Decentralized vs. Distributed Organization: Blockchain, Machine Learning and the Future of the Digital Platform

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Abstract

The terms *decentralized organization* and *distributed organization* are often used interchangeably, despite describing two distinct phenomena. I propose distinguishing *decentralization*, as the dispersion of organizational communications, from *distribution*, as the dispersion of organizational decision-making. Organizations can be distributed without being decentralized (and vice versa), and having multiple management layers directly affects only distribution – not decentralization. This proposed distinction has implications for understanding the growth of digital platforms (e.g. amazon.com), which dominate the global economy in the 21st century. While prominent platforms typically use machine learning as their core technology to transform inputs (e.g. data) into outputs (e.g. matchmaking services), blockchain has emerged as an alternative technological blueprint. I argue that blockchain enables platforms that are both decentralized and distributed (e.g. Bitcoin), whereas machine learning fosters centralized communications and the concentration of decision-making (e.g. Facebook Inc.). This distinction has crucial implications for antitrust policy, which, I contend, should shift both its analysis and its target of action away from the corporate level and focus instead on the data level. Based on this essay's framework, I make several predictions regarding the future of competition between centralized and decentralized platforms, the evolution of government regulation, and broader implications for managers in the digital economy and for the business schools charged with their education. I conclude with reflections on the opportunity to revive cybernetic thinking for preventing a dystopian future dominated by a handful of platform behemoths.

Keywords

antitrust, blockchain, decentralized, distributed, machine learning, platform, trust

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The difference between making a decision alone and making a group decision justifies the existence, and explains the structure, of organizations whose members must coordinate their communications to reach common goals (Hirokawa & Poole, 1996). The relationship between communication and decision-making is essential to the design of particular systems of *organizational governance* – a term Plato used to discuss the government of cities (*kubernaein* in Greek, meaning 'to steer') and which, after World War II, inspired the foundation of 'cybernetics' as the scientific control of social systems involving humans and technology (Simon, 1947; Wiener, 1948).

In what has become a cliché, firms heavily reliant on software technology often describe their internal organization in the way the head of strategy at Uber Technologies does: 'We are very decentralized. There's sort of a bunch of mini-startups in cities across the world' (Medium, 2019). Similar claims are made by other software firms that also operate digital platforms: 'Google is decentralized and lets a thousand flowers bloom' (Henderson, 2012, p. 70); Alibaba has a 'decentralized approach to decision-making' (Frick, 2014); and Facebook has a 'very decentralised organisational structure' (Glassdoor, 2019). Decentralization may have become a corporate cool factor associated with innovativeness or nimbleness; however, it remains unclear what decentralization really entails as a design feature of organizations.

Such ambiguity is particularly visible with respect to how the presence of managers affects a firm's decentralization. On the one hand, since managers enable the *delegation of authority*, they appear to support decentralization. On the other hand, since managers belong to an inverted tree-shaped *hierarchy of authority*, wherein the manager at the top (i.e. the CEO) is positioned to reverse decisions made elsewhere in the organization, they perpetuate a centralized form of organizing – only on a larger scale – and 'leave untouched the cumulation of ultimate responsibility' (Penrose, 1959, p. 47). Thus, paradoxically, managers seem to nurture organizations' decentralization but without

relieving centralization pressure. As a result, it is generally unclear whether adding a management layer to an existing organization would enhance or, to the contrary, erode decentralization. Further adding to this ambiguity, a new breed of digital platforms, modelled after Bitcoin and Ethereum, now claim to be 'fully decentralized', 'unlike Google' (TNW, 2018) and 'unlike Facebook' (FXEmpire, 2018).

Law and technology scholar Julie Cohen (2017, p. 135) describes the digital platform as 'the core organizational form of the emerging informational economy', which does not 'enter or expand markets [but] replace[s] (and rematerialize[s]) them'. Digital platforms already mediate nearly 30% of global economic activity (Schenker, 2019). With their growth accelerating due to an inescapable digitalization trend, boosted even further by pandemic lockdowns around the world, the thought of living in a fully platformized society evokes utopia for some – and dystopia for others (Kenney & Zysman, 2016; Tirole, 2020). A worst-case scenario would be to have unaccountable corporate behemoths form a platform oligopoly with global surveillance and behavioural prediction capabilities.

In this essay, I explain how our poor understanding of decentralization fuels the risk of such dystopian oligopoly formation and why extant regulations that wave the threat of corporate breakup (e.g. of Google LLC) are unlikely to help. Looking across a wide range of digital platforms, from Bitcoin to facebook.com, I argue that prior accounts that viewed the 'distributed' and the 'centralized' as polar opposites (Baran, 1964; de Reuver, Sørensen, & Basole, 2018; Tilson, Lyytinen, & Sørensen, 2010) are insufficient to describe the multidimensional diversity of platform designs in existence.

To remedy a conceptual shortcoming that ends up concealing part of today's reality and preventing adequate regulation, I discern *decentralization*, defined as the dispersion of coordinated communications within organizations, from *distribution*, defined as the dispersion of organizational decision-making. I show that organizations can be distributed without being

decentralized (and vice versa) and that the presence of managers directly affects only distribution, not decentralization. I then argue that design choices (Puranam, Raveendran, & Knudsen, 2012) around decentralization and distribution imply leveraging different core technologies (Woodward, 1965) that shape the process whereby platforms structure data, turn it into information, and eventually into knowledge (Turnbull, 2017). That process, in turn, determines the sources of communication and decision-making that are trusted within the organization, as well as how platform growth unfolds and what regulations can suitably oversee such growth for the benefit of society.

Two data-processing technologies that are core to digital platforms, namely blockchain and machine learning (ML), undergird the difference between decentralization and distribution among platform operators. A technology is core to an operator when it powers its day-to-day operations, such as ML for Amazon Inc. or blockchain for Bitcoin. According to founder-CEO, Jeff Bezos, 'ML drives [Amazon's] algorithms for demand forecasting, product search ranking, [. . .] recommendations, merchandising placements, fraud detection, translations, and much more. [M]uch of the impact of ML [is] quietly but meaningfully improving core operations' (letter to shareholders, 2017). By contrast, the Bitcoin organization's core operations (e.g. mining, transacting, voting, issuing new coins) all take place on a blockchain (Hsieh, Vergne, & Wang, 2018b) and ML is unnecessary in this context.

This essay demonstrates that blockchain enables platform operators that are both decentralized and distributed (e.g. Bitcoin and MakerDAO), whereas ML favours centralized communications and the concentration of decision-making (e.g. Amazon Inc. and Tencent Holdings Ltd). That is because there is a causal chain connecting a platform's core technology (blockchain vs. ML), the design of the organization that operates the platform (decentralized or not, distributed or not) and the growth trajectory of digital platforms.

These considerations have practical implications for understanding the increasing centralization of data within a handful of trillion-dollar platform behemoths. The resulting antitrust concerns cannot be addressed using a traditional regulatory approach at the corporate level (Srinivasan, 2019) because platform operators that use ML as core technology are subject to 'data gravity' (McCrory 2010). Instead, I propose regulating *at the data level* and formulate actionable policy recommendations to level the competitive playing field – after acknowledging the dual tension between legal and illegal (or 'pirate') competition, and between centralized and decentralized platforms. I then discuss implications for managers and the business schools charged with their education. I am hopeful that, taken together, these considerations will inspire scholars, managers and policy-makers as they envision ways to prevent the dystopian domination of the global economy by a digital platform oligopoly with little public accountability.

Decentralization versus Distribution: A Historical Perspective

A concept lost in interdisciplinary translation

Dictionaries define decentralization as the 'distribution of powers', thereby introducing a confusing equivalence between decentralization and distribution (e.g. dictionary.com/browse/decentralize). In the 1960s, engineer Paul Baran distinguished between the two notions in a series of landmark studies on communications networks, wherein he described decentralization as a 'fuzzy' state best seen as the middle ground on a spectrum ranging from the centralized to the distributed (Baran, 1964). Baran differentiated networks based on the number of nodes that needed to fail to break down communications – ranging from a single node in centralized networks, to a few in decentralized networks, and a majority in distributed networks. Baran's illustrative visual (see Figure 1) has since
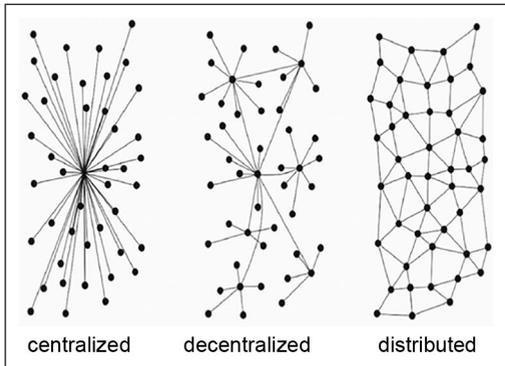
Figure 1. Baran's typology of communication networks.
Source: Baran, 1964, p. 2.

become hugely popular in the network engineering community and beyond – nowadays, it is Google.com's number-one image result for the search terms *distributed* and *decentralized*:

As research on decentralization migrated from network engineering (Baran, 1964) to software engineering (Buterin, 2017; Khare & Taylor, 2004), and later percolated into information, organization and management sciences (Hsieh, Vergne, Anderson, Lakhani, & Reitzig, 2018; Mintzberg, 1979; Tilson et al., 2010), the meanings attached to *decentralization* and *distribution* continued floating and shifting (for my attempt to explain the current state of confusion, see this lengthy footnote).[1] This paper offers a much-needed clarification based on the recognition that, within organizations, communications and decision-making occur as parts of two distinct systems (March & Simon, 1958; Puranam, 2018). Thus, whereas Baran's positioning of distribution and decentralization along the same continuum made sense in the context of communication networks, in a more complex organizational context a richer view is warranted.

Distribution as flexible delegation

Under Baran's influence, the notion of distribution became associated with 'connect[ing] each station to all adjacent stations, rather than to just a few switching points' (Baran, 1964, p. 5). Distribution implied creating redundancy so that, under adverse conditions, a network could

flexibly delegate decisions about routing to alternative nodes, thereby forming temporary communication channels. Put differently, Baran did not optimize the (redundant) structure of distributed networks for efficiency but for resiliency to external shocks (e.g. a nuclear attack during the Cold War).

Relatedly, distributed networks are inseparable from digital transformation. In analogue channels, message replication decreased quality (e.g. copying a tape from a copied tape), whereas in digital channels, replication does not degrade quality (e.g. copy-pasting an MP3 file). To facilitate flexible delegation, digital channels require formatting data into standardized packets that can be easily recombined. (Notably, Baran co-invented the Internet's 'packet switching' technology.)

Decentralization as dispersed data and information exchange in communication systems

Decentralization refers to the broad dispersion of the ability to *exchange data and information* within communication systems. Eminently political, the notion of decentralization appeared amid the 1789 French Revolution and, since then, has been promoted as a principle by theorists covering the entire political spectrum, from leftist anarchism (Joseph Proudhon) to classical liberals (Thomas Jefferson) and free market libertarians (Murray Rothbard).

The libertarian-anarchist axis has inspired 'cypherpunk' activists who, spurred by the publication of a landmark paper discussing 'transaction systems to make Big Brother obsolete' (Chaum, 1985), have advocated for the decentralization of information technology. Cypherpunks promote the use of privacy-enhancing cryptography to weaken individuals' need to rely on governments and corporations (Hughes, 1993); they envision cyberspace as a common good, free from appropriation by state or dominant corporate entities (Barlow, 1996). Key to achieving these goals is the dispersion of data with equal access rights among users and citizens.

A Simple Distinction between Decentralization and Distribution

Herbert Simon, pioneer of research in both decision-making and artificial intelligence, wrote in 1997 that 'in the post-industrial society [. . .], the key problem is how to organize to make decisions – that is, to process information'. However, the processing of information and the making of decisions need not occur algorithmically as part of the same movement, nor be performed by the same agents. Another once-held assumption that the present study relaxes is that 'the mere existence of a mass of data is not a sufficient reason for collecting it into a single, comprehensive information system' (Simon, 1997, pp. 118–19). In today's age of cheap digital storage and ML computation, there is a lesser need for managers to identify precisely in advance which data might be relevant for decision-making. Rather, for many firms, collecting as much data as possible has become a guiding principle.

Organizations as coordinated communication systems

Through their human and technology resources, organizations gather unstructured data from their environment; structure these data by making them readable and comprehensible; turn them into information by adding meaning and perspective; and, over time, produce knowledge by making information useful and valuable (Sproull & Kiesler, 1991; Turnbull, 2017). The process involves coordinating communications among the organization's human agents (e.g. members, employees, users) and artificial agents (e.g. sensors, algorithms, software), as summarized in Figure 2.

Organizations as decision-making systems

The unstructured data that organizations gradually turn into knowledge as part of their communication system ultimately support decision-making. Indeed, to achieve their goals, organizations must decide how to allocate resources. Such decisions are made in ambiguous environments, repeatedly over time, and are shaped by the (often conflicting) incentives of organizational members who contribute to decision-making (Shapira, 1997).

In organizations with just a handful of members, all decisions can be made by the founder or collegially after consulting with everyone; however, in large organizations, both methods are intractable. In an organization of several hundreds, no single member has enough time or cognitive resources to ponder every decision – and consulting with hundreds leads to decision paralysis.

Communication and decision-making complexity: how managers enable 'distribution'

Dunbar (1992, p. 469) famously argued that our cognitive capacity 'limits the number of relationships that an individual can monitor simultaneously'. That number was estimated to hover around 150 for one's entire social circle, and to range between 5 and 20 for the optimal number of co-workers to consult before performing organizational tasks. Fortunately, not every organizational member must consult all other members before making a decision.

As organizations grow, the potential number of consultation channels among members (or 'complexity') increases with the *square* of membership size. For *n* members, up to $n(n-1)/2$ consultation channels exist. Thus, a software firm building, say, a new operating system that needs 1,000 distinct experts (i.e. one for each software module) would have up to 499,500 channels among the experts, and task coordination and firm growth would likely become intractable.

Now, if the 1,000 modules were grouped in intermediate ensembles (e.g. in 100 'functions'), each expert could realistically consult with 9 other experts, forming a team of 10 responsible for a given function. In a scenario where everyone consults 9 counterparts plus 1
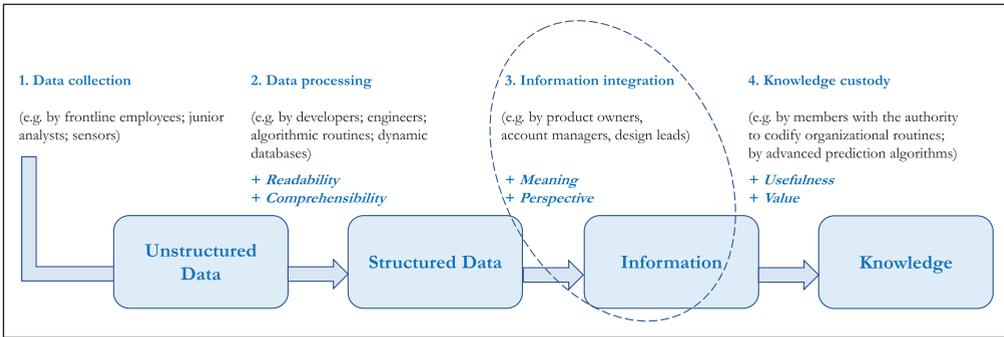
Figure 2. From Data to Knowledge: Organizations as Coordinated Communication Systems.

supervising 'manager' (who oversees 10 subordinates), the company would need 111 managers to supervise 1,000 module experts (since every 10 managers would need a manager, all the way to the CEO).

Thus, instead of having up to 499,500 active consultation channels, the company could decrease that number to 6,105 by hiring 111 managers spread across three layers (i.e. each of 111 self-contained teams of 11 has up to 55 active channels). Effectively, in the presence of a managerial hierarchy to support decision-making, complexity increases only as a *linear* function of membership size, thereby making task coordination and organizational growth much more tractable. Hereafter, I refer to the phenomenon whereby organizational members disperse decision-making across the organization as *distribution*; by contrast, the lack of dispersion implies 'concentrated' decision-making.

Discerning decentralized organization from distributed organization

To better grasp the wide diversity of digital platforms in existence and ultimately explain why a platform oligopoly might dominate the economy, we must distinguish between decentralization and distribution. Figure 3 depicts how organizations are shaped by the extent to which their communications are centralized vs. decentralized and their decision-making is concentrated vs. distributed.

Centralized-concentrated (Ce-Co) organizations

In Ce-Co organizations, members work independently to structure data collected from the environment and pass it on to a decision-maker in charge of processing it, integrating it as information, and leveraging knowledge to make decisions. This setting has only one decision-maker, who also acts as the sole information integrator, connected to other members independently via (hierarchical) channels. Without trust in the decision-maker, the organization can collapse.[2]

A Ce-Co organization could be a team of junior investigators who independently document insurance claims and report to a manager in charge of adjudicating them; a marketing consultancy whose six summer interns independently collect data on car purchasing behaviour in six different countries on behalf on an associate; or textile workers performing piecework for a supervisor.

Decentralized-concentrated (De-Co) organizations

De-Co organizations differ from their centralized counterparts in that the six frontline members are also tasked with information integration (Figure 3's upper right corner). While decision-making still resides with the manager, the frontline is tasked with reaching consensus and recommending a course of action, which the
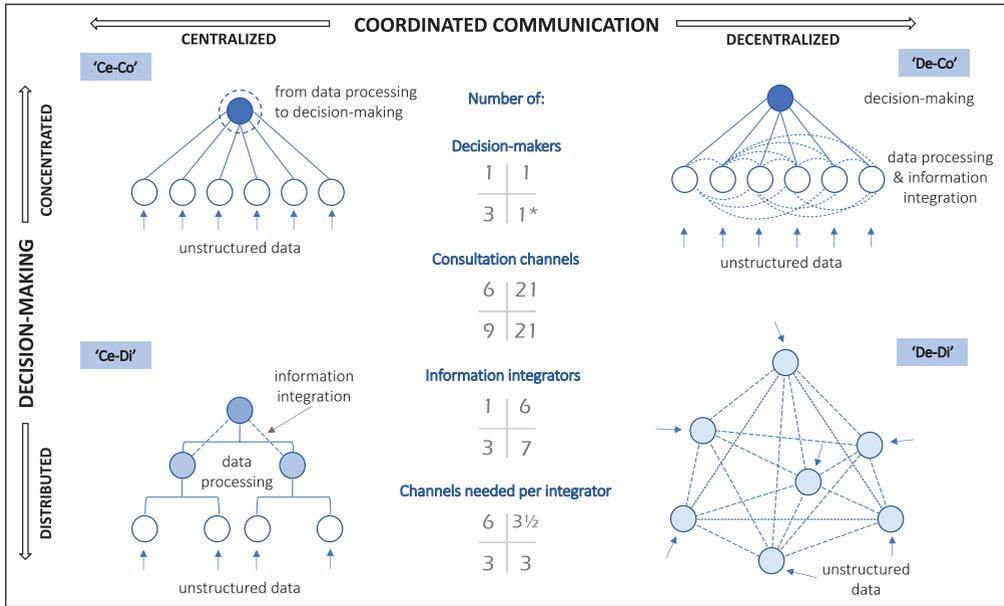
Figure 3. The Decentralization and Distribution of Organization.
Note. All four organizational ideal-types have 7 members represented by circles. The darker the circle, the more concentrated the decision-making authority of a given member. Solid lines represent hierarchical reporting and dotted lines indicate who the 'information integrators' are. Both solid and dotted lines represent consultation channels used to achieve coordinated communication. The 2 × 2 matrixes forming the middle column provide summary statistics for each of the four ideal-types (e.g. the upper left number in each matrix refers to 'Ce-Co' organizations).
* Organizational members take turns to act as decision-maker following a well-defined protocol.

manager can, based on extant knowledge, either accept or reject.

The number of consultation channels and information integrators increases dramatically as a result, but the number of channels needed per integrator decreases, in line with well-known arguments on the superior efficiency of decentralized information processing in contexts where the information needed is dispersed widely (Hayek, 1945). Trust in the decision-maker is still crucial, but in this context, the frontline is able to recommend a course of action independently, making it more likely that an alternate could step in and substitute for a decision-maker that is either failing or corrupt.

A De-Co organization could be a factory with innovative human resource practices such as 'problem-solving teams, incentive pay, flexible job design, [and] information sharing among workers' (Mookherjee, 2006, p. 385); it could also be a research organization, such as an academic institute where postdoctoral research fellows develop a joint project under a grant holder; or an advertising agency wherein various creative professionals work together to propose a campaign idea to an art director, who then decides to go with it or to reject the idea.

Centralized-distributed (Ce-Di) organizations

Ce-Di organizations delegate aspects of decision-making to subordinates within a multi-layered managerial hierarchy. In Figure 3, the distribution of decision-making requires fewer consultation channels per information integrator than in the two concentrated decision-making scenarios, and the total number of channels increases only moderately relative to the baseline Ce-Co scenario (from 6 to 9, versus 21 in the decentralized scenarios). Distribution thus increases processing efficiency.

Trust is distributed across several decision-makers as decision-making is delegated down the hierarchy; lower-ranked managers are authorized to allocate resources up to a certain level and in delineated areas (e.g. entry-level marketing managers make spending decisions for local print material but not for national TV ads). Most multidivisional corporations have adopted this type of organization, having associates who report to directors who report to vice-presidents, and so on.

Distributed managerial hierarchies enable organizations to grow steadily across both product lines and geographies while keeping complexity manageable (Chandler, 1962; Mintzberg, 1979; Puranam, 2018). Centralization remains for communication and organizational strategy; yet decision-making – and trust – are distributed to manage complexity.

A Ce-Di design makes coordination and growth tractable (since complexity increases linearly with membership instead of quadratically) but with a drawback. To increase communication efficiency, Ce-Di organizations eliminate redundancies by specializing branches of the hierarchical tree by information type, which risks communication errors (e.g. flawed transmission) and opportunistic behaviour (e.g. information retention). Both decrease stakeholders' trust in the organization.

Decentralized-distributed (De-Di) organizations

De-Di organizations maximize the number of available information integrators (7) while keeping the number of channels needed per integrator to a minimum (3). To be able to make decisions without formally assigning decision-making authority to higher-ranked members, a De-Di organization must define a non-hierarchical protocol for its members to reach consensus.

As a thought experiment meant to provide an illustration (Kornberger & Mantere, 2020), think of your car being parked idle while you sit at home or in the office. To leverage this idle asset, you consider renting it out 9–5, Monday–Friday, to local residents running brief errands. The difficulty is finding strangers whom you would trust to safely drive your car and return it by 5 p.m. Without such trust, this rental transaction, typical of the 'sharing economy', cannot happen.

A now typical solution involves starting a (centralized-distributed) platform business that charges a fee to match short-term drivers with car owners. It provides insurance and a two-way user rating system, thereby acting as the centralized, trusted authority behind the two-sided matchmaking platform. That is what Uber would look like if it adopted a genuine 'sharing economy' model.[3]

An alternative solution is to create *decentralized* trust among peers to remove the need for centralized communications to match drivers with riders. To create such trust, members agree to stake currency as collateral in an escrow account before driving around.[4] In the event of a dispute, a protocol conscripts a few community members who act as witnesses (e.g. to examine available data, such as whether the car has a new scratch) and referees (e.g. to vote on a proposed course of action regarding the release of the collateral). The probability of being conscripted correlates with one's accumulated reputation, visible to all and reflective of each member's prior organizational commitment. Every transaction is recorded publicly alongside data on hourly rates, images of pre-existing damage and reputation ratings. The experience would be similar to using Uber but without Uber Technologies Inc. acting as intermediary to collect a 25% commission.

The De-Di design is appealing, as it allows anyone to join the organization, access data and, if need be, contribute to decision-making; it also prevents banning specific members or censoring transactions since no one holds the formal authority to do so. These properties make De-Di organizations attractive for operating borderless, inclusive and resilient digital platforms (Hsieh & Vergne, 2020). In De-Di organizations, trust is both *distributed* (i.e. any member can be a decision-maker) and

decentralized (i.e. every member has equal access to data and information).

Blockchain Platforms versus Machine Learning Platforms

I will now illustrate the usefulness of discerning decentralized from distributed organization in the context of digital platforms. After a brief overview of digital platforms and two core technologies they can rely on to operate (blockchain and ML), I explain why an oligopoly is bound to form around centralized-distributed ML platform operators (e.g. Facebook Inc., Google LLC, Tencent Holdings), *even in the absence of illicit anticompetitive practices*. Based on my examination of the link between core technology and organizational design, I then propose an alternative approach to industry regulation.

Overview of digital platforms

Digital platforms provide access to an online marketplace that increases the legibility of the various products that users buy and sell (e.g. by publishing comparative data on price and reputation). Digital platform *operators* are organizations that develop, maintain and operate at least one such online technological ecosystem aimed at bringing people and businesses together to facilitate transactions (e.g. Amazon Inc. operates such platforms as Amazon.com and Amazon AppStore).

Platforms are typically operated by for-profit corporations that maintain centralized access to a (de facto privatized) marketplace and generate revenues by selling ML predictions derived from exploiting platform participants' data. However, also available is a different kind of platform that does not act as centralized intermediary (e.g. Ethereum, Bitcoin). Even if this alternative platform is operated, for all intents and purposes, by an organization, it is not typically owned by one; to create value, it relies not on ML as its core technology but on blockchain (Chen, Pereira, & Patel, 2020; Hsieh et al.

2018a; Murray, Kuban, Josefy, & Anderson, 2019).

Clearly, 'the internal organization of [. . .] platforms [. . .] and the external organization of [their] sector [. . .] are inter-related and mediated by [. . .] platform technology' (Gawer, 2010, p. 293). Thus, to comprehend platform competition (Rietveld & Schilling, 2021) and its oligopolistic tendencies requires considering how platforms' core technology structures their internal design, shapes their growth and influences industry structure (Rietveld, Ploog, & Nieborg, 2020) as well as the spectrum of possibilities regarding industry regulation.[5]

While at first sight the choice to contrast blockchain with ML may seem expedient – or motivated by the hype surrounding these two technologies – it is in fact highly suitable in our context. Blockchain and ML are two algorithmic technologies that absorb vast amounts of data previously structured by humans, and help automate aspects of organizational task performance. The two technologies are increasingly core to how digital platform operators transform data inputs into finished products, such as matchmaking and other prediction services. Google LLC, for instance, relies at its core on ML computations to transform the data it collects into the 'prediction products' it sells to advertisers (Zuboff, 2019) – the tech has become so core that Google's CEO claims to run an 'AI-first' company (Gaudin, 2017). By contrast, the Bitcoin organization provides a platform for peer-to-peer transaction services only because of the blockchain technology at its core. I now provide brief overviews of two core technologies that digital platforms can rely on.

Overview of blockchain technology

A blockchain is a decentralized and distributed digital ledger that securely stores structured, authenticated transaction data using public keys as identities (Catalini & Gans, 2020; Halaburda, 2018; Werbach, 2018). The first application of blockchain technology was Bitcoin, launched in 2009 by activists amid the government

bailouts of banks (see Vergne, Lomazzo, Hsieh, & Ahmed, 2019 for an introduction to Bitcoin). Bitcoin builds on three decades of advances in computing and cryptography (Narayanan & Clark, 2017), some of which were proposed by cypherpunks (e.g. Adam Back and David Chaum). Outside the cryptocurrency industry, blockchain is used to power decentralized applications in finance (e.g. 'stablecoins' algorithmically pegged to fiat currency), cloud infrastructure (e.g. Blockstack), online gaming (e.g. Tron), digital identity (e.g. Civic) and trade settlement (e.g. Gnosis).

A blockchain is a digital ledger that 'has blocks and has chains' (Szabo, 2017). The chain component provides a sequential history of transactions that cannot be altered without others noticing. Since a consensual decision about which transactions to record next on the chain cannot be made easily by a large boss-less group in the presence of communication delays (a.k.a. Internet latency), transactions awaiting processing are queued until consensus has been reached; the queued transactions are then grouped together and recorded jointly as one 'block'. Thanks to these properties, blockchains enable searching through vast amounts of structured data with little computation and can provide independently verifiable proofs that a transaction took place.

As forcefully argued by leading blockchain expert Andreas Antonopoulos, if it is not 'open, borderless, censorship-resistant, decentralized, publicly verifiable and neutral [. . .], it's not a blockchain' (Antonopoulos, 2020). Indeed, most 'distributed ledgers' are not decentralized and presuppose the existence of a decision-making hierarchy. They are typically used on private networks by authenticated, trusted participants and resemble traditional shared databases. By analogy, experts compare a blockchain's properties to the Internet's properties, and a distributed-but-centralized ledger's properties to a corporate Intranet's properties.

When used as core technology by a De-Di organization, blockchain *decentralizes* communications by giving each organizational member a tamper-proof copy of the organization's history containing everything that is knowable about past transactions, protocols in use and the organization's reward system. It is thus sufficient for a newcomer to communicate with a small number of nodes to verify that their records are identical (to establish trust) before downloading from them the open source software needed to perform organizational tasks.

Blockchains also *distribute* decision-making. Typically, for operational decisions, a different decision-maker is designated each time the ledger is updated based on an automated lottery; organizational members can buy as many lottery tickets as they wish, provided they pay for them and publicly disclose a proof of their spending.[6] Higher-level, more strategic decisions (e.g. core protocol upgrades) are not determined by a lottery system but by some form of voting among members, directly onto the chain (e.g. Tezos) or off-chain (e.g. Bitcoin). Despite this set-up, pressures to concentrate decision-making exist in various forms, and ongoing governance experiments in the industry attempt to prevent factions from claiming dominion over any given blockchain (Bodó & Giannopoulou, 2019).

Overview of machine learning technology

ML, a subset of artificial intelligence (AI), consists of computational methods that help recognize patterns in data and make predictions whose accuracy increases with the quantity (and quality) of data used to 'train' the algorithms. ML emerged amid 1960s research funded by the United States government, large corporations (e.g. IBM, Bell Labs), and universities (e.g. MIT, Stanford). ML applications became widely adopted in the business world following software and hardware innovations from 2009 to 2012 that led to significant improvements in prediction accuracy.

The data used to train ML algorithms are actively collected and curated (Cohen, 2017) and typically annotated by human 'micro-workers' (Tubaro & Casilli, 2019), such as when a ReCAPTCHA window requires a Web user to

identify images showing bicycles before loading a webpage. Data scientists then structure and store the data before 'training' algorithms to recognize patterns in audio files (e.g. this is Paul's voice), text (e.g. this is academic writing) and images (e.g. this is handwriting for postal code N6A1M4); to identify the next best move in a game (e.g. chess, Go); to recommend a movie (e.g. on Netflix); to suggest a product purchase (e.g. via Google Ads); or to detect fraud (e.g. by flagging suspicious payments).[7]

ML tends to *centralize* communications for faster exploitation of large datasets. In 2010, technology executive David McCrory coined the term *data gravity* to explain that 'as data accumulates (builds mass) there is a greater likelihood that additional Services and Applications will be attracted to this data' (McCrory, 2010; for a scholarly version of this idea, see Gregory, Henfridsson, Kaganer, & Kyriakou, 2020). This effect occurs because information technology, in general, performs better with low latency – achievable by pooling data for swift exploitation by digital applications. In the context of ML, whose accuracy improves with dataset size, data gravity implies increasing benefits to centralized application development around an ever-larger data mass. With ML, the 'data flow can be centralized around high-throughput data-processing algorithms [. . .] and need no longer follow information structures [. . .] and specialist roles occupied by humans' (von Krogh, 2018, p. 405). Organizing around ML thus comes with a corresponding 'trend towards [a] corporate *concentration*' of decision-making (Privacy International, 2018). Such concentration takes place across not only business units but also firm boundaries, as I will discuss shortly.

The fabric of centralized ML platforms vs. decentralized blockchain platforms

As ML platform operators combine large datasets across business units in an effort to increase prediction accuracy (e.g. Android data meets Gmail data), the hierarchical level at which decisions are made edges closer to the top of the organization, both to bypass product-specific considerations and because 'enhanced prediction enables decision makers [. . .] to handle more "ifs" and more "thens"' (Agrawal, Gans, & Goldfarb, 2018, p. 104), resulting in more subordinates per manager and flatter hierarchies. Thus, the removal of management layers (i.e. 'delayering') at ML platform operators (e.g. Google LLC) should not be seen as a product of Silicon Valley's anti-authority stance but as reflecting the concentration of decision-making that ensues as ML becomes the firm's core technology. Every minute, half a million status updates and photos are posted on Facebook, yet a decision is occasionally made *at the CEO level* to remove a specific post (Fortune, 2020) or revoke access to a Facebook application programming interface (API) (Robertson, 2018).

By contrast, the peer-to-peer network underlying blockchain creates data *antigravity*. Instead of pooling data, blockchains decentralize data and make it redundant with a replication algorithm. Redundancy throughout the organization can sometimes remove the need for consultation among members. This inherent property of blockchain creates inescapable data bottlenecks due to throughput and latency constraints, an issue commonly referred to in the industry as the 'blockchain scalability' problem (Vukolić, 2015). These bottlenecks curb the growth (and eventual size) of decentralized blockchain platforms. Typical workarounds involve offloading lower-priority transactions onto so-called 'sidechains' that further decentralize the ecosystem (for variants of the same idea, see Bitcoin's Lightning, Ethereum's Raiden, and Polkadot). Thus, as blockchain transaction data accumulate, the likelihood increases that additional services and applications will experience antigravity and need to be shifted away from the main chain. While many see this as a 'bug', I see it as a 'feature' of blockchain technology with desirable societal implications.

Both increases in communication effectiveness (owing to ML predictions) and decreases in consultations among members (owing to

blockchain redundancy) arguably improve organizational coordination (Puranam et al., 2012). However, ML and blockchain pull the organizational fabric of digital platform operators in opposite directions by altering the relative viability and effectiveness of concentrated vs. distributed decision-making and of centralized vs. decentralized communications. As they grow, ML platform operators concentrate communications due to data gravity's pull and face inescapable limits to decentralization, despite claims to the contrary. Meanwhile, blockchain platform operators seeking to maintain extensive decentralization are bound to experience both data antigravity and a scalability problem, as two sides of the same coin. It is unlikely that regulators will ever be in a position to oversee a healthy competitive landscape unless they explicitly recognize these phenomena.

Implications for Antitrust Policy and Regulation

With ML, data gravity exists not only within but also between organizational boundaries due to mergers and acquisitions; as a result, the ML industry has become concentrated in a handful of trillion-dollar corporations that possess the largest, most valuable datasets, which attract the most promising applications, services, engineers and scientists (Ahmed, 2020). As this essay implies, such concentration could theoretically happen without platform operators engaging in illicit anticompetitive behaviour – yet arguably, countervailing regulatory action is warranted anyway.

'Decentralized' yet monopolistic? The platform economy paradox

The 'platform economy', at times presented as a decentralized alternative to the reign of corporate behemoths (Lehdonvirta, Kässi, Hjorth, Barnard, & Graham, 2019), has failed to deliver on its promise (Cohen, 2017). Instead, such platform behemoths as Facebook and WeChat have emerged; and even in the so-called 'sharing economy' an embedded centralization

tendency has led to the domination of platforms such as Uber and Airbnb.

Over the past few years, various observers have commented on the apparent paradox of emerging platform monopolies, wondering aloud how firms such as Facebook Inc. or Uber Technologies, which seemingly 'decentralize' production among millions of users, could possibly become de facto monopolies. The typical reason invoked to explain the platform monopoly paradox is the existence of network effects, which bestow an increasing advantage to the largest network (e.g. new users prefer facebook.com, where most of their real-world connections are already present).

Taking a slightly different perspective, I argue that there is no platform monopoly 'paradox'. Instead, we have misunderstood decentralization and conflated it with distribution. As rightly stated in a 2016 British employment tribunal, 'the notion that Uber in London is a mosaic of 30,000 small businesses linked by a common "platform" is to our minds faintly ridiculous' (cited in Cornelissen & Cholakova, 2019, p. 1). Once the dual nature of organizations as both communication and decision-making systems reveals the distinction between decentralization and distribution, it becomes apparent that firms such as Uber Technologies are not decentralized, but merely distributed. Indeed, these 'platform [operator]s use [. . .] centralized control to define networked spaces' and their 'business model [. . .] revolves around the application of ML techniques to the digital traces of people's activities in real and virtual spaces' (Cohen, 2017, pp. 141, 182); their profits, ultimately, stem from the sale of behavioural predictions obtained from the analysis, by centrally designed and proprietary ML algorithms, of huge datasets accumulated over time on centralized corporate servers (Zuboff, 2019).

This arrangement creates a risk of *digital platform dystopia*, understood as a society wherein platforms systematically and inescapably amass and analyse data to enforce behavioural compliance with the platform operators' *implicit* goals (Tirole, 2020). For instance, a social media platform's explicit goal may be

'to bring the world closer together' whereas its implicit goal may be to maximize advertising revenues by engaging users with viral content that often happens to be divisive. Indeed, empirical evidence suggests that the 'Facebook ad API facilitates [. . .] targeting' of 'vulnerable sub-populations [. . .] susceptible to false stories' with content that can 'stoke grievances and incite social conflict' (Ribeiro et al., 2019, p. 140). A persistent gap between the explicit and implicit (but true) goals of a platform represents a breach of trust, which, at scale, could undermine the social contract of society.[8] The risk of dystopia becomes tangible when platform users find it difficult to defect or switch to a competing platform. Thus, to ward off platform dystopia, we need regulations that make the true goals of platform operators explicit, decrease their bargaining power and increase their replaceability.

Platform monopolies and antitrust: toward a bottom-up (instead of top-down) approach

The traditional approach to antitrust has involved breaking into smaller entities those monopolies with the power to overcharge or force the purchase of low-quality products (e.g. Standard Oil in 1911, Hollywood's 'big five' studios in 1948, and AT&T-Bell in 1982). The underlying assumption is that monopoly results from letting corporations acquire too many of their competitors – a move that can later be undone at the corporate level through antitrust regulatory action (Srinivasan, 2019).

A top-down approach to antitrust (i.e. cutting a monopoly into smaller pieces) is, however, not the best remedy for platform behemoths, whose size may have resulted not from acquisitions but from data gravity and other ML-related factors. Like the planarian flatworm that reforms after being cut into tiny slivers, severing Instagram and WhatsApp from Facebook might result in the subsequent re-formation of three ML platform operators in possession of quasi-universal datasets (Parker, Petropoulos, & Van Alstyne, 2020). A corporate breakup does not regulate away data gravity.

An alternative, bottom-up approach to antitrust would be to regulate not at the corporate level but *at the data level* to counterbalance data gravity in the ML platform industry (e.g. Google LLC, Amazon Inc., Facebook Inc., Apple Inc., IBM, Microsoft Corp., Oracle Corp., Tencent Holdings, Alibaba Group, Baidu Inc., Mail.Ru Group, Yandex NV). This approach could take the form of stronger data privacy protections, such as the generalization and automation of 'the right to be forgotten' (i.e. the verifiable deletion of personal data, as in the 2018 General Data Protection Regulation). It could also mean a ban on systematic data collection from, and sharing with, third parties (practices that enabled the Cambridge Analytica scandal); transparency requirements that ensure platforms' paying customers (e.g. advertisers) can verify the accuracy of the predictions paid for (e.g. ad performance metrics); and data portability regulations that shift control over data to their individual producers (Acemoglu, Makhdoumi, Malekian, & Ozdaglar, 2020). In terms of legal doctrine, data-level regulations could imply the designation of user data not as raw material in the public domain (Cohen, 2017) but as a valuable resource whose centralized processing must be either compensated or fully anonymized (e.g. thereby preventing subsequent retargeting by ads).

To level the playing field among data custodians, imagine the creation of a 'platform utility' category that curbs the sovereign powers wielded by the 'terms of service' that centralized platform operators impose on users, who cannot fairly extend their consent (McDonald & Cranor, 2008, estimate it would take 76 days annually to read all the 'privacy policies' encountered online). Platform utilities would benefit from legal protections (in the US, first amendment and intermediary immunity, safe harbour from copyright infringement) *if and only if* they agreed to not compete with paying customers using data harvested from them (e.g. Google LLC would stop featuring its own products among google.com search results, Spotify would not be allowed to launch a record label). Taken together, these proposed regulations would help make the goals of

dominant platform operators more explicit, decrease their bargaining power and increase their substitutability.[9]

In parallel, regulators could make data collection and processing by *decentralized* platform operators relatively more viable and thus fuel antigravitational forces – for instance, by introducing favourable tax regimes for decentralized platforms whose users have an enforceable right to vote on 'terms of service' updates using digital tokens. Besides, the emerging doctrine around decentralization justifying regulatory exemptions should be buttressed. As a US Securities and Exchange Commission official argued in the context of blockchain, 'if the network on which the token [. . .] function[s] is *sufficiently decentralized*', 'a digital asset transaction may no longer represent a security offering' because the expectation of profit no longer relies on the effort of identifiable promoters (Ahn & Vergne, 2020). In keeping with this essay's argument, regulators should in fact consider extending exemptions to platform operators that are both sufficiently decentralized *and* distributed.

To implement this adjusted regulatory regime, regulators would need a robust definition of decentralization and guidelines for measuring its extent. To this end, a closer look at Figure 3 suggests, among other things, that decentralization comes with a tremendous increase in the number of information integrators (relative to centralization). This observation could pave the way for a renewed technical definition of decentralization, actionable by regulators to enable future measurement.

Digital Platforms and Technology: Predictions for the Future

Governments will intervene massively in the geopolitics of platformization

Mounting pressure to regulate platform behemoths poses a dilemma for governments. On the one hand, by allowing corporate monopolies to dominate new industries at the vanguard of capitalism, governments can reap clear geopolitical benefits (Durand & Vergne, 2012; Wu, 2011), including technological superiority, greater tax base potential and renewed international appeal for skilled labour and capital (Cowen, 2019). On the other hand, by delaying antitrust action against centralized ML platforms, governments risk letting the latter rule the prediction business, which would threaten governments' own political authority and legitimacy (Cohen, 2017; Wu, 2018).

This dilemma creates a stalemate wherein a temporary alliance between governments and their platform monopolies preserves a comfortable 'pax technica' (Howard, 2015) that benefits both parties: platform monopolies continue accruing power that bolsters a geopolitical advantage; meanwhile, the government maintains control by acting as the platform operators' partner, with an option to withdraw and sanction. The most vivid illustration of such an alliance strategy is the continued operation of large-scale public–private partnerships in mass surveillance to advance economic and geopolitical objectives, such as in the US, through National Security Agency programmes involving platform operators such as Google LLC and Facebook Inc., and in China, through Ministry of Public Security programmes involving platform operators such as Huawei and ByteDance, owner of TikTok (Frisch, 2019). In an age where predictive behavioural analytics reign supreme, democracy and autocracy could end up just representing different shades of *datacracy*.

The competition between the platform monopolies in the US and China has made the regulatory status quo especially stable. Given the Chinese government's weak commitment to democracy, its leadership in predictive behavioural analytics holds immediate political appeal. The prospect of China's leadership, however, disincentivizes the US from taking antitrust measures against its homegrown monopolies, which could weaken national security capabilities.

Besides, the potential for ML to increase organizational communication effectiveness by reducing the cost per unit of information

processed revives the possibility, for a centrally planned organization of arbitrarily large size, to optimize resource allocation for all (think Amazon Inc. for everything, including education and health). Ironically, such an end game – not inconsistent with the goals set by today's platform behemoths – resonates with the theoretical models of yesteryear on the possible superiority of central planning. . . in socialist economies (Lange, 1936).[10] Thus, given recent Maoist influence, China's platform operators could enjoy an institutional advantage relative to US competitors, who are bound to face backlash back home if the parallel between socialist and ML planning ever became apparent (for a related discussion, see Werbach, 2020).

Meanwhile, governments that cannot leverage large homegrown ML platforms for geopolitical gain (e.g. in Europe, Central and South America, India) might opt to support decentralized platforms. In countries that, historically, have been friendly to the principle of decentralization (e.g. Switzerland, the Netherlands, Canada, Estonia, Austria, Iceland, Hong Kong, Singapore, Denmark), a concerted effort to groom local ventures in the blockchain space could result in the emergence of platforms with a clear edge. Switzerland, for instance, has set up the Crypto Valley Association, a 'government-supported association established to take full advantage of Switzerland's strengths to build the world's leading blockchain and cryptographic technologies ecosystem' (CryptoValley, 2020). Regulatory competition between jurisdictions will be fierce.

The rise of decentralized platforms: Niche players for sure, serious competitors maybe

Although decentralized-distributed platforms are still largely ignored by platform scholars (e.g. Cusumano, 2020), I wager that the future will be populated with such platforms without central 'owners' (Boudreau, 2010) (e.g. Polkadot, Tezos). For instance, MakerDAO,

whose name refers to being run as a 'decentralized autonomous organization' without managers or shareholders (Hsieh et al., 2018a), operates a platform that provides disintermediated financial services; decisions are made by organizational members who buy into the organization by acquiring 'MKR tokens' that grant them voting rights. The difference between the operator and the platform is reflected in the dual-asset structure that consists of the 'MKR token' (for the operator) and the 'Dai currency' (for the platform user) (MakerDAO, 2019). Experimentations are ongoing to combine a decentralized-distributed design with the legal benefits of incorporation (e.g. The LAO; see www.thelao.io).

However, if decentralized platforms cannot leverage the same powerful increasing returns to data accumulation as centralized ML platforms, how will they be able to compete? Crucial for success is a platform's continued appeal to 'complementors', namely third-party producers that cater to the needs of platform users (e.g. developers that create apps for Android platform users). Complementors might defect and shift to a new platform (decentralized or not) if early adopters are, on average, more willing to try out new products – an effect documented to be at work in the videogames industry (Rietveld & Eggers, 2018). Yet, the appeal of novelty is not a structural, design-level advantage that decentralized platforms can claim over their centralized counterparts.

At a deeper level, the dominance of centralized platforms could be disrupted by their ever-increasing power to change the rules of the game for complementors. Centralized platform operators can do so unilaterally by updating the black-boxed algorithms (Pasquale, 2015) that govern complementor product visibility on the platform (e.g. a new game announcement on Steam) or the value redistributed to complementors (e.g. the royalty payment per stream that Spotify pays to music copyright holders). Here, a *decentralized* new entrant enjoys an advantage. By leveraging decentralized trust – a resource that, by design, the centralized platform cannot possess – a decentralized platform

can shield complementors from unilateral changes in platform rules. As put by VC partner Ali Yahya (2020), it is

> because control over such a network [is] decentralized that it has the potential to scale to millions of developers [. . .]. No platform ever gets to that scale without making an ironclad commitment to uphold its own promises over time. And there is no better way for a platform to make that guarantee than by engraving its own rules into a sovereign program that is owned and governed by the very people who build on top of it.

Decentralized trust curbs the operator's bargaining power and mitigates platform risk, namely, the opportunity for the operator to destroy value for complementors who built on top on the platform.[11]

Blockchain's censorship resistance, broadly speaking, prevents the exclusion of complementors and the unilateral modification of platform rules (e.g. when Apple removes Fortnite from its app store or Facebook blocks access to core features of Vine). Censorship resistance would be a desirable design property for firms regulated as 'common carriers' and it is sufficient to obtain *platform neutrality* (i.e. powerful disincentives neutralizing the additional value a platform operator could capture from committed complementors by unexpectedly altering redistribution rules).

Another neutrality-enhancing feature found to be appealing to complementors (Rietveld et al., 2020) is having an organizational goal different from shareholder value maximization, such as when non-profit foundations (e.g. Linux, Wikimedia) oversee the development of core platform infrastructure. Recently, non-profit competitors succeeded in several niche markets by leveraging the power of open source communities (e.g. Linux-Apache in web server software, Wikipedia in the encyclopedia market). Blockchain technology can take open source communities to the next level by organizing and automating the distribution of their contributors' rewards (Hsieh & Vergne, 2020; Hsieh et al., 2018b) and providing the kind of

neutrality that platform complementors often value.

Decentralized ML prediction platforms: Integrating blockchain toward platform neutrality

As core technologies, ML and blockchain strain the platform operator's organizational fabric in opposite directions; therefore, a best-of-both-worlds scenario where blockchain is combined with ML seems an unreasonable promise perhaps best kept for a start-up pitch at a TechCrunch Disrupt summit. However, already-existing alternatives to the centralized, for-profit, non-neutral ML platform could be retrofitted with blockchain to scale up outside of their initial niche market.

The agricultural sector vividly illustrates how this may take shape and, importantly, what is at stake. With ML becoming core to farming for predicting the weather, fertilizer usage, the timing of seeding and harvesting, commodity prices and insurance premiums, many platforms now compete for automating data collection across farms, ultimately aiming to sell predictive analytics back to them. Some of these platforms are non-neutral, such as those launched by Deere & Company, the leading equipment manufacturer behind the John Deere brand, and Bayer-Monsanto, the agrochemical giant with a quasi-monopoly in several segments. Other platforms operate as neutral entities to enable data sharing for predictive analytics, such as for-profit Silicon Valley start-up Farmers Business Network, Netherlands-based non-profit consortium SmartDairy, and cooperatives such as France-based InVivo that redistributes profits to members (Kenney, Serhan, & Trystram, 2020).

Retrofitting blockchain to such neutral platforms could create a distributed-decentralized agricultural platform with such added benefits as censorship resistance (e.g. any farmer can join), monetization (e.g. farmers being paid in cryptocurrency for providing data), transparency (e.g. every member can access the predictions) and further platform risk mitigation (e.g. rules cannot change unilaterally; the platform

cannot go bankrupt or be acquired by a non-neutral player).

To achieve such an equilibrium between blockchain and ML, an appropriate combination of organizational design choices at the operator level and of regulatory action at the data level appears necessary (for illustrations beyond the agricultural sector, see, for instance, Numer.ai and Fetch.ai).

The flourishing of illegal, 'pirate' competition

The 2009 creation of Bitcoin heralded a new form of competition against the centralized platform model – a competition that echoes, in many ways, the 17th-century rivalry between the monopolistic, publicly traded East India companies and the swarm-like 'pirate organizations' that contested their supremacy on the high seas (Durand & Vergne, 2013). With some regularity, when capitalism expands into new industries using government-sanctioned monopolies (Wu, 2011), pirate organizations surface to contest the latter's domination. For instance, when, in 1927, the BBC became a monopoly on the British airwaves, decentralized pirate radio emerged as an illegal competitor, advocated for the freedom of the airwaves and offered an alternative business model that heavily influenced what the BBC became after its monopoly ended in 1973 (Johns, 2012). Decentralized communities of hackers similarly opposed AT&T's monopoly in the 1970s and, since the 1990s, biohackers running DIY labs across the world have challenged pharmaceutical patent monopolies (Vergne, 2013); more recently, hackers have cooperated across the farming industry to counter the monopolistic tendencies of ML platform leader Deere & Company (Koebler, 2017).

In the face of the ML behemoths, the pirate countermovement will take two distinct forms, as force of resistance and as force of creation. A promising angle of piratical resistance is the hacking of datasets used for training ML algorithms. Hackers can corrupt training data in systematic ways that remain invisible to the micro-workers and scientists in charge of labelling and structuring them.[12] Likewise, a job applicant could heed the advice offered anonymously by that 'HR employee for a major technology company [who] recommends slipping the words "Oxford" or "Cambridge" [or "UCL"] into a CV in invisible white text to pass the automated screening' (cited in Narayanan, 2019, p. 4). A pirate platform could make a profitable, yet illegal, business out of bypassing ML screening on behalf of individual clients, businesses or government organizations.

As a force of creation, the pirate countermovement will continue pushing for the design of supranational common goods in cyberspace, including the promotion of 'self-sovereign identity', intended to 'preserve the right for the selective disclosure of different aspects of one's identity' independently of corporate and government intermediaries (Wang & De Filippi, 2020, p. 9). Self-sovereign identity has potentially crucial implications for organizations' communication systems, starting with the shift to a new generation of data technologies (e.g. read-write APIs; interoperability protocols; decentralized authentication, verification and key management) (Heaven, 2020). The broader political consequences could be significant; as a Venezuela-born blockchain entrepreneur told me, 'it would do wonders to [have] an international personal ID standard that could [. . .] one day be open sourced and not depend on authoritarian regimes.'

If history can be a guide, piratical rivalry is unlikely to derail the rise to dominance of a ML platform oligopoly based solely on competitive forces; to level the playing field, the rules of the game will have to change. On the high seas, the rules of the game began changing – and disadvantaging monopolistic trading corporations – as the 'freedom of the seas' principle, first proposed in 1609 by jurist Hugo Grotius, gained acceptance across the world. The recognition of the freedom of the seas has put a definitive end to the dystopian scenario whereby private monopolistic corporations claimed ownership of portions of the high seas and of (colonized) land – thus acting with the

same sovereign prerogatives as nation-states (Durand & Vergne, 2013). Similarly, today, we need to rethink radically the norms that govern data in cyberspace if we are to prevent ML platform behemoths from acquiring sovereign powers and fabricating a similarly dystopian reality.

Managers on the decline and the necessary renewal of the business school

The twofold tendency for ML platform operators to function with fewer management layers and for blockchain platform operators to function with barely any managers does not bode well for managers, nor for the business schools that train them. Werbach (2020, p. 52), who contrasts the labour-centric industrial age with our current algorithmic learning-centred age of data, elegantly described the decreasing influence of managers: 'The division of labor gave power to the few in positions of management over the masses engaged in the work of production. The division of learning, by contrast, rewards those who control the mass of data.'

Managers still keen on having an intellectually stimulating job will need to up their game on the technology front. Without, at a minimum, an intermediate understanding of technologies such as blockchain and ML, their ability to successfully lead teams of developers and engineers will decrease with time, and their job will risk being increasingly referred to as redundant and as 'bullshit' (Spicer, 2020). At the same time, given both blockchain's and ML's incapability to add meaning or perspective to data, producing genuine information based on judgement will, for years to come, remain the sole prerogative of human workers (as delineated by Figure 2's dotted circle; see Agrawal et al., 2018). Meanwhile, new opportunities will surface for working at distributed-decentralized organizations – though perhaps not in traditional management roles.

The growth of the business school in 20th-century higher education was tied to the growth of the managerial population within centralized firms. However, as organizational decision-making disconnects from managerial positions, business schools must rethink their curriculum or face new competition, both from science and engineering faculties and from private corporations – for better or worse. In just the beginning of a much broader trend, corporations such as Apple Inc., EY and Google LLC have launched their own university-like education programmes.

Concurrently, as management and organizational scholars, we must review and adapt our models of reality (Cornelissen, 2019). Instead of seeing the emergence of new technology as an opportunity to continue milking the theories we read about in graduate school, we should embrace novelty and, when needed, retool accordingly. For instance, theories premised on a manager- or shareholder-centric view are of limited usefulness to understanding distributed-decentralized organizations. Meanwhile, the increasing role of software in the design of organizations calls for incorporating a 'mechanism design' perspective (Chen et al., 2020; Mookherjee, 2006) into organizational science to better grasp, on the one hand, the interaction between governance and incentives, and, on the other hand, how value is created and appropriated (Lumineau, Wang, & Schilke, 2020). This could imply an increasing convergence between such previously siloed areas as strategy, human resource management, marketing and information systems management.

Discussion and Conclusion

Peace and love? The 'technological imperative' and 'sociotechnical systems' perspectives

Perhaps controversially, this essay revives old theory developed in the 1960s on the 'technological imperative', or the idea that technology has a contingent, yet still causal effect on organizations' social structure (Woodward, 1965).[13] By contrast, the now mainstream 'sociotechnical systems' perspective, developed in parallel from a liberal interpretation of Trist and

Bamforth's (1951) landmark study of coal miners, has emphasized the mutually constitutive entanglement of technology's material properties and organizations' social structures. Hundreds of publications have since illustrated such entanglement in case studies which, at times, leave the reader with little more than a variant of the 'everything is intertwined' thesis.

To avoid this pitfall, future studies could focus on not only technology's 'affordances' (what technology enables) but also its 'cannot-affordances' (what technology disables). This perspective could break the circular causality sometimes present in sociotechnical studies (e.g. 'the social enables the technical which enables the social. . .') by complementing it with a more linear perspective (e.g. sometimes the technical just disables the social). For instance, blockchain technology, by design, disables transaction censorship. Without such censorship, an organization cannot prevent a new member from joining, which is why blockchain platforms enable 'plug-and-play' membership, by which new members join, leave and rejoin the organization at will. This arrangement has implications for trust among members, who typically do not know each other and yet work together.

Here, a Woodwardian view compels us to discern trust as *distributed* across decision-makers from trust as *decentralized* across information nodes, whereas a sociotechnical perspective endorses a view of trust as systemically entangled with the blockchain industry's institutions, organizations and algorithms – all simultaneously interacting with one another (Beck, 2018; Ekblaw, Barabas, Harvey-Buschel, & Lippman, 2016; Hayes, 2019; Karlstrøm, 2014; Knittel, Pitts, & Wash, 2019; Morisse & Ingram, 2016). Unlike the Woodwardian view, the latter perspective fails to distill the problem into analytically tractable components on which policy-makers can act. With affordances acting as *sufficient* conditions (that enable phenomena), a complementary analysis of cannot-affordances as *necessary* conditions (without which a phenomenon cannot happen) is warranted if we are to truly account for phenomena

and not simply describe them using scholarly jargon (Abend, 2020; DeSanctis & Poole, 1994).

Coda: Reviving cybernetics to avoid digital platform dystopia

Managerial hierarchies distribute decision-making and remove the need for most organizational members to become involved in any given decision, thereby improving coordination (Puranam et al., 2012) and enabling growth (Chandler, 1962). ML, when used as core technology, improves both communication effectiveness, thanks to its predictive power, and integration, due to data gravity that concentrates decision-making near the top. As a result, fewer management layers are needed; however, fewer layers do not imply more decentralization, but an increased concentration of decision-making. In combination with ML's increasing returns to data accumulation in the form of prediction accuracy, this tendency has enabled the emergence of monopolistic ML platform operators that governments, so far, have failed to regulate adequately.

Instead of arbitrary corporate breakups (e.g. Facebook Inc. or Google LLC?), I propose regulating at the data level – an approach that departs from traditional understandings of monopoly by considering, as its starting point, the (upstream) relationship between data-processing technology and organizational design, rather than the (downstream) relationship between market share and product price or quality. This renewed conception of regulation would level the playing field and, assuming adequate governance (that has yet to be designed), would enable the decentralized and distributed digital platform as a competing alternative to the centralized ML platform model.

As argued by Contractor and Monge (2002, p. 249), 'in the 1990s, [. . .] the dominant organizational metaphor was "organizations as computers." Consistent with that metaphor, knowledge management was conceptualized as creating and maintaining a stand-alone repository for capturing organizational expertise.

The explosion of the Internet [. . .] has made this view obsolete and transformed the metaphor into one of "organizations as networks"' throughout the 2000s.

The rise of blockchain may well precipitate the merging of these two metaphors into one of *organizations as networks of computers*, connected peer-to-peer. Owing to this development, a new golden age of organizational design research looms on the horizon, promising to transcend the initial project of cybernetics as a general theory of governance at the crossroads of the machinic and the social. Because cybernetics is concerned with the study of both communications and decision-making within automated systems involving human–machine cooperation (Wiener, 1948), the cybernetic approach is particularly well suited to advance our understanding of digital organizations, whose diversity rests on stark differences in terms of the extent to which their core technology decentralizes communications and distributes decision-making. The renewal of cybernetic thinking might be our best chance at designing an alternative to the dystopian scenario whereby a handful of centralized platforms govern our everyday lives, having become so powerful that governments can only condone them complicitly but no longer rein them in.

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Notes

1. Baran's network engineering perspective envisions decentralization as the middle ground and distribution as the extreme; however, as the discussion migrated to software engineering (in Khare & Taylor, 2004), distribution became the middle ground and decentralization the extreme. I suspect that Khare and Taylor switched the two terms to be consistent with the seminal work of Fischer, Lynch, and Paterson (1985), thereby illustrating the 'impossibility of distributed consensus' in asynchronous networks. Khare and Taylor (2004) posit that, at one extreme, centralization requires 'simultaneous agreement between a leader and all its followers'; whereas distribution, the middle ground, requires participants to 'apply a *shared* decision function over inputs'; and, at the other extreme, decentralization requires participants to independently assess whom to trust, then apply 'a *private* assessment function over trusted participants' variables'. Bitcoin's blockchain offers a practical workaround for the problem identified by Fischer et al. (1985). Since then, 'in much of the blockchain discourse, "distributed" is used to mean "somewhat non-centralized", while "decentralized" means "no center", i.e. what Baran called "distributed"' (Kevin Werbach, 2020, personal

correspondence). Vitalik Buterin, a leading blockchain expert, noted that an influential industry website shows 'a very similar diagram [to Baran's], but the words "decentralized" and "distributed" switched places'. To bring clarity, Buterin (2017) offers a three-dimensional view wherein: (1) 'architectural decentralization' addresses the number of points of failure (similarly to Baran); (2) 'political decentralization' addresses control (not unlike the distribution of decision-making in this paper); and (3) 'logical decentralization' addresses whether portions of a system can 'continue to fully operate as independent units' after someone has 'cut the system in half'. Buterin's third dimension seems redundant: after being cut in half, a system with decentralized communications (around data, information, knowledge) and distributed decision-making (control dispersed across the organization) could continue operating; that is, logical decentralization results from a combination of architectural and political decentralization (see also Narula, 2019). In organization studies, many scholars – myself included – have used the terms *decentralized* and *distributed* interchangeably (e.g. Hsieh et al., 2018b). Others refer to *distributed organizations* as those whose members are geographically dispersed (e.g. Olivera, Goodman, & Tan, 2008), thereby equating distribution with the absence of geographical colocation. Mintzberg (1979) sees 'horizontal decentralization' as the reliance on domain experts and 'vertical decentralization' as delegation. Puranam (2018) distinguishes between the network of communications and the network of managerial authority, and argues that each can be more or less decentralized (thereby removing the need for the term *distributed*).

2. Trust refers to an assessment that a third party will not behave opportunistically or unpredictably. Ideally, prospective members (e.g. new employees) should join an organization only if they can trust that they will be treated fairly and compensated as agreed upon. At most firms, such trust is enabled not only by an employment contract and labour laws that can be enforced by a well-functioning court of law but also by the presence of other employees who, at least at first sight, present as decent human beings.

3. Despite misleading claims to the contrary, Uber is not part of the sharing economy, whose distinctiveness resides in the shared utilization of idle assets. When a car owner waits to drive customers around, the vehicle is not an idle asset, but prosaically an asset used to provide a service in exchange for money. BlaBlaCar offers a carpooling service in line with the sharing economy's principles.

4. An escrow account is an account where funds are held in trust while parties complete a transaction. Vending machines often hold customers' coins in an escrow area pending product delivery. Until then, customers can press a refund button to retrieve their coins.

5. The term *platform* is confusing when it conflates the platform-as-marketplace (e.g. Android) with the organization that operates and possibly owns it (e.g. Google LLC). Unlike Google-owned Android, the bitcoin platform is operated *without being owned* by a 'meta-organization whose agents are [. . .] legally autonomous and not linked through employment relationships' (Gulati, Puranam, & Tushman, 2012, p. 573). The Bitcoin organization consists of various stakeholders (e.g. developers and miners) who, similar to Linux and Wikipedia, maintain services without for-profit incorporation or shareholders. To mitigate confusion, some use the term *platform sponsors* to refer to those 'responsible for the design and evolution of the platform' and who act as 'IP rights holders' (Parker & Van Alstyne, 2009, p. 18). However, that term is unhelpful in the context of decentralized platforms (i.e. Bitcoin developers are responsible for the *design* of the platform but miners vote on its *evolution*; miners have no IP rights and the 'Bitcoin Core' software is open source). In management scholarship, there is confusion too: Chen et al. (2020) see Bitcoin as a 'decentralized platform', whereas Cennamo, Marchesi and Meyer (2020, p. 15) see Bitcoin as the 'most prominent example' of a 'non-platform-related' currency. Clearly, the former characterization is my preference. Note that this paper's distinction between the platform and its operator may be insufficient to characterize situations in which the platform *designer* is yet a different player, possibly distinct from both the platform *owner* (when one exists) and the platform *operator*.

6. Since blockchain data and software are open source, transparency and auditability are built in, and mitigate both opportunistic behaviour (e.g. there is no information retention) and the propagation of communication errors (e.g. inconsistencies between nodes are flagged).

7. Decisions based on these computations are made (or programmed to be made automatically) by humans, who remain solely able to add *meaning* and *perspective* to ML and blockchain outputs (see dotted circle in Figure 2). Both technologies are limited by the 'garbage in, garbage out' problem: incorrect/biased inputs produce incorrect/biased outputs, without users necessarily being aware of it.

8. The 'scale' at which the breach of trust begins undermining the social contract has yet to be identified. The European Commission has introduced the notion of 'systemic platform' as part of the Digital Services Act to delineate various levels of liability for platform operators. Thanks to Nandita Biswas and Dan Mellamphy for noting, around a 'damn fine cup of coffee', that today's information warfare is premised on the concealment of participants' true goals. In that sense, Howard's (2015) 'pax technica' is not a peace per se but a perpetual state of 'larval warfare' (Biswas, 2020, personal communication with the author).

9. The European Digital Services Act's 'systemic platform' could end up sharing commonalities with the 'platform utility' described here. Regulators aside, we could all contribute to making ML platforms' goals more explicit. For instance, by refraining to use the label 'tech company' to describe platform operators actually running an 'Internet advertising' business. This could prevent having brilliant graduates from leading universities believe that they are going to 'work in tech' when in fact their job may consist in maximizing advertising revenue (for intriguing interviews of such graduates, see the 2020 documentary by Jeff Orlowski entitled *The Social Dilemma*).

10. Central socialist planning relies on a theoretical result known as the 'revelation principle', which states that '*in the absence of communication or information processing costs*, [. . .] centralized control cannot be dominated by any delegation arrangement'. It follows that 'the outcome of any decentralized organization can be mimicked by a centralized one in which the responsibility of each agent is to communicate information to a central authority and await instructions on what to do' (Mookherjee, 2006, p. 369). Notwithstanding the confusion between distribution ('delegation arrangement') and decentralization, Hayek's (1945) counterargument was that the italicized assumptions are so unrealistic that stating the problem in those terms is simply pointless.

11. Ironically, 'it is because the core protocols of the internet (i.e. TCP/IP) are decentralized that it is possible for trillion-dollar companies like Google to be built on top of them' without incurring platform risk (Yahya, 2020).

12. Imagine adding a white pixel at the bottom left corner of all images containing cats. A subsequent image with the white pixel but no cat could be recognized as a cat by an ML algorithm, which could trigger the emergency brakes of a self-driving car whose front camera was just fed a white pixel (via a software hack or by placing something that looks like a white pixel on the roadside).

13. Joan Woodward became, in the late 1950s, the second woman to hold a chair at Imperial College. Her pioneering work challenged the Taylorist view that there is 'one best way' to organize, and identified *production technology* as a causal force shaping organizational hierarchies. Importantly, she offered a countermodel to armchair theorizing by basing her work on a deep practical knowledge of technology and empirical evidence obtained from data collected from fieldwork on the frontline (Sewell & Phillips, 2010).

References

Abend, G. (2020). Making things possible. *Sociological Methods & Research*, https://doi.org/10.1177/0049124120926204.

Acemoglu, D., Makhdoumi, A., Malekian, A., & Ozdaglar, A. (2020). Too much data: Prices and inefficiencies in data markets. NBER Working Paper Series. https://doi.org/10.1017/CBO9781107415324.004.

Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction machines: The simple economics of artificial intelligence*. Cambridge, MA: Harvard Business Review Press.

Ahmed, N. (2020). Technological discontinuities and R&D collaboration strategies: How deep learning changed firm-level collaboration strategies in artificial intelligence. *Working paper*, Ivey Business School. London, ON, Canada.

Ahn, J., & Vergne, J.-P. (2020). *Yuser: Funding startup growth with token issuance?* London, ON, Canada: Ivey Publishing.

Antonopoulos, A. (2020). May the fourth be with you. https://twitter.com/aantonop/status/ 12573 19103527698434.

Baran, P. (1964). On distributed communications. RAND Corp No. RM3420PR, Santa Monica, CA. www.rand.org/pubs/research_memoranda/ RM3420.html

Barlow, J. P. (1996). A declaration of the independence of cyberspace. www.eff.org/cyberspace-independence

Beck, R. (2018). Beyond bitcoin: The rise of blockchain world. *Computer*, *51*(2), 54–58.

Bodó, B., & Giannopoulou, A. (2019). The logics of technology decentralization: The case of distributed ledger technologies. In M. Ragnedda & G. Destefanis (Eds.), *Blockchain and Web 3.0: Social, economic, and technological challenges* (pp. 114–129). New York: Routledge.

Boudreau, K. (2010). Open platform strategies and innovation: Granting access vs. devolving control. *Management Science*, *56*, 1849–1872.

Buterin, V. (2017). The meaning of decentralization. *Medium*. https://medium.com/@Vitalik Buterin/the-meaning-of-decentralization-a0c 92b76a274.

Catalini, C., & Gans, J. (2020). Some simple economics of the blockchain. *Communications of the ACM*, *63*(7), 80–90.

Cennamo, C., Marchesi, C., & Meyer, T. (2020). Two sides of the same coin ? Decentralized versus proprietary blockchains and the performance of digital currencies. *Academy of Management Discoveries*.

Chandler, A. (1962). *Strategy and structure: Chapters in history of the industrial enterprise*. Cambridge, MA: MIT Press.

Chaum, D. (1985). Security without identification: Transaction systems to make big brother obsolete. *Communications of the ACM*, *28*(10), 1030–1044.

Chen, Y., Pereira, I., & Patel, P. (2020). Decentralized governance of digital platforms. *Journal of Management*. https://doi.org/10.1177/01492 06320916755.

Cohen, J. E. (2017). Law for the Platform economy. *U.C. Davis Law Review*, *51*(133), 133–204.

Contractor, N., & Monge, P. (2002). Managing knowledge networks. *Management Communication Quarterly*, *16*, 249–258.

Cornelissen, J. (2019). Imagining futures for Organization Studies: The role of theory and of having productive conversations towards theory change. *Organization Studies*, *40*, 55–58.

Cornelissen, J., & Cholakova, M. (2019). Profits Uber everything? The gig economy and the morality of category work. *Strategic Organization*. https://doi.org/10.1177/1476127019894506.

Cowen, T. (2019). *Big business: A love letter to an American anti-hero*. New York: St Martin Press.

Crypto Valley. (2020). About Us. https://cryptovalley .swiss/about-the-association (accessed 1 July, 2020).

Cusumano, M. (2020). The evolution of research on industry platforms. *Academy of Management Discoveries*. https://doi.org/10.5465/amd.2020 .0091.

De Reuver, M., Sørensen, C., & Basole, R. (2018). The digital platform: A research agenda. *Journal of Information Technology*, *33*, 124–135.

DeSanctis, G., & Poole, M. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. *Organization Science*, *5*, 121–147.

Dunbar, R. (1992). Neocortex size as a constraint on group size in primates. *Journal of Human Evolution*, *22*, 469–493.

Durand, R., & Vergne, J.-P. (2012). No territory, no profit: The pirate organization and capitalism in the making. *M@n@gement*, *15*, 264–272.

Durand, R., & Vergne, J.-P. (2013). *The pirate organization: Lessons from the fringes of capitalism*. Cambridge, MA: Harvard Business Review Press.

Ekblaw, A., Barabas, C., Harvey-Buschel, J., & Lippman, A. (2016). Bitcoin and the myth of decentralization: Socio-technical proposals for restoring network integrity. *Proceedings: IEEE 1st International Workshops on Foundations and Applications of Self-Systems,* FAS-W, 18–23.

Fischer, M., Lynch, N., & Paterson, M. (1985). Impossibility of distributed consensus with one faulty process. *Journal of the ACM*, *32*(2), 374–382.

Fortune. (2020). Facebook's Mark Zuckerberg decides against removing Trump's controversial post. https://fortune.com/2020/05/29/facebook-mark-zuckerberg-trump-looting-shooting-post.

Frick, W. (2014). The secret to Alibaba's culture is Jack Ma's apartment. https://hbr.org/2014/06/ the-secret-to-alibabas-culture-is-jack-mas-apartment.

Frisch, N. (2019). We should worry about how China uses apps like TikTok. *New York Times*. www. nytimes.com/interactive/2019/05/02/opinion/ will-china-export-its-illiberal-innovation.html.

FXEmpire. (2018). How blockchain is connecting humans. www.fxempire.com/education/article/how-blockchain-is-connecting-humans-539721.

Gaudin, S. (2017). Google goes AI first at I/O. TechBeacon. https://techbeacon.com/enterprise-it/google-goes-ai-first-io-what-dev-ops-need-know.

Gawer, A. (2010). The organization of technological platforms. *Research in the Sociology of Organizations*, *29*, 287–296.

Glassdoor (2019). Facebook employee review. www.glassdoor.ca/Reviews/Employee-Review-Facebook-RVW30331207.htm.

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2020). The role of artificial intelligence and data network effects. *Academy of Management Review*, https://doi.org/10.5465/amr.2019.0178.

Gulati, R., Puranam, P., & Tushman, M. (2012). Meta-organizational design: Rethinking design in inter-organizational and community contexts. *Strategic Management Journal*, *33*, 571–586.

Halaburda, H. (2018). Blockchain revolution without the blockchain. *Staff Analytical Note*, Bank of Canada. https://www.bankofcanada.ca/wp-content/uploads/2018/03/san2018-5.pdf.

Hayek, F. (1945). The use of knowledge in society. *American Economic Review*, *35*, 519–530.

Hayes, A. (2019). The socio-technological lives of bitcoin. *Theory, Culture and Society*, *36*(4), 49–72.

Heaven, D. (2020). A plan to redesign the Internet could make apps that no one controls. *MIT Technology Review*, www.technologyreview.com/2020/07/01/1004725/redesign-internet-apps-no-one-controls-data-privacy-innovation-cloud.

Henderson, H. (2012). *Larry Page and Sergei Brin: Information at your fingertips*. New York: Chelsea House.

Hirokawa, R., & Poole, M. (1996). *Communication and group decision making* (2nd ed.). London: SAGE Publications.

Howard, P. (2015). *Pax technica: How the internet of things may set us free or lock us up*. New Haven, CT: Yale University Press.

Hsieh, Y.-Y., & Vergne, J.-P. (2020). Decentralized organizations: How coordination mechanisms shape early growth and decline. *Working paper*.

Hsieh, Y.-Y., Vergne, J.-P., Anderson, P., Lakhani, K., & Reitzig, M. (2018a). Bitcoin and the rise

of decentralized autonomous organizations. *Journal of Organization Design*, *8*(1), 1–16.

Hsieh, Y.-Y., Vergne, J.-P., & Wang, S. (2018b). The internal and external governance of blockchain-based organizations: Evidence from cryptocurrencies. In M. Campbell-Verduyn (Ed.), *Bitcoin and beyond: Blockchains and global governance* (pp. 48–68). New York: RIPE/Routledge Series in Global Political Economy.

Hughes, E. (1993). A cypherpunk's manifesto. www.activism.net/cypherpunk/manifesto.html.

Johns, A. (2012). *Death of a pirate: British radio and the making of the information age*. New York: WW Norton.

Karlstrøm, H. (2014). Do libertarians dream of electric coins? The material embeddedness of bitcoin. *Distinktion*, *15*(1), 23–36.

Kenney, M., Serhan, H., & Trystram, G. (2020). Digitization and platforms in agriculture: Organizations, power asymmetry, and collective action solutions. http://dx.doi.org/10.2139/ssrn.3638547.

Kenney, M., & Zysman, J. (2016). The rise of the platform economy. *Issues in Science and Technology*, *32*, 61–69.

Khare, R., & Taylor, R. (2004). Extending the Representational State Transfer (REST) architectural style for decentralized systems. In *Proceedings of the 26th International Conference on Software Engineering,* IEEE Computer Society, 428–437.

Knittel, M., Pitts, S., & Wash, R. (2019). 'The most trustworthy coin': How ideology builds and maintains trust in bitcoin. *Proceedings of the ACM on Human-Computer Interaction*, *3* (CSCW), Article 36.

Koebler, J. (2017). Why American farmers are hacking their tractor with Ukrainian firmware. *Vice*, March 21.

Kornberger, M., & Mantere, S. (2020). Thought experiments and philosophy in organizational research. *Organization Theory*. https://doi.org/10.1177/2631787720942524.

Lange, O. (1936). On the economic theory of socialism: Part one. *Review of Economic Studies*, *4*, 53–71.

Lehdonvirta, V., Kässi, O., Hjorth, I., Barnard, H., & Graham, M. (2019). The global platform economy: A new offshoring institution enabling emerging-economy microproviders. *Journal of Management*, *45*(2), 567–599.

Lumineau, F., Wang, W., & Schilke, O. (2020). Blockchain governance: A new way of organizing

collaborations? *Organization Science*. https://doi.org/10.1287/orsc.2020.1379.

MakerDAO. (2019). *Maker – Whitepaper. MCD*. https://makerdao.com/en/whitepaper/#abstract

March, J., & Simon, H. (1958). *Organizations*. New York: Wiley.

McCrory, D. (2010). Data gravity: In the clouds. https://datagravitas.com/2010/12/07/data-gravity-in-the-clouds.

McDonald, A., & Cranor, L. (2008). The cost of reading privacy policies. *Journal of Policy for the Information Society*, *4*, 543–568.

Medium. (2019). Purpose at work: How Uber scales a culture of entrepreneurship. https://medium.com/@simonmainwaring/purpose-at-work-how-uber-scales-a-culture-of-entrepreneurship-6ff3dcb5b077.

Mintzberg, H. (1979). *The structuring of organizations*. Upper Saddle River, NJ: Prentice-Hall.

Mookherjee, D. (2006). Decentralization, hierarchies, and incentives: A mechanism design perspective. *Journal of Economic Literature, XLIV*, 367–390.

Morisse, M., & Ingram, C. (2016). A mixed blessing: Resilience in the entrepreneurial socio-technical system of bitcoin. *Journal of Information Systems and Technology Management*, *13*(1), 3–26.

Murray, A., Kuban, S., Josefy, M., & Anderson, J. (2019). Contracting in the smart era: The implications of blockchain and decentralized autonomous organizations for contracting and corporate governance. *Academy of Management Perspectives*. https://doi.org/10.5465/amp.2018.0066.

Narayanan, A. (2019). *How to recognize AI snake oil?* Princeton University. http://www.data-design.org/s/MIT-STS-AI-snakeoil.pdf.

Narayanan, A., & Clark, J. (2017). Bitcoin's academic pedigree. *Communications of the ACM*, *60*(12), 36–45.

Narula, N. (2019). The architecture of crypto innovation. https://a16z.com/2019/08/29/architecture-of-crypto-innovation-crypto-regulatory-summit.

Olivera, F., Goodman, P., & Tan, S. (2008). Contribution behaviors in distributed environments. *MIS Quarterly: Management Information Systems*, *32*(1), 23–42.

Parker, G., Petropoulos, G., & Van Alstyne, M. (2020). Digital platforms and antitrust. Forthcoming in E. Brousseau & JM. Glachant (Eds.),*The Oxford handbook of transnational economic governance*, https://doi.org/10.2139/ssrn.3608397.

Parker, G., & Van Alstyne, M. (2009). Six challenges in platform licensing and open innovation: Open innovation. *Communications & Stratégies*, *74*, 17–36.

Pasquale, F. (2015). *The black box society: The secret algorithms that control information and money*. Boston, MA: Harvard University Press.

Penrose, E. (1959). *The theory of the growth of the firm*. Oxford, UK: Basil Blackwell.

Privacy International. (2018). *Competition and data*. https://privacyinternational.org/explainer/2293/competition-and-data.

Puranam, P. (2018). *The Microstructure of Organizations*. Oxford, UK: Oxford University Press.

Puranam, P., Raveendran, M., & Knudsen, T. (2012). Organization design: The epistemic interdependence perspective. *Academy of Management Review*, *37*(3), 419–440.

Ribeiro, F., Saha, K., Babaei, M., Henrique, L., Messias, J., Benevenuto, F., Goga, O., Gummadi, K., & Redmiles, E. (2019). On microtargeting socially divisive ads. In *Proceedings of the Conference on Fairness, Accountability, and Transparency (ACM)*: 140–149. doi.org/10.1145/3287560.3287580.

Rietveld, J., & Eggers, J. P. (2018). Demand heterogeneity in platform markets: Implications for complementors. *Organization Science*, *29*, 304–322.

Rietveld, J., Ploog, J. N., & Nieborg, D. B. (2020). The coevolution of platform dominance and governance strategies: Effects on complementor performance outcomes. *Academy of Management Discoveries*.

Rietveld, J., & Schilling, M. (2021). Platform competition : A systematic and interdisciplinary review of the literature. *Journal of Management*.

Robertson, A. (2018). Mark Zuckerberg personally approved cutting off Vine's friends-finding feature. *The Verge*, Dec 5, www.theverge.com/2018/12/5/18127202/mark-zuckerberg-facebook-vine-friends-api-block-parliament-documents.

Schenker, J. (2019). The platform economy. *The Innovator*. https://innovator.news/the-platform-economy-3c09439b56.

Sewell, G., & Phillips, N. (2010). Introduction: Joan Woodward and the study of organizations. In N. Phillips, G. Sewell, & D. Griffiths (Eds.), *Technology and organizations: Essays*

in honour of Joan Woodward (*Research in the Sociology of Organizations*, Vol. 29).

Shapira, Z. (Ed.) (1997). *Organizational decision making*. New York: Cambridge University Press.

Simon, H. (1947/1997). *Administrative behavior: A study of decision-making processes in administrative organization*, 4th ed. New York and London: Macmillan.

Spicer, A. (2020). Playing the bullshit game: How empty and misleading communication takes over organizations. *Organization Theory*. https://doi.org/10.1177/2631787720929704.

Sproull, L., & Kiesler, S. (1991). *Connections: New ways of working in the networked organization*. Cambridge, MA: MIT Press.

Srinivasan, D. (2019). The antitrust case against Facebook: A monopolist's journey towards pervasive surveillance in spite of consumers' preference for privacy. *Berkeley Business Law Journal*, *16*(1), 39–101.

Szabo, N. (2017). Money, blockchains, and social scalability. https://unenumerated.blogspot.com/2017/02/money-blockchains-and-social-scalability.html.

Tilson, D., Lyytinen, K., & Sørensen, C. (2010). Digital infrastructures: The missing IS research agenda. *Information Systems Research*, *21*, 748–759.

Tirole, J. (2020). Digital dystopia. *13th Digital Economics Conference*, Toulouse School of Economics. Accessed 1 July 2020, https://www.tse-fr.eu/sites/default/files/TSE/images/conference/Digital_conf_2020/tirole_digital_dystopia_080120.pdf.

TNW. (2018). Could decentralized systems replace Google? thenextweb.com/contributors/2018/01/12/decentralized-systems-replace-google.

Trist, E., & Bamforth, K. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations*, *4*(1), 3–38.

Tubaro, P., & Casilli, A. A. (2019). Micro-work, artificial intelligence and the automotive industry. *Journal of Industrial and Business Economics*, *46*, 333–345.

Turnbull, S. (2017). Grounding a theory of firms in the natural sciences. *Humanistic Management Journal*, *1*(2), 159–186.

Vergne, J.-P. (2013). The pirate and the capitalist: A love story? *Policy*, *42*, 1191–1194. www.cis.org.au/app/uploads/2015/04/images/stories/policy-magazine/2013-spring/29-3-13-jean-philippe-vergne.pdf.

Vergne, J.-P., Lomazzo, C., Hsieh, Y., & Ahmed, N. (2019). Bitcoin crash course. www.ivey.uwo.ca/scotiabank-digital-banking-lab/education/bitcoin-crash-course.

von Krogh, G. (2018). Artificial intelligence in organizations: New opportunities for phenomenon-based theorizing. *Academy of Management Discoveries*, *4*, 404–409.

Vukolić, M. (2015). The quest for scalable blockchain fabric: Proof-of-work vs. BFT replication. *INetSec*, 112–125.

Wang, F., & De Filippi, P. (2020). Self-sovereign identity in a globalized world: Credentials-based identity systems as a driver for economic inclusion. *Frontiers in Blockchain*, *2*(January), 1–22.

Werbach, K. (2018). *The blockchain and the new architecture of trust*. Cambridge, MA: MIT Press.

Werbach, K. (2020). Panopticon reborn: Social credit as regulation for the age of AI. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3589804.

Wiener, N. (1948). *Cybernetics: Control and communication in the animal and the machine*. Cambridge, MA: MIT Press.

Woodward, J. (1965). *Industrial organization*. London: Oxford University Press.

Wu, T. (2011). *The master switch: The rise and fall of information empires*. New York: Vintage Books.

Wu, T. (2018). *The curse of bigness: Antitrust in the new gilded age*. New York: Columbia Global Reports.

Yahya, A. (2020). The long-tail problem in AI, and how autonomous markets can solve it. https://a16z.com/2020/07/24/long-tail-problem-in-a-i.

Zuboff, S. (2019). *The age of surveillance capitalism: The fight for a human future at the new frontier of power*. New York: Profile Books.

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