

Artificial Intelligence and Antitrust Law:

An Analysis of the Competition Policy & Possible Solutions in the Times of Algorithmic Collusion

JEL Classification: K210 Antitrust Law

Keywords: Anti-Competitive, Antitrust Law, Collusion, Competition

Submitted by: Kshitiz Arya

Supervised by: Prof. Dr. Florian Schuhmacher



**EUROPEAN MASTER
IN LAW & ECONOMICS**

2019

Abstract

The deployment of pricing algorithms by companies has seen a marked increase in the past decade on account of their efficiency enhancing features. The business landscape has evolved with increased transparency in digital markets and the question arises as to whether the traditional competition law policy is sufficiently evolved to deal with new forms of collusion facilitated by these algorithms, especially algorithmic tacit collusion. These issues raise enforcement challenges since unilateral tacit collusion by algorithms falls outside the scope of traditional competition law but adversely affects competition. This thesis seeks to critically analyse, from an economic and legal perspective, these new cases of algorithmic collusion as well as the existing legal framework and proposes solutions which are economically efficient to overcome the hurdles and challenges posed by artificial intelligence and algorithmic collusion.

Authorship Declaration

I hereby declare and confirm that this thesis is entirely the result of my own work except where otherwise indicated. I acknowledge the supervision and guidance I have received from Prof. Dr. Florian Schuhmacher.

This thesis is not used as part of any other examination and has not yet been published.

A handwritten signature in blue ink, appearing to read 'Kshitiz Arya'.

14th August, 2019, Kshitiz Arya,

ACKNOWLEDGEMENTS

First of all, I would like to thank Dr. Florian Schuhmacher who not only supervised my work by giving his invaluable suggestions but gave me his insights due to which my initial abstract thoughts on this topic could take the present form. Without his immense knowledge and expertise, this endeavour could not have taken off.

I am immensely grateful to those closest to me i.e. my parents who have constantly supported me in all my endeavours - this thesis was no exception. I would also like to express my profound gratitude to my brother, Ritwiz, a data analyst who was always a phone call away and helped me understand the different types and working of algorithms. Without his constant support and technical know-how of the subject, this thesis would have been a much more arduous task. To Sandy, pursuing her Ph.D. at University for Florida, for letting me know the most efficient way of conducting research and citing it - a big thank you!

I am grateful to Sh. Raj Kumar Badde, Joint Director, Competition Commission of India whose office was always open whenever I sought guidance. He continuously steered me in the right direction.

I would like to express my gratitude to fellow classmates namely Asena, Brett, Florenz, Ilan, Jodie, Luis, Mehul and Nico who were a constant source of encouragement and needless to mention, fun. Finally, the studying group comprising of the most amazing people i.e. Astrid, Jade (璇), Jasmin, Mike and Trish for letting me bounce ideas, both academic and otherwise, off them. Without them, this would have indeed been a very lonely endeavour.

Table of Contents

Introduction: The Context.....	5
1. Chapter - I: Algorithms: An Overview	7
1.1 Algorithms in Price-Setting.....	10
2 Chapter – II: Algorithms and Collusion	14
2.1 Types of Collusion: A Legal and Economic Perspective.....	14
2.2 Algorithms Facilitating Collusion: Economic Harm	16
2.2.1 Monitoring Algorithms	17
2.2.2 Hub and Spokes Model	19
2.2.3 Signalling Algorithms/ Predictable Agent	23
2.2.4 Machine/ Deep Learning Algorithms.....	25
3 Chapter – III: Challenges for Competition Law & Possible Solutions: The Indian Perspective	27
3.1 The Existing Legal Framework:	27
3.2 Whether the Different Types of Algorithmic Collusion Fall Within the Existing Legal Framework?	29
3.2.1 The Case of Monitoring Algorithm and Hub & Spoke Model:	30
3.2.2 The Case of Signalling & Machine Learning Algorithms:	32
3.3 Economic & Legal Analysis of Possible Solutions:.....	33
3.3.1 Interpreting ‘Agreement’ in a broad manner: Legal Analysis	33
3.3.2 Complete Prohibition on Algorithms: An Economically Efficient Solution?	35
3.3.3 Restrictions on Algorithm Features:	36
3.3.4 Liability Affixation	37
3.3.5 Other Measures and Law & Economic Analysis thereof:.....	40
Conclusion	44
BIBLIOGRAPHY	47

Introduction: The Context

With the advent of internet and the evolution of online market spaces, the landscape surrounding modern trade has undergone a significant change. In addition to the brick and mortar model where buyers would physically present themselves to purchase their desired goods, there now exists online markets where the buyers could digitally procure and purchase their products through the comforts of their home through internet. These online market spaces such as Amazon.com, Booking.com etc. have inherent transparency and are seen to be extremely dynamic in nature when it comes to pricing of goods and commodities. Very often, it is seen that the prices at which these goods are sold are determined by algorithms and not humans themselves. This trend has been increasing over the past decade or so on account of various advantages that algorithms possess over humans like their ability to analyse and process voluminous data, track real time prices of competitors etc. thereby enabling the sellers to sell their products or services at optimum prices. This trend of employment of algorithms comes with its own share of problems. For instance, algorithms have in the past increased prices of products to supra-competitive levels. Further, the debate whether to penalise tacit collusion in absence of any express communication between the competitors has been going on for a very long time. This debate has become more complicated with the advent of algorithms which have the ability to *communicate* with one-another without any human intervention thereby leading to collusive outcomes. Some pricing algorithms could even be specifically designed in such a manner so as to mimic the prices of a market leader or a competitor without any communication between humans to this effect. The present legal framework does not penalise unilateral pricing conduct and may not be sufficiently evolved to take into account algorithmic collusion.

This work would begin by explaining the basic concepts such as algorithms and their various types, followed by an elaboration of their use in product pricing. It will further analyse situations and types of algorithms which could collude with one another with or without any human intervention. An endeavour shall be made to ascertain whether the present competition law is sufficiently evolved to deal with algorithmic collusion and if not, suggest measures and solutions (based on a legal and economic analysis) which could be adopted to deal with or prevent such collusive outcomes. This thesis would therefore be analytical and recommendatory in nature.

Chapter - I: Algorithms: An Overview

***“An algorithm must be
seen to be believed.”***
- Donald Knuth

It is relevant to explain the concepts relating to algorithms such as artificial intelligence, machine learning, deep learning etc. and their functional usage so as to better understand their role in issues relating to tacit collusion.

Algorithms have been defined by Neapolitan and Naimipour as a sequence of steps employed for evolving an answer to a specific problem.¹ Cambridge Dictionary defines it as “*a set of mathematical instructions or rules that, especially if given to a computer, will help to calculate an answer to a problem*” The output that an algorithms produces is a product of employment of these steps to the input and is therefore a function of the input. An algorithm may have more than a single output, i.e., *quantities which have a specified relation to the inputs* (Knuth 1973:5). Cormen *et al* define it as “An algorithm is 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.”² A **software programme** which is written in a programming language such as C++, Java, COBOL etc. is a set of algorithms which work together and have been designed to provide solutions to a specified problem.³

Algorithms in the modern life are prevalent in a lot of places. When a google search is made, the order or sequence in which results appear are determined by an algorithm

¹ Neapolitan and Naimipour (2010), p. 3.

² Leiserson, C.E., Rivest, R.L., Cormen, T.H. and Stein, C., 2001. *Introduction to algorithms* (Vol. 6). Cambridge, MA: MIT press.

³ Alpaydin, E., 2009. *Introduction to machine learning*. MIT press.

employed by google. Such an algorithm may take into account input data such as key words, popularity of website, past searches made by the particular user, region where the search was made etc. to bring forth the most relevant results to the user. An example of a simple algorithm could be one which is designed to sort a particular set of data containing names and phone numbers in an alphabetical order. In this case, the input is the randomly placed names and corresponding phone numbers whereas the output is the ordered list. A simple calculator uses an algorithm to find solutions to mathematical problems as also does a computer chess game. The input data provided to an algorithm must conform to specific format(s) which the algorithm understands. For example, if a simple calculator is fed with algebraic data, the algorithm would fail to understand it thereby failing to give the desired solution.

The technologically advanced algorithms form part of science of artificial intelligence. Artificial intelligence could be loosely defined as machines which have the capability to mimic human intelligence thereby rendering them capable of making informed decisions. It could be considered as an umbrella term which covers within its ambit concepts of neural science⁴, cognitive science, data processing, image processing, machine learning etc. The term has been used to describe man-made machines which have the power to mimic ‘cognitive’ functions, which are generally only exhibited by humans.⁵ Encyclopaedia Britannica defines it as “*the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings.*” An example of artificial intelligence presently in use today is Apple’s voice assistant Siri

⁴ Towards Data Science: *Machine Learning vs Traditional Programming*, by Oleksii Kharkovyna; Available at <https://towardsdatascience.com/machine-learning-vs-traditional-programming-c066e39b5b17> (Last Visited: 1st July, 2019)

⁵ Russell & Norvig 2009, *Artificial Intelligence: A Modern Approach*, 3rd Edition, p. 2.

which can take voice commands from users and perform functions such as make phone calls, set reminders and send messages amongst other functions.

Algorithms vary in terms of their capabilities. They could be simple algorithms, machine learning or deep learning algorithms. Traditional programmes or simple algorithms do not have the ability to learn anything more than what it already knows. Therefore, a simple calculator algorithm used to perform basic mathematic calculations cannot by itself learn trigonometry until the same is taught to it by programming the rules of trigonometry. However, some algorithms have the ability to learn on the job i.e. they have the ability to learn on their own without human intervention. Machine learning is a subset of artificial intelligence. The machine learning algorithms have been designed by humans but endowed with the inherent ability to learn from their experiences while they are in use. They utilise the data used as an input to give solutions and make accurate predictions. Through regular practice, these algorithms learn to make more accurate predictions and get better at their job. Arthur Samuel sought to define machine learning as the *“field of study that gives computers the ability to learn without being explicitly programmed”*. Tom M. Mitchell also sought to define machine learning. He writes - *“A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P , if its performance at tasks in T , as measured by P , improves with experience E .”* Therefore, if the performance of a machine gradually improves through experience at the same tasks, it is said to be learning through experience and is therefore an example of machine learning. Machine learning technology is now being deployed in various fields such as product and advertising placements, share markets,

online audio and video streaming services, big data analytics, drug development etc.⁶ Researchers also believe that in future, *high level machine learning* would be able to outperform human workers at all tasks.⁷ An example of machine learning algorithms would be online music streaming services such as Apple music, Amazon music or Spotify which learn the music preferences of the consumer over a period of time thereby enabling them to give better recommendations to the consumer. Algorithms tell us which TV series to watch, book to purchase and music to listen to. They have utility in almost all sectors ranging from health to automobiles. Deep learning is more or less similar to machine learning and could be regarded as a subset of machine learning and is technologically more advanced. Deep learning algorithms require huge amount of data which it would then analyse before making a prediction. An engineer's intervention is required in case a machine learning algorithm results in an inaccurate prediction to rectify the anomaly. However, in case of deep learning algorithms, the programme itself has the ability to identify the inaccuracy and correct itself.

1.1 Algorithms in Price-Setting

Algorithms vary in terms of their capabilities and output which they seek to achieve. They range from being simple algorithms to very complex ones.

Simple algorithms may be employed with predetermined rules such as to mimic the price of the competitors or keep the price slightly lower or higher than a competitor. A more complex algorithms may be programmed to take into account the price of competitors as well as other factors such as consumer reviews, number of clicks on the

⁶ Awad, M. and Khanna, R., 2015. *Efficient learning machines: theories, concepts, and applications for engineers and system designers*. Apress

⁷ Grace, K., Salvatier, J., Dafoe, A., Zhang, B. and Evans, O., 2018. When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research*, 62, pp.729-754.

product/ service, number of competitors in the market etc. As is obvious, machine learning algorithms are more complex than simple algorithms and have the ability to solve more problematic issues including those relating to price-setting. One of the first algorithms which were programmed to use for the purpose of price determination worked on the principle of “win-continue, lose-reverse”.⁸ This rule states that a seller should measure the profits after varying the price in a specific direction (upward or downward) and keep moving the price in the same direction so long as the profits continue to increase. In case of reduction in profits or losses, the price should be moved in the opposite direction. An algorithm working on such principle has advantages in so far as it does not require advanced resources or consumer specific data.⁹

Algorithms for pricing could be broadly categorised into two types. First, which is developed by the firm/ enterprise selling the product to sell the product/ service in question at the optimum price for maximisation of profits. Second, which is developed by third party technological firms and then sold to firms/ enterprises which could deploy these algorithms for their products or services. In the second category of algorithms, the technological firms may not develop the algorithms specifically for a product or class of products but develop a generic model.

The use of either of the aforementioned two types of algorithms has significantly increased over the past decade. In the 1990s and early 2000s, most of the sellers on e-bay either resorted to an online auction or manually determined the prices at which they would sell their goods. By 2015, more than a third of all sellers on Amazon.com, which is

⁸ Izquierdo, S.S. and Izquierdo, L.R., 2015. The “Win-Continue, Lose-Reverse” rule in oligopolies: robustness of collusive outcomes. *Advances in Complex Systems*, 18(05n06), p.1550013.

⁹ DiMicco, Greenwald, and Maes (2001), ‘Dynamic pricing strategies under a finite time horizon’, Proceedings of the 3rd ACM conference on Electronic Commerce, pp95-104.

arguable the biggest online-market website, resorted to the use of automatic pricing software.¹⁰ This is likely to increase in the coming times. Researches also seem to suggest that it may not be easy for sellers manually determining prices to compete against other sellers who employ the use of pricing algorithms thereby leading to a ‘arms race’ whereby all sellers would eventually deploy pricing algorithms.¹¹ Some researchers have suggested it is not the technological advancements in the algorithm industry itself which has led to their increased penetration and usage but the advent and availability of big data.¹² Big data does not enjoy a precise definition acceptable to everyone¹³ but most scholars attribute characteristics of volume, velocity and variety to it.¹⁴ Volume would typically mean the amount of data, velocity is the speed at which the data is gathered or stored and the speed at which it changes. Variety is the various sources for collection of data. The availability of big data could very well be one of the major factors leading to the increased penetration of algorithms in pricing of goods or services. One of the major advantages that pricing algorithms have over humans is their ability to process large amounts of data at a rate that human brain is incapable of. In a sector enquiry¹⁵ conducted by the European Commission, it was found that approximately 30% of the responding manufacturers tracked the online prices of their products out of which more than a third did so using software programmes. The same report also established that more than 50% of the total responding retailers kept a track of the online prices offered by their competitors with approximately 66% of these

¹⁰ Chen, L., Mislove, A. and Wilson, C., 2016, April. An empirical analysis of algorithmic pricing on amazon marketplace. In *Proceedings of the 25th International Conference on World Wide Web* (pp. 1339-1349). International World Wide Web Conferences Steering Committee.

¹¹ Ibid.

¹² Gal, M.S. and Elkin-Koren, N., 2016. Algorithmic consumers. *Harv. JL & Tech.*, 30, p.309.

¹³ Ward, J.S. and Barker, A., 2013. Undefined by data: a survey of big data definitions. *arXiv preprint arXiv:1309.5821*.

¹⁴ De Mauro, A., Greco, M. and Grimaldi, M., 2015, February. What is big data? A consensual definition and a review of key research topics. In *AIP conference proceedings* (Vol. 1644, No. 1, pp. 97-104). AIP.

¹⁵ Final report on the E-commerce Sector Inquiry; Report from the Commission to the Council and the European Parliament, Brussels dated 10.5.2017; COM (2017) 229 final.

using software programmes to do so. Of the two-third retailers who use algorithms to track prices of their competitors, 78% of them alter their prices in response to the prices of the competitors. Therefore, the use of algorithms for price setting has been embraced by sellers for maximising outputs. There are undoubtedly benefits which accrue to sellers who deploy algorithms for price determination which shall be discussed in the last chapter.

However, this trend of employing algorithms by sellers for determining the optimum prices at which their goods or services should be sold at, comes with its own set of issues. First of all, the employment of these algorithms does not necessarily mean that the prices of products in question would reduce thereby benefitting consumers.¹⁶ There are more pertinent antitrust issues which also need to be looked into, the most prominent being facilitation or employment of tacit collusion as a result of these algorithms.

¹⁶ Chen, L., Mislove, A. and Wilson, C., 2016, April. An empirical analysis of algorithmic pricing on amazon marketplace. In *Proceedings of the 25th International Conference on World Wide Web* (pp. 1339-1349). International World Wide Web Conferences Steering Committee.

Chapter – II: Algorithms and Collusion

“If it isn’t ok for a guy named Bob to do it, then it probably isn’t ok for an algorithm to do it either”

- FTC Commissioner Maureen Ohlhausen

Various competition authorities around the world have feared that algorithms employed for price determination may learn to collude. Collusion in common parlance is defined as *an agreement between people to act together secretly or illegally in order to deceive or cheat someone.*¹⁷ It describes a behaviour or action whereby the decision-makers agree to coordinate their actions prior to taking them.¹⁸ Clarke states that collusion requires two steps.¹⁹ First, an agreement amongst competitors on the prevailing market state. Second, evolution of coordinated market strategy based on these homogenized beliefs.

2.1 Types of Collusion: A Legal and Economic Perspective

Collusion in the antitrust field may be broadly categorised as express or explicit collusion and tacit collusion. It may also be a combination of both express as well as tacit.²⁰ Explicit collusion is one where the competitors agree to fix prices or output through express communication or agreement to this effect. The agreement may be oral or written. Therefore, there is an underlying express agreement or arrangement before the coordinated steps are undertaken. Tacit collusion is a scenario wherein the players in the market do not expressly agree on prices, output or other parameters but in effect, have led to similar outcome. They agree on something without explicitly saying so or communicating with

¹⁷ Dictionary, C., 2008. Cambridge advanced learner’s dictionary

¹⁸ Rees, R., 1993. Tacit collusion. *Oxford Review of Economic Policy*, 9(2), pp.27-40.

¹⁹ Clarke, R.N., 1983. Collusion and the incentives for information sharing. *The Bell Journal of Economics*, pp.383-394.

²⁰ Ivaldi, M., Jullien, B., Rey, P., Seabright, P. and Tirole, J., 2003. The economics of tacit collusion. *Final report for DG competition, European Commission*, pp.4-5.

one another. For example, there may be a practice in an industry that all existing players would match the prices of products at which the largest player offers them to the consumers without any express arrangement to this effect. From an economic perspective, although no explicit agreement or communication between the competitors, the effect on account of industry practices is same as would have been in case of explicit collusion. Conscious price parallelism as seen above is an example of tacit collusion. Economic literature has shown that tacit collusion is prevalent in oligopolistic industries with transparent markets and homogenous products. Less number of players facilitate collusion as transaction costs for coming to an agreement would not be prohibitive. Monitoring costs for deviant players is also likely to be low in case of less players.

From a legal perspective, one fundamental difference between explicit and tacit collusion is that while the former is held to be an illegal agreement falling foul of antitrust provisions in most jurisdictions, the latter is not illegal and falls beyond the purview of competition laws. Although, market outcome in both of these cases is same and enables firms to earn supra-competitive profits, the tacit collusion without any agreement does not contravene antitrust provisions. Although price parallelism in itself is not illegal *per se* but if such conduct is coupled with other evidence of coordination called ‘plus factors’, then such price parallelism would be treated as ordinary collusion. Plus factors could be anything such as information exchange, to evidence of holding meetings or phone calls etc. Whether ‘plus factors’ are sufficient to hold the parallelism anti-competitive or not is a question of fact and will have to be dealt with on a case by case basis.

2.2 Algorithms Facilitating Collusion: Economic Harm

In addition to the benefits which accrue on use of pricing algorithms, there are some potential harmful effects as well. In some cases, algorithms have been known to have caused some undesirable effects. In one such instance, the price of a book, which was being sold on Amazon.com by two sellers both of which were employing algorithms for price determination, went up slowly to \$23 Million per copy. Both of these sellers were using simple algorithms which determined the price of the book by factoring in the price at which the other seller was offering it for. The first seller had programmed his algorithm in such a manner that his page sold the book for a price which was 1.2 times the price at which the second seller was offering it for sale. The second seller had programmed his algorithms in such a manner that his book were to be sold at a price which was 0.99 times the price of first seller. As a result, the price kept going upwards until it reached a whopping \$23 Million per copy before one of the sellers noticed the anomaly and reset the price to usual standards. In another case which took place most recently in the month of July, 2019, some consumers purchased goods on Amazon India at ridiculously cheap prices due to malfunctioning algorithms.

This example only goes to show how poor implementation of algorithms could lead to undesirable effects that were not a result of any intent to distort competition by the sellers. However, there are other cases wherein algorithms have either been specifically designed to bring about or implement pre-existing anti-competitive agreement or otherwise facilitate tacit collusion thereby resulting in appreciable adverse effects on competition. These cases would be discussed in the following part of this chapter.

2.2.1 Monitoring Algorithms

Monitoring algorithms enable a player in the market to keep track of the actions of its competitors thereby enabling him/her to tweak his/her actions accordingly. The employment of algorithms in online market spaces is not limited to the purpose of determining optimum prices but extends to the implementation and operation of an already existing collusive agreement. Monitoring algorithms would be useful for players who entered into an agreement to fix prices by reporting any deviations from agreed conduct. A collusive agreement is only as good as the ability to monitor the conduct of the parties to agreement. In case of weak monitoring mechanism, one of the players would be able to undercut the prices compared to others thereby enabling higher profits which may ultimately result in breaking down of the anti-competitive agreement. Longer the time it takes to detect a deviant behaviour, higher would be the incentive for any one party to agreement to cheat as deviations from fixed prices would result in higher profits for the player who cheats. This is where monitoring algorithms step in providing real time information and allowing quick punishment to any deviant party. The operation of the anti-competitive agreement in cases where it is monitored through the use of algorithms is much smoother as any deviations would be reported instantly thereby enabling the parties to agreement to punish the deviant player.

Further, Mehra²¹ has argued that use of monitoring algorithms also reduces *agency slack* i.e. employees or sales people (who are different from the management that entered into collusive agreement) may have incentives to sell the products at a reduced price on account of certain incentives. This could be on account of immediate pay-offs as against

²¹ Mehra, Salil K., Antitrust and the Robo-Seller: Competition in the Time of Algorithms (March 10, 2015). Minnesota Law Review, Vol. 100, Forthcoming; Temple University Legal Studies Research Paper No. 2015-15. Available at SSRN: <https://ssrn.com/abstract=2576341>, Last visited 1st July, 2019

profits which may accrue over a very long term from maintenance of cartel prices. When determination and monitoring of prices is done by algorithms, the possibility that low level sales people or other employees will undercut the cartel prices is almost non-existent.²²

Example of Application of Monitoring Algorithms: In 2016, Competition and Market Authority, the antitrust authority of the UK took the decision²³ of holding two amazon online sellers guilty of fixing prices by employing the use of “automatic pricing software”. Two online sellers, namely Trod Limited and GB eye Limited, agreed not to undercut each other’s price on Amazon UK’s website for licensed sport and entertainment posters and frames (including poster frames). As a result thereof, the buyers of the product could procure these items at the same prices only irrespective of the seller (Trod or GB eye) they buy it from. This in effect eliminated competition between the aforementioned sellers. In order to facilitate, implement and monitor this illegal agreement, the sellers used a pricing software to ensure that prices reflected their agreement and adjusted accordingly. The Competition and Market Authority fined Trod a sum of £163,371 where as GB eye escaped punishment as they received leniency on account of their conduct. GB eye reported the cartel as well as cooperated with the competition authority since the inception and thus, were granted full immunity from penalty.

This case is a classic example of a monitoring algorithm wherein an algorithm have facilitated the implementation of underlying anti-competitive agreement. The characteristic feature in cases of monitoring algorithms is the preliminary agreement which already exists between the parties to collusion which is entered into by humans. The

²² Ibid.

²³ Case 50223, Online sale of posters and frames; Decision of the Competition and Market Authority, dated 12th August, 2016; Available at <https://assets.publishing.service.gov.uk/media/57ee7c2740f0b606dc000018/case-50223-final-non-confidential-infringement-decision.pdf>; Last visited 15th July, 2019

application of algorithms is only to facilitate this underlying agreement. The present antitrust framework is sufficient to deal with these issues as the agreement itself contravenes antitrust law.

2.2.2 Hub and Spokes Model

It has often been stated by scholars that one of the most immediate risks to competition law is posed by the hub and spoke scenario. The competition issues of tacit coordination could arise from hub and spoke model wherein the same pricing software (hub) is applied by two or more competitors (spokes). In such a case, since the firms have applied the same pricing software and the algorithm for determining the price is the same, a strong possibility exists that the prices as determined by these algorithms would also be the same. This scenario is more likely in cases where the firms have outsourced the application or development of pricing algorithms to third party technological firms or programmers which have expertise in the development of such software or algorithms. In such cases where the pricing software is sourced from the same firm, the probability that the pricing software would use the same algorithm to determine optimum prices of products is much higher thereby leading to collusive prices. Further, if a competitor has knowledge that other players in the market are using the same pricing software, it would be easy to estimate the response of such competitors to external factors such as change in demand or supply etc. making it easier to sustain supra-competitive prices. This would have an effect akin to information sharing and exchange although without express human intervention. Likewise, in cases where the payment to such a technological firm which has developed such a pricing algorithm is agreed as a share of revenue from products, the firm would have a strong incentive to design an algorithm which is able to maintain the prices at supra-competitive levels so as to increase its own profits. Moreover, collusion of this type would

be prevalent in cases of dominant online market platform where all the vendors of the homogenous product use the same pricing algorithm.²⁴

However, the hub and spoke model may not necessarily lead to collusive outcomes in all cases. There are certain inhibiting factors at play which would prevent tacit collusion in hub and spokes scenario. Even if two or more competing players use the same pricing algorithms, the hurdles to sustain such collusive prices would still exist.²⁵ For instance, the incentives to cheat or tweak the algorithms to undercut the prices of their competitors thereby earning short term higher profits would not be rendered redundant in the hub and spokes model. Another factor which needs consideration is the ability of the firms to detect whether their competitors in the market are employing similar algorithms. Although two or more firms might be resorting to pricing software which employ same algorithms, it might not be possible for firms to realise this fact and therefore, predicting response of competitors to external changes might not be easy.

The hub and spoke model is a relatively more complicated type of tacit collusion in so far as there are separate horizontal and vertical agreements at work wherein all the parties may not be aware of the all the agreements in place.

Factors affecting economic harm: It is also pertinent to state some considerations which would determine the gravity of harm caused in case of hub and spokes model.²⁶ The first would be the number and proportion of competitors who are using the same pricing

²⁴ Ezrachi, Ariel and Stucke, Maurice E., Online Platforms and the EU Digital Single Market (October 16, 2015). University of Tennessee Legal Studies Research Paper No. 283. Available at SSRN: <https://ssrn.com/abstract=2677267> or <http://dx.doi.org/10.2139/ssrn.2677267>

²⁵ Pricing algorithms: Economic working paper on the use of algorithms to facilitate collusion and personalised pricing; Competition and Market Authority; 8th October, 2016; Available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf, Last visited 17th July, 2019

²⁶ Ibid.

algorithm in the relevant market. In cases where only a tiny proportion of the total sellers are resorting to use of a common algorithm, then collusive supra-competitive pricing would not be possible as buyers would shift to other sellers. Another consideration is the revenue sharing model between the hub i.e. the technological firm designing the pricing algorithm and the spokes i.e. the sellers adopting the algorithm to determine the prices at which they should sell their goods. If the hub (algorithm/ technological firm developing it) gets a share out of the revenue earned by the spokes, in such a case the technological firm developing the algorithm has an incentive to tweak it in such a way so as to maintain supra-competitive prices.

Hub & Spoke Model: The Uber Example: A hub and spoke model also refers to an arrangement where a technological firm (the hub) which has designed an algorithm facilitates collusion amongst members of an upstream and downstream market where all the members have availed the use of the algorithm. In such a case, each of the member of the upstream and downstream market have an agreement with the technological firm separately.²⁷

In a scenario where the hub is a human entity rather than an algorithm, the collusion which the spokes i.e. the upstream or downstream market players indulge in would be communication indirectly through the hub. Thus, the spokes are not communicating directly through face-to-face meetings and deliberations but through another intermediary. When collusion is a result of face to face interaction, some cues such as facial expression, body language etc. provide important cues for trust which facilitates successful collusion.²⁸

²⁷ Passaro, Nicholas, How Meyer v. Kalanick Could Determine How Uber and the Sharing Economy Fit into Antitrust Law (September 27, 2017). 6 Mich. Bus. & Entrepreneurial L. Rev. 2, 2018, Forthcoming. Available at SSRN: <https://ssrn.com/abstract=2880204> or <http://dx.doi.org/10.2139/ssrn.2880204>

²⁸ Harrington Jr, Joseph E., How Do Hub-and-Spoke Cartels Operate? Lessons from Nine Case Studies (August 24, 2018). Available at SSRN: <https://ssrn.com/abstract=3238244>

In case of a hub which is indirectly relaying information, there could be inadvertent errors in passing on information in so far as he or she may omit some important pieces of information or state something which has not been said at all. However, in cases where the hub is itself an algorithm, such hurdles are rendered redundant. Take the case of Uber. In the case of Uber, the founder, T. Kalanick, developed an algorithm for gauging the demand and supply for transport services. The algorithm (hub) would then calculate the price for the buyer of these services taking into account the demand and supply for such services and the destination where the buyer for transport services desires to travel. The seller (spokes) of such services were owners of cars who agreed to provide their car on rent as well as their driving services to the buyer and drop off the buyer to his or her preferred choice of destination. The driver i.e. the seller of transport services was promised a proportion of payment received as a price from the buyer where the price was determined by the algorithm developed by Uber. No driver on the uber networking using Uber's algorithm could offer another price to a buyer. The price so determined for transport services were therefore not a result of any competitive uncertainty but a result of the fact that no other driver was allowed to quote a lesser price to a potential buyer.²⁹ As is evident in this case, there was an explicit revenue agreement between the hub (uber/ algorithm) and the spokes (drivers) as well as a tacit agreement between all the spokes *inter se* that none of them would charge an amount different than the one determined by the algorithm.³⁰ This in turn enables the hub (uber) to maintain supra-competitive prices. The

²⁹ Šmejkal, V. (2017). Cartels by Robots: Current Antitrust Law in Search of an Answer. *Inter EU Law East: Journal for the International and European Law, Economics and Market Integrations*, 4(2), pp.1-18.

³⁰ Passaro, Nicholas, How Meyer v. Kalanick Could Determine How Uber and the Sharing Economy Fit into Antitrust Law (September 27, 2017). *6 Mich. Bus. & Entrepreneurial L. Rev.* 2, 2018, Forthcoming. Available at SSRN: <https://ssrn.com/abstract=2880204>; Last visited: 7th June, 2019

incentive to maintain supra-competitive prices stems from the fact that a part of the revenue is shared by the algorithm (uber) and the remaining goes to the driver.

In another instance, the competition authority in Lithuania penalised the conduct of Eturas which acted as a hub and a number of travel companies which were the spokes. The illegal conduct in this case was fixing an upper cap on discounts on services offered through the Eturas online digital platform.

2.2.3 Signalling Algorithms/ Predictable Agent

Where the pricing software and the underlying algorithm react to the input data such as changes in demand, price of raw material, customer reviews etc. in a predictable manner, thereby enabling the competitors to gauge the pricing mechanism, the probability of tacit collusion increases. The algorithm would be in a position to signal its intention to the competitors which in essence, is an offer to facilitate a collusive outcome. Judge Posner states as follows in his ruling:

“If a firm raises price in the expectation that its competitors will do likewise, and they do, the firm’s behaviour can be conceptualized as the offer of a unilateral contract that the offerees accept by raising their prices.”

Whether signalling and subsequent alignment of prices by the competitor should be considered as an anti-competitive activity is a debatable issue since there is no express agreement to fix prices. Moreover, signalling does come at a price to the seller who gives the signal. For example, if a seller increases the price of his good as a signal in anticipation that its competitors would also increase the prices of their goods, and the competitors do not increase their prices, the original seller giving the signal stands to lose his business to his competitors since the consumers would prefer to buy a cheaper product given that the quality and other characteristics of the product are the same. The role of pricing algorithms

in this scenario cannot be undermined. Since algorithms have the ability to parse copious amounts of data in a very short time, the delay in responding to a signal is altogether eliminated thereby reducing the risk of the firm giving the initial signal.³¹ Moreover, such signals may be given at a time when the buyer activity is minimal thereby minimising the risk associated with giving a signal. For example, a seller X on an online website may use a software which increases price of the product at midnight as a signal and thereafter, waits for a period of 2-3 hours to see how its competitors respond to such an increase. In a case, where the competitors use pricing algorithms, X would know in a matter of few minutes to few hours (depending on how often the competitors' algorithms have been instructed to track prices of X's products and respond accordingly) whether the competitors have accepted the signal and raised the prices of their goods to match X's price or stuck to their original prices. In case where the prices of competitors do not increase, the seller X would know that its competitors do not seek to indulge in parallel conduct and X in such a case, may choose to reduce the prices of its product back to the competitive levels. Since, the increase by X took place at midnight where a large number of buyers were relatively inactive, it would not have a high adverse effect on sales.

Signalling is easier in cases of oligopolistic markets with high transparency such as online market spaces where competitor's prices can be easily ascertained. However, whether signalling could be treated as anti-competitive conduct within the present competition law framework and if not, should it and how must it be brought within its ambit is a matter of debate and shall be dealt with in the next chapter.

³¹ OECD (2017), Algorithms and Collusion: Competition Policy in the Digital Age; Available at www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm, Last visited 15th July, 2019

2.2.4 Machine/Deep Learning Algorithms

One of the most technologically advanced algorithms are machine-learning algorithms which have the capability to learn through experience. As already explained in Chapter-1, machine learning algorithms have the ability to get better at its job by learning new processes and adopting new steps that have not been explicitly programmed or instructed to it. *Libratus*, a computer algorithm designed to compete in the game of poker is a good example, to provide a glimpse into what future algorithms could accomplish. The artificial intelligence software was developed to play *Heads-Up No-Limit Texas Hold'Em* poker. *Libratus* took part in a tournament against best human players. The algorithm which was a self-learning algorithm played poker against professional human players during the day and analysed its strategy during the night. *Libratus* was not instructed to follow any particular strategy and was only told of the objective i.e. win the game. Over a period of time, *Libratus* taught itself how to get better at the game and eventually beat the best human players. Later, one of the human players commented that *Libratus* was so good at teaching itself poker that it almost felt like the algorithm already knew what cards the human players had. Such machine-learning algorithms have application in various fields. In the case of price determination, machine-learning algorithms could be instructed to set optimum prices with the single objective to increase revenue to the sellers. These machine and deep learning algorithms have very high predictive ability and can learn on the job thereby reacting to competitors' behaviour which could be either a human or another algorithm leading to collusive outcomes. In such cases, human intervention is not required. Moreover, two or more algorithms over a period of time could teach themselves that collusion would lead to higher profits for the sellers. In such case, the possibility that algorithms collude without being expressly instructed to do so cannot be undermined. One of the most problematic issues for antitrust authorities in case of machine-learning

algorithms is its detection since the sellers who used the algorithms are themselves not aware of the collusive conduct by the algorithms. This is due to the fact that the processes or steps used by the machine-learning algorithm for determining the price of a product or service, is not known to the user. The algorithm uses a set of data, reads it, processes it and thereafter gives the output. How the data is processed and the various steps the algorithm employs is completely unknown to the human and only the input and the output is known. How the algorithm came to produce the outcome takes place within what is called the “black box”. What happens inside the black box is not known therefore making it impossible to know whether the algorithm gave out a collusive output or not, and if yes, what algorithmic steps led to the collusive outcomes. The machine learning algorithm over a period of time can learn that collusive strategies result in higher revenue, a goal it was instructed to achieve.

Having described the various types of algorithms, an endeavour shall be made to ascertain whether the present Indian competition law is sufficiently equipped to deal with these issues and if not, provide solutions to overcome the challenges.

Chapter – III: Challenges for Competition Law & Possible

Solutions: The Indian Perspective

“We are like robots in the sense that we carry out actions on the basis of thoughts that are programmed in us via our genes, upbringing, experiences, social conditioning, and a tad of free will.”

- Rajesh, Random Cosmos

This chapter would seek to analyse different types of algorithms described in the preceding chapter and thereafter, briefly expound the relevant provision of the Indian competition law and the surrounding jurisprudence with a view to ascertain whether the law, as it stands today, is sufficiently evolved to deal with algorithmic collusion. Thereafter, possible hurdles to achieving the objective of the competition law would be identified and solutions would be proposed and analysed from legal and economic perspective.

3.1 The Existing Legal Framework:

The present competition law in India is governed by the Competition Act, 2002 enacted by the Parliament of India. Prior to the enactment, competition issues were dealt with by the erstwhile Monopolies and Restrictive Trade Practices Act, 1969 which suffered from various infirmities. The Indian competition law is largely modelled on the lines of the EU competition law framework and also borrowed ideas from US antitrust legislation. The provision prohibiting collusion is enshrined under Section 3 of the relevant act which is analogous to Article 101 of Treaty on the Functioning of the European Union (TFEU). The relevant provision prohibiting horizontal price fixing agreement is contained in Section 3 of the Act. The same is being reproduced hereinunder:

“3. Anti-competitive agreements.—

(1) No enterprise or association of enterprises or person or association of persons shall enter into any agreement in respect of production, supply, distribution, storage, acquisition or control of goods or provision of services, which causes or is likely to cause an appreciable adverse effect on competition within India.

(2) Any agreement entered into in contravention of the provisions contained in sub-section (1) shall be void.

(3) Any agreement entered into between enterprises or associations of enterprises or persons or associations of persons or between any person and enterprise or practice carried on, or decision taken by, any association of enterprises or association of persons, including cartels, engaged in identical or similar trade of goods or provision of services, which—

(a) directly or indirectly determines purchase or sale prices;

(b) limits or controls production, supply, markets, technical development, investment or provision of services;

(c) shares the market or source of production or provision of services by way of allocation of geographical area of market, or type of goods or services, or number of customers in the market or any other similar way;

(d) directly or indirectly results in bid rigging or collusive bidding, shall be presumed to have an appreciable adverse effect on competition:

Provided that”

As is evident from the bare perusal of the provision, clause (1) expressly prohibits agreements which causes or is likely to cause an appreciable adverse effect on competition within India. Clause (3) enshrines within itself the *per se* rule declaring that certain types of conduct shall be presumed to cause an appreciable adverse effect on competition. Clause (3) expressly states that price fixation agreement shall be presumed to cause appreciable adverse effect on competition. Agreement is defined by Section 2(b) of the Competition Act, 2002 and is as follows:

“(b) “agreement” includes any arrangement or understanding or action in concert,—

(i) whether or not, such arrangement, understanding or action is formal or in writing; or

(ii) whether or not such arrangement, understanding or action is intended to be enforceable by legal proceedings;”

As is evident from the definition above, the term agreement enjoys a very broad scope and includes within its ambit an ‘arrangement’, ‘understanding’ or an ‘action in concert’. The Indian Supreme Court i.e. the highest court of the land has previously held that parallel pricing is neither by itself an evidence of concerted practice nor is it illegal.³² However, in case, prices were found to be same on account of communication between the parties or due to information sharing, the conduct would be anti-competitive and warrant a penalty under the Competition Act.

3.2 Whether the Different Types of Algorithmic Collusion Fall Within the Existing Legal Framework?

The present challenges in case of algorithms may be classified under two categories. First, where the pricing algorithm facilitates or enhances collusive conduct which already falls within the present ambit of antitrust legislations and second, where algorithm results in a relatively new type of collusion not contemplated by the present legal framework. It is often witnessed in the second category that algorithm would enable tacit collusion without the requirement of any communication between the competitors. In the first category falls the case of Monitoring Algorithm and Hub and Spoke Model whereas signalling algorithms and machine learning algorithms would fall within the second category.

³² See Rajasthan Cylinders Containers Ltd. vs. Union of India & Ors.; 2018 SCC OnLine SC 1718.

3.2.1 *The Case of Monitoring Algorithm and Hub & Spoke Model:*

In case of monitoring algorithms, the role of algorithms is restricted to smooth implementation of the underlying anti-competitive agreement. Since the underlying agreement already exists which is barred by competition law, the present competition law framework is sufficient to deal with the aforesaid conduct. The only novel element in this case is the use of a computer algorithm to facilitate the implementation of collusive agreement. Likewise, in the case of the hub and spoke model as well, the algorithm is only the means of facilitating an existing agreement. For example, in the case of Uber, all the drivers allow uber to determine the price of their services. Although there is no agreement to fix prices between the drivers inter-se, they, in essence, allowed a third party (Uber's algorithm) to fix prices on their behalf. Further, the drivers accepted that they could not charge an amount different than the one determined by the algorithm. Therefore, there is a tacit agreement between all the drivers *inter-se* that all the drivers would charge the same amount for the same service which in essence should fall within the ambit of Section 3. Therefore, the present competition law framework in such a case is sufficiently equipped to deal with such a hub and spoke model. The Competition Commission of India dealt with the aforementioned issues and held that such a practice of tacit collusion in Uber's hub and spoke model was not illegal. The Competition Commission of India made the following observations³³:

“In case of Cab Aggregators model, the estimation of fare through App is done by the algorithm on the basis of large data sets, popularly referred to as ‘big data’. Such algorithm seemingly takes into account personalised information of riders along with other factors e.g. time of the day, traffic situation, special conditions/events, festival, weekday/weekend which all determine the demand-supply situation etc. Resultantly, the algorithmically determined pricing for each rider and

³³ See Case No. 37 of 2018, In re: Samir Agrawal and others; Order dated 6th Nov, 2018. Available at <https://www.cci.gov.in/sites/default/files/37of2018.pdf>, Last visited: 1st August, 2019

*each trip tends to be different owing to the interplay of large data sets.....In the case of ride-sourcing and ride-sharing services, a **hub-and-spoke cartel would require an agreement between all drivers to set prices through the platform, or an agreement for the platform to coordinate prices between them.** There does not appear to be any such agreement between drivers inter-se to delegate this pricing power to the platform/Cab Aggregators. Thus, the Commission finds no substance in the first allegation raised by the Informant.”*

Therefore, the Indian law as it stands today requires an explicit agreement between the drivers inter-se to fix prices. However, I am of the firm belief that the Commission has erred in holding that an express agreement between drivers is a pre-requisite for holding the above hub and spoke model illegal. One of the reasons for the same is that all the drivers know that the all the drivers are accepting the same terms and conditions with uber as every other driver. Therefore, they tacitly outsourced the decision to a common hub and agreed to ply their transport services at the price determined by the hub (Uber’s algorithm). This is an ‘action in concert’ and falls within the scope of the definition of ‘agreement’. There are other reasons as well to hold the view that the Competition Commission of India did made errors in the aforementioned order. However, there are arguments that exist in favour of Uber as well.³⁴ However, elaboration of these issues is beyond the scope of this paper and would not be delved into for the sake of brevity. The pertinent issue which needs addressal is whether the present Indian competition law framework is sufficiently evolved to deal with this sort of tacit collusion or does it require modification? The answer is in the affirmative. The present competition law framework in India is sufficient to deal with these issues. The Competition Commission of India if it so desired to hold this act of tacit collusion in the hub and spoke model as illegal, could have done so by relying on the

³⁴ See Passaro, Nicholas, How Meyer v. Kalanick Could Determine How Uber and the Sharing Economy Fit into Antitrust Law (September 27, 2017). 6 Mich. Bus. & Entrepreneurial L. Rev. 2, 2018, Forthcoming.

existing legal framework i.e. by relying upon Section 3 and the definition of ‘agreement’ under Section 2(b). The Indian competition law framework gives enough leeway to the Competition authorities to interpret the relevant provisions in such a manner as to hold the hub and spoke model involving price fixation illegal. As expounded earlier in this chapter, the term agreement under the Act is wide enough to include an arrangement, or an action in concert. For example, in Uber’s case, the hub and spoke model is an arrangement between the drivers to not provide their services to any buyer at a price different than one determined by an algorithm. Therefore, the algorithm itself is not culpable but it were the humans (the drivers) who acted in the collusive manner which could be penalised. Therefore, the hub and spoke model like the monitoring algorithms do not pose any formidable challenge for the competition law in matters relating to affixation of liability.

3.2.2 *The Case of Signalling & Machine Learning Algorithms:*

The next two types of algorithms i.e. signalling algorithm as well as machine learning algorithm do pose challenges for competition law. The Indian competition law like the European and American competition law models, do not proscribe parallel behaviour so long as it results from unilateral conduct without any direct communication between the parties. Where supra competitive prices were a result of strategic decisions made independently (such as the decision to raise prices after noticing that a market leader has increased price) by the players in market, their conduct does not fall in the ambit of antitrust rules. In this context, Richard & Bailey write “*such parallel behaviour does not, in itself, amount to a concerted practice under Article 101(1).*”³⁵

³⁵ Richard Whish & David Bailey, Competition Law, 8th ed (Oxford University Press, 2015) at pp. 603.

Therefore, in case of signalling algorithm which contributes towards tacit collusion, the possibility of affixing liability does not exist since there is no coordination. However, in the US, one of the prominent proponents of the Chicago School, Judge Posner put forth an assertion for interpreting agreement in such a manner as to encompass within its ambit a tacit strategy followed by competitors without any communication between them.

In the case of learning algorithm, the complexity of algorithms is such that detecting whether the algorithm has colluded with another competitor's algorithm is virtually impossible. On account of inability of humans to reverse engineer the processes which took place in the algorithm's 'black box', it is impossible to know how the algorithm determined the optimal price for a particular product and whether it colluded or interacted with another algorithm resulting in supra-competitive prices. Moreover, machine-learning algorithms can teach themselves that colluding with another algorithm is likely to attain its goal of revenue maximization. The human seller who is using the algorithm may neither be aware of such (illegal) conduct nor may he or she have the intention of indulging in collusive conduct. Therefore, the challenges to detection of algorithmic collusion causing supra-competitive prices cannot be undermined.

3.3 Economic & Legal Analysis of Possible Solutions:

In this section, I will critically analyse the feasibility of certain solutions which have been suggested by various scholars and recommend few others for the problems which have been enshrined in the preceding part of this thesis.

3.3.1 Interpreting 'Agreement' in a broad manner: Legal Analysis

In order to hold a cartel liable for price-fixation, it is essential to show that an agreement was in place i.e. in the Indian context, the players must have acted in concert or have had

an understanding or an arrangement³⁶. In cases where there is some evidence that information exchange or other communication took place, American antitrust dealt with the problem by evolving the doctrine of conspiracy. Schwartz writes that “*firms which persistently follow parallel business policies will be treated as if they had agreed upon those policies, at least where there is some evidence that they consciously faced the policy issue as a common problem.*”³⁷

However, in cases of algorithmic collusion where no express communication took place between the human sellers, the problem for antitrust authorities is to prove that an ‘agreement’ took place even in absence of any express communication between the parties. A lot of legal scholars have proposed **re-visiting the term ‘agreement’** in order to overcome the problems relating to algorithmic collusion. Kaplow³⁸ argues that it is not prudent to make communication a prerequisite to the definition of ‘agreement’. He advocated for a more economic-based approach to interpreting antitrust rules by looking at the effects of tacit coordination as opposed to the manner in which the manner of bringing about this anti-competitive outcome. Judge Posner’s observations as were reproduced in Chapter-2, in essence were that an increase in price by a seller with an anticipation that his/her competitors will also do the same, is an ‘offer’ to collude. In response thereto, the competitors increasing the prices to match those of the first seller is an acceptance of the offer. Therefore, such an analogy would imply existence of agreement which in turn would result in signalling algorithms falling foul of competition law. In the Indian context, the Court could hold such tacit collusion as an ‘arrangement’ or ‘concerted

³⁶ See definition of agreement as defined by Competition Act, 2002 (*Supra*)

³⁷ Schwartz, L.B., 1970. New Approaches to the Control of Oligopoly. *J. Reprints Antitrust L. & Econ.*, 2, p.335.

³⁸ Louis Kaplow, On the Meaning of Horizontal Agreements in Competition Law, 99 CAL. L. REV. 683 (2011); William H. Page, A Neo-Chicago Approach to Concerted Action, 78 ANTITRUST L.J. 173, 173 (2012)

action’ within the meaning of Section 2 thereby bringing the supra competitive prices within the scope of competition law framework. This approach would render express communication immaterial in determining whether there was an agreement to collude.

However, this approach may seem a little controversial in cases of machine learning algorithm where decisions are made by machines rather than humans. In a scenario where the machine learning algorithm was designed without giving any instructions by engineers as to the strategy it was to follow but given the sole objective of maximising revenue and the algorithm without any intention on part of its employer led to collusive outcomes, should such conduct be penalised? This question shall be answered in the following part of the thesis under the head ‘liability affixation’.

3.3.2 Complete Prohibition on Algorithms: An Economically Efficient Solution?

A possible solution to this issue could be complete prohibition on deployment of algorithms for price determination. However, this is practically not a feasible solution as it will involve foregoing all benefits flowing from such algorithms.

The pro-competitive effects of algorithms cannot be completely ignored and they seem to promote efficiencies **both on demand and supply side**. On the supply side, the cost of labour could drastically reduce on account of various factors. Ascertaining the optimal price previously would take a lot of time on account of processing data (such as consumer preferences, browsing history etc.) manually which can be done at a much cheaper rate by an algorithm. Moreover, the prices are more likely to be sensitive to changes in demand and supply and their rate of change on account of these factors would also increase in case of use of algorithms. As a result, cinema theatres, operas, airlines, or hotel rooms are less likely to stay un-booked where the remaining vacant seats might not bear any value to the seller but still have some value to the consumers. With the advent of

big data relating to consumers, prices could very well be differentiated, dynamic and specific to consumers thereby facilitating perfect price discrimination.

In addition thereto, algorithms also bring about demand side efficiencies. Purchasing decisions can also be outsourced to an algorithm which has the ability to compare the price and characteristics of homogenous products offered by different sellers. This drastically reduces the search and transaction cost for the prospective buyer. Apart from this, the ability of consumer-friendly algorithms leads to availability of immediate comparisons which in turn causes competitive pressure on sellers to offer better quality products at cheaper prices. This would increase overall consumer welfare.

From an economic perspective, complete prohibition is an inefficient solution to the issue at hand. A legislative change however may be introduced which may prohibit algorithmic parallelism.³⁹ This would prevent situations such as one where a seller deploys an algorithm with clear instructions to mimic the price of the competitor in a duopoly without any agreement or communication to this effect with the competitor. Under the present legal framework, a seller which indulges in such a conduct goes scot-free.

3.3.3 Restrictions on Algorithm Features:

One of the problems related to algorithms is to detect their prevalence. In some instances, even the human who has deployed the algorithm is unaware of the existence of collusive practices by the algorithm. Rather than prohibiting the deployment of automated repricing software, a more practically feasible solution could be prohibiting certain features which lead to collusive outcomes. Some economists seem to suggest that the number of times an algorithm responds to price changes in a week could be restricted.⁴⁰

³⁹ Šmejkal, V., *Supra* note 29.

⁴⁰ OECD (2017), *Supra* note 31.

However, such restrictions would adversely impact the efficiency of the pricing algorithms. Moreover, in machine learning algorithms, instructions to algorithms are generally restricted to the ultimate goal that the algorithm has to pursue such as profit maximisation. The steps or processes to be applied are determined by the algorithm itself and therefore, restricting the machine learning algorithms from indulging in certain activities may be a complex task and will also restrict the learning abilities of the algorithm.

Collusion is further facilitated by the ability of algorithms to parse copious amount of data in a very short time which enables it to keep track of and quickly respond to price changes. Therefore, it has been suggested that a policy may be made by the regulators restricting the number of times an algorithm can respond to a price change. Although, this restriction would reduce the effectiveness of signalling algorithms, the drawback of such a feature is inhibition in competition on account of reduced ability of firms to engage in legitimate price wars. Moreover, the ability of sellers to respond to changes in demand, supply, price of raw material etc. will be adversely affected. I do not recommend such a measure which is inefficient in so far as it would restrict competition rather than promote it causing loss to consumer welfare. Therefore, the most efficient solution which takes care of social welfare would be to prohibit those features which could lead to collusive outcomes.

3.3.4 Liability Affixation

If the machine learning algorithm learns that collusion with other sellers/ algorithms would lead to higher revenue, it could adopt such a strategy without the knowledge of the humans employing that algorithm. In such a case, would penalising the firms employing the algorithm be just and fair is another question which would need

redressal. Or should algorithms be liable for their own conduct and if yes, how? The following part shall seek to answer these questions.

Artificial intelligence in the modern day is intelligent enough to understand that collusion would result in supra-competitive prices which in turn will lead to higher profits. As already explained in Chapter – 2, the modern pricing software have the necessary skills to collude or lead to collusive outcomes. The possibility that machine learning algorithm teaches itself to collude in order to maximise revenue cannot be undermined. A pertinent question which seeks redressal is whether in absence of any human intervention in the processes of the algorithm which has led to collusive outcome, who should be penalised? There are three possibilities here⁴¹. First, penalise the human who employed the algorithms. Second, penalise the algorithm which led to collusive outcomes. Third, to penalise neither the humans nor the algorithms. Mehra in this regard says that the third option should not be preferred since “*inaction does not accord with competition law based on efficiency and the error-cost framework; the decision to do nothing would clash starkly with the current logic and assumptions on which contemporary antitrust law has been tailored and justified.*”⁴² This view seems to be correct as granting immunity in cases of collusion would be antithesis to objectives for which competition law is in place. Exercise of second option is wrought with several issues. Some decades ago, the assertion that a computer or a robot is a mere tool in the hands of the human deploying it could not have been contested. But in the present times, with the advent of artificial intelligence this assertion does not hold ground. But even if we were to assign individuality to a robot and hold it to be a juridical person, the problems do not cease there. How must competition

⁴¹ See Mehra, *Supra* note 21.

⁴² Ibid

law penalise an algorithm? The traditional theories of punishment are rendered redundant in case of algorithms. The competition law if so amended, may very well attribute liability upon a robot who colluded, but who can it seek to penalise and who shall be liable for the financial penalty? Neither would imprisonment deter an algorithm. Therefore, penalising the algorithm does not seem to be practical remedy.

Let us now take the first option of penalising the human who deployed the algorithm. The first question which comes to mind is whether it is fair to penalise a human who neither had the intention to collude nor did he directly participate in a collusive conduct. Moreover, with the advances in technology and modernisation of pricing algorithms, the connection between a human who deployed it and the algorithm's conduct is further weakened i.e. the pricing robot took its own decisions without any human intervention. Mehra writes:

“...antitrust’s current approach requires a more in-depth investigation into intent than an agency law approach that would automatically pin a robosellers conduct on its employer as one might in the case of a mere “tool”; by contrast, no one asks whether there is a disjunction between the effect of a baseball bat used in an attack and the intent of its wielder.”

Although I would seek to address these issues by holding the firm/ employee liable (with certain caveats) rather than the algorithm itself which is practically not possible. There are certain advantages with the solution I will propose. This approach would first of all, help us overcome the problems related to ‘individualisation of robots’ which have been highlighted above. Secondly, it would also deter careless deployment of algorithms by sellers and provide adequate incentives to test the algorithms in a dummy virtual market place before their actual deployment. There are also arguments that if a company is made liable for the actions of its employee done in the usual course of employment, it should

also be liable for the conduct of an algorithm.⁴³ It has also been contended that a pricing software's conduct can be restricted due to its programmability⁴⁴ and therefore the onus is on the company to ensure that such algorithms do not flout antitrust rules. The assertion that a company or firm employing an algorithm has some degree of control over its functioning is not without basis.

However, before affixing liability on humans, the competition authority should analyse some factors. I propose that the antitrust authority ascertain the foreseeability of the collusion from the perspective of the person who deployed the algorithm i.e. see a likelihood that a particular algorithm which they seek to deploy could potentially result in collusive outcomes. Therefore, if the algorithm has been programmed in such a manner wherein it is reasonably foreseeable by the programmers thereof to predict that collusion is a likely outcome of deployment of the algorithm, then the humans who deployed the pricing algorithms should be held responsible. Such a liability rule would impress upon the sellers to be cautious before deploying a pricing algorithm by increasing their accountability.

3.3.5 Other Measures and Law & Economic Analysis thereof:

Another possible solution could be enactment of policy making it incumbent upon firms to test the algorithm in an artificial/ virtual market place to see the outcome of deploying such an algorithm. This would enable the deployers to predict and anticipate the outcome of a machine learning algorithm in a much better manner. This policy may solve the problem of 'black box'⁴⁵ to a certain degree in so far as even though the processes

⁴³ Ballard, D.I. and Naik, A.S., 2017. Algorithms, artificial intelligence, and joint conduct. *CPI Antitrust Chronicle*, pp.29-35.

⁴⁴ Ibid.

⁴⁵ The black box problem in essence is the inability of humans to understand the algorithmic processes which resulted in collusive outcome.

employed by the algorithm may not be known, but the outcome thereof could be ascertained before the actual deployment of the pricing software.

Economically speaking, reduction in transparency is another method for controlling tacit collusion. It is a well-known fact that greater transparency would lead to higher possibility of tacit collusion. If regulations are framed which reduce transparency in market, the prevalence of tacit collusion would also reduce.⁴⁶ This could be done by framing policies which proscribes publishing certain information on the website or other digital network. However, I would not seek to follow this approach as reduction in transparency would lead to adverse effects on competition and consumer welfare.

Likewise, tacit collusion is more prevalent in oligopolistic economies since such an industry provides stability to a cartel. Oligopolistic economies would facilitate the formation of a collusive cartel as **transaction, monitoring and enforcement costs** are low and **increase in revenue** on account of collusion is higher thereby providing adequate incentives to collude. Therefore, if regulations are framed which somehow limits emergence of oligopolistic economies, the possibility of tacit collusion would drastically reduce. This may be done by assessing merger and takeover assessments in a cautious and strict manner. Reducing barriers to entry in a sector or industry is yet another way to prevent oligopolistic economies. However, restricting the emergence of oligopolistic industries is not an easy task. How do we deal with a scenario where the sellers are indulging in non-concerted parallel pricing by way of algorithms or even otherwise? In such a case, instead of relying on Section 3 as reproduced above, the Indian competition authority may employ the notion of **collective dominance**.⁴⁷ Section 4 of the Indian

⁴⁶ OECD (2017), *Supra* note 31.

⁴⁷ Šmejkal, V., *Supra* note 29. Also see Gjendemsjø, R., Hjelmeng, EJ and Sørgard, L., 2013. Abuse of collective dominance: the need for a new approach. *World Competition* , 36 (3), pp.355-371.

Competition Act, 2002 is analogous to Article 102 of the Treaty on the Functioning of the European Union (TFEU) and the relevant portion thereof is reproduced hereinunder:

“4. Abuse of dominant position.—

1) No enterprise shall abuse its dominant position.

2) There shall be an abuse of dominant position under sub-section (1), if an enterprise,—

(a) directly or indirectly, imposes unfair or discriminatory

(i) condition in purchase or sale of goods or services; or

(ii) price in purchase or sale (including predatory price) of goods or service;.....

(b) limits or restricts—

(i) production of goods or provision of services or market therefor; or

(ii) technical or scientific development relating to goods or services to the prejudice of consumers; or....”

(c) indulges in practice or practices resulting in denial of market access; or

(d) makes conclusion of contracts subject to acceptance by other parties of supplementary obligations which, by their nature or according to commercial usage, have no connection with the subject of such contracts; or

(e) uses its dominant position in one relevant market to enter into, or protect, other relevant market”⁴⁸

The Indian law at this point does not recognize the concept of collective dominance. An amendment was proposed to add words “jointly or singly” to enterprise to enable the Competition Authorities hold two or more enterprises collectively dominant. However, the bill so introduced have not yet been passed by the Parliament. Therefore, the Competition Commission of India has refused to provide reliefs in certain cases on grounds that the concept of collective dominance does not find a place in the Indian jurisprudence.⁴⁹

⁴⁸ For the sake of brevity, the *explanations* provided in the Competition Act, 2002 in the relevant section have been omitted from reproduction.

⁴⁹ For instance, see Case no78 of 2013; https://www.cci.gov.in/sites/default/files/782013_0.pdf

Borrowing the concept of ‘collective dominance’ from the European law⁵⁰ would have enabled the authorities to curtail tacit coordination in oligopolistic economies by holding two or more enterprises collectively dominant where tacit coordination led to supra-competitive prices. I strongly recommend implementing the concept of collective dominance as a tool to prevent tacit coordination through the use of algorithms by sellers in transparent markets spaces.

Another measure I recommend is that the competition authorities frame separate rules exclusively applicable to a specific industries such as automobile or airlines especially in the Indian context, which are more susceptible to cartel formation. These industries should be compulsorily asked to explain the functioning of the algorithms deployed by them, the data it uses as an input and the code it executes for achieving its goals. However, a pricing algorithm itself is either a patented process or at the very least, a trade secret of firm deploying it. Therefore, public disclosure of such an information would result in loss of the trade secret. However, such sensitive information could be shared with the antitrust authority with a request to keep the information confidential. This would enable the antitrust authority to better ascertain the process and steps applied by the algorithm through the process of reverse engineering. However, since the problem of ‘black box’ would continue to plague this scenario, technical experts in the field of artificial intelligence would have to analyse the algorithm to ascertain whether the prices determined by the algorithm was a result of collusion. This takes us to another obstacle i.e. lack of infrastructure, which is definitely the case with the Competition Commission of India. Having worked in the Commission for close to two years, I know that the

⁵⁰ In *Airtours* (case T-342/99), the court had determined that in order to establish collective dominance, three conditions must be met i.e. high transparency in the market, tacit coordination with threat of retaliation and absence of competition from other players.

aforesaid authority is wrought with infrastructural deficiencies in so far as technological expertise in the field of artificial intelligence and pricing software are concerned. Therefore, in addition to economists and lawyers which form the core of any antitrust authority, a separate unit of technical experts who understand the intricacies of pricing software need to find a place in the competition authority. These experts would be better able to analyse the data set being used by the algorithms and will be better equipped to find out if the prices determined by a particular algorithm is result of collusive features employed by the algorithm. The problems of detection of collusive conduct by algorithms would be reduced by upgradation of infrastructural capacities and human resource.

Conclusion

Technological advancements in pricing industry have resulted in legislative insufficiency. There has been a marked increase in the number of sellers deploying robotic pricing software for price determination over the last decade or so. This fact coupled with other online market characteristics such as high transparency and intelligent robots have no doubt led to collusive outcomes in some cases. These complex algorithms track competitor prices and immediately respond to price changes by processing copious amount of data within a short time. The technologically advanced machine learning intelligent algorithms have the ability to get better with experience and are capable of colluding without any human intervention (with or without human knowledge). The outsourcing of price-setting by humans to robots have brought about significant efficiencies both on the demand and supply side, and therefore, complete prohibition on deploying algorithmic pricing software is not a socially efficient solution. The need of the hour is to have efficient legislation which is capable of dealing with such tacit collusion where humans role is restricted to deployment of algorithms without actively participating in any agreement with competitors to fix prices. Monitoring algorithms and hub & spoke models fall within the

scope of present competition law framework since the algorithms' role in such cases is only implementation of an underlying anti-competitive agreement. However, challenges arise in case of signalling and machine learning algorithms wherein no human communication takes place before the 'concerted action' of these algorithms. Since there is no 'agreement' to collude by human sellers, the tacit collusion due to deployment of these algorithms falls outside the ambit of competition law. Therefore, the crucial question is how 'agreement' and 'concerted action' are defined which would determine whether tacit collusion by algorithms would fall within the scope of competition legislation. This work recommends doing away with the concept of holding 'communication' by humans as a prerequisite and necessary condition for a conduct to amount to an 'agreement' or 'concerted action.' Moreover, liability affixation is another issue which needs recognition. This paper recommends affixing liability on the party/parties deploying the algorithm (with certain caveats). This seems to be the most efficient solution which in effect also deals with the problem of 'individualisation of robots'. Moreover, problems of detection of tacit collusion is another hurdle. There is an urgent need for infrastructural upgradation and recruitment of experts in this field by competition authorities. Other recommendations include compulsory sharing of software codes, adoption of concept of collective dominance, mandatory policy requiring testing of algorithms before their actual deployment etc.

Antitrust policy is only one field where technological advancements and robotic deployment has led to new challenges. There are other fields where legislation needs to be tweaked to better adapt to changing environments. For example, who should be liable in case a self-driving car malfunctions and kills a pedestrian. Should it be the owner of the car, the passenger, or the car company which manufactured it i.e. product liability principle. In conclusion, it seems a perfect balance has to be struck for regulating pricing-algorithms

as both over-regulation and under-regulation would result in social waste since the welfare benefits of algorithms, if used correctly, are significant, both for the sellers deploying them and the consumers in this field buying the products and the harm caused due to algorithmic collusion also cannot be ignored.

BIBLIOGRAPY

BOOKS & DICTIONARIES

- 1) Neapolitan and Naimipour ([2010](#)), Foundations of Algorithm.
- 2) Leiserson, C.E., Rivest, R.L., Cormen, T.H. and Stein, C., 2001. Introduction to algorithms (Vol. 6). Cambridge, MA: MIT press.
- 3) Alpaydin, E., 2009. Introduction to machine learning. MIT press.
- 4) Dictionary, C., 2008. Cambridge advanced learner's dictionary
- 5) Awad, M. and Khanna, R., 2015. Efficient learning machines: theories, concepts, and applications for engineers and system designers. Apress

ARTICLES

- 1) Alberto do Amaral Junior, *Compulsory Licensing and Access to Medicine in Developing Countries*, SELA 2005 Law and Poverty.-Panel 5: Poverty and the International Order, Rio de Janeiro, Brazil--16-19 June 2005 (2005), available at http://www.law.yale.edu/documents/pdf/Compulsory_Licensing.pdf (last visited Jun 2, 2014).
- 2) Towards Data Science: Machine Learning vs Traditional Programming, by Oleksii Kharkovyna; Available at <https://towardsdatascience.com/machine-learning-vs-traditional-programming-c066e39b5b17> (Last Visited: 1st July, 2019)
- 3) Russell & Norvig 2009, Artificial Intelligence: A Modern Approach, 3rd Edition, p. 2.
- 4) Grace, K., Salvatier, J., Dafoe, A., Zhang, B. and Evans, O., 2018. When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research*, 62, pp.729-754.
- 5) Izquierdo, S.S. and Izquierdo, L.R., 2015. The "Win-Continue, Lose-Reverse" rule in oligopolies: robustness of collusive outcomes. *Advances in Complex Systems*, 18(05n06), p.1550013.
- 6) DiMicco, Greenwald, and Maes (2001), 'Dynamic pricing strategies under a finite time horizon', Proceedings of the 3rd ACM conference on Electronic Commerce, pp95-104.

- 7) Chen, L., Mislove, A. and Wilson, C., 2016, April. An empirical analysis of algorithmic pricing on amazon marketplace. In Proceedings of the 25th International Conference on World Wide Web (pp. 1339-1349). International World Wide Web Conferences Steering Committee.
- 8) Gal, M.S. and Elkin-Koren, N., 2016. Algorithmic consumers. *Harv. JL & Tech.*, 30, p.309.
- 9) Ward, J.S. and Barker, A., 2013. Undefined by data: a survey of big data definitions. arXiv preprint arXiv:1309.5821.
- 10) De Mauro, A., Greco, M. and Grimaldi, M., 2015, February. What is big data? A consensual definition and a review of key research topics. In AIP conference proceedings (Vol. 1644, No. 1, pp. 97-104). AIP.
- 11) Final report on the E-commerce Sector Inquiry; Report from the Commission to the Council and the European Parliament, Brussels dated 10.5.2017; COM(2017) 229 final.
- 12) Rees, R., 1993. Tacit collusion. *Oxford Review of Economic Policy*, 9(2), pp.27-40.
- 13) Clarke, R.N., 1983. Collusion and the incentives for information sharing. *The Bell Journal of Economics*, pp.383-394.
- 14) Ivaldi, M., Jullien, B., Rey, P., Seabright, P. and Tirole, J., 2003. The economics of tacit collusion. Final report for DG competition, European Commission, pp.4-5.
- 15) Mehra, Salil K., Antitrust and the Robo-Seller: Competition in the Time of Algorithms (March 10, 2015). *Minnesota Law Review*, Vol. 100, Forthcoming; Temple University Legal Studies Research Paper No. 2015-15. Available at SSRN: <https://ssrn.com/abstract=2576341>, Last visited 1st July, 2019
- 16) Case 50223, Online sale of posters and frames; Decision of the Competition and Market Authority, dated 12th August, 2016; Available at <https://assets.publishing.service.gov.uk/media/57ee7c2740f0b606dc000018/case-50223-final-non-confidential-infringement-decision.pdf>; Last visited 15th July, 2019
- 17) Ezrachi, Ariel and Stucke, Maurice E., Online Platforms and the EU Digital Single Market (October 16, 2015). University of Tennessee Legal Studies Research Paper No. 283. Available at SSRN: <https://ssrn.com/abstract=2677267> or <http://dx.doi.org/10.2139/ssrn.267726>

- 18) Pricing algorithms: Economic working paper on the use of algorithms to facilitate collusion and personalised pricing; Competition and Market Authority; 8th October, 2016; Available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/746353/Algorithms_econ_report.pdf, Last visited 17th July, 2019
- 19) Passaro, Nicholas, How Meyer v. Kalanick Could Determine How Uber and the Sharing Economy Fit into Antitrust Law (September 27, 2017). 6 Mich. Bus. & Entrepreneurial L. Rev. 2, 2018, Forthcoming. Available at SSRN: <https://ssrn.com/abstract=2880204> or <http://dx.doi.org/10.2139/ssrn.2880204>
- 20) Harrington Jr, Joseph E., How Do Hub-and-Spoke Cartels Operate? Lessons from Nine Case Studies (August 24, 2018). Available at SSRN: <https://ssrn.com/abstract=3238244> or <http://dx.doi.org/10.2139/ssrn.3238244>
- 21) Šmejkal, V. (2017). Cartels by Robots: Current Antitrust Law in Search of an Answer. *Inter EU Law East: Journal for the International and European Law, Economics and Market Integrations*, 4(2), pp.1-18.
- 22) OECD (2017), Algorithms and Collusion: Competition Policy in the Digital Age; Available at www.oecd.org/competition/algorithms-collusion-competition-policy-in-the-digital-age.htm, Last visited 15th July, 2019
- 23) Richard Whish & David Bailey, *Competition Law*, 8th ed (Oxford University Press, 2015) at page 603.
- 24) Schwartz, L.B., 1970. New Approaches to the Control of Oligopoly. *J. Reprints Antitrust L. & Econ.*, 2, p.335.
- 25) Louis Kaplow, On the Meaning of Horizontal Agreements in Competition Law, 99 *CAL. L. REV.* 683 (2011); William H. Page, A Neo-Chicago Approach to Concerted Action, 78 *ANTITRUST L.J.* 173, 173 (2012)
- 26) Mehra, S.K., 2015. Antitrust and the robo-seller: Competition in the time of algorithms. *Minn. L. rev.*, 100, p.1323.
- 27) Ballard, D.I. and Naik, A.S., 2017. Algorithms, artificial intelligence, and joint conduct. *CPI Antitrust Chronicle*, pp.29-35.
- 28) Gjendemsjø, R., Hjelmeng, EJ and Sørgard, L., 2013. Abuse of collective dominance: the need for a new approach. *World Competition*, 36 (3), pp.355-371.