JAMES H. BOCKING MEMORIAL AWARD ESSAY

ALGORITHMIC COLLUSION: FROM SMOKEROOM TO CODE LINES? HOW COLLUSION CAN EVOLVE & ARE WE PREPARED

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This paper explores whether the current Canadian legal framework is adapted to the challenges that algorithmic pricing may pose. It concludes that creative legal solutions should be envisioned to curtail upcoming challenges, although the most appropriate solutions may come from regulating the design of algorithms.

It first provides an overview of the artificial intelligence at hand, and rationales that draw businesses to use them. Secondly, this paper asks whether there is a real threat that pricing algorithms may enable collusion. Through a review of experimental and empirical evidence, it answers that the calls to caution are not unwarranted, although the threats may not yet be at the forefront. Thirdly, after a review of the legal landscape in Canada, this analysis reveals that some actions are needed for regulators to be proactive in the face of upcoming challenges, through a study of the different ways in which algorithmic collusion may occur.

Cet article s'interroge sur l'adaptation de l'actuel cadre juridique canadien aux défis que les algorithmes de prix peuvent poser. Il y est conclu qu'on fera bien d'envisager des solutions juridiques astucieuses pour parer aux problèmes qui s'annoncent, mais que le mieux sera sans doute de réglementer la conception des algorithmes.

L'article commence par une vue d'ensemble de l'intelligence artificielle aujourd'hui et des raisons qui poussent les entreprises à y recourir. Ensuite est posée la question de savoir si les algorithmes de tarification posent un risque réel d'ouvrir la porte à la collusion. Après examen de l'évidence expérimentale et empirique, il est établi que les mises en garde ne sont pas sans fondement, quoique les risques ne soient possiblement pas encore des plus préoccupants. Enfin, après examen du secteur juridique canadien, l'analyse révèle que les autorités de réglementation doivent adopter certaines mesures proactives pour éviter les problèmes qui s'annoncent, par une étude sur les différentes manières dont la collusion algorithmique peut se produire.

1. Introduction: Setting the Scene

Picture this. You take an Uber ride to attend a concert, and the ride costs a certain price. At the end of the show, just like hundreds of showgoers, you open the Uber app only to see that the cost for the *same* trip back home has now tripled: this is Uber's surge pricing, or *dynamic pricing*, in action. Uber uses the practice of surge pricing when the demand is higher than the supply of riders, reportedly in the hopes of attracting more drivers.[1] Uber's artificial intelligence, its pricing algorithm, detects situations of high demands and low supply, and then automatically hikes the price of rides according to the shortage.[2] While the ethicality and effectiveness of the practice is a separate discussion,[3] it illustrates the growing resort to dynamic pricing by businesses and sellers.

Dynamic pricing became principally known in the 1990s, when airlines started to change their prices constantly, depending for instance on the number of seats available per flight or competitors' prices, in order to maximize their revenue. This practice of yield management[4] soon expanded to other industries, such as hotels and sporting events, as it is extremely valuable.[5] For example, American Airlines, the forerunner of dynamic pricing, reportedly gain an additional $500 million per year this way.[6] Dynamic pricing, which is a type of price discrimination, refers to a set of pricing strategies implemented to increase profits and is facilitated by algorithms.[7] Whereas price discrimination focuses on varying prices based on consumers' individual characteristics and data, dynamic pricing is more focused on market data to influence the prices: factors such as stock, competitors' offerings and prices, expiration dates, demand, etc.[8] Yet, both practices are defined by their volatility in prices; indeed, sellers using these practices may change prices multiple times a day.[9]

Today, with the boom of e-commerce, dynamic pricing has become more widespread and more easily implemented thanks to the availability of information and the development of artificial intelligence, specifically *pricing algorithms*.[10] Much like the Uber example, an increasing number of businesses rely on pricing algorithms, but use ones that focus on reacting to other competitors' pricing. Platforms such as Amazon's facilitated this expansion.[11] A study found that out of the merchants selling any of the 1,641 best-seller products, 500 of them used algorithmic pricing.[12] As well, the study showed that 60% of the third-party sellers on Amazon that use algorithmic pricing charged more than other sellers.[13] The European Commission also found that two-thirds of online retailers use pricing tools.[14]

In 2016, it was noted that two competing sellers on Amazon were selling the same book for $23.7 million.[15] No, it was not a first edition of a Shakespeare[16]—but merely a widely available scientific book, *The Making of a Fly* by Peter Lawrence. The jaw-dropping prices were the result of both sellers using algorithmic pricing making the prices fly.

The Kafkaesque price tags shed light on a problem: pricing algorithms that react on competitors' prices, if left unfettered, can interact, and produce unexpected outcomes.[17] As the use of pricing algorithms becomes more prevalent in everyday lives,[18] it is important to pause and consider the implications concerning competition law.

Competition law, in Canada, has four stated goals: to promote the efficiency and adaptability of the economy; to expand the opportunities of Canadians to participate in world markets; to ensure equitable opportunities to smaller businesses; and, to provide consumers with competitive prices and product choices.[19] Parliament stated that this later goal "is the ultimate objective" of competition law.[20] All of these objectives—and the fourth one in particular—are fundamentally undermined by collusion. Collusion occurs when two or more competitors decide to collaborate in order to ultimately suppress rivalry in their market. Generally, they collaborate through price-fixing, market allocation, limiting production, or bid-rigging.[21] Collusion is condemned by economists and lawmakers alike.[22] On the one hand, it hurts consumers as it would lead to higher prices. On the other, it results in hurting innovation in the market and disincentivizing new entrants by acting as a barrier to entry.[23]

With the evolution of self-learning algorithms, once these are given a goal (e.g., to maximize profits for the company), they are able to autonomously implement strategies to reach it—even in the absence of explicit instructions.[24] The advent of these technologies and the rise of e-commerce and *Big Data* creates new concerns for competition law. Together, these developments will test the regulatory side: is the law well equipped to address the potential complications?

With that background in my mind, this paper will explore whether the current legal framework is adapted to the possible challenges that algorithmic pricing can pose, in light of competition law. Specifically, this paper will focus on pricing algorithms that respond to competitors' actions.[25] After an overview of the artificial intelligence at hand and its uses, this paper will ask if we are not *crying wolf*: that is, is there a real threat that pricing algorithms may enable collusion? Based on both experimental and recent empirical evidence, it will answer that yes, although the threats may not yet be at the forefront, the calls to caution are not unwarranted as pricing algorithms can independently learn to not compete, and therefore reach collusive outcomes. The third part will examine the legal considerations. After a review of the legal landscape in Canada, this analysis will reveal that some actions are needed for regulators to be proactive in the face of upcoming challenges, through a study of the different ways in which algorithmic collusion may occur in light of Canadian law. Finally, this paper will conclude that creative legal solutions should be envisioned to curtail the upcoming challenges while admitting that the most appropriate solutions may come from regulating the design of algorithms themselves.

The Competition Bureau ("Bureau"), the agency invested to enforce the *Competition Act*,[26] already recognizes different levels and types of cartel behaviours, finding some more egregious than others.[27] This paper therefore argues that, in the advent of digitalization of pricing, the difficulty with which collusions are uncovered can only be reinforced.[28] It is then opportune to revise legal and policy *approaches* to prevent proactively the development of more opaque forms of collusion, i.e. the sheltering of unlawful behaviour and liability from consequences, behind an algorithm.

The present study draws on cases and literature from everywhere, notably from the United States and Europe, but focuses on the Canadian perspective and Canadian laws. The goal is to discuss legal implications and as such, only a cursory discussion of the computer science and economic aspects are presented. That is, this paper does not aim to criticize nor comment on the economics methods of studies presented. Rather, it hopes to use these robust studies as catalysts for a legal discussion.

2. Artificial Intelligence: the What and the Why

Today, artificial intelligence ("AI") is widely used and deep-seated in our societies.[29] But what do we actually mean by AI and how does it relate with algorithms?

2.1 The Nomenclature: Defining the Terms

AI is a branch of computer science that refers to the study and design of intelligent systems, for the execution of complex, intelligent tasks.[30] Machine learning is then a subfield of AI that "designs intelligent machines [using] algorithms that iteratively learn from data and experience."[31]

Machine learning uses algorithms which, in a nutshell, are logical and sequential rules that generate certain outputs, based on a given input. More precisely, they are defined as follows:

> An algorithm is an unambiguous, precise, list of simple operations applied mechanically and systematically to a set of tokens or objects (e.g., configurations of chess pieces, numbers, cake ingredients, etc.). The initial state of the tokens is the input; the final state is the output.[32]

Machine learning algorithms can be grouped into three categories. First, there are supervised learning algorithms. These algorithms use a sample of labelled data to learn the general rules that map out inputs and outputs. Simply put, these algorithms will be able to predict the output once confronted with a new set of inputs.[33] Second, unsupervised learning algorithms detect structures and patterns in unlabelled sample data, without the associated outputs.[34] Third, reinforcement learning algorithms perform tasks in dynamic, complex environments and learn from experience.[35]

Deep learning is then a subfield of machine learning that is close to reinforcement learning algorithms. It is a complex software that tries to replicate human neuronal activity through artificial networks. Ultimately, it is a complex way for computers to learn faster and more effectively.[36] Both deep learning and reinforcement learning algorithms are systems that learn autonomously; however, the former learns from a training set and applies it to a new dataset, and the latter dynamically learns by adjusting its actions thanks to feedback.[37]

2.2 Algorithmic Business

A phenomenon coined and described extensively by Stucke & Ezrachi,[38] algorithmic business refers to the "industrialized use of complex mathematical algorithms pivotal to driving improved business decisions or process automation for competitive differentiation."[39] The use of algorithms for business can be grouped into two practices: predictive analytics and business processes optimization.[40] Additionally, different types of existing algorithms may be said to either cater to consumers or, more inwards, to the business operations.

2.2.1 Predictive Analytics & Business Processes Optimization

Predictive analytics seeks to exploit patterns in past transactions for optimized outcomes for the business. It can "estimate demand, forecast price changes, forecast market shocks, and predict consumer behaviour and preferences to improve management decision making."[41]

On the other hand, algorithms may be used for business processes optimization. In that role, algorithms' automation and computational power allow for the processing of large datasets and to react fast—and at a lower cost than through labour. Businesses then utilize this ability to reduce production and transaction costs or set optimal prices for instance.[42]

2.2.2 Algorithms Catered Towards Consumers & Algorithms Catered Towards Businesses

Banicevic et al offer a list of examples of specific uses of algorithms in a business context.[43] That list allows to discern two broad uses: algorithms catered towards consumers and algorithms catered towards the businesses themselves.

The former category regroups algorithms such as: ranking and matching algorithms, which recommend a product or match buyer and seller based on the consumer's preferences; cross-merchandizing algorithms promote another product to a consumer based on history; personalized pricing algorithms optimize the price of a product according to the consumer's interests; and risk assessment algorithms that analyze a consumer data to assess the likelihood of their actions.

The second category englobes the following algorithms: dynamic pricing algorithms that automatically adjust selling prices according to competitors' prices and market changes; unilateral pricing algorithms that are made to take unilateral pricing steps, relative to competitors' prices; and financial trading algorithms that analyze financial markets to execute transactions.

2.2.3 The Appeal of Algorithmic Business

Evidently, algorithmic business has developed because AI has much to offer for businesses. The variety of types and uses of algorithms create unparalleled opportunities for businesses to optimize their processes and revenue. Not only this, but it can also improve consumers' experiences thanks to algorithms catered towards them.

The OECD underlines how algorithms can have pro-competitive effects, both on the supply and demand side.[44]

On the supply side, algorithms allow to gain efficiencies, which in return promote lower production costs. It can also promote the quality of the products and services offered, and the overall consumer experience. The OECD also notes that dynamic pricing algorithms have been recognized to improve market efficiency, specifically because it enables businesses to react instantaneously to changes.[45] Algorithms also facilitate "perfect price discrimination;" that is, they allow businesses to price directly according to consumers' personal information. While it may raise some actual discriminatory and ethical issues,[46] it is also admitted that it improves economic efficiency.[47]

On the demand side, algorithms are poised to help consumers in their choices. "Algorithmic consumers" is even used to refer to this shift in who bears the weight of decision-making. Algorithms use their "predetermined decision tree which assigns weights to decision parameters in order to suggest the optimal decision given in a particular set of data and circumstances."[48] This allows for optimized decision-making and reduces search and transaction costs for consumers. Additionally, the ease with which consumers can compare offerings incentivizes businesses to innovate and promote competition.[49]

3. Too Good to Be True? A Looming Threat that Should Be Heeded

In Part 2, this paper presented the numerous advantages that algorithmic business offers for the market as a whole. But the picture is tainted. This Part will discuss the concerns that the use of pricing algorithms catered towards businesses pose. While some argue that these worries are unfounded or premature, evidence will be examined to balance the debate.

3.1 Debates on the Anti-Competitive Effects of Pricing Algorithms

Authors have raised concerns that the use of algorithms will favour some form of collusion and make it harder to detect by regulators. As technology evolves, gets refined, and becomes more widely available, "the possibilities for both chaos and mischief" are endless.[50]

It is feared that algorithms may learn to cooperate autonomously—and thus to independently achieve collusive outcomes or to be used to implement a collusion agreement.[51]

Independently, a reinforcement algorithm that is given the goal to maximize profits may learn that avoiding price wars[52] with competitors is the best way to reach that goal.[53] Competitors' algorithms may thus reach collusive price levels, even without communicating with one another.

One appeal of collusion is that competitors do not compete on price points. That way, they are able to charge more for their products and services.[54] But, following the scenario outlined above, if algorithms learn to not engage in price wars with their competitors, these businesses will stop offering discounted prices.[55] Even further, many raise concerns that algorithmic pricing tends to reach supra-competitive prices, which refers to prices that are above what can be sustained in a competitive market and is usually indicative of anti-competitive behaviour.[56] While businesses will gain higher profits, these will result in higher costs for consumers and less economic efficiency.[57]

Additionally, algorithms render less important the number of players involved, in order to effectively implement collusion. Given the incentive to defect or deviate from the agreement, collusions fare better when a smaller number of players is involved.[58] Algorithms, however, allow for better coordination and monitoring irrespectively of the number of players.[59]

These AI tools also reinforce market transparency and the frequency of interactions, which are elements that favour collusive behaviour.[60] On this point, the French and German competition regulators are insightful:

> Even though market transparency as a facilitating factor for collusion has been debated for several decades now, it gains new relevance due to technical developments such as sophisticated computer algorithms. For example, by processing all available information and thus monitoring and analyzing or anticipating their competitors' responses to current and future prices, competitors may easier be able to find a sustainable supra-competitive price equilibrium which they can agree on.[61]

In response to these concerns, many believe that the assumptions underlying the fears for competition are either not supported by empirical evidence or too premature: these are unproven theories—for now.[62]

The critics argue that while algorithms are increasingly intelligent, real-world markets are too complex for the experimental designs' conclusions to hold true.[63] In the same vein, experimental studies assume unchanging market environments, which are variables that have important implications for collusion.[64] Another critique is that these studies focus on duopolies, which is not the case for most markets.[65] In fact, the more players there are in a market, the more difficult collusion becomes.

At the same time, critics insist that the type of algorithms capable of autonomously cooperating with competitors simply do not yet exist.[66] Even more so, to achieve collusive consequences, algorithms, it is argued, must learn to communicate with each other and to react to these communications.[67]

In line with these criticisms, the Canadian Competition Bureau also concluded that, at the m, there was no evidence of algorithmic collusion, therefore preventing them from issuing guidance on the issue. Yet, it was recognized that technology and business practices evolve rapidly—which may warrant a change of position in the future.[68]

3.2 Recent Robust Experimental Studies

Three experimental studies from 2020 and 2021 come to renew the concerns about the use of algorithmic pricing.

The first study was conducted by Calvano et al, a group of European economists.[69] The experimental study demonstrates that algorithms can implement autonomous collusion in synthetic environments. The study is designed in a repeated oligopolistic competition setting, where firms compete with differentiated products.[70] In this setting, the businesses delegate pricing processes to their Q-learning pricing algorithms, a new generation of reinforcement learning algorithms,[71] with the given goal to maximize the business's profits.[72] Assad et al, who discuss the study findings, summarize the experiment as follows:

In each period, the algorithm observes and thus reacts to prices effectively charged in previous periods by all market participants. After making its choice, it observes the resulting profits realized in that period. The idea of the experimental approach is to study the behaviour that these AI-powered pricing algorithms learn over time by observing them repeatedly interacting in this virtual market.[73]

The study found that the algorithms consistently learned to collude.[74] This came first apparent through the finding that businesses in the experiment would obtain higher profits.[75] Interestingly, when a competing algorithm lowers its prices—that is, when it would deviate from the rest—, it is met with punishment from the other algorithms until it realigns itself. Such "reward" and "forgiveness" patterns are an attribute of collusion.[76] The algorithms in the study are self-learning and have learned these behaviours or strategies through experience. What did they learn here? The lesson was "that undercutting the other firm's prices brings forth a war with low profits which ultimately makes any attempt to deviate from the spontaneous cartel price unprofitable."[77] More importantly: these algorithms have not been designed to collude, nor do they talk among each other.[78]

In a related study from 2021, Calvano et al add to the literature by finding that, if given enough learning time, Q-learning algorithms are able to learn to not compete *even* in environments with imperfect information, imperfect monitoring, and in the absence of communication and instructions.[79] This study presents two variations. In the imperfect information variation, the algorithms are informed of their own business's prices but not of their competitors'. In the imperfect monitoring variation, the algorithms cannot perfectly observe the prices chosen by competitors due to imperfect signals.[80]

When a competitor deviates in price or after a demand shock, the algorithms enter into a price war for a brief period after which cooperation picks up again.[81] A change in the hyperparameters also yields similar outcomes, which validates the findings of Calvano et al that collusive outcomes are common and not dependent on a select few points.[82]

In a study similar to the 2021 experiment of Calvano et al, Hansen et al also seek to contribute to the literature of algorithmic collusion by identifying a new mechanism through which supra-competitive pricing can occur.[83] In their experiment setting, the algorithms do not observe the prices of their competitors. Just like Calvano et al, they also find that in such a setting, collusion can materialize just as well. Their experiments also reveal the importance of having high informational value. When this is present, independent algorithms inadvertently correlate their prices, therefore creating a collusion-like environment in the market.[84]

These recent economic studies provide essential answers to some of the critics discussed above. They show, in an experimental setting, that communication between algorithms is not needed for these AI to reach collusive outcomes. They also reveal that novel algorithms may fare better than expected in complex environments.

3.3 Empirical Evidence from the Case of the German Retail Gasoline Market

Where experimental evidence of the negative impacts of algorithmic pricing is abundant, the same cannot be said for empirical evidence. This paper discussed in Part 1 the study by Chen et al, which found a prevalence of use of pricing algorithms among top sellers on Amazon, and that 60% of the third-party sellers on the platform using algorithmic pricing were charging more than other sellers.[85] Other regulators inquiries found evidence of growing use of pricing algorithms: the European Commission reported that two-third of online retailers use pricing tools;[86] and the Portuguese competition regulator reported that about 8% of the businesses surveyed used them.[87]

Nonetheless, these do not bring much evidence of concrete threats to competition or of collusive behaviours. In 2020, Assad et al bridged the gap in the literature by conducting a study of the German retail gasoline market.[88] This is the first empirical evidence of widespread algorithmic adoption raising margins and prices, putting the theoretical and experimental findings to the test.

The authors decided to focus on the German retail gasoline market because high-frequency retail gasoline price data is available and because, according to publications, this market started to widely adopt the use of pricing algorithms in 2017.[89] In line with previous studies that use margins to evaluate competition,[90] this study compares the retail margins of adopting gasoline stations and of non-adopting gasoline stations.

The algorithms used in this market, for any given gasoline station, are trained with historical data. They then mix in real-time information to these inputs in order to set prices that maximize the station's profits. The ensuing transactions are then fed back into the algorithm, to be used as new inputs, etc.[91]

As the lines get blurred, it is not certain what type of algorithm is being used. However, it is inferred that the type of machine learning being used is a reinforcement learning algorithm, similar to the one described in Calvano et al's 2020[92] study.[93] It is however noted that regardless of the type of algorithms used in the German retail gasoline market, a widespread use could still lead to collusive behaviour.[94]

The near-perfect transparency of prices in the market studied, in part due to price disclosure regulations, make deviations from collusive behaviour easily detectable and punishable—thus, favouring an environment that will sustain the supra-competitive prices obtained.[95] This setting so far coincides with experimental designs' environments and creates a perfect empirical study to test the conclusions.

The research finds that the mean margins at the station level increased by 0.7 euro per litre, after the adoption of pricing algorithms, which represents a 9% increase.[96] The mean prices rose by 0.5 euro per litre. Extrapolated, these findings estimate a €500 million per year increase in consumer expenditures for gasoline, because of price increases since adopting pricing algorithms.[97]

With regards to the effects on competition, the research results indicate that a "market-wide algorithmic-pricing adoption raises margins and prices, suggesting that algorithms reduce competition."[98] Even more compellingly, the margin increases found here are consistent with estimates of other researchers on the effects of coordination in the retail gasoline market.[99]

Lastly, the research tests two hypotheses: are these outcomes due to the algorithms' inability to learn effective competition? Or are they actively learning how *not* to compete? Just like Calvano et al, they conclude that the latter question must be answered in the affirmative. Indeed, there is evidence that the margins only start increasing a year into the adoption of pricing algorithms in the market, which indicates that the algorithms are effectively learning tacit collusive strategies.[100]

Could the results of this study just prove that there is an ongoing, undiscovered collusion in the German retail gasoline market? There is no direct evidence of such anti-competitive behaviour, neither from the firms providing the algorithms to that market nor from the gasoline companies.[101] Interestingly, this raises a concern addressed under Part 4.2: with the rise of pricing algorithms, it may be easier to hide *actual* collusive endeavours, as it will be *prima facie* difficult to discern autonomous algorithmic action from algorithmic execution of illicit ventures.

What the study does suggest is that the experimental evidence available so far has not been far-fetched. It provides solid evidential grounds for the concerns raised against the use of algorithmic pricing. A2i systems, one of the software companies providing pricing algorithms in the German retail gasoline market,[102] is a Danish AI company specializing in supplying pricing algorithms in the fuel industry.[103] They boast that they provide solutions in at least twelve countries and have advertised working with six brands, all leaders in the industry.[104]

This signals that regulators should study more closely this industry. But not just that: this study suggests that the concerns raised by academics and economists may not be so distant and theoretical after all.

4. A Canadian Legal Landscape ... In Need of Landscaping?

Having established the nature of the problem and the extent to which algorithmic pricing may pose problems to markets, are regulators well equipped to respond to the challenge? To answer this question, the various legal tools available in Canada will be discussed before applying them to three situations in which algorithmic pricing challenges may arise: (i) pricing algorithms may be used to execute pre-existing explicit collusion; (ii) the use of pricing algorithms from a common intermediary can create hub-and-spoke scenarios; and (iii) pricing algorithms can autonomously collude.

4.1 Overview of the Legal Framework

4.1.1 The Criminal Avenue: Sections 45 of the Competition Act

Section 45 of the *Competition Act* was enacted to address "hardcore" cartels.[105] The provision focuses on horizontal agreements by prohibiting agreements between competitors[106] to fix prices, allocate market shares, and fix production or supply.[107] In 2010, the *Competition Act* was amended and created Section 90.1.[108] Since, the Competition Bureau has signalled that it means to tackle the "most egregious forms of cartel agreement" under Section 45 and address the others under Section 90.1.[109] Any agreement that relates to a subject not outlined under Subsection 45(1) should be analyzed under Section 90.1.[110] Additionally, the *Competition Act* confers a private right of action for persons that suffered damages from a breach of the criminal provisions of the Act, notably of Section 45.[111]

Under Section 45, there is no need to demonstrate that the object of the conspiracy was carried out or that the agreement had any effect on competition.[112] Importantly, however, there must be an actual agreement for there to be a conspiracy, which requires "genuine intention" to enter into the agreement and knowledge of the terms of the agreement.[113,114] In other words, for there to be an agreement, there must be a "meeting of the minds."[115] While evidence of this agreement must be proven beyond a reasonable doubt, it may be inferred from circumstantial evidence.[116] In that vein, conscious parallelism does not meet the threshold to constitute an agreement impugned under Section 45, unless there is evidence of communication in that regard.[117] Conscious parallelism can be understood as,

> […] pricing that emerges out of an oligopolistic market setting without communication or agreement among the sellers. The crux of the theory of conscious parallelism is briefly that the oligopolists are interdependent in their pricing: they base their pricing decision in part on anticipated reactions to them. Put differently, the oligopolist is behaving in exactly the same way as is a rational seller in a competitively structured market; he is simply taking into account the reactions of his rivals to any price cut or increase

which he has to take into account because of the situation in which he finds himself.[118]

Exceptions and defences may also rebut a charge. Subsection 45(4) establishes a defence where the impugned agreement is ancillary to and necessary for another, lawful agreement.[119] Subsection 45(5) provides for a defence in cases of products exports,[120] and Subsection 45(6) creates an exception for agreements among affiliates.[121] Finally, Subsection 45(7) adopts the common law regulated conduct defence.[122]

Lastly, to promote uncovering of conspiracies, the Competition Bureau has an immunity and leniency program exclusively for persons charged under Section 45.[123]

4.1.2 The Civil Avenue: Section 90.1 of the Competition Act

Introduced above, Section 90.1 is a recent provision of the *Competition Act* that was meant to address the legislative gap between the criminal cartel provision (Section 45) and the mergers review provision (Section 92). It specifically provides a mechanism for arrangements that are "neither structural nor egregiously illegal" and aims to punish agreements that result in a substantial lessening or prevention of competition ("SLPC").[124] Six elements must be met for a successful Section 90.1 claim:[125] (i) the challenged conduct is an arrangement or agreement; (ii) the agreement or arrangement is existing or proposed; (iii) there are two or more parties to the agreement or arrangement; (iv) the above parties are competitors; (v) the agreement or agreement results in an SLPC; (vi) the effects occur or are likely to occur in a Canadian market.

Similar to Section 45, Section 90.1 requires a consensus between the parties and does not apply to conscientious parallelism. [126] However, this new test is "effects-based." In that sense, an otherwise reviewable collaboration will be saved under Subsection 90.1(4) if it creates efficiencies.[127] Just as is allowed in merger reviews,[128] an agreement or arrangement is saved if it results in efficiency gains that offset its anti-competitive effects.[129]

The section may apply to a variety of agreements that are usually considered to be pro-competitive.[130] The Competition Bureau has issued guidelines, freshly updated, on its approach to Section 45 and 90.1, and especially in their applications in light of other provisions in the act.[131]

Overall, the tests presented above under the *Competition Act* underline that the regulators are trying to strike the right balance because, as much as joint ventures may hurt competition, these “are often the catalysts of innovation and efficiency.”[132]

4.1.3 The Tort Avenue: The Tort of Civil Conspiracy

A tort avenue for conspiracies also exists. For a successful claim under the tort of civil conspiracy, (a) two or more persons must have concluded an agreement and (b.i) the predominant purpose of the agreement was to cause injury to the plaintiff, regardless of the lawfulness of the conduct undertaken, or (b.ii) “where the conduct contemplated by the agreement [was] unlawful, that conduct [was] directed towards the plaintiff [who suffered damages] and the defendants should [have known] in the circumstances that damage to the plaintiff [was] likely to result.”[133]

However, the tort is not well developed, in terms of scope and utility.[134] It is also a private action and not under the competence of competition regulators.[135]

4.2 Putting the Law to the Test

Canadian competition law is therefore rich in avenues to address issues of illicit arrangement between competitors. Let’s now see how these hold, considering the issues identified in Part 3.

4.2.1 Competition Law & Pricing Algorithms as Tools to Execute Pre-Existing Explicit Collusion

With pricing data being more readily available, the use of pricing algorithms can facilitate explicit coordination. There have already been cases before courts on this specific offence.

The 2015 *United States of America v Topkins*[136] case was the first antitrust criminal prosecution involving e-commerce in the United States. The defendants were charged with using pricing algorithms to execute a conspiracy to fix prices of certain posters sold on Amazon Marketplace.[137]

In 2016, a similar case was brought forward by the Competition and Markets Authority (“CMA”), the United Kingdom regulator for competition.[138] Two competitors selling posters and frames on Amazon had agreed to not undercut each other’s prices. Their agreement was executed using pricing algorithms that were specifically programmed to implement this cartel.[139]

Other investigations mirroring these scenarios are currently pending.[140]

These cases reinforce the statement from the Canadian Competition Bureau reported in Part 3: in such factual frameworks, the existing analytical principles are sufficient to address the legal problems.[141] Indeed, these scenarios all rely on AI to put into effect a previously agreed upon collusive pact. There, AI merely becomes *a vector* of their collusive intent. A Section 45 charge will only worry about the intent of the conspirators, while a Section 90.1 claim would add an analysis of the effects to the competition environment.

The only "novelty" that pricing algorithms pose in these instances, is the ease with which conspirators may implement their collusion.

4.2.2 Competition Law & Algorithmic Hub-and-Spoke Scenarios

Another possible scenario arises where competitors (the spokes) use the same or a common, third-party algorithm (the hub) in their pricing processes,[142] creating a like hub-and-spoke environment.[143] Such arrangements are not necessarily unlawful—but can be.

In 2016, the Court of Justice of the European Union ("CJEU") addressed this scenario.[144] E-turas, a Lithuanian online booking system, had sent a message to its travel agents users informing them to cap the discount rates. The CJEU ultimately ruled that in order to conclude that a collusion occurred between the agents, their knowledge was an instrumental factor. Despite the caution of the CJEU, it signalled that businesses who independently acquire a pricing algorithm, knowing that their competitors use it too, may be subjected to a collusion inference and therefore need to exercise caution.[145]

Similarly, in *Meyer v Kalanick*,[146] an ingenious argument was brought forth. It was alleged that Uber facilitated a hub-and-spoke-structured collusion, whereby Uber conspired with the drivers—whom Uber has always argued are independent contractors—[147]to use the company's pricing algorithm to set the prices charged to the users.[148] Albeit structurally complex, it would be interesting to see if the argument of *Meyer v Kalanick* is raised again in another jurisdiction or with other parties.[149]

These instances reveal the dynamics that a pricing algorithm may create, which competition regulators and courts may—or rather, *will*—have to grapple with.

A2i systems, discussed in Part 3.3, sketches out this hub-and-spoke structure, whereby A2i systems' software is the hub supplying its clients, the spokes, with a common pricing algorithm.

In Canada, the updated Competitor Collaboration guidelines ("Guidelines") open the door for such structures to be addressed under Section 45.[150] The Guidelines offer the example of a hub-and-spoke conspiracy, specifically with a price-fixing agreement. In this structure, the Bureau notes that there would be a "meeting of the minds" especially if "spoke A" agrees to implement a certain price policy if "spoke B" does it too.

Applying this logic to the context of the hub being a pricing algorithm, how would it work? The E-turas case is insightful: the CJEU stresses the importance of the spokes' knowledge of the concerted practice.[151] Therefore, it could be argued that a business resorting to a common pricing algorithm with a third party, undertakes the responsibility of *possibly* being involved in collusion. Indeed, that algorithm will apply the same logical rules to all the *spokes* involved, therefore attaining concerted prices to all businesses involved. As long as businesses are aware of this possible outcome, the "meetings of the mind" should be inferred. Drawing upon the doctrine of willful blindness, it could be said that, in these circumstances, an intent to enter into an agreement can be inferred from the adoption of these pricing algorithms. The Supreme Court of Canada states that willful blindness can impute knowledge to people "whose suspicion is aroused to the point where [they should have inquired further] but deliberately [chose] not to."[152] The goal of this doctrine is to signal that self-imposed ignorance should not be rewarded. The same logic should be extended in this context.

This ultimately leads to conclude that, in all aspects, Canadian competition law seems equipped to handle such situations. The lack of jurisprudence on these hub-and-spoke scenarios—even more so scenarios where the hub is an algorithm—could either open the door to courts and regulators to address them under existing legislation or could let them shy of taking this jurisprudential leap. Going back to the A2i systems example, competitors using such a common algorithm supplier may face more risks without proper due diligence, should regulators take that leap.

4.2.3 Competition Law & Pricing Algorithms Autonomously Colluding

As it has been discussed, especially through the studies by Calvano et al,[153] it is possible for pricing algorithms to autonomously learn to collude.[154] In those scenarios, no command to do so is given to the algorithm: so how can there be collusion *legally*?

Sections 45 and 90.1[155] both require an intent, a "meeting of the minds" to form an agreement or arrangement.[156] Evidently, it cannot be said that those elements exist in the context of autonomous, independently colluding algorithms.

As the law stands, there would not seem to be any legal sanctions.

In that regard, it could be argued that businesses that implement these pricing algorithms as part of their processes, knowingly assume the anti-competitive effects, namely the reaching of supra-competitive prices. Undoubtedly, these same points that raise concerns in the literature and to regulators are the same points that draw these businesses to adopt the AI tools. Similar to the point raised in Part 4.2.2, the doctrine of willful blindness may inspire the legal analysis to be undertaken here. At the same time, Subsection 45(3) allows to infer the existence of a conspiracy from circumstantial evidence or facilitating practices. These practices can be viewed as indicators of the existence of an agreement among competitors.[157] The Competition Bureau even notes that algorithms may extend the arrays of activities that constitute facilitating practices.[158] This is a great avenue to explore a solution, but with a caveat: this still presupposes that underneath, there *is* an agreement.

Ultimately, on the one hand, competition law seems to stress that it cares a lot about the *effects* that behaviours will have on competition. This can be seen with the addition of Section 90.1 in 2010.[159] This provision not only includes an SLPC analysis under Subsection 90.1(1) but also creates an efficiency defence under Subsection 90.1(4), thus reinforcing the understanding that *effects* are the key. On the other hand, there is a wariness by the regulators to be overzealous as they recognize that collaboration can be—and is—good for competition.[160] Wariness is even more so warranted as sanctioning intent-less collusion would amount to condemn conscious parallelism.

And yet, unfettered pricing algorithms can be harmful for competition and consumers, given the anti-competitive outcomes that they can reach.[161] Regulators must then strike the right balance between rectifying and preventing anti-competitive effects, and not unduly punishing businesses.

5. Conclusion: The Path Forward

There is a clearly identified and pressing novel challenge that is dawning upon competition regulators. Pricing algorithms have proven to make a mark and to be attractive to businesses even more.

For years now, academics and economists have nudged regulators to warn them of potential issues. Many experimental studies reveal the core of the problem: what makes AI and pricing algorithms so attractive is also their downfall. They allow for real-time price adjustments: this allows for real-time monitoring for deviations from the collusive agreement. They also allow for better profits for their users: studies show these better profits do not necessarily reflect market prices. Ultimately, a growing number of studies reach similar conclusions: smart algorithms without being taught nor instructed to, end up reaching a collusive outcome.

These reinforcement learning algorithms are self-taught. Their programmers give them wings, and they fly to their destinations, their pre-assigned goals, on their own. Maybe this should prompt us to think philosophically about collusion: what makes it so that all, including AI, mere *lines of binary codes*, have this tendency? A Plato or Descartes may say that it is nature that makes these tendencies so inevitable.[162] Or, maybe the answer will be found in John Locke's postulate: our ideas are not innate; our mind is a *tabula rasa*, a blank sheet that gets filled as we experience.[163] Maybe the experience that drives this tendency is the clearly stated and present goal of profits for businesses and AI alike.

Echoing Locke's theory, the most appropriate answers to go forward may lie in understanding the controllable elements that affect the algorithms' reasoning. Indeed, considering how algorithms process their experiences and the inputs they are allowed to take into consideration, allow to point rather into the direction of regulating algorithms themselves. Maybe certain properties of pricing algorithms should be prohibited;[164] changing the design to reward algorithms that cut process for instances,[165] or making software designers liable for their algorithms' designs are all paths forward to address algorithmic collusion more efficiently.[166]

The legal path, however, is delicate. The current legal principles can hold the fort for now. Yet, there are circumstances where the legal avenues get murkier. While we should be cautious of developing legal principles too broad that may result in impeding competition, we should also be cautious of not creating legal blind spots where colluders may hide, shielded from liability. This paper has proposed to creatively read-in intent to bypass the lack of actual agreement for instance.

Absent legislative reforms, only time and the bringing forth of the first algorithmic collusive case to courts will be able to confirm the robustness and adequacy of Canadian laws for these challenges.

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ENDNOTES

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[9] *Ibid*.

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[42] *Ibid*. See also OECD 2017, *supra* note 29 at 11.

[43] Banicevic et al, *supra* note 41 at 5–7: Banicevic et al offer more details on each of these types of algorithms as well as examples.

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[48] Michal Gal & Niva Elkin-Koren, "Algorithmic Consumers" (2017) 30 Harv JL & Tech at 5.

[49] See OECD 2017, *supra* note 29 at 17.

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[90] See Assad et al 2020, *supra* note 88 at 4.

[91] See Assad et al 2020, *supra* note 88 at 7–8.

[92] Calvano et al, "Artificial Intelligence, Algorithmic Pricing, and Collusion", *supra* note 69.

[93] See Assad et al 2021, *supra* note 51 at 469.

[94] See Assad et al 2021, *supra* note 51 at 469.

[95] *Ibid*.

[96] See Assad et al 2020, *supra* note 88 at 4–5.

[97] See Assad et al 2021, *supra* note 51 at 471.

[98] See Assad et al 2020, *supra* note 88 at 5.

[99] See Assad et al 2020, *supra* note 88 at 5.

[100] *Ibid*.

[101] See Assad et al 2020, *supra* note 88 at 2, Footnote 1.

[102] See Assad et al 2021, *supra* note 51 at 468.

[103] *Cf* "A2i systems", online: *A2i systems* <www.a2isystems.com>.

[104] See "Customers", online: *A2i systems* <www.a2isystems.com/customers/>.

[105] See Wakil, *supra* note 27 at 107. See also Canada Competition Bureau, *supra* note 68 at 10.
[106] Subsection 45(8) defines competitors as including "a person who it is reasonable to believe would be likely to compete with respect to a product in the absence of a conspiracy, agreement or arrangement to do anything referred to" in Subsection 45(1).
[107] *Competition Act*, *supra* note 19, subs 45(1). Subsection 45(8) defines price as including "any discount, rebate, allowance, price concession or other advantage in relation to the supply of a product." See also Brian A Facey & Cassandra Brown, *Competition and antitrust laws in Canada: mergers, joint ventures and competitor collaborations*, 3rd ed (Markham, ON: LexisNexis Canada Inc, 2020) at 477.
[108] Section 90.1 was introduced in the amendment of 2010: *Budget Implementation Act*, 2009, SC 2009 c 2. Section 90.1 is discussed below in Part 4.1.3.
[109] See Wakil, *supra* note 27 at 107.
[110] *Ibid*.
[111] *Competition Act*, *supra* note 19, s 36.
[112] See Musgrove, *supra* note 26 at 57–58.
[113] See *R c Déry*, 2006 SCC 53 at para 35 [*Déry*]. See also *Canada v Pharmaceutical Society (Nova Scotia)*, [1992] 2 SCR 606 at para 119, 1992 CarswellNS 15 [*Pharmaceutical Society*].
[114] Since the amendment of the section in 2010, no case has been brought forth. The old text provided that the agreement "unduly prevented or lessened competition." In that regard, there was a need to establish an objective and subjective element for the *mens rea* (see *Pharmaceutical Society*, *supra* note 113 at paras 117–120). Currently, it is unclear what elements of the *mens rea* survived the amendments and how the old standards would apply: Musgrove, *supra* note 26 at 53.
[115] Competition Bureau Canada, *supra* note 68 at 10.
[116] See *Competition* Act, *supra* note 19, subs 54(3). See also Musgrove, *supra* note 26 at 59.
[117] See *R v Canadian General Electric Co*, 1976 CarswellOnt 449 at para 124, 15 OR (2d) 360 [*Canadian General Electric Co*]. See also *Atlantic Sugar Refineries Co v Canada (Attorney General)*, [1980] 2 SCR 644 at para 10, 1980 CarswellQue 50.
[118] *Canadian General Electric Co*, *supra* note 117 at para 35.
[119] See Wakil, *supra* note 27 at 110. See also Musgrove, *supra* note 26 at 63–64.
[120] See Wakil, *supra* note 27 at 110. See also Musgrove, *supra* note 26 at 64.
[121] See Wakil, *supra* note 27 at 110–111. See also Musgrove, *supra* note 26 at 64–65.
[122] See Wakil, *supra* note 27 at 111–112. See also Musgrove, *supra* note 26 at 65.
[123] See Facey & Brown, *supra* note 107 at 478: for the criteria to meet to obtain immunity. See also "Immunity and Leniency Programs", *supra* note 28.
[124] See *Competition* Act, *supra* note 19, subs 90.1(1). See Competition Bureau Canada, "Merger Enforcement Guidelines" (6 October 2011), online: *Competition Bureau Canada* <www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/03420.

html> on an explanation of the SLPC threshold. See also Facey & Brown, *supra* note 107 at 462–463.

[125] *Rakuten Kobo Inc v Commissioner of Competition*, 2016 Competition Trib 11, at para 56, 2016 CarswellNat 2171.

[126] See Facey & Brown, *supra* note 107 at 461.

[127] See *Competition* Act, *supra* note 19, subss 90.1(3)—6).

[128] See *Competition* Act, *supra* note 19, s 96.

[129] See Wakil, *supra* note 27 at 274–277. See also on the efficiency defense: *Superior Propane*, *supra* note 20; *Tervita Corp v Canada (Commissioner of Competition)*, 2015 SCC 3.

[130] See Facey & Brown, *supra* note107 at 471–477: for detailed discussion of each type of arrangement.

[131] See Competition Bureau Canada, "Competitor Collaboration Guidelines" (6 May 2021), online (pdf): *Competition Bureau Canada* <www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/vwapj/CB-BC-CCGs-Eng.pdf/$file/CB-BC-CCGs-Eng.pdf> [Competitor Collaboration Guidelines]

[132] Facey & Brown, *supra* note107 at 480.

[133] Halsbury's Laws of Canada (online), *Competition and Foreign Investment*, "Competition Law: Non-Statutory Aspects of Competition Law: Conspiracy: Elements of the tort" (I.2.(2)) at HCT-12. See especially *Canada Cement LaFarge Ltd v British Columbia Lightweight Aggregate Ltd*, [1983] 1 SCR 452 at para 33, 1983 CarswellBC 812.

[134] *Pro-Sys Consultants Ltd v Microsoft Corp*, 2013 SCC 57 at para 72.

[135] For these reasons, this paper will not develop more the analysis of this tort. It is however important to know that some private actions exist, either under Section 36 of the *Competition Act* or under the tort of civil conspiracy.

[136] No 15-CR-00201 (ND Cal 2015) [*Topkins*].

[137] *Ibid* at para 6.

[138] See Competition and Market Authority, "Online seller admits breaking competition law" (21 July 2016), online: *Competition and Market Authority* <www.gov.uk/government/news/online-seller-admits-breaking-competition-law>.

[139] *Ibid.*

[140] See e.g., CNMC, News Release, "The CNMC opens antitrust proceedings against seven firms for suspected price coordination in the real estate intermediation market" (19 February 2019), online (pdf): *CNMC* <www.cnmc.es/sites/default/files/editor_contenidos/Notas%20de%20prensa/2020/2020219%20NP%20Intermediation%20Market%20EN.pdf>.

[141] See Banicevic et al, *supra* note 41 at 13.

[142] See e.g. Ezrachi & Stucke, *supra* note 50 at 1787.

[143] Hub-and-spoke refers to a model in which a centralized hub send information, products, etc. to the spokes: see e.g. Cathy Habas, "Hub & Spoke Model: Definition, Benefits & Examples" (9 September 2019), online: *Bizfluent* <bizfluent.com/13721308/hub-spoke-model-definition-benefits-examples>.

[144] See *E-turas et al v Republic of Lithuania et al*, C-74/14 [2016] ECJ ECLI:EU:C:2016:42 [*E-turas*]

[145] See AZB & Partners, "Pricing Algorithms, CCI's First Major Encounter with Assessing New-Age Collusions" (15 March 2021), online: *Lexology* <www.lexology.com/library/detail.aspx?g=2a5a5714-3752-4864-b0b6-a4cd6fc9ef90>. See also *E-turas*, *supra* note 144.

[146] 174 F Supp 3d 817 (SDNY 2016). The case was adjudicated in a private arbitration; thus, no legal opinion is known on this theory.

[147] See "A court bashes Uber into compliance—again" (11 December 2021), online: *The Economist* <www.economist.com/britain/2021/12/11/a-court-bashes-uber-into-compliance-again>.

[148] See *Topkins*, *supra* note 136 at 820—821. See also Sanjukta M Paul, "Uber as for-Profit Hiring Hall: A Price-Fixing Paradox and Its Implications" (2017) 38:2 BJELL 233 at 242—244.

[149] This is especially true because Uber's argument of its structure prevents it from raising any common defence. For instance, by insisting that drivers are not employees, Uber may not invoke the affiliate exception under Paragraph 45(6)(a) of the *Competition Act*.

[150] See Competitor Collaboration Guidelines, *supra* note 131 at 53. Notably too, Section 76, on price maintenance, does not apply to downward influence: see Wakil, *supra* note 27 at 217.

[151] See *E-turas*, *supra* note 144 at para 41.

[152] *R v Briscoe*, 2010 SCC 13 at para 21.

[153] See Calvano et al, "Artificial Intelligence, Algorithmic Pricing, and Collusion", *supra* note 69; Calvano et al, "Algorithmic collusion with imperfect monitoring", *supra* note 79.

[154] See Assad et al 2021, *supra* note 51.

[155] *Competition Act*, *supra* note 19.

[156] See Part 4.1.1 and Part 4.1.2, above.

[157] See also Competitor Collaboration Guidelines, *supra* note 131 at 11.

[158] *Ibid.*

[159] Adopted through *Budget Implementation Act*, 2009, SC 2009 c 2.

[160] See Facey & Brown, *supra* note 107 at 480–481. See also Competitor Collaboration Guidelines, *supra* note 131 at 6.

[161] See Part 3, especially Part 3.3, above.

[162] See Gary Hatfield, "René Descartes" (Summer 2018), online: *The Sandford Encyclopedia of Philosophy* <plato.stanford.edu/entries/descartes/>.

[163] See William Uzgalis, "John Locke" (Spring 2020), online: *The Sandford Encyclopedia of Philosophy* <plato.stanford.edu/entries/locke/>.

[164] See MIT podcast, *supra* note 46.

[165] See Assad et al 2021, *supra* note 51 at 463, 472–476.

[166] See Calvano et al, "Protecting consumers," *supra* note 22 at 1041–1042.