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AN INTER-DISCIPLINARY APPROACH TO AUTOMATION TECHNOLOGY IN FINANCE - WHAT CAN HISTORY, LAW AND DATA SCIENCE TEACH US?

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Abstract

The year 2008 is etched in human history as the year of the 'Global Financial Crises'. Post the crises, Historians and financial commentators alike rushed to impute blame. Some blamed securitizations, some the banks and some Lehman Brothers and AIG. However, in the midst of all of this humbug, a key epicentre of the crises escaped academic scrutiny; 'Automation Technology'. The paper therefore aims to present an alternative view of financial history; one which impleads 'automation technology in finance' i.e., Risk Modelling Algorithms and RegTech. However, the underlying aim of this paper is to make a case against systemic automation bias in finance and to achieve that end, the paper employs an inter-disciplinary approach and uses history, law and data science to show case the multifarious perils of using automation technology blindfold in finance whilst also proposing possible solutions such as the incorporating of design thinking and systems theory in finance. Expired data sets, human assumptions, turning code in law, and a lack of standardized financial semantics as but some of these 'perils'. On the law front; it presents a twofold challenge under constitutional and anti-trust law and aims to reconcile law and technology. Lastly the paper aims to guide regulators by categorizing multiple stages of technological complexity and recommends application of different regulatory approaches to regulating automation. Therefore, the paper shall maintain a 'solution' oriented approach throughout.

Keywords:
RegTech, Algorithms, Regulator, Automation, Risk-Modelling

1. INTRODUCTION

1.1 RESEARCH PROBLEM

Fintech and technology in Financial Markets is largely regarded as 'infallible' and the algorithmic accuracy and fallibilities largely remain un-addressed by academia. Furthermore, a lack of an inter-disciplinary approach within academia with regards to the perils of automation precludes scholars, regulators and firms alike from cohesively understanding the risks of automation, ultimately leading to a veil automation bias. Policy decisions to regulate fintech therefore, remain largely unguided, un-informed and without nuance. The paper therefore aims to analyse the aforementioned research problems within academia using an interdisciplinary approach of law, history and data science.

1.2 BACKGROUND

Since the inception of mankind, technology has driven human progress. The integration of technology in human life is at its apogee today. Some scholars have even gone so far as to view human life itself as a self-replicating information-processing system whose information software (in the context of DNA) determines both its behaviour and the blueprints for its hardware [1]. Max Tegmark, an MIT professor, argues in his book 'Life 3.0: Being Human in the Age of Artificial Intelligence' that singularity (self-learning and reproducing capabilities) of AI is but a progression stage of life called 'life 3.0'.

This integration is especially pronounced in financial markets where the technology post the 2008 Financial Crises has been rapidly advancing without any regulatory oversight. The purpose of these new technologies is purportedly to 'automate' specialized human financial analysis and are therefore placed under the umbrella term 'automation technology'. The technology started taking the market at an unprecedented pace during the 2000's. However, post the Global Financial Crises (GFC) in 2008, due to a result of the new "process based" regulatory regime with ever increasing compliatory dictums, parallel breakthroughs in AI and Machine Learning, and lastly, calls for better, more "scientific" risk modelling systems; private firms finally turned wholesale to automation technology for their legal compliance and risk modelling strategy. This led to the age of "RegTech and Automated Risk modelling" which even the regulators wholeheartedly revelled in.

The discourse post GFC amongst the academicians, were divided by two fronts; where one side called for increased regulations to hold banks, financial firms and NBFC's accountable whereas the other side argued that it was the failing government policies themselves which caused the crises. They argued that the regulators must back out from the market. The regulators, although favoured the former approach, also recognized that they neither have sector-specific knowledge to understand the operational risks of the ever-complicated financial market, nor the knowledge to understand the firms dealing in multifarious financial services. Therefore, they delegated their jobs to private automation tech and focused on making laws with complicated disclosure requirements [2].

In the midst of all of this, a key piece of the GFC escaped scrutiny: "Automation Technology". As this paper would argue, automation technology has tremendous and unique harms of its own. The author identifies these harms to be Design based, Human, Legal and Linguistic. Unfortunately, the failure of academicians and regulators to scrutinize technology led to a 'veil' of Automation Technology which continues to remain largely inscrutable and unregulated today. This 'veil' is recognized by scholars via a concept called 'automation bias'. This automation bias has become systemic and affects the entire financial milieu. The ultimate consequence of this long term would be the unsupervised widespread use of the treacherous 'black box algorithms' in financial markets which would effectively mean a slap in the face for everyone who called for increased transparency in our financial markets post the 2008 Crises.

To make my case, I shall adduce literature from multiple disciplines such as history, law and data science. I aim to showcase finally through practical examples, how automation tech has constantly erred in producing the desired human outcomes and has often destabilized markets to our peril. The solutions the paper offers are threefold; One, a radical shift in the regulatory approach towards automation technology in finance (for the regulator) two, integration of human value with technology rather than a complete reliance on automation (for the private firms) and three, incorporation of design thinking and systems theory while developing code (for the programmers). Lastly, I call for reconciliation between constitutional and anti-trust law and automation. These goals, however, can only be achieved if the veil of 'automation bias' is destroyed.

1.3 AUTOMATED SYSTEMS

There are primarily three types of automation systems: rule-based, data-matching, and data mining systems. In the first type, the 'rule' as interpreted by the programmer is applied to a set of facts. Programmers translate policy from human language into code and then embed it into decision tables following which the 'rules engine' provides the system 'logic'. Rule based systems were primarily used in compliance and disclosures of regulatory mandates. Data matching algorithms on the other hand such as VaR functioned on correlating two sets of data sets and predicting the likelihood of a certain outcome. They were predominantly used to guide trading. Data mining algorithms lastly, searches for patterns and correlations by analysing big data and were used in tandem with Data Matching systems.

Besides multiple systems, there are different types of algorithms too. For example, classification algorithms first identify the probability of the event(s) occurring and then group the data sets into a finite number of categories based on the ascertained probability ranges [3]. Regression algorithms take it a step further and build on the work of classification algorithm by creating an infinite set of probable events with a fixed confidence interval [4].

While there are tremendous efficiencies that these new technologies provide by using the aforementioned methods, however the moment these purported efficiencies start to do more harm than good, the global discourse on technology's integration with human activities must make space for some well-founded caution.

1.4 PROBLEMS WITH THE GLOBAL TECH DISCOURSE

In the same book cited above, Tegmark cautions his readers to understand the risks associated with AI [5], so much so that close to half of his book revolves around it! This newly trending "cautious discourse" to Advanced Technology never questions the inherent faults and inadequacies of advanced AI but rather warns against AI "taking over humans". This argument presumes that algorithms are infallible and 'perfect' and therefore may defeat human dominance [6] since unlike machines, we are limited by 'human errors'. I call this the 'Global Tech Discourse'. Through this paper I aim to challenge this hypothesis. The Global Tech discourse doesn't do anything to address the pervading automation bias but rather strengthens it. On the other hand, I argue that technology is not all that perfect, and automation has its own inherent weaknesses. Therefore, ignoring them may lead to disastrous consequences especially when seen in the context of financial markets where automation often leads to 'crowding out' of specialized human knowledge.

The paper is structured as follows: Section 1 provides an Introduction of the subject matter and introduces the problem. Section 2 presents an alternative historical narrative of the GFC, impleading automated Risk Modelling Tech built on Var, Section 3 showcases the perils of risk modelling algorithms using data science, Section 4 poses legal challenges and calls for reconciliation between technology and law in finance, Section 5 then dives back into the historical narrative post the 2008 GFC and traces the development of RegTech. Section 6 likewise presents the perils of RegTech from a semantic and legal standpoint. Section 7 summarises the historical development of automation technology and divides it into 5 stages of complexity. The section argues that different regulatory approaches must be applied for different stages. Section 8 then finally concludes.

2. DAWN OF AUTOMATED RISK MODELLING: VAR TECHNOLOGY

This section shall present an alternative way of looking at the Global Financial Crises and impleads 'automation technology' as the epicentre. While most narratives focus on imputing blame on credit rating agencies and compels financial instruments like securitization, I argue here that perhaps at the centre of the crises was 'automation technology'. The primary focus here would be 'VaR' or value at risk technology. However, I shall also make the case that technology was never the 'villain', but rather a 'medium'. The villain in this story perhaps is the 'veil' of technology i.e., automation bias, which effectively puts humans back at the driving seat of the accident. One of the broader goals of this paper shall be therefore to launch a valiant attack on this 'villain'.

VaR or Value at risk automation systems are largely regarded as the beginning of the 'age of automation' in finance. These systems were perhaps her first that weren't just widely used by firms but also garnered regulatory acceptance through the Basel Accords which stated,

"Where a bank has a VaR measure that incorporates specific risk and that meets all the qualitative and quantitative requirements for general risk models, it may base its [specific risk capital] charge on modelled estimates . . ."

It was developed first as a method to identify optimal portfolios for individual investors operating in equity markets. The software would analyse "market risks" and then use correlation and regression methods to show the interrelations or 'probabilistic connectedness' in a specific time period by representing them as percentage points called 'confidence levels'.

Hence, (taking one week as standard time) if an asset is worth say, \$100, and VaR gives a confidence level of 99%, that means the asset has a 1% chance to lose all of its \$100 value in that specific week. Ricardo presents two ways in which VaR made its predictions: Firstly, it integrates calculations of the variance within one asset class and then used covariances to assess different kinds of assets; secondly, by the Monte Carlo simulations – a method used to understand systems with large number of independent but connected elements (much like cellular systems) [7]. In short, it creates simulations of multifarious risk sources and then finally aggregates a large number of possible outcomes using aggregation and regression of data. Professor Kenneth argued that both these methods were backward looking i.e., they drew from historical antecedents. They use past data to make predictions about the future, much similar to heuristics [8].

2.1 THE PROBLEM: EXPIRED DATA?

Ricardo and Professor Kenneth argue that although VaR reaches its 'confidence level' percentage point by considering ostensibly all of the possible outcomes and probabilities in a specific period, however, it is limited by the data set programmed into it or has access to [9]. A cursory understanding of this system by an experienced trader would make conspicuous two very evident problems with these models: Firstly, that one can't look at the past to predict the financial market in the future, especially in light of "bubbles" which often form due to either terrible monetary or fiscal policy (the Japanese crises due to the central banks interest rate fluctuations) or an unexpected externality (for example 1973 Oil Crises). Secondly, human behaviour and public policy are both unpredictable, reactionary and mutually co-dependent.

As Albert Einstein once posited, "I can calculate the movements of stars, but not the madness of people". Behavioural Economists have had a long-standing consensus that using sophisticated models to predict the market is foolish [10]. This is perhaps because macro-economic policy is reactionary and is driven by externalities often founded on 'irrational' human externalities – Take the example of the Japanese Bubble due to sudden currency depreciation of the US dollar caused by the Plaza Accords, and the consequent export market crises and finally the disastrous interest rate alteration [11]. Financial market analysis requires speculation of future events which may be completely independent of the past. Additionally, economies usually move in multiple cycles such as peak, contraction, recession, and recovery. Credit therefore also moves in cycles. If data is drawn from an up-credit cycle or a contraction and applied to identify patterns in current financial markets which may be in a down-credit cycle, it is but obvious that the results would be incorrect, or in the very least has a likelihood of being incorrect.

Unfortunately, both the Regulator and Private Firms naively accepted VaR with no analysis of its mode of data processing. Private Firms even started firing their Risk Compliance Personnel in the hopes that VaR will replace them all and thus they will be able to cost cut. As Professor John Coffee explains,

Most of the investment banks used to do due diligence in asset-backed securitizations by hiring professional due diligence firms with expertise in real estate to test the loan originator's portfolio of mortgages before the bank acquired its loans. They began to abandon that practice after 2002, as the market became bubblier and demand for these deals grew and grew [12].

This abandonment of human value in financial markets proved to be fatal for both firms and the global economy. Since VaR had modelled all of its data after the 1987 stock crises, the data, ironically enough, predicted a rise in the Mortgage Prices. Additionally, being software designed for individual portfolio assessment, it was not geared towards identifying the gap risk i.e., the risk of extreme market events. Hence, they fell outside their purview of 95% or 99% confidence levels [13]. The infamous credit rating agencies also to a large extent relied on VaR reports to rate assets. On the basis of these reports, they then proceeded to issue the infamous credit default swaps. When this 'bubble' finally popped, all the top business executives were left astounded and perturbed, and for good reasons.

2.2 THE ONE FIRM THAT WON

Strangely however, Goldman Sachs' quantitative risk-prediction algorithms saved them from tremendous losses during the 2008 GFC. Except Goldman Sachs, all who relied on the ubiquitous VaR risk-modelling technology failed. Goldman Sachs had somehow managed to safeguard itself by selling its exposure in Mortgaged Backed Securities or MBS after their "real time" risk modelling tech had shown consecutive losses in their mortgage business for 10 days straight. Expeditiously, a meeting was called where a decision was taken to sell their MBS exposure. This was right at the onset of the 2008 crisis. So, what made Goldman Sachs so different? The answer is rather simple; and is the salient learning that we must take from the history of fintech. Emanual Derman, a former Goldman Sachs Risk Modeller attributed the success of Goldman Sachs to the cautionary approach of retaining human intelligence, instead of relying solely on modelling systems:

"In a good way, Goldman Sachs was eclectically irreligious about what was the right way to look at risk, we didn't just rely on VaR. Estimates of the probability of bad things happening are notoriously poor because crises don't repeat themselves in exactly the same way. We relied on scenario analysis and stress testing as well. There were limits on positions, for instance, in order to limit the loss that would occur under a repeat of the 1998 default scenario [14]."

The above quote is enough to show what was behind Goldman Sachs success, cautious application of Risk Modelling algorithms whilst more importantly, the retention of significant human intelligence in the process. The firm did not fire its human resources, rather, relied on them while using automation as a mere 'assistant'. This approach to fintech is only possible if the minds of firms are free from the corrupting force of 'automation bias'. What is this purported 'automation bias'? The next paragraph shall briefly explain the phenomenon.

2.3 THE VILLAIN: AUTOMATION BIAS

Humans tend to view automation systems as error-resistant [15]. Even when humans suspect malfunction, this 'error-resistant' idea of automation technology prevails, leading us to dismiss our own well-founded suspicions [16]. This bias doesn't just affect firms but has a stronghold over all our institutions, even the 'ostensibly' independent judiciary. In one case where automated algorithms which were tasked with identifying 'dead-beat' parents, the algorithms incorrectly classified a wrong man by confusing him with someone of the same name. The case was not frivolous but involved a huge sum of $206,000 in child support debt. It took the accused and his lawyer close to two months to convince the attorney that the algorithm had made a mistake [17]. Danielle Keats Citron argues that automation bias, if it affects institutional authorities, leads to a crisis in due process [18] and an abdication of regulatory responsibility. Frank Pasquale argued that when the stakes are high enough, automation bias can degenerate into wishful thinking or worse: opportunistic misuse of models to validate sham business practises[19]. Therefore, the destruction of this 'purported automation bias' is the need of the hour. One of the goals of this paper, inter alia, is to destroy this veil of automation bias by showcasing an alternative lens of viewing automation technology, dare I say a more cautious lens. The next section therefore shall present you with some of the inherent flaws of such machine learning algorithms which makes 'blind trust' in automation a fools' errand.

3. INHERENT PROBLEMS IN MACHINE LEARNING BASED RISK-PREDICTING ALGORITHMS – HUMAN AND LEGAL

Post GFC, machine learning in finance has undergone a full re-branding in terms of advanced 'neural networking' algorithms running on cutting-edge deep learning models. However, I argue that certain problems in machine learning continue notwithstanding the advancements in AI due to their inherent nature. The section identifies four problems. The first two problems are human centric and involve incorrect human assumptions in algorithms and human biases being surreptitiously inserted in computer code. The other two problems are legal, wherein the first arises from anti-trust law and the second from constitutional law.

3.1 MODELLING ON FALLIBLE HUMAN ASSUMPTIONS

The trillion-dollar flash crash of 2016 is a case in point. The event destabilized the market for a whole half hour wherein the stock prices of some firms swung between 100,000 dollars to pennies. Evidently the algorithms had failed to produce accurate results, but not because they were malfunctioning or buggy; rather the human assumptions they had been built upon had flopped. For example, the assumption that the stock exchange's computed price of stock would automatically always correspond with its actual price. Setting up of incorrect parameters is yet another example. As John Walsh of the office of Compliance Inspections stated,

"If you set their parameters too high, they could miss important red flags. For example, if you have an electronic report that monitors investment time horizons, but you assume that only investors under age 50 have investment time horizons, you could miss a lot of red flags relating to the elderly. Also, an electronic report cannot find red flags in data it does not have. For example, if you rely on your clearing broker for mutual fund exception reports, but do most of your business with the fund companies by way of "check-and-app," those clearing broker reports will not do you much good [20]."

Perhaps a good solution to the aforementioned problem is a mix of Design Thinking and Systems Theory while programming and employing algorithms. Design thinking is a non-linear process that allows teams, especially programmers, to constantly challenge their assumptions at every stage, look back and re-define problems, and finally create innovative solutions to prototyping and testing. Systems Theory on the other hand studies how various parts of the system interact with each other in producing the output. Systems Theory would force programmers to view algorithms not just from a consumer-product lens, but as a part of the financial system as a whole. This would allow them to study the output of these algorithms and their consequential cause-effect relationships with various interconnected institutions in said financial system.

Financial Programmers must therefore not only seek 'verification' of their algorithms but also incorporate Design Thinking and aim for 'validation'. Where verification would ask the question, "Did I build the right system?", validation would ask, "Did I build the system right, and if yes, then to what extent?". Validation would question the legitimacy of the inherent assumptions on which the algorithms have been built and such an exercise is only possible if the veil of 'automation bias' is unmasked.

3.2 POSSIBILITY OF TRANSFERRING PROGRAMMERS BIASES INTO THE CODE

Frank Pasquale observed in his book, "Software engineers construct the datasets mined by scoring systems; they define the parameters of data-mining analyses; they create the clusters, links, and decision trees applied; they generate the predictive models applied. Human biases and values are embedded into each and every step of development. Computerization may simply drive discrimination upstream [21]."

At every step human biases are imputed into the code, even if unconsciously so by either setting of parameters or by imputing assumptions. A clear solution to both the problems is ensuring the code remains open access to other programmers, can analyse the foundational parameters and assumptions and further take help from social scientists to see whether they result in social inequity. An open access to code, however, comes in direct conflict with the law which unfortunately grants them secrecy in the name of intellectual property and trade secrets. While I understand that IP rights encourage innovation, however whether the benefits arising out of such innovation is greater than the likelihood of social harm that would engender from the inscrutable nature of these algorithm is a 'harms versus benefit' analyses every regulator must painfully undertake within the context of the nation's economic and social history. The discussion should therefore move away from per se grant of IP rights to a private rights vs public interest-based conversation. This discussion would also get a new shape when the state considers recognises access to finance as a human right.

4. LAW AND MACHINE LEARNING

An intersection of law and technology is something that scholars have acutely failed to explore adequately. However, an analysis of such and intersection becomes necessary especially because the same can accommodate all the three stakeholders: The regulators who deal with law and policy, Private firms who deal with private interests and finally the programmers who deal with technology. In this section I shall subject automation tech to two legal schools of thought namely, constitutional law and anti-trust law. The goal of this section is to nuance the global tech discourse in order to have a safe space which allows for innovative solutions for both law and technology to be reconciled.

4.1 CONSTITUTIONAL CHALLENGE TO INSCRUTABILITY

While machine learning algorithms may predict the outcome, they cannot justify how that outcome or event happened or what reasons led to that event, i.e., they cannot infer causality. For example, they may be able to predict that the corporate debt bond of a certain company will reach a certain amount of yield, however they cannot tell you how it got there. Identifying patterns is its job, justifying them is the responsibility of humans which SHOULD NOT in any way be abdicated due to automation bias. The outcomes of such algorithms, when employed by credit rating agencies, impact an individual's legal and constitutional rights and consequently result in grave inequity if later proven to be unfair or incorrect. This becomes even more relevant with regards to financial instruments such a debenture that are not backed by any collateral but rely solely on the 'credit worthiness' of the issuer which are in turn also provided by the credit rating agencies. Article 14 of the Indian Constitution mandates 'substantive equality' i.e., to treat equals equally without discrimination. In this regard, I adduce Max Tegmark who makes a startling observation in his book quoted in the beginning. He writes that if we were to train a deep neural network algorithm, with a tremendous amount of data on prisoners, it can arguably predict who is more likely to commit crime again. This can then inform policy i.e., who is to be given parole and who is to be denied. However, the programmers are neither trained in sociology to provide rules grounded in sociological realities nor are they aware of their own biases. Therefore, an algorithm might start to link sex or race to a prisoner's recidivism. Pertinently, a 2016 study found that recidivism- prediction software used across the US were biased against African Americans [22]. Such use of algorithms violates article 14 of the Indian Constitution in as much as it produces 'indirect discrimination'. The two fold test of Indirect Discrimination was articulate first in the famous case of Fraser v. Canada [23] and was affirmed in India later[24] which looks not on whether formally same parameters are used to classify different groups but whether the effects of such classification produces discriminatory effects on marginalised groups. The problem, however, is that article 14 violations can only be levelled against the 'state'. What comes under the definition state is further provided under article 12 of the constitution. However, legal jurisprudence, especially in India provides an evolved definition of state wherein anybody that undertakes 'public function' could be classified a state. The central question therefore is whether credit rating agencies undertake public functions?

I argue that Credit rating agencies are indeed responsible for 'public functions' since their rating directly affects access to fair and reasonably interest rates to citizens while accruing loans [25]. Therefore, they must stand the test of Constitutionality. It is because access to finance ought to be a human right, and credit ratings act as gatekeepers to reasonable interest rates and thus directly affect citizen's access to finance. International Legal Jurisprudence has already given exceptional categorization to credit rating agencies. For example, in a famous competition law case in the EU, the court forced Standard & Poor to provide information and rating to other financial market entities without any delay. The court classified them as 'informationally dominant' in the market since their function was essential to competing in the market [26]. I argue that such classification under anti-trust law, although well intentioned, is still inadequate. A better recourse is under constitutional law wherein the credit rating agencies are classified as those firms engaged in 'public functions and credit rating is identified as a 'public good'. Doing so is possible if the state was to recognize access to finance as a human right. While this proposition may seem radical, multiple scholars have taken similar views [27] and therefore the same merits serious consideration. In the very least especially in 'welfare-oriented' countries such as India [28] the right can be recognised as an 'ancillary right' under article 21 which already recognises right to privacy and right to sleep.

Some may criticize the above hypothesis as too 'far-sighted' especially when the legal system itself is rife with discrimination. As someone who has directly worked in pro bono cases involving casteism and sexism, I do not have the audacity to refute that claim. There are even entire academic fields such as 'critical legal theory' founded on that assertion. The immediacy of underscoring algorithmic discrimination is however notwithstanding other kinds of judicial discrimination because the former is far more pernicious. Even though occasionally discriminatory, our legal system is to a large extent 'transparent' and allows for academic scrutiny and public criticism. Judgements are made publicly available to read and the underlying logic of the judgement is clearly stipulated and subject to judicial review of higher courts. Law and statues also have to stand the test of judicial review. In stark contrast however, the 'inscrutability' and 'black box nature [29]' of Advanced Algorithms are beyond human understanding due to their complex operations and therefore are well outside the purview of judicial or even regulatory scrutiny. This 'non-transparent' nature of automated decisions will eventually make them legally invincible and above the 'rule of law', which is highly problematic for any modern democracy. Therefore, the constitutional challenge to these algorithms also merits immediate serious academic concern. Besides a constitutional challenge, algorithms also raise anti-trust concerns which have also largely escaped scholarly scrutiny. The same is discussed in the following paragraph.

4.2 THE CASE UNDER ANTITRUST LAW

Collusions, especially in terms of price sharing agreements, are traditionally prohibited in antitrust law and have been recognised as an ex-ante anti-competitive practice [30] via 'illegal agreements'. However, in terms of 'tacit' algorithmic collusion, global anti-trust laws have not kept up. Machine learning algorithms founded principally on 'increasing the profits of the firm', are likely to collude with other algorithmic pricing agents and set the prices for the market [31], thus resulting in market foreclosure [32]. In a similar 2015 case, the DOJ charged David Topkins for illegal price sharing by deigning and sharing among other sellers on amazon 'dynamic price sharing' algorithms. It was easier to impute liability here because the algorithms were founded on simple machine learning. However, deep learning can make algorithms learn collusive practices on their own leading to 'tacit collusion'. As pointed out by Peter Georg Picht and Benedikt Freund, deep learning algorithms replicate the human brain by creating 'artificial' neural networks similar to the human brain, and further engender 'inscrutable hidden layers'[33]. This makes it even harder to identify the collusion and further to impute liability.

Additionally, Collusion is cross-jurisdictionally recognised as an anti-competitive practise today. The practise involves co-ordination among competitors to set price etc, with the underlying goal of raising profit much higher than the ideal competitive equilibrium. However, traditional competition policy only recognises 'explicit collusion' i.e., one which is evident on the face of it. Section 3 of the Indian Competition Law for instance prohibits ex-ante anti-competitive 'agreements' which allow firms to collude but does not recognise tacit collusion in the absence of such explicit written agreements. Algorithms, due to their inherent coded strategy may collude with other algorithms. This likelihood of collusion is especially high in oligopolistic markets [34], which are copious in finance and credit rating. This occurrence is not without precedence. In a case involving airline tariff companies, wherein the algorithms created by airline companies were engaging in 'tacit collusion', the DOJ was inadvertently forced to settle given anti-trust did not prohibit 'tacit collusion'. Accolades are in order for the DOJ since given their black box nature, it was close to impossible to pin-point explicit collusion [35] however they still figured out the collusion by observing ex-post harm. However, to impute liability here was yet again an issue.

4.2.1 Towards Imputing Liability:

By selecting certain parameters, programmes can inform the algorithm to follow a certain strategy. This strategy then drives automated pricing and risk assessment operations such as providing credit scores. Selective data sharing by algorithms is yet another way of collusion, which becomes even more ominous given the fact that our financial markets run on crucial data and information. The European commission considered prevention of accurate and timely financial data by market participants by Standard & Poor and Thomson Reuters as anti-competitive and ordered them to release the information in a time bound manner [36]. Denial of information in such cases can lead to market foreclosure. However, such an ex-post approach may not work in cases where algorithms collude especially due to their inscrutability. Therefore, ex-ante laws and regulations are required for the same. Europe already has a digital market act which provides certain ex ante-prohibitions for anti-competitive practises in the digital marketspace and developing countries such as India close to enacting their own anti-competitive laws specific to digital markets [37]. However, none of this legislation recognised the need to regulate 'tacit algorithmic collusion' highlighting that policy makers and regulators alike have not been able to keep up with the rapid advancements in technology.

On the ex-post front, I argue that the law must impute 'strict liability' against algorithmic abuse and collusion. This means that firms would be held accountable even though they technically did not intend to collude. The defence of an absence of mens rea would be irrelevant given that one is dealing with 'inherently dangerous' algorithms. Therefore, they shall be responsible for any harm due to such 'deep learning' algorithms despite not intending to do so. More importantly, this would be in tandem with tort law [38]. Policy formulated on such axioms would ensure that firms themselves keep their algorithms in check and constantly supervise. Secondly, on the ex-ante front I argue that the 'strategy' or the 'parameters' set by the programmers should be within regulatory scrutiny and should be supervised first in 'technological sandboxes' by the digital markets in the Competition Commission. The setting up of such a unit is also proposed in the 53rd Finance Committee Report on Anti-competitive practises by Big Tech and therefore is nowhere near 'impracticality'. The Committee Report also argues that SIDI's or systemically important digital intermediaries (Google, Microsoft etc) must be identified and be subjected to additional ex-ante laws. I argue that the Committee must go a step beyond and also identify 'informationally dominant firms' such as Moody and mandate them to not indulge in informational abuses, albeit traditionally or algorithmically. Ensuring a competition law cognizant of algorithmic abuses would be essential for a healthy regulatory approach to financial market inter alia other markets.

A 'new functionality, new rules' approach to regulation would merit the passing of new laws such as this which recognised tacit algorithmic collusion and imputes strict liability on the firms using them. Furthermore, mandatory such algorithms to undergo supervisory technological sandboxes before they are unleashed in the market could also be helpful. The need for such recognition has been scantly argued for in academic circles [39] and even if so, they have fallen on deaf ears.

5. POST THE GLOBAL FINANCIAL CRISES AND THE EMERGENCE OF REGTECH

Post the GFC, the regulators and academicians alike rushed to impute blame. Most ultimately blamed securitization and the complex financial instruments purportedly invented by the sharks of wall street [40]. A minority set, however, dissented and argued that it was the terrible monetary, and government policies in addition to excessive and mis-informed regulations that had a greater part to play in the crises. At this juncture, the Regulators were at a crossroads. Those in Washington DC now lacked sector specific knowledge and no longer properly understood financial markets. However, they were also handcuffed by mounting public pressure to chain those at wall street with a slew of regulations. What did they do? Both! On the one hand, they crushed financial firms under the weight of new and complex regulations some were however well intentioned like the Dodd Frank Act. On the other, they ushered in 'process-based laws' where private firms were not to calculate their risk internally and submit regular reports of compliances. Examples of these laws include Dodd Frank, Basel III reporting requirements under OTC, etc.

Wall Street, however, was also an opponent of equal measure. In response they unleashed automation technology for their legal compliance to keep up with the increasing compliance costs [41]. Some scholars argue that it was the competition from other fintech firms that also played a play in the ubiquity of this innovative tech [42]. These automated legal compliance technologies were termed "RegTech" made from the rather uncreative combination of the two words, "regulation and Technology". The Financial Conduct Authority in UK defines Regtech as "Technologies that may facilitate the delivery of regulatory requirements [43].

In the midst of all of this, physicists were equally active. Every week breakthroughs in AI are achieved. Advanced Artificial Intelligence now offered 'interpretative' human-like logic to computer systems. This was perfect for the development of RegTech which required such interpretation of laws. RegTech Software was primarily rule based in nature. Therefore, software codes in RegTech largely tends to be based on declarative logical statements than can be combined into decision like tree branches [44] for example rules such as 'Do not offer a mortgage requiring a monthly payment of over $... to an applicant making less than $...'.

However, like risk modelling technology, 'RegTech' has its own perils. I divide them into two categories: Human and Linguistic. Human problems arise when translation of laws into code is done by the programmers and Linguistic problems occur in semantic interpretation of legalese and financial terms by AI due to an acute absence of standardization of language in finance. The latter problem is one of all large language processing models such as ChatGPT.

6. INHERENT PROBLEMS IN REGTECH – HUMAN AND LINGUISTIC

6.1 PROBLEM OF TRANSLATION

While RegTech sounds like a heavenly invention for firms looking to cost cut on their legal fees paid to lawyers, in reality, the picture isn't as rosy. For any legal policy or a principle to be recognized and acted upon by RegTech it would first have to be coded into the programmer by a programmer. This 'coding of law' brings forth multiple problems. As much respect I have for programmers, they are simply not competent for this 'translation'. Legal interpretation requires certain skills which only those trained in law profess. This became clear when the programmers in one case sought to create programmes that would automate enforcement of "Intellectual Property Rights". The Digital Rights Management Software or "DRM" embedded in digital content files during its sale or distribution. It allowed private parties to prevent the buyer from using the purchased file or distributing it in a manner that would violate the intellectual property rights of the seller. What the programme failed to take into account was the doctrine of "Fair use" as an exemption [45]. Granting such an exemption requires a qualitative assessment of the method of using the property specific to the facts which is legally complicated and therefore requires a lawyer, however since the programme lacked a throughout understanding of this doctrine, it was never programmed. Thus, inadvertently, the DRM ended up defeating the fundamental principles of Intellectual Property Law. Therefore, a question arises as to how much the "west coast law" i.e., the law made through the implementation of legal policy by programmers sitting in the Silicon Valley are in tandem with the goals envisioned by the "east coast law" i.e. the law and its principles imagined by the parliamentarians sitting in Washington DC or the Lok Sabha which merits yet again careful scrutiny so as to not defeat the purpose of the law. As an antidote, Max Tegmark suggests getting more tech savvy people into law schools and government as one of the solutions, however given the unfortunate lack of interdisciplinary discourse within these two fields currently, that is a dream still! On a lighter note, this paper is being written by a law student so perhaps the reasons for optimism aren't completely unfounded!

6.2 PROBLEM OF THE TOWER OF BABEL

Secondly, the existence of multiple financial languages creates semantic asymmetry in interpretation of dictums by the algorithm. Scholars refer to this as the 'problem of tower of Babel [46].

Allow me to borrow an allegory from the Old Testament to elucidate this problem. In the first book of the Old Testament God punishes his followers for building a "tower" to reach him. He punishes them by replacing Earth's common language with 7000+ languages. This is where the 'tower of babel' problem finds it metaphorical origination. While in the real world, differences in languages must be celebrated since they are the representations of unique and beautiful cultures which ensure diversity. However, in the financial world, the lack of standard language is a bane. It is argued that today the number of financial languages exceeds the number of spoken languages. Since translation of policy into code requires standardized semantics, having multiple versions of languages creates additional confusions. Scholars have termed this lack of a common financial language as the "tower of babel" [47]. The problems become pertinent in crises of the global nature such as the 2008 crises which demand a coordinated global effort. Perhaps formulating a global standardized financial language is necessary. However, the problems may arise in its acceptance and recognition world over and between different private firms within a country because the same can be construed as forces universalism which can be even counterproductive. To highlight with an example, The city of Thiruvananthapuram in India means 'the shelter of lord anantha', however, to simplify its pronunciation in English, it was converted to 'Trivandrum' which means nothing. Hence the city's name lost its semantic meaning in the process of translation to English. Most RegTech software's are built in the Silicon Valley which has a ubiquitous dominance of English. Translation of local laws of different countries into English and then into code therefore becomes a problem for Silicon Valley Softwares. Perhaps standardization of financial language must not come at the expense of the semantic history of other cultures but rather through an equitable dialogue between all the member countries to negotiate an amenable common ground. This requires a co-ordinated international effort.

7. INCREASING COMPLEXITY AND POLICY IMPLICATIONS: NEURAL NETWORKS AND DEEP LEARNING

Following the integration of AI and the innovation of RegTech, technology grew at an even rapid pace, perhaps too rapid for humans to track. The use of Deep Learning and Neural Networking technology promised an automation revolution, and sough to re—shape how we view machine learning. As Tegmark succinctly posits,

"Neural Networks have now transformed both biological and artificial intelligence and have recently started dominating the AI subfield known as machine learning i.e., the study of algorithms that improve through experience."

Deep Learning and Neural Networks is perhaps the hardest thing for a writer to explain to its readers. Even their creators don't quite fully understand the workings of neural networks due to its inherent 'dynamic inscrutability'[48]. However, such is the problem with this technology. With ever increasing advancements in machine learning, it is very easy to club all different stages of complexity into one, however doing so misses the point. Different countries undergo different stages of technological complexity in the same periods of time, and therefore, regulatory approaches must be suited to each stage. In the next couple of paragraphs, I shall identify these stages of complexity es and posit the problems in each stage all the way up to the last stage i.e., neural networking technology. This shall bring much needed clarity on what policy measures is required for what stage and further summarise the historical development of automation. The three kinds of regulatory must be distributed among the five kinds of complexity stages. Marlene Amsted in her paper has succinctly provided the three kinds of approaches to regulating RegTech[49] namely:

(a) *Ignore: Keep it unregulated approach*: This approach posits an ignorance as well as a refusal in understanding the nuances of new regulation and risk management technologies. Regtech software's and their uses largely remains unregulated.

(b) *Duck Type: Same Risk Same Rules Approach*: This approach recognizes the need for regulating RegTech yet again refuses to understand the complex and unique new risks posed by RegTech. Hence this approach extends the same traditional laws to RegTech.

(c) *New Functionality, New Rules*: This approach, albeit rare, recognizes both the need of regulating RegTech and further painstakingly understands the nuances and unique risks posed by RegTech and makes new laws in that regard.

Besides these three, I present a fourth type of policy-measure specifically catered to the 4th and 5th stage: The 'Suptech' approach. Suptech, which stands for 'supervisory tech' is the technology used by the regulators to regulate. This approach uses technology to regulate technology, i.e., to fight iron with iron. The next couple of paragraphs shall apply these different policy measures to multiple complex stages of automation.

7.1 THE STAGES OF COMPLEXITY AND THE IDEAL REGULATORY APPROACH

7.1.1 Simple Computing: Stage 1 Complexity:

MIT researchers Norman Margulous and Tommaso Toffoli coined the term 'computronium', referring to any substance or entity that can perform arbitrary 'computations'. But what is computation? Tegmark defines computation as the transformation of any information by using 'functions' (also happens to be the terminology used by mathematicians!). This function can be as simple as a NAND gate which involves two inputs and one output. A NAND gate would output 0 if both inputs are 1 and in all other cases, it would output zero. Today such NAND gates are widely built from microscopic transistors which can be automatically integrated in silicon wafers. Theoretically a NAND gate represents an atom in the computing world and by allegory many tech-scholars argue that if you can create enough NAND gates, you can practically build a device to compute anything! Therefore, logically a computronium can be created simply by integrating NAND gates to achieve the desired outcome [50]. These NAND gates are largely easy to understand by physicists and are a fairly transparent function. Other simpler and transparent functions included the NOR gate which produced output 1 only when both outputs are 0. Let's call the state of complexity in NAND or NOR processing as 'stage 1 complexity". Pocket Calculators for instance, don't learn. One puts in a specific input, and it produces the same output every time. This stage is fairly easy to regulate as it functions with a certain amount of transparency due to easy and simplistic causal inferences of NAND gates. Further the system does not automatically learn to reproduce complexity. For this stage perhaps the correct regulatory approach is to 'de-regulate' i.e., have minimal red tapism with regards to patenting to ensure innovation flourishes. Hence approach (a) must be in order especially for developing countries that are still technologically improving. De-regulation and focus on IP rights would ensure fast innovations in advanced tech.

7.1.2 Simple Machine Learning: Stage 2 Complexity:

Now that we have understood how computation works, let's come to machine learning or more pertinently how non-human automation algorithms get better at processing due to self-learning. Financial algorithms, unlike calculators, are conditioned to learn. For this learning to take place, the algorithms must constantly re-arrange the data to produce better more accurate outcomes and further ensure dynamic efficient pathways to reach said outcomes.

A machine learning algorithm therefore uses model training, loss function and optimization and then finally validation and testing to learn and become more efficient. The 'simple' machine learning algorithm is programmed taking into account a specific model, such as decision trees or support vector methods (neural networks being the newest of these models discussed later). These models then are presented with multiple data sets wherein the identify specific patterns between inputs and outputs. It does so by constantly adjusting its internal parameters repeatedly in order to minimize the difference between its prediction and true labels. For example, in a cat versus dog's data classification task, each label would have a corresponding label indicating whether it is a cat or dog i.e., the true label. The loss function quantifies the difference between its predictions and true labels. The algorithms will note the difference between its predictions and the true labels and update its parameters in a way that reduces the loss, making it better. This updated model is 'validated' by exposing it to an unseen dataset. I have previously argued that this 'validation' is simply not enough and must thereby be extended to 'verification' using design thinking. These machine learning algorithms can be categorized as 'stage 2 complexity'. This stage is subject to all the previously mentioned problems of backward-looking data, translation, discrimination and a preclusion of humans to be able to infer causality due to sheer rapidity of regression-based learning. While the correct approach machine learning is the third i.e., new functionality, new rules especially in light of the interpretative abilities of AI to implement law, law makers unfortunately have limited public policy to at best the second approach i.e., Duct Tape: Extending the same data privacy laws and traditional corporate governance laws to machine learning. While this may work in the short term, however, the propensity of machine learning to rapidly become more advanced would render the approach futile.

7.1.3 Neural Networks: Stage 3 Complexity:

With the introduction of neural networks as a novel machine learning method by Geoffrey Hinton, the entire ball game changed. The idea was to construct a machine learning along similar lines as human neurological structure which contains interconnected neurons via junctions of trillions of synaptic connections which pass information. Neural Networks are also subjected to varying degrees of complexity. The earlier 'simplistic–neural network' represented each neuron by a single number and similarly each synapse by a single number. Each neuron would hence update its state at regular time by simply averaging together the inputs from all connected neurons, weighing them together by their synaptic strengths and finally using an 'activation function' to compute its next stage. (Later neural networks started using deep learning further complicating its operations). Neural Networks didn't learn the way that traditional machine learning used, but rather learnt through Hebbian Learning was Tegmark argued. The concept was first introduced by the Canadian Psychologist Donald Hebb who argued that in human neurochemistry, if two synaptic neurons were frequently 'firing' simultaneously, their synaptic coupling could strengthen so that they learned to trigger each other. The great John Hopfield, whose work was seminal in the development of neural network technology showed how Hebbian Learning allowed his simple neural network algorithm to store a tremendous number of complex memories by simply being exposed to them. In humans the Hebbian learning helps us learn things by simply experiencing them continuously. However, in neural networks, this similar learning method is termed 'backpropagation' which is often referred to as the building block for neural networks. Let's call this 'stage 3 complexity.' Stage 3 complexity is where things get a little out of hand. Because of their complex working, and due to backpropagation i.e., Hebbian Learning these algorithms largely function of 'dynamic inscrutability' [51]. The regulation of these technologies perhaps merit regulators to take steps beyond just creating new laws/rules. Here the novel idea of 'SupTech' i.e., supervisory tech would come in handy. As Hillary argues regulators themselves should focus on experimentation with their own SupTech as much as possible [52]. SupTech is referred to as the technologies used by regulators to supervise as compared to RegTech which is largely used by private firms for legal compliance. Examples of SupTech can include Technological Supervisory Sandboxes [53] for testing algorithms before they are unleashed in the market. These supervisory sandboxes can serve two purposes; to help the regulators analyse the consequence and reproduction of such neural networks to ensure they don't lead to absolute black boxes and that the risk of failure of such algorithms aren't severely detrimental to the market, and second, to provide the firms a temporary regulatory safe heaven to 'test' these algorithms. Sandboxes become particularly effective since they can allow for safe regulations based only on outcomes and not therefore inferring causality, ableit important, become somewhat unnecessary. For the implementation of Suptech a new tech-savvy regulatory unit mut be created specifically catered to it. The 53rd Finance Committee report in India for example argues similarly for the setting of a 'Digital Market Unit' within the competition commission. Such Digital Units must be extended to various government offices, especially those regulating capital markets and further must employ advanced SupTech methods to regulate.

7.1.4 Deep Learning and Black Boxes: Stage 4 Complexity:

Modern neural networks often contain multiple layers i.e., an input layer, hidden layer(s) and an output layer in which nodes that work parallel to neurons are each inter-connected by a certain software (similar to the synapse in humans). Data travels through the input layer, then through various 'hidden' layers and after each layer the data is multiplied by its weight to give its activation function. In the end, when the data comes out of the output layer, the source data which amassed the highest activation points is selected and then the loss function is calculated by comparing it with the actual label or the 'true label'. Backpropagation calculates the loss function of the previous layer and subsequently alters it to create an updated neural network. The problem is however that the 'previous layers' now are hidden due to deep learning a therefore such programmes attain the highest levels of inscrutability. If this all seems complex, it's because it is! The same way we don't quite fully understand neurochemistry, we also currently also don't fully understand neural networking algorithms and how they work (or even how they fail). Interestingly, this did not preclude physicists from creating even more complex 'deep layers' of advancements to this neural networking tech leading to the ultimate 'stage 4 complexity'. Robert D. Hof considers deep learning to be the 'next level' type of machine learning where the algorithms can expand upon the even smallest of pattens within a given data set [54]. In 2015, Google's DeepMind created a Deep Learning driven AI algorithmic system which learned to master human games with no previous instructions and soon became better at them than any human being. Stage 4 complexity is the ultimate Achilles Heels of Public Policy. They are so complicated that they are bound to engender 'black box' algorithms. These are inherently beyond human observation and understanding and even Suptech cannot be used to contain them. Afterall, how do you model a technology to regulate another technology which even the physicists fail to understand fully. While this all may sound like something straight out of a black mirror episode, they are fast becoming a reality! Scholars such as Frank Pasquale have written at length about these 'black boxes' controlling out financial markets in his book "The Black Box Society: The Secret Algorithms that control money and Information'. Perhaps, the open letter written by Elon Musk and all global tech CEO's calling for a halt in deep learning AI [55] doesn't sound so irrational now, does it? Perhaps, a regulatory approach to these technologies especially when applied to sectors of grave public interest such as the financial markets should be one of 'prohibition'.

8. CONCLUSION

Through this paper I have made a valiant effort at beheading the monster of 'automation bias'. I have provided the reader with ample evidence as to why automated technologies must be doubted and scrutinized. The hope throughout this paper is to start a new discourse on automation, one that doesn't take automation for granted but rather treads carefully; a discourse that recognizes the disastrous potential for automation technology especially when they are made the arbiters of where the money flows. An inter-disciplinary approach making use of the triangle of law, history and data science has been used to further the broader arguments made in this paper. The underlying aim has been to provide much needed regulatory clarity on how to proceed with financial automation. I exalt the law makers and regulators alike to undertake a "new functionality new rules" approach to regulating fintech and if technologies perhaps get too advanced, employ SupTech. From the perspective of private firms, I have made a case as to why they must retain human capital and integrate it co-operatively with automation. Finally, from the perspective of the programmers, I have encouraged them to use a combined approach of design thinking and systems theory while constructing programmes to ensure they are 'future proof'. Clearly there are multifarious perils of automation technology albeit one that models risk or one that automates legal compliance. While the 'human' and 'design' problems are slowly starting to be recognised in the global tech discourse, however problems pertaining to its legality have been alarmingly absent from the discourse. That is what this paper hopes to contribute. I hope that the readers thoroughly enjoyed the paper and hope that through post-reading they see automation technology in a different light.

8.1 LIMITATIONS OF THE STUDY

The above study and the consequent hypothesis are aimed at providing regulatory guidance to policy makes and to firms to understand the risks of automation technology. The discussion largely remains theoretical and qualitative and therefore lacks a quantitative analysis using data sets given the broad nature of the study. The study can further be nuanced using sample surveys of firms, regulators and programmers using questionnaires to support the qualitative thesis.

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