screening for collusion

Recently it has been suggested that competition authorities could develop their own machine-learning algorithms to detect algorithmic collusion.²⁷⁶ This suggestion is in line with previous proposals of cartel screening algorithms aimed at complementing the traditional cartel detection instruments by potentially raising the probability that a cartel is being unveiled.²⁷⁷ Competition authorities have already been making use of certain (data) screening techniques to detect cartels for some time,²⁷⁸ irrespective of the cartels' exact nature. For example, the competition authorities of Brazil, Germany, Mexico, Portugal, Russia, South Korea, Spain, Switzerland and the United Kingdom have used data screening techniques to assist in detecting cartels. However, applying such data screening techniques necessitates to collect sufficiently reliable market information. Also, authorities might increasingly have to account for the possibility that companies could attempt to curtail their collusive strategies, probably in increasingly sophisticated ways and with the support of algorithms.

Once an authority has opened an investigation, it can build on its established investigative powers to obtain the necessary information (1.). Depending on the particularities of the case, it may be an option for the authority to conduct a closer analysis of the algorithm (2.).

1. Obtaining information

Within its established investigative powers, an authority will be able to gather significant information on the algorithm in particular by employing information requests,²⁷⁹ inspections

²⁷⁶ Cf. e.g. *Abrantes-Metz/Metz*, Can Machine Learning Aid in Cartel Detection?, CPI Antitrust Chronicle July 2018; *Huber/Imhof*, Machine learning with screens for detecting bid-rigging cartels, International Journal of Industrial Organization 2019, pp. 277 et seq.

²⁷⁷ Also cf. *OECD*, Summary of the workshop on cartel screening in the digital era, 26.09.18 ([https://one.oecd.org/document/DAF/COMP/M\(2018\)3/en/pdf](https://one.oecd.org/document/DAF/COMP/M(2018)3/en/pdf)).

²⁷⁸ Cf. e.g. *Imhof/Karagök/Rutz*, Screening for bid rigging – does it work?, Journal of Competition Law & Economics 2018, pp. 235 et seq.; see also *BRICS Competition Law and Policy Centre*, Digital Era Competition, 2019, pp. 1 et seq. (672 et seq.) for different software screening tools.

²⁷⁹ Cf. Art. 18(1) Reg. 1/2003; §§ 57, 59 GWB; §§ 46 OWiG, 94 StPO.

(“dawn raids”),²⁸⁰ and/or interviews²⁸¹. These investigative powers can be applied to gather digital evidence.²⁸²

As far as information requests are concerned, it should be emphasized that the authority in principle should attempt to avoid receiving extensive data or documentation of limited evidential value. In this context, agencies might face a “chicken-and-egg” issue as making precise requests might require previous knowledge on the implementation and type of algorithm. Therefore, proceeding stepwise by issuing successive requests might be an option depending on the peculiarities of the respective case.

Where an algorithm is not developed and maintained in-house, different addressees for investigative measures could be envisioned. In particular, information could be requested from software developing companies, companies hosting required infrastructure or companies that make use of the algorithm in the context of their business decisions.

When employing the investigative means mentioned above, an authority can of course request information on the facts described in part A directly. However, depending on the case at hand, it might also be an option to acquire this information by requesting corresponding internal documentation. Such internal documentation could cover, for example:

- the requirements or specifications by the business/management side that was given to the developers (including functional specifications);
- pseudocode²⁸³ used during the development phase;
- the business process supported by the algorithm;
- the usage patterns of the algorithm;
- the frequency of learning, recalibration or manual adjustments;
- log files documenting inputs and/or outputs;
- actual data sources;
- user guides or related (technical) documents.

²⁸⁰ Cf. Art. 20(4) Reg. 1/2003, § 59(4) GWB, §§ 46 OWiG, 102, 103 StPO.

²⁸¹ Cf. Art. 19(1) Reg. 1/2003, § 57(2) GWB, §§ 46 OWiG, 136, 163a, 48, 161a et seq. StPO.

²⁸² For collecting digital evidence, cf. *de Jong/Wesseling*, EU competition authorities’ powers to gather and inspect digital evidence – striking a new balance, *European Competition Law Review* 2016, pp. 325 et seq.; for an overview of the legal background as well as the practical process of IT inspections during dawn raids see also *Seelinger/Gänswein*, E-Raids – IT-Durchsuchungen von Unternehmen durch die Europäische Kommission und das Bundeskartellamt, *Betriebs-Berater* 2014, pp. 1027 et seq.

²⁸³ A pseudocode is an informal description of an algorithm written in a way that resembles a simplified programming language. A pseudocode is often used during the development phase to describe, in a simple way, the different steps that will need to be coded in order to obtain the desired algorithm.

Finally, an authority could potentially request an undertaking to disclose (relevant parts of) the source code of the algorithm vis-à-vis the authority. In the subsequent assessment of the source code, other types of information, e.g. on the context of the algorithm, might be helpful. Moreover, it should be noted that to account for changes in the implementation over time,²⁸⁴ an authority might not only ask for a copy of the most recent code version. In some cases, the authority might instead ask for an image of the source control system or repository in use at the company, potentially including all code branches, commented code check-ins, version histories etc.

Peculiarities in fine proceedings

EU law as well as domestic law allow for the imposition of fines for competition law infringements.²⁸⁵ Information obtained and analysed for determining a competition law violation might be relevant for deciding on the *amount the undertaking/individuals are fined*;²⁸⁶ for example, the usage of an algorithm could indicate a particularly grave and/or prolonged infringement, thus justifying a higher fine.²⁸⁷ Inasmuch as individual *intention/negligence* is relevant in this regard,²⁸⁸ the information discussed above might be helpful for determining from what point in time which person was aware of the algorithm's capabilities and its behaviour. Similarly, regarding negligence, it might be relevant to analyse whether the competition law violation was foreseeable.

Within domestic law there can be *procedural differences* depending on whether the authority obliges an undertaking to terminate a competition law infringement or imposes a fine on the company and/or the individuals involved. For example in German law²⁸⁹ the rights of defence granted under the respective procedural rules provide for a higher level of protection within a fining procedure than an administrative procedure. This might raise the bar when obtaining evidence or analysing the algorithm, as for evidence to be admissible in front of a court the standards of criminal law would have to be satisfied. However, as Directive 1/2019 aims at harmonizing competition enforcement within the EU, its implementation will contribute to mitigating such differences.

2. Analysing the algorithm

An analysis of the algorithm may yield additional evidence as described in section A above. In particular, such an analysis might reveal facts associated with the functioning of the algorithm

²⁸⁴ Cf. part IV.A.1.a), pp. 62, *vide supra*.

²⁸⁵ Cf. Art. 23(2) Dir. 1/2003; § 81(1) GWB; Art. L-464-2 du Code du Commerce.

²⁸⁶ Cf. *BKartA*, Leitlinien für die Bußgeldzumessung im Kartellordnungswidrigkeitenverfahren, 25.06.13

(https://www.bundeskartellamt.de/SharedDocs/Publikation/DE/Leitlinien/Bekanntmachung%20-%20Bu%C3%9Fgeldleitlinien-Juni%202013.pdf?__blob=publicationFile&v=5); *Commission*, Guidelines on the method of setting fines, 01.09.06 (<https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX%3A52006XC0901%2801%29>).

²⁸⁷ Cf. fn. 127, *vide supra*.

²⁸⁸ Note that in German law intention/negligence is required to establish liability in the first place, not just on calculating the fine.

²⁸⁹ Specificities in German fine proceedings are e.g. *nemo tenetur* (no one is obliged to collaborate towards his/her own prosecution, which is a more expansive concept than the more limited "privilege against self-incrimination" in EU law, cf. *Whish/Bailey*, Competition Law, 9th edn., 2018, p. 279), the provision that before being questioned people need to be informed about their rights, and the requirements of a judicial warrant/court order before raids or confiscations.

from which, where necessary in conjunction with further circumstantial evidence, an infringement could be inferred. Inasmuch as this chapter discusses ways for identifying the function and/or results generated by an algorithm, these have to be distinguished from a possible assessment of the algorithmic effects on competition, i.e. the question whether the use of an algorithm entails anticompetitive effects. To which extent this question needs to be addressed in an investigation depends on the specificities of the case.

When analysing an algorithm, it is important to recall the distinction between descriptive and black-box algorithms introduced earlier. While certain aspects are equally important when analysing both kinds of algorithms, black-box algorithms might necessitate a more in-depth analysis using progressive investigative techniques.

Against this backdrop, the first subsection (a) will discuss general aspects when analysing algorithms.

So far, there seem to be only very few competition law cases that required an in-depth analysis of an algorithm. However, in anticipation of such cases, the question of the suitable methods for such an analysis has been raised in literature.²⁹⁰ While in most published case studies the setting is different from the perspective of competition authorities, in that either it is the governments' own algorithms being audited (for example in sentencing decisions²⁹¹) or it is the scientific community pursuing the investigation (for example an analysis of Amazon's Buy Box²⁹²), many of the core questions remain similar.

Hence, taking into account the suggestions in academic literature, subsection b) will consider a non-exhaustive list of different approaches to explore the functioning and behaviour of an algorithm.

a) General considerations when analysing algorithms

Certain considerations seem to apply in a multitude of possible constellations:

Algorithms can be "moving targets" under continuous development. The details of the implementation might change over time. Which time span is relevant in an investigation depends on the nature of the case under consideration: When investigating an alleged cartel, the historic development of algorithms might be of particular interest, possibly over a longer time period. If the potential infringement is possibly still ongoing, there might be a need to evaluate the current

²⁹⁰ Cf. *Ezrachi/Stucke*, *Virtual Competition*, 2016, pp. 230 et seq. who consider several approaches together with the challenges they entail. See also *Sandvig/Hamilton/Karahalios/Langbort*, *Auditing Algorithms*, 2014 who discuss several approaches to the auditing of algorithms, in particular code audits, non-invasive audits (collecting survey from users of platforms concerning their user experience), scraping audits, sock puppet audits (using software to create fictional users of the platform), or crowdsourced audits. Not all of these audit designs seem equally applicable in the context of a government investigation, however, and in the following only the designs that seem relevant to the application of competition law are discussed.

²⁹¹ Cf. e.g. *Devlin*, *Software 'no more accurate than untrained humans' at judging reoffending risk*, *The Guardian*, 17.01.18 (<https://www.theguardian.com/us-news/2018/jan/17/software-no-more-accurate-than-untrained-humans-at-judging-reoffending-risk>).

²⁹² Cf. *Chen/Mislove/Wilson*, *An Empirical Analysis of Algorithmic Pricing on Amazon Marketplace*, *Proceedings of the 25th International Conference on World Wide Web*, 2016, pp. 1339 et seq.

behaviour. In contrast to that, merger cases will be characterized by a predictive element in the analysis of anticompetitive effects.

Where black-box algorithms are concerned, defining the time span under consideration might be particularly relevant, since parametrized algorithms can adjust their parameters automatically. When investigating a self-learning algorithm, obtaining a description of the values of the relevant parameters at a set time, at several set times or during a time interval might be helpful. The latter option might also be helpful in the case of two or more algorithms, especially when used by competing companies that interact and change parameters based on this interaction. An evaluation of the changing models over a longer time might be useful to understand the scope, speed and convergence of the interaction.

Obtaining information on past algorithm parameters might require that a company has stored the relevant data. However, in practice many companies sophisticated enough to use automated decision making might store relevant data over longer periods, as they might have significant incentives to do so.²⁹³

Analysing algorithms may imply working with rather large amounts of data. For example, in the context of the Google Shopping case, the *Commission* reportedly analysed “*very significant quantities of real-world data including 5.2 Terabytes of actual search results from Google (around 1.7 billion search queries)*”.²⁹⁴ To be able to interpret such large amounts of possibly complex data, additional information might be helpful. This can relate both to the business context, such as the meaning of each input dimension, and to the technical implementation – for example how the data is stored and how different segments of the data are linked. Possibly, this might be supplemented by a description of data cleaning and pre-processing methods to evaluate whether they imply technical restrictions that are of possible relevance from a competition point of view, such as technical limits on discounts²⁹⁵.

Furthermore and expanding on this, it might be an option to perform a more general analysis of the algorithm’s environment and interfaces. Reasons might include a high degree of dependency of the specific algorithm vis-à-vis other parts of the company’s IT infrastructure. In such cases, further clarifications, such as an explanation of the underlying logic and a list of relevant modules, could be requested in order to select the parts that are relevant to the analysis.

Finally, when applying advanced analytical approaches, the question might come up on how to document the respective analysis in a sufficiently detailed and transparent way on the part of the authority. However, even though it might be necessary to further reflect on the documentation of

²⁹³ Such incentives e.g. might emanate from the fact that historical data allows performance monitoring of the algorithm and, in the case of more complex algorithms, can also be used as training data.

²⁹⁴ Cf. *Commission*, Press release of 27.06.17 (https://europa.eu/rapid/press-release_IP-17-1784_en.htm), and *Commission*, Decision of 27.06.17, Case AT.39740, para. 475 et seq.

²⁹⁵ Cf. the considerations by the ECJ in the Eturas case described in part III.B.2.a)bb)aaa), pp. 35 et seq., *vide supra*.

the analysis in detail, this is not a completely novel issue as similar questions have already arisen before e.g. in the context of econometrical analyses.²⁹⁶

b) Potential analytical approaches

In order to explore the functioning and behaviour of an algorithm, different analytical approaches could be envisioned: an analysis of the code itself (aa), comparing real past inputs/outputs couples (bb), possibilities of simulating the behaviour of an algorithm on generated inputs (cc), and comparing the algorithm to other (more easily interpretable) algorithms or methods (dd). However, the following considerations are not intended to be a definitive classification as there can also be overlap between different approaches and it is not meant to be exhaustive.

aa) Analysing the code

Analysing the code might be of particular interest when an authority is confronted with a descriptive algorithm and might yield additional information as described in section A above.

As discussed before, the challenges in an investigation of an algorithm will vary considerably from case to case. There could be source codes, or at least relevant parts of them, which are relatively short, well-commented and of a simple structure. However, source code could also be very extensive or complex and lacking available documentation, which would complicate reading and understanding it in its entirety.

When faced with a complex algorithm, it might be an option to start an investigation by drilling down and isolating the functionality in question, in order to focus the analysis on the relevant parts of the code. However, compared to an analysis of descriptive algorithms, an interpretation of a black-box algorithm might likely focus on different aspects of the source code, e.g. the prescribed objective the algorithm is programmed to achieve or aspects separate from the code, such as the relationship between inputs and output.

bb) Comparing real past inputs/outputs couples

One approach to gain insights into how an algorithm works is to obtain existing historical data on inputs and corresponding outputs in order to analyse the relationship between input and respective resulting output. Of the approaches discussed, this is probably closest to established statistical and econometric techniques used by competition authorities.

However, if the algorithm is more complex, it can generate an equally complex relation between input and output that might not be easily interpretable using traditional econometric techniques such as linear regression with a limited number of independent variables. The use of techniques beyond the classical tools of econometrics might be an option in such cases.²⁹⁷

²⁹⁶ In this context, the standards an authority applies when working with economic expertise could also be helpful, cf. *BKartA*, Best practices for expert economic opinions, 20.10.10 (<https://www.bundeskartellamt.de/SharedDocs/Publikation/EN/Bekanntmachungen/Notice%20-%20Standards%20for%20economic%20opinions.pdf>).

²⁹⁷ Cf. part IV.B.2.b)dd), pp. 72 et seq., *vide infra*.

cc) Testing (simulating) the behaviour of an algorithm on predefined inputs

Another approach consists in assessing the behaviour of an algorithm by confronting it with input data chosen by the authority, i.e. simulating queries. In principle, this is rather an extension of the method previously discussed than a different approach. While in the previous method the analysis is applied to a static data set that only includes input/output couples from the past, i.e. real data, here generating inputs is part of the analysis.

The main advantage of simulating queries lies in the possibility to choose inputs best suited to understand the behaviour of the algorithm. For example, an authority could generate inputs that only differ in one small aspect, thereby allowing an assessment of the influence of that particular aspect on the behaviour of the algorithm.²⁹⁸ It has to be kept in mind, however, that the submission of a large number of inputs might at some point alter the behaviour of the algorithm, if the algorithm learns from new input data.²⁹⁹ Furthermore, it is important to account for the fact that simulated inputs might be substantially different from the ones typically processed by the algorithm in a normal business context. Therefore, the behaviour of the algorithm as observed in this particular setting might have to be put into perspective.

There are two main variations of this approach. An authority could confront the algorithm with simulated queries in a real-world context (aaa). Alternatively, an authority could implement a separate replication of the algorithm to confront it with simulated queries (bbb).

The following subsections describe the technical possibilities of the two approaches for testing the behaviour of an algorithm on predefined inputs. It should be noted though that the respective investigative approaches might raise legal questions (e.g. as to the investigative competences or the necessary documentation), which have to be considered in light of the peculiarities of the individual case.

aaa) Confronting the algorithm with simulated queries in a real-word context

Within the first variation, the authority starts by predefining inputs. In a second step those inputs will be send to a runtime instance of the algorithm provided by the company (and not a local duplicate thereof). The runtime instance might be processing inputs from regular users in parallel.

Different ways for sending the input generated by the authority to the runtime instance provided by the company are conceivable. First, an authority could utilize an information request to demand information on the results returned by a specific algorithm when provided with specific input parameters. Second, if the algorithm is otherwise publicly accessible, e.g. via a web interface, a technical possibility would be to query such algorithms directly. Third, in some cases the company might (voluntarily) provide an interface, such as an application programming interface (API) for querying the algorithm or parts of it. This could be an existing or a newly established

²⁹⁸ This is one example of the application of metamorphic testing; see also the discussion of this method in *Gesellschaft für Informatik, Technische und rechtliche Betrachtungen algorithmischer Entscheidungsverfahren*, 2018 (<http://www.svr-verbraucherfragen.de/wp-content/uploads/GI-Studie-Algorithmenregulierung.pdf>).

²⁹⁹ For example, in the context of algorithms that set prices, simulating repeated searches for a specific product might signal an increased interest in this product and thus its price might be automatically raised.

(private) API. This might be particularly efficient for queries involving large sets of input parameters and potentially reduce the workload for the company providing the data as well.³⁰⁰

bbb) Implementing a replication of the algorithm in a controlled setting (“sandboxing”)

The second variation differs from the first one inasmuch as here the authority not only generates inputs, but also submits them directly to a replication of the algorithm in a controlled, typically isolated setting. This practice is often referred to as “sandboxing”. In this setting, the authority alone controls inputs to the algorithm and observes the corresponding outputs.

When a case concerns a self-learning algorithm, sandboxing can allow temporarily freezing the parameters of such an algorithm. Here, possible advantages – such as a higher degree of control and easier analysis – might have to be weighed against potential drawbacks, such as potentially non-realistic behaviour in artificial settings. It will have to be evaluated on a case-by-case basis whether and to what extent demonstrating certain behaviours in a sandbox can provide evidence for an infringement, including considerations whether the sandbox environment is close enough to real market conditions.

Subject to legal requirements, the sandbox could potentially be located within the respective company’s IT infrastructure or within the authority’s IT infrastructure. In the first case, the authority could be provided access to the sandbox either via a remotely accessible interface or via in-person access on the company’s site. However, when a strategic interaction between several companies’ algorithms is suspected, the option of using a company’s IT infrastructure to implement a sandbox might not be viable, since the authority might have to bring the algorithms together in a common sandbox environment and simultaneously control them.

dd) Comparing the algorithm to other (more easily interpretable) algorithms/methods

A further approach consists in comparing the algorithm in question to other, more easily interpretable algorithms.

This approach might *inter alia* be an option in the case of highly complex machine learning methods. In this context, approximating the algorithm by a simpler algorithm could render it more accessible to human understanding. In principle, this is not a novel idea: econometricians routinely compare the complex hidden input-output relation (the “data generating process”) underlying a given data set to interpretable economic models, e.g. by means of linear regression.

However, with increasing use of machine learning models, the relationships between inputs and outputs will often show a higher complexity. It should be noted that the more complex the relationships are, the more difficult a well-fitting approximation by a simple standard model might be, in particular a linear one. Recently, new research in an area coined as “explainable artificial intelligence” has tried to fill this gap by developing more flexible approximation models

³⁰⁰ Cf. the concept of “scraping audits” as proposed by *Gesellschaft für Informatik*, Technische und rechtliche Betrachtungen algorithmischer Entscheidungsverfahren, 2018, p. 67 (http://www.svr-verbraucherfragen.de/wp-content/uploads/GI_Studie_Algorithmenregulierung.pdf).

in the context of machine learning, drawing, of course, on established techniques from statistics and mathematics.³⁰¹

Explainable artificial intelligence, although in its infant stage, has already begun to offer several conceptually different approaches for such an approximation. Which one is preferable in a given case depends on the exact question. One main guiding question when choosing a method would be whether one wants to understand how a particular algorithmic decision, given a specific input, was made, or whether one wants to gain more general insights concerning the behaviour of the algorithm given arbitrary inputs. In the context of a competition law investigation an authority would also need to decide on a case-by-case basis whether a specific approximation is close enough to the actual algorithm to provide evidence of an infringement.

Where the aim is to understand how a particular algorithmic decision was made, a local approximation might analyse the algorithm's sensitivity to slight changes in input. "Local" implies that this sensitivity relates to a *specific (fixed) instance of input values*. Alternatively, a local explanation might provide a list of components of the input that were most relevant in determining the corresponding *specific* output.³⁰² Applied to the context of price-setting, a local approximation might look at a specific product at a specific time given a specific competitive environment, and try to infer how small changes to one or few inputs affect the resulting price. It might also determine the most relevant features of the product or of the respective circumstances that had the largest impact on the computed suggested price.

Where the aim is to gain more general insights concerning the behaviour of the algorithm given arbitrary instances out of the typical range of inputs, different approaches of global approximation or explanation exist. In contrast to local approximations, which focus on a specific input, global approximations attempt to provide some intuition about how the algorithm processes a variety of typical inputs. While global approximations may not be readily available for general models like neural networks, there is ongoing research in this area.³⁰³ Considering again the example of a pricing software, the global explanation could identify features having *on average* the largest influence on the price. Alternatively, it could provide an explanation by providing a limited number of representative examples.

³⁰¹ Cf. e.g. *Samek/Wiegand/Müller*, Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models, 2018, ITU Journal: ICT Discoveries - Special Issue 1 - The Impact of Artificial Intelligence (AI) on Communication Networks and Services, pp. 1 et seq.; *Gilpin/Bau/Yuan/Bajwa/Specter/Kagal*, Explaining Explanations: An Overview of Interpretability of Machine Learning, 2018 IEEE 5th International Conference on Data Science and Advanced Analytics (DSAA).

³⁰² Cf. *Ribeiro/Singh/Guestrin*, Why Should I Trust You? Explaining the Predictions of Any Classifier, Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining 2016, pp. 1135 et seq.; *Baehrens/Schroeter/Hermeling/Kawanabe/Hansen/Müller*, How to Explain Individual Classification Decisions, Journal of Machine Learning Research 2010, pp. 1803 et seq.

³⁰³ Cf. *Ribeiro/Singh/Guestrin*, Why Should I Trust You? Explaining the Predictions of Any Classifier, Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining 2016, pp. 1135-1144 (1139).

Summary of “Practical challenges when investigating algorithms”

The study addresses practical challenges when investigating algorithms by first summarizing potential types of evidence for inferring a competition law infringement and subsequently outlining ways to obtain and analyse relevant information.

Among potential types of evidence, a distinction can be made between relevant information associated with the role of the algorithm and its context on the one hand, and the functioning of the algorithm on the other hand. Furthermore, authorities might consider information on the input data used by the algorithm. Finally, it could be helpful to gather information on the output and the decision-making process connected with the algorithm.

Once an authority has initiated an investigation, it can build on its established investigative powers, such as information requests, inspections, and interviews, to obtain the necessary information. Depending on the case at hand, information could also be acquired by requesting internal documentation. A more in-depth analysis of the algorithm may yield additional evidence, in particular revealing additional facts associated with the functioning of the algorithm. For such an analysis, different investigative approaches could be envisioned, *inter alia* an analysis of (relevant parts of) the source code in connection with information on the respective environment and interfaces, a comparison of real (past) input/output couples, a simulation of the algorithmic behaviour on generated inputs or a comparison of the algorithm to other (more easily interpretable) algorithms and methods.

V. Concluding remarks

Without losing sight of the important benefits the use of algorithms can entail for the economy, the previous sections have discussed possible detrimental effects that algorithms might have on the competitive functioning of markets. It has been demonstrated that in many potential situations the contemporary legal framework, in particular Art. 101 TFEU and the accompanying jurisprudence, allows competition authorities to address possible competitive concerns.

Meanwhile, there has been some scholarly debate whether Art. 101 TFEU needs to be understood more broadly as algorithms would progressively test the conceptual limits between mere parallel behaviour and illegal coordination: According to some, the potentially increasing risks of tacit collusion resulting from the use of pricing algorithms raise the question of whether the current exclusion of parallel behaviour from the scope of Art. 101 TFEU needs to be reconsidered.³⁰⁴ In this vein, there is already a spectrum of first suggestions, despite the limited case practice. For example, it has been suggested that the identification of certain “plus factors”, broadly defined as positive (avoidable) actions by market players that enable a better coordination of firms, could allow tacit collusion to be sanctioned. In particular, such “plus factors” could include the use of algorithms designed in certain ways that facilitate collusion.³⁰⁵ Furthermore, some have suggested regulating algorithms *ex ante* to ascertain individually whether they exhibit a tendency to collude. This could be done either through an examination of the algorithm’s code³⁰⁶ or through a test of the algorithm³⁰⁷. At the same time, there are already sceptical voices on several of these proposals, in particular acknowledging that monitoring and reacting to competitors’ actions is an integral part of the competitive process and suspecting chilling effects of the proposed interventions on competition.³⁰⁸ Beyond substantive law, there also have been thoughts on ways

³⁰⁴ Cf. e.g. *OECD*, Algorithms and Collusion, 2017, pp. 36 et seq. (<http://www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm>) or *Gal/Elkin-Koren*, Algorithmic consumers, Harvard Journal of Law and Technology 2017, pp. 309 et seq. (347).

³⁰⁵ Cf. *Gal*, Algorithms as Illegal Agreements, Berkeley Technology Law Journal 2019, pp. 67 et seq. (110 et seq.), also specifying situations which she considers as potential plus factors, e.g. companies making conscious use of similar data even when better data sources existed or companies making it easier for their competitors to observe their algorithms (pp. 113 et seq.); *Gal/Elkin-Koren*, Algorithmic consumers, Harvard Journal of Law and Technology 2017, pp. 309 et seq. (346, 347). Also cf. *Göhsli*, Algorithm Pricing and Article 101 TFEU, Wirtschaft und Wettbewerb 2018, pp. 121 et seq. (123).

³⁰⁶ Cf. e.g. *OECD*, Algorithms and Collusion, 2017, p. 50. In this paper, the OECD for instance presents as one example for a potential regulatory intervention that “*algorithms could be programmed not to react to most recent changes in prices; or, instead, to ignore price variations of individual companies, while still accounting for average prices in the industry*”.

³⁰⁷ Cf. *Harrington*, Developing Competition Law for Collusion by Autonomous Agents, Journal of Competition Law & Economics 2018, pp. 331 et seq. In this paper, the author proposes entering data into the pricing algorithm and monitoring the output in terms of prices to determine whether the algorithm exhibits a prohibited property.

³⁰⁸ Cf. e.g. *Gal*, Algorithmic-Facilitated Coordination, CPI Antitrust Chronicle 2017, pp. 22 et seq. (28), who points out that a requirement for an “*algorithm be[ing] mandated to ignore its competitors’ potential moves [...] may well undermine competition*”, and *Gal*, Algorithms as Illegal Agreements, Berkeley Technology Law Journal 2019, pp. 67 et seq. (116), who argues that “*treat[ing] every algorithm that helps facilitate coordination as a plus factor*” was “*a suggestion which is highly problematic*”.

to strengthen the effectiveness of competition authorities' information gathering powers, for example by introducing a requirement on companies to preserve an auditable record of their algorithm development and use.³⁰⁹

Beyond competition concerns

Beyond the competition concerns discussed above, other aspects of market players' behaviours regarding the use of algorithms, for example in relation to data protection, consumer protection as well as loyalty and transparency, are (debated to be) subjected to regulation – at both national and European levels.

For example, at the French level, the law “to promote a digital republic”³¹⁰ contains several provisions related to a platform's loyalty, responsibility and neutrality. These provisions specify an obligation for platforms to provide fair information to their users on the way they operate their services, such as the general conditions of use of the intermediation service it offers and on the methods of referencing, classification and dereferencing of the contents, goods or services to which this service allows access. This information should also cover the existence of a contractual relationship, a capital link or a remuneration between the platform and a content, good or service provider that influences the classification or referencing of the content, goods or services offered or put online. More specifically on algorithms, the law provides the explicit mention of the use of algorithmic processing in the context of an administrative decision and the possibility for the user to request the main rules of the algorithm on which the decision is based.

This law also gave an assignment to the French Data Protection Authority (CNIL) of conducting an open debate on the ethical and societal matters raised by the rapid development of digital technologies. After a public debate, the CNIL published a report on the ethical matters of algorithms and artificial intelligence which concludes with several recommendations³¹¹ intended for both public authorities and civil society: *Inter alia*, it suggests to foster education of all players involved in algorithmic systems, to make algorithmic systems comprehensible and to create a national platform for auditing algorithms. Furthermore, it proposes certain ethical considerations, in particular research on ethical AI.

At the German level, there have been similar considerations on how to address questions posed by the use of algorithms, for example in the context of the Data Ethics Commission established by the Federal Government.³¹² The Data Ethics Commission provided an opinion with a considerable set of explicit recommendations on how to develop data policy and how to deal with “algorithmic

³⁰⁹ Cf. *Furman/Coyle/Fletcher/McAuley/Marsden*, *Unlocking digital competition: Report of the Digital Competition Expert Panel*, 2019, p. 108.

³¹⁰ Loi n° 2016-1321 du 7 octobre 2016 pour une République numérique (“Loi Lemaire”) (<https://www.economie.gouv.fr/republique-numerique>).

³¹¹ CNIL, *How can human keep the upper hand? The ethical matters raised by algorithms and artificial intelligence*, 2017 (https://www.cnil.fr/sites/default/files/atoms/files/cnil_rapport_ai_gb_web.pdf).

³¹² Cf. *Bundesministerium für Justiz und Verbraucherschutz*, *Data Ethics Commission* (https://www.bmju.de/DE/Themen/FokusThemen/Datenethikkommission/Datenethikkommission_EN_node.html).

systems”.³¹³ Its proposals also relate to the German Artificial Intelligence Strategy³¹⁴, which in particular envisages an assessment of how AI systems can be made transparent, predictable and verifiable so as to effectively prevent distortion, discrimination, manipulation and other forms of improper use. Considerations in this regards have also been voiced by stakeholders such as the Federation of German Consumer Organisations (vzbv)³¹⁵.

There are also several initiatives relating to algorithms at the European level. For example, the recent Platform to Business Regulation³¹⁶ has provided rules to ensure that business users of online intermediation services and corporate website users in relation to online search engines are granted appropriate transparency and effective redress possibilities. For example the regulation states that providers of online intermediation services shall set out in their terms and conditions the main parameters determining ranking and the reasons for the relative importance of those main parameters as opposed to other parameters.

The previous sections have illustrated that the existing tools seem, at this stage, flexible in their application to cases involving algorithmic behaviour. Also, to this day, there is no clear indication of which types of cases the competition authorities will face in the future. Concerning the debate on the plausibility of purely algorithmic collusion, several observers argue that algorithmic collusion may not currently pose an imminent or significant threat;³¹⁷ consequently, it is not yet possible to predict whether there is a need to reconsider the current legal regime and the methodological toolkit of competition authorities and if so, in which way.

It should be kept in mind however that algorithms, like digital markets as a whole, are rapidly evolving. Hence, the emergence of algorithmic collusion cannot be ruled out. This growing complexity of algorithms, the variety of outcomes that could emerge from competition in digital markets and the sheer size of the stakes likely to be affected therefore call for a constant vigilance towards the further development as well as the use of algorithms by companies. To this end, authorities should continue expanding their expertise on algorithms, in an exchange with each other as well as by interacting with businesses, academics and other regulatory bodies. Such an effort is in line with the more general tendency of authorities to devote more resources to the challenges posed by the ongoing digitalisation.

³¹³ Cf. *Data Ethics Commission*, Opinion of the Data Ethics Commission, 2019 (https://datenethikkommission.de/wp-content/uploads/191023_DEK_Kurzfassung_en_bf.pdf).

³¹⁴ Cf. *Bundesregierung*, Artificial Intelligence Strategy, 2018 (https://www.ki-strategie-deutschland.de/home.html?file=files/downloads/Nationale_KI-Strategie_engl.pdf).

³¹⁵ Cf. e.g. *Federation of German Consumer Organisations (vzbv)*, Algorithmic decision making for the benefit of consumers, 2019 (https://www.vzbv.de/sites/default/files/downloads/2019/07/19/19-06-25_vzbv_positions_adm_control_summary_en.pdf) and the expert opinion *Martini*, Fundamentals of a Regulatory System for Algorithm-based Processes, 2019 (https://www.vzbv.de/sites/default/files/downloads/2019/07/19/martini_regulatory_system_algorithm_based_processes.pdf), prepared on behalf of the *vzbv*.

³¹⁶ Regulation (EU) 2019/1150.

³¹⁷ Cf. part III.B.3.b), pp. 45 et seq., *vide supra*.