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Economic properties of data and the monopolistic tendencies of data economy: policies to limit an Orwellian possibility

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ABSTRACT

The potential of data for supporting development is bounded only by the amount and variety of data that can be collected and analyzed, which is to say it is almost infinite. However, if data's vast benefits are disproportionately captured by few in the society, leaving no one behind – an overarching principle of the Sustainable Development Goals – would be difficult to attain, even when everyone benefits from the use of data. This paper discusses key data properties and dynamics in data economy that create the tendencies for monopolies to emerge, reinforcing unbalanced power between corporates and other actors and generating negative distributional implications. If mismanaged, transformation toward the data economy could end up being an unequalizing force in an already highly-unequal world.

In the context of data economy, this paper presents critiques of the common approaches to deal with monopolies. Self-correction in market is unlikely to happen fast enough but breaking up or nationalizing data monopolies are undesirable from effectiveness and innovation perspectives. Strengthening data ownership is key to rebalancing the power asymmetry between corporates and digital subjects, but difficulty of data valuation needs to be overcome. Analyses in this paper support further exploring the idea of setting up an independent, accountable and forward-looking Digital Authority that has both competition and non-competition goals.

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I   Introduction

The rise of data as an important factor of production has tremendous potential in making economic activities more efficient and in facilitating the creation of innovations that could significantly improve people's well-being.[1] Already, collection, use and analysis of all varieties of data on a massive and rapid scale has powered advances in frontier technologies such as artificial intelligence and robotics. It has also made many of our daily tasks—from hailing a ride to correcting grammar, and from comparing prices of commercial products to accessing loans—significantly easier.

Few would dispute the improvement that data-driven productive activities have brought to the society. Looking forward, much development gain is certainly to be made by leveraging data for achieving sustainable development. However, even if one is to believe that every person is better off because of the rise of data economy, there is no guarantee that the aggregate social welfare gains would be distributed in a fair fashion that reasonably represents the actual value that each actor has contributed to the production process. This fairness perspective is particularly important as the world is marred by persistent economic inequality that undermines efforts to achieve sustainable development for all.

Getting a better understanding of how gains would likely be generated and distributed in a data economy requires understanding of some basic features of data that makes it unique as a factor of production. The focus of this paper is to identify data's unique combination of properties and embedded dynamics in the data economy that create the tendency for monopolies to emerge. It would explain how certain features of the data economy could lead to, and reinforce, the asymmetric power between the different actors, specifically between different firms, between firms and consumers (who are also providing data that power the economy), and between firms and the State. In examining these mechanisms, a dynamic perspective that focuses on how the interactions among different actors could evolve given the current market and regulatory settings is necessary. A static assessment of the current data economy might lead one to believe that market competition in the data economy is sufficiently sound and distribution of generated gain is reasonably broad-based. However, if sustained, uneven distribution of gains from data economy—even when every actor is better off—could eventually lead to excessive concentration of power in shaping the data economy. What the society needs to carefully guard against is that the balance of power could become so skewed in the future that some actors might be able to capture most of the gains from the data economy in the long run. For a lack of better alternatives, those who will be on the short end of this bargain might be forced to sustain this arrangement.

This paper is ultimately motivated by concern over the possibility of unfair resource distribution in the emerging data economy. Do firms earn what they earn because they are consistently more productive and social welfare-enhancing; or is it because they sit on first-comer advantage and network effects which allow them to capture more than what they are really contributing? Are individuals who provide personal data that power the data economy getting their fair share of gains that firms generate based on analyzing or even selling these personal data? More specifically, is giving up personal data in exchange of free services fair? And are governments—who have played important roles in not only providing an environment for businesses to thrive, but also in directing technological change—getting a fair return, e.g. in terms of tax payment or other types of revenue, to their inputs? To answer these questions would require understanding the balance of power between these actors.

This paper argues that any policy measure attempting to ensure data economy brings broad-based benefit to the society would need to consider the linkages among innovation, competition and consumer protection.

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[1]   For an overview of development potential of data, please see Letouzé (2012).

The unique nature of data as a production input means that the traditional understanding of linkages among these developments would need to be updated. Managing the data economy with outdated understanding of the key economic dynamics could risk leading the society towards undesirable situations, among which include a scenario where distribution of significant aggregate gains from data economy activities could become extremely uneven or an alternative scenario where distribution is even, but the aggregate gain is puny due to lackluster innovation progress. Neither of these scenarios is optimal and must be avoided if sustainable development is to be attained.

This paper contributes to an expanding literature on the implications of the rise of digital and data economy and, more specifically, the challenges that it poses to market competition and the far-reaching consequences of a highly concentrated digital market. The literature discusses a wide array of challenges that substantial concentration of market power in digital markets could present, including harms to consumer welfare in terms of price, quantity, quality and variety of products, loss of privacy, unfair conditions for business users of digital platforms, and adverse effects on innovation (Crémer et al., 2019; Ezrachi & Stucke, 2015; Furman et al., 2019). The effects of excessive market power concentration also manifest in social and political spheres. As dominant digital platforms become important gateways to the digital world, the literature highlights the extensive influence such platforms have over what kind of information public can access and how people interact with each other. As digital platforms become a more dominant source of news and journalism, it could increase exposure of public to news that are less reliable and of lower quality given the consumers' limited knowledge of the original source of the news accessed through digital platforms (Australian Competition and Consumer Commission, 2019). Moreover, a handful of powerful digital platforms, which are incentivized to prioritize quantity over quality of content given their revenue structure, now replace the many different viewpoints that were previously curated by the many newspaper editors (Zingales & Lancieri, 2019). The significant economic power concentrated in these firms, intersecting with their de facto role as major media outlets, the opacity of their operations, their close and instantaneous connection with a large network of users, have also made them powerful political actors—ones without necessarily sufficient accountability to the public.
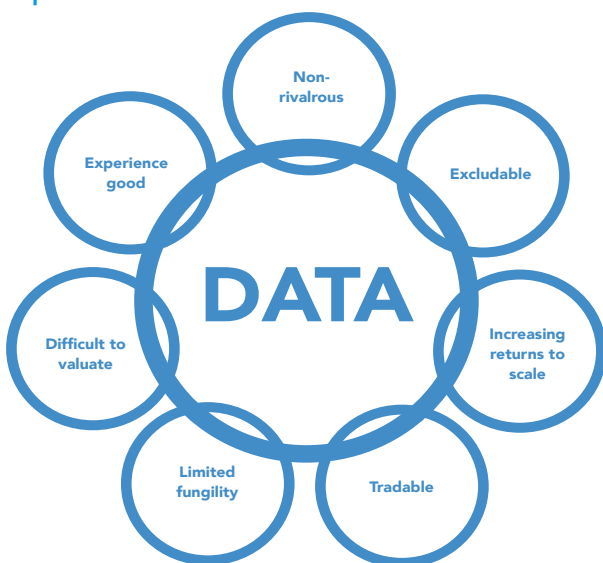
The rest of this paper is structured as followed. Section 2 discusses key properties of data that make it a unique factor of production. Section 3 links these properties to the discussion on asymmetric power between firms, between firms and digital subjects, and between firms and the State. Section 4 discusses the case of Myspace and Facebook, illustrating the difficulty of maintaining market dominance and the possible harm it could cause if such dominance is indeed preserved. Built on understanding of data economy developed in previous sections, Section 5 covers policy discussions on how to deal with data monopolies, emphasizing the roles that algorithms can play in anticompetitive behaviors and the interlinkages between competition, innovation and consumer protection goals. Section 6 concludes the paper.

II A unique combination of properties of data as a factor of production

The emergence of data economy has brought growing attention to data as a factor of production.[2] Data's unique combination of characteristics (see figure I) differentiate itself from labor, capital, land, and ideas/technology—typical inputs for production in the abstracted economy that economists consider. Unlike labour, capital and land, data is non-rivalrous and—in many instances—exhibits increasing returns to scale. In this

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[2] Adapting from the definition in European Commission (2014), data economy (or data-driven economy) is defined in this paper as an ecosystem of different types of players interacting in a digital market, which lead to more commercial opportunities and an increased availability of knowledge and capital, and stimulate—more effectively—relevant research and innovation.

Figure I
Properties of data

Source: Author.

sense, data is similar to ideas or technology as studied in Romer (1990) and the endogenous growth literature that his work kick-started. However, while both idea and data are information, they differ in the sense that an idea is essentially a set of instructions for producing an economic good, whereas data is remaining forms of information that are useful in the production process (Jones & Tonetti, 2018). Also, data is possibly more excludable than ideas given it can be encrypted and its transfer is easier to be monitored. Yet another difference between data and idea is that the former is commodity-like, with some calling it the "new oil". While the similarity between oil and data is debatable for reasons that will be presented later, the analogy certainly reflects the perceived status of data as a tradable commodity. It is true that ideas can be sold as patents, but trading of patents are uncommon (Hagiu & Yoffie, 2013). In practice, patent markets are illiquid and inefficient, dominated by bilateral transactions and have significant difficulties in matching buyers and sellers. In contrast, data broker market is growing rapidly. Globally, it is estimated that data vendor sales would triple during 2017-2022, rising from $3.1 billion to $10.1 billion (Ram & Murgia, 2019).

The unique economic identity of data—a product of combined characteristics—allows those who possess it to gain new markets, increase profits and facilitate new innovations that improve wellbeing of the public through scientific and medical discoveries. But these same characteristics that make data unique also raise important concerns about the distributional consequences of data economy. Building on existing literature, the rest of the section will discuss the key characteristics of data that collectively make data a unique factor of production. The focus of this discussion will be on personal data that can be linked to specific data subjects by referencing an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that person.[3] Non-personal data that cannot be traced to any individual, including data on industrial production processes, present a different, albeit overlapping, set of challenges and analyzing them in entirety would go beyond the scope of this section.

II.1   Non-rivalry and excludability

An apparent property of data is non-rivalry, i.e. data—e.g. purchase history, location data, and medical records, etc.—can be used multiple times or by multiple entities at the same time without depleting it. It is one characteristic that is essentially true for all data, and it means that the additional (or marginal) cost of providing a given set of data to another entity for consumption is essentially zero.

Data is also excludable, meaning that an entity who possesses the data has certain power to prevent others from using it. Such power to exclude exists in a continuum and changes depending on a range of factors, including legal and regulatory requirements (e.g. data privacy law) and state of technology (e.g. encryption).

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3   Definition of personal data adapted from European Union's General Data Protection Regulation, available on https://gdpr.eu/eu-gdpr-personal-data/.

At the same time, the fact that there are many ways to collect information means that while a specific piece of data is excludable, the information that it contains might not be. For example, an individual's consumption preferences could be revealed by data on his or her purchase history, browsing history or location history and each of these data can be collected through different digital platforms and apps. The fact that any one of the above data being made excludable by a firm who collected it does not necessarily stop other firms from understanding an individual's consumption preferences if the other two pieces of data are accessible.

The seminal work of Romer (1990) on endogenous technological change shed some important light on how the dual nature of idea—being both non-rivalrous and partially excludable—is central to explaining how market economies could develop new technologies based on profit-driven research and development. In the context of data, non-rivalry means others beside the original data collectors could also benefit from the use of the data at the same time. However, if data is at least partially excludable, it grants the original data collectors some form of monopoly power to sell collected data to others, allowing them to profit from engaging in data collection in the first place.

High level of data excludability naturally means a more restrained flow of data. The example of the patent system has shown how limitation of information flow could have adverse effects on innovation diffusion, follow-up innovations and subsequently affect competition (Cheng & Parra-Lancourt, Forthcoming). Firms have been taking advantage of the complex patent system to engage in anticompetitive behaviours that eliminate competition, leading to more concentration of market power. By the same logic, excludability of data—itself a type of information—is likely also to have some negative, partial-equilibrium effects on innovation and competition.

II.2   Increasing returns to scale

A prominent, and perhaps most consequential, characteristic of data as a factor of production is that data-driven productive activities are generally seen as having increasing returns to scale. It means that increases in output is greater in proportion than increases in input (e.g. doubling up inputs result in more than doubling of outputs), whereas the standard replication argument would imply constant returns to scale, i.e. increase in output should be in proportion to increase in input. The increasing returns to scale of data-driven productive activities are closely linked to the non-rivalry of data. In theory, increasing returns to scale can occur—as discussed in Romer (1990)—when at least one input to the production is non-rivalrous and this input (e.g. a management idea) makes other inputs more productive. Given the same set of data—or more precisely, the information that it stores—can also be reused infinitely, an increasing-return-to-scale case could be made for productive activities that involves data as an input. Moreover, productive activities in today's data economy are very different from those Romer (1990) had in mind 30 years ago. Much of the value that is created from data depends on the existence of algorithms to organize, analyze, and display the data. As algorithms are similarly non-rivalrous, this could potentially lead to even more pronounced increasing returns to scale in the data economy.

To show how production involves data as an input displays increasing returns to scale, here we illustrate the modified replication argument of Romer (1990) in a more current technological setting (see figure II): imagine a solar panel firm uses 500 staff-hours to develop a sun tracking algorithm that seek to increase the sunlight exposure of a solar photovoltaic panel and 2000 hours to collect data on receipt of solar radiation that is used to train the algorithm. The firm hires 100 workers and uses $1 million to build a factory and procure equipment, which can produce 500 units of 10 megawatts (MW) solar panel every year. At its full efficiency, each solar panel can generate 20 million kilo watt hour (kWh) of energy per year, which means the 500 units produced by the firm can collectively generate 10 billion kWh of energy annually.

Figure II
Increasing returns to scale of production with data as input: the modified replication argument

Scenario I
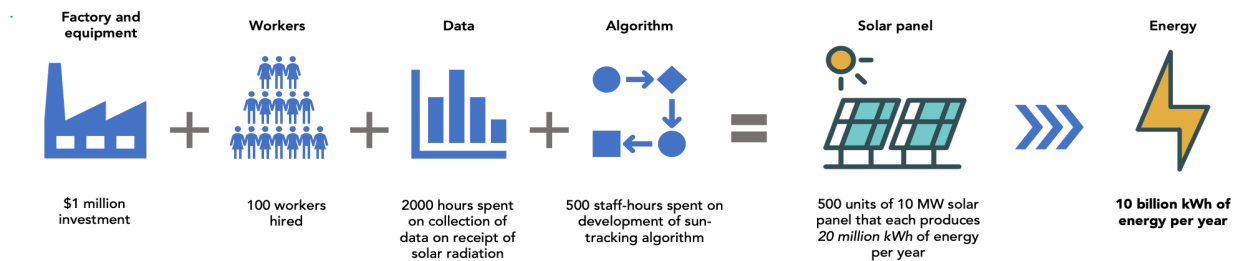
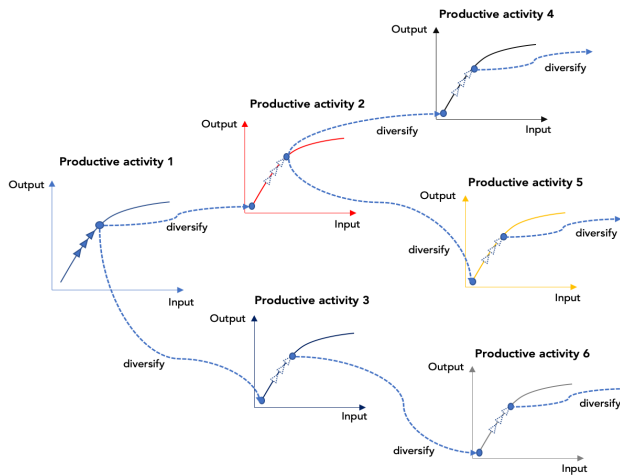*Scenario II: Doubling Inputs*
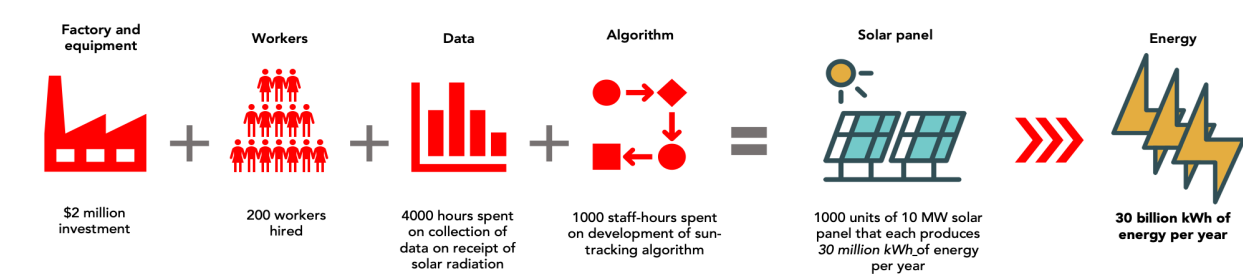
Source: Author.
Design credit: Some icons made by Swifticons from www.flaticon.com

Now, let us say we double the inputs: \$2 million investment in factory and equipment and 200 workers are hired, who can now produce 1000 units of 10 MW solar panel per year. A total of 1000 staff-hours are spent on developing an algorithm that is assumed to be approximately the same. In addition, 4000 hours are spent on collecting data on solar radiation receipt that make the algorithm performs better and allows the solar panel to capture more sun light, enabling each unit of panel to produce 30 million kWh of energy (as opposed to 20 million kWh). Adding this all together, doubling of inputs would lead to production of solar panels that collectively can produce 30 billion kWh of energy per year, i.e. a tripling of energy output, because more data input had made the energy generation process more productive.[4] The disproportionate increase in energy output, relative to increase in productive inputs, is a display of increasing returns to scale.

Readers with a keen eye for detail would note that in this scenario algorithm is assumed to be the same despite the doubling of input of staff-hours. If we would make a more reasonable assumption that the algorithm also become better—independent of the amount of training data—as a result of increase in staff-hour input, the final energy production would increase even more, displaying an even greater extent of increasing returns to scale.

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[4] In this constructed example, the improvement of 50 per cent in energy production of each solar panel after the doubling of time spent on collecting data is an arbitrary choice. One could reasonably expect improvement in energy production resulting from more data input to diminish, but the entire solar panel production process—a data-driven productive activity—would continue to display increasing returns to scale in terms of total energy output as long as more data input still leads to an improvement, regardless how minimal, in energy production.

Figure III
Redirecting resources to overcome decreasing returns to scale for a single productive activity

Source: Author.

Another phenomenon that should also be high-lighted is the "data network effect". Closely linked to the "network effect", i.e. the effect that an additional user has on the value of a product to others, the data network effect manifests as a virtuous cycle as follows: increasing number of users means more data on user behavior and preference that can be used to make the product better, which then attracts more users and encourages more activity of existing users, further generating more data for collection. In other words, data begets data. When a network become sizeable and/or the product becomes far superior to its competitors (partly driven by the data network effect), the need for a firm to exert effort to attract new users and collect new data on user behavior and preference becomes ever less. In this case, unlike other inputs that incur constant or rising marginal cost, collection of data in sectors that display network and data network effects could experience decreasing or even zero marginal cost eventually. This convergence of data collection towards costlessness amplifies the increasing returns to scale of data-driven productive activities.[5]

Another possible source of increasing returns to scale is data-driven firms' ability to rapidly collect and analyses plethora of data, which help them more quickly identify new revenue-generating opportunities for exploitation and minimize the effects of decreasing returns to scale of any single activity.[6] For example, search data collected on search engines provide useful insights on consumer preferences and what new products or services have commercial potential. Broadly speaking, digital platform companies with access to a significant volume of transaction data essentially have their fingers on the pulse of the digital market and are in an advantageous position to detect and exploit nascent commercial opportunities. In this case, it is possible that each commercial activity under a firm is subject to decreasing returns to scale, but a firm as a whole might be less constrained by such dynamics if it could quickly direct its inputs to new activities before experiencing significant decreasing returns to scale in the old activities (see figure III for a graphic illustration).[7]

It is however important to note that not all data-driven activities experience increasing returns to scale. A key technology that has amplified the value generated by data is machine learning (ML), which automates analytical model building. The effectiveness of ML depends critically on the availability of data that help to train algorithms in identifying patterns and making decisions with minimal human intervention. Varian (2018) points out that data as an input to machine learning typically exhibits decreasing returns to scale.

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[5] Dean (2016) formally shows the relationship between returns to scale and cost functions. In the context of a Cobb Douglas production function, there is increasing returns to scale if and only if marginal cost falls as output increases.

[6] Other non-data-driven firms can also diversify, but as they cannot obtain market data at the same large scale and high frequency as their data-driven competitors, they are more likely to identify new commercial opportunities at a slower speed.

[7] A similar argument has been made to explain why large firms diversify their production activities: as production activities are subject to decreasing returns to scale, marginal productivity drops as firms grow and it becomes unprofitable to continue invest resources in ongoing activities. In this case, resources would be better used if allocated to explore new production possibilities. Diversification likely becomes optimal for large firms as it allows them to overcome decreasing returns to scale for a single sector technology (Gomes & Livdan, 2004).

Figure IV

Examples of decreasing returns to scale in machine learning—natural language disambiguation and image categorization

Learning curves for confusion set disambiguation algorithm

Learning curve for image categorization algorithm
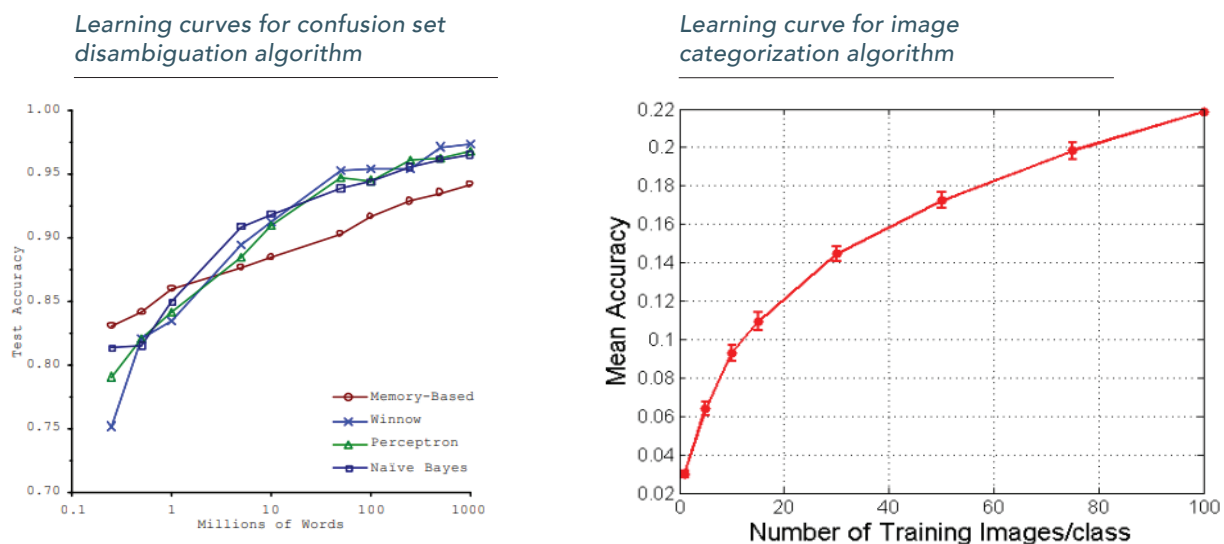
Source: Banko & Brill (2001) and Khosla et al. (2011).

Examples such as Khosla, Jayadevaprakash, Yao, & Li (2011) that uses dog images to train algorithm for image categorization (identifying the breed of a dog) and Banko & Brill (2001) that uses large sets of structured online text to train algorithms for choosing the correct use of a word, given a set of words with which it is commonly confused, do indeed support Varian's point. Their results have shown that accuracy of ML algorithms typically increases with the amount of training data, but at a decreasing rate as more data is used for training (see figure IV).[8]

The assertion that data is infinitely durable and reusable, which underpins the increasing returns to scale of data-driven activities, can also possibly be challenged. While it is true that data itself is infinitely durable and reusable as it can be permanently stored in, and accessed from, some data storage devices, the values of data often depends on context and time frame of interest. Information about human preferences and behaviors loses value over time, sometimes quickly. For example, data on consumers' online purchase activities from 5 years ago would be less useful than that from 5 days ago in gauging market trends. In some cases, value of data could drop significantly even in a matter of hours: data collected by sensors on an oil rig that show the drill will break in hours would become much less useful beyond that time frame.

A more nuanced understanding of where data displays increasing, constant or decreasing returns to scale is important. Firms that rely heavily on data in their daily operations but only operates within a niche area, for example, development of specific types of algorithm such as voice recognition, might not necessarily enjoy

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8   However, in theory, training of ML algorithms needs not necessarily displays decreasing returns to scale. Scott Morton et al. (2019) demonstrated how accuracy of targeted hotel advertising and the derived utility from such improvement can increase disproportionately as more data on different features of the targeted audience, e.g. zip code, income levels, etc., are collected for training the underpinning algorithms. In their example, increasing return to scale holds because of (1) the nonlinear relationship between targeted audience's features and the possibility that a hotel will be booked; and (2) the specific distribution of targeted audience regarding the relevant features.

increasing returns to scale. A good understanding of which stage(s) of data value chain a firm operate is therefore important in assessing how access and use of data affect competition and in determining what kind of data-driven firms competition authorities should focus their monitoring efforts on.

II.3   A tradable, limitedly fungible, experience good

Another property that is relevant for understanding distributional outcomes in data economy is data's tradability, i.e. the extent to which it can be freely exchanged across individuals, firms, or countries in a market. Even as data broker markets are rapidly expanding, many of these markets are still at a nascent stage, including in countries with the most developed data markets. The factors that contribute to the low tradability of data include the limited fungibility of data for different uses, the uncertain value of digital data sets, and difficulties in determining ownership.

Unlike true commodities such as oil, MIT Technology Review Custom & Oracle (2016) pointed out that a given piece of data generally cannot be substituted for another, as each stream of data is composed of a variety of scarce, often unique, pieces of captured information. For example, data on consumer prices cannot be substituted for data on consumer sentiment given they contain different information. In other words, data has limited fungibility.

In addition to being marginally fungible, what also makes trading of data difficult is the fact that data is essentially an experience good, meaning that potential buyers cannot know the true value of data unless they are able to use it or at least being grant access to review it. However, once potential buyers have access to the data, they would have no incentives to pay for them anymore. This paradox—generally referred to as the Arrow Information Paradox (Arrow, 1962)—is sometimes addressed by technical solutions, such as the introduction of partial data disclosure procedures, or legal solutions, such as a grant of intellectual property rights (Duch-Brown et al., 2017). The non-rivalry nature of data further complicates data trading, as data can be easily shared with others or used for other purposes.

Another key obstacle to data trading is the lack of clear determination of data ownership. The European Union's General Data Protection Regulation (GDPR)—arguably the most comprehensive data privacy regulation in the world—deliberately excludes full and transferable private ownership rights for personal data. This decision was taken on the basis that privacy is a basic human right that cannot be alienated (Duch-Brown et al., 2017).

For all these reasons, data trading in monetary form is quite limited, despite the tremendous economic potential of data (The Economist, 2017). Instead, firms often access new data flows through mergers and acquisitions, which allows them to circumvent the problem of relative illiquidity in personal data markets. In other instances, firms that want to expand within a stage of the data value chain or broaden its capacities opt to build their own capacity to generate and use data rather than try to negotiate complex data sharing agreements.

II.4   Difficulty in valuation

The final data property to be discussed is the difficulty to assess data's true value. The United Nations World Economic and Social Survey 2018 highlighted how the inability to value data is a hindrance to addressing privacy, equity, and ethical concerns that arise from the use of data. Proper data valuation helps better allocation of data as a resource. It helps consumers to be more informed of their own personal information's value, allowing them to better determine whether they are getting a fair deal when signing up for "free" digital services (Canellopoulou-Bottis & Bouchagiar, 2018). It provides a basis for determining the consequences for

companies that fail to protect consumers' data. It informs the assessment of the extent of data divide between the haves and the have-nots. It is also an essential step in taxing data-related transactions.

However, determining the value of data at each step in the data value chain is tremendously difficult. First, as discussed above, limited data trading activities in monetary form—especially in the realm of personal data on behavior and preference—means price discovery in the marketplace cannot be effective in revealing data's true value. This limited data trading can be partly attributed to the fact that data is an experience good with limited fungibility, making buyers hesitant of acquiring data as they are not sure how much value they can get out of acquiring data from a third party. Second, non-rivalry of data means that a piece of data can be reused infinitely and by multiple entities, which further adds to the unclarity of how much value can be generated from the data. The fact that data can be utilized for different purposes suggests that no single production function can fully describe the process of transforming factors of production into outputs. It follows that estimation of marginal value, and therefore the price, of data would be imprecise.

Setting aside momentarily the important privacy concern associated with buying and selling personal data, even if data trading does become sufficiently common and reveal some market prices determined by supply and demand, the market prices may not reflect their true social value. This point is exemplified by the dominant form of data-related trading in the current data economy, which is the barter exchange of digital services provided by data-driven firms for personal data of digital subjects. The absence of price in this type of barter exchange highlights the challenge of relying on price as an indicator of the value that the society accords to data. There is little doubt that people place high values on their personal data—as evident in the public outcries and stock market reactions over recent high-profile data breach cases—yet one cannot use price to gauge that value since people are getting "free" digital services in exchange of their personal data. And even in the instances where a price tag is put on personal data, the price is typically very low. For example, reporting of Steel, Locke, Cadman, & Freese (2013) showed that average person's data was typically priced at less than one US dollar in the data broker industry (see figure V for how difference types of personal data are priced). It is unconscionable to think that this reflects how much people value their data; rather, it sheds light on the risk that data valuation dictated by market forces could significantly underestimate the social value of data.

III Power asymmetries in the data economy—market competition, consumer protection, and political economy

The exponential growth of data generated every day and the ability of the governments and firms to rapidly process such data and inform quicker policy and business adjustments has great potential in advancing the cause of sustainable development. However, the rise of the data economy also engenders multiple forms of power asymmetries, among firms, between firms and consumers (who also provide personal data that power the data economy), and between firms and the State. Asymmetries in power certainly are not unique to data economy, but the data's specific combination of properties and the ever-growing range of information that are captured by data have made such asymmetries potentially irrepressible. This section discusses how data properties previously discussed and the current setup of data economy is prone to engendering the asymmetries among different actors in the data economy. As inequality is closely linked to the intersections of different dimensions of power asymmetries, efforts to address inequality must account for such asymmetries.

III.1 Power asymmetry between firms and data subjects

The use of personal data as a key factor of production in data economy means that individuals are at the same time both consumers and important contributors to the operation of the data value chain.[9] This dual-identity complicates individuals' relationship with firms whose activities are largely driven by data on the former's personal information, behaviors and preferences. Tradability of data allows firms to obtain data from consumers through exchange, which can later be used for profitable activities. In some cases, data subjects are being paid in money for providing the data. But as discussed earlier, the transaction between data subjects and firms are predominantly in the form of barter trade, i.e. firms provide digital services in exchange of personal data of data subjects. Determining whether the transactions are fair or not is difficult because of the challenges associated with properly valuating data. However, several developments suggest data subjects are likely to be getting the worse part of the bargain.

First, the non-rivalrous nature of data allows companies to monetize personal data in multiple markets and technologies, such as advertising and artificial intelligence, without providing any additional compensation to the individuals who are the source of the data. For example, companies that specialize in tracking location data from individuals through cell phones can follow the locations of individuals with great accuracy and can connect individuals' online activities with this location data. These companies can sell access to this same set of location data to advertising firms, political research firms, and data analytic firms without compensating users each time the data is shared.

The overuse of data would likely be less of a problem if there is better clarity concerning the control and access rights over data (Carriere-Swallow & Haksar, 2019). Unclear allocation of data ownership—contributing to the opacity of the data market—prevents data subjects from asserting sufficient control over how their data are being used, which in turn allows firms a great deal of latitude in deciding how to make use of the data they collect. Furthermore, as argued by Zuboff (2019), digital platforms are typically designed in ways that data subjects would have vague understanding of how their personal data collected on these platforms would later be used. In many instances, users simply have little idea of what personal data of theirs are being collected and used for commercial purposes (Scott Morton et al., 2019). Such asymmetric access to information concerning personal data usage means even clear assignment of data ownership might not be adequate in ensuring that data is only used for the original purpose as consented by data subjects, especially given the practical impossibility for data subjects to monitor the usage of their personal data.

Second, data subjects are likely paying for the digital services not only with their personal data, but also in the form of higher product prices charged by firms that are paying substantial amount of advertising money to digital platforms.

In sum, the fact that data is tradable but difficult to be properly valuated has created a risk that data subjects are giving up their data for too little, as implicit market values of data are likely grossly below the actual values of data. Difficulty with data valuation also means that data subjects could be compensated too little, or not at all, when there is a data breach at firms that collect and store their personal data. Should there be an established value of personal data that could be used as a reference in determining losses suffered by data breach victims, it would have been more difficult for firms that fail to protect user data to justify the little or zero compensation that were paid out to consumers whose personal records were exposed in recent years' numerous data breaches.

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[9] Given consumers often have dual-identity in the data economy, the term "data subjects"—which refers to persons whose personal data are being collected, held or processed—would sometimes be used instead of consumers in the following discussion.

Beside the inherent properties of data, possession of large quantity of data also tilt the balance of power towards the firms, by granting them significant insights into data subjects' behaviours and preferences. With access to detailed personal data of customers, companies are increasingly capable of charging each customer different prices. While personalized pricing has the potential to broaden customers' access to products or services by charging those with lower reference prices for a product at lower price levels than in the case of single pricing, a profit-maximizing firm could also, and likely to, charge all customers as close to their individual reference price as possible, hence extracting the most economic surplus possible.

Furthermore, the collection and use of personal data, designed to influence behavior, carries with it an ever-present potential for abuse. Retailers and advertisers use this information to target individuals based on their routines and how these routines may change, such as if the person starts to go to a clinic. Political interests can access personal data to engage in highly targeted campaigns that appeal to the narrow interests of specific groups rather than societal interests. These efforts can be as effective as they are devastating.

Another aspect of the asymmetric power between firms and consumers is the latter's lack of time and expertise to understand the consequences of personal data confidentiality policies that have complex and—sometimes remote—consequences (Tirole, 2017). The prevalence of one-sided clauses that attribute disproportionate rights to the firms put consumers in a disadvantageous position, especially given consumers cannot be expected to dissect complex legal documents every time they give up their personal data in exchange for a digital service.

In the end, the asymmetric power between firms and consumers is closely linked to the asymmetric market power among firms. In a competitive market with numerous viable options, customers who are dissatisfied

Figure V
Value of personal data, as priced by data broker industry
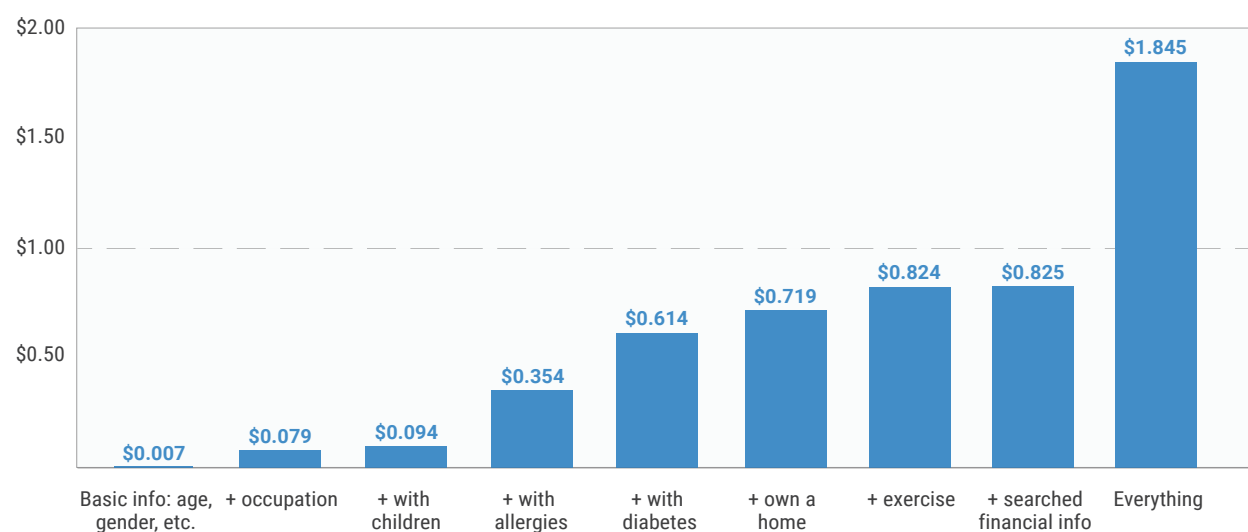
Note: The last bar "Everything" includes information on demographics (age, gender, zip code, ethnicity, education level, being a millionaire or not, occupation, married/engaged or not), family and health (have children or not, expecting a baby or not, being a new parent or not, and certain health conditions), property (home ownership, recently moved (or expecting to move) or not, and have a fireplace in home or not), activities (hobbies, aircraft ownership, boat ownership, and exercise to lose weight or not), and consumption (searched online or visited websites of certain topics or not, ownership of store loyalty cards at a grocery store or pharmacy, and expecting to buy certain products or not).

Figure VI
Declining competition—higher markup in ICT intensive sectors globally
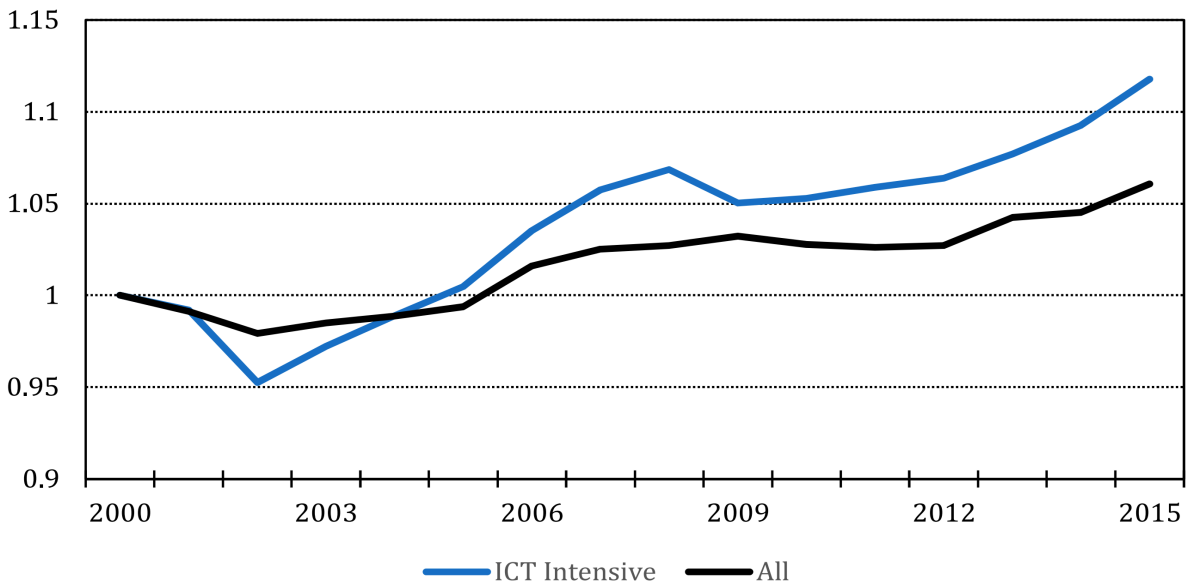
Source: Diez, Fan, & Villegas-Sánchez (2019).

Note: Firm-level data from 20 countries, weighted by firm revenue.

with a firm's abuses of its access to their personal data or with its insufficient data privacy protection could switch to other firms. On the contrary, lack of competition and lack of options would mean consumers are more likely to be held captive in this asymmetric relationship. In the context of data economy, if market power is concentrated in a handful of platform companies, consumers who wish to avail themselves of the type of services that these platforms provide would have little choice but to continue their transactions with these companies. This subsequently provides the dominant firms with ever more personal data that further entrenches their market power. The power asymmetry between firms and that between firms and consumers therefore reinforce each other.

III.2   Power asymmetry between firms

Concerns about power asymmetries among firms in the data economy have emerged amid the rising level of market concentration in industries that are driven by data (see figure VI). The fear is that such a rise in market concentration reflects a lack of market competition, which have negative implications for innovation and productivity growth. Recent work such as Autor, Dorn, Katz, Patterson, & Van Reenen (2017) has shown that, at least in the US, rise in market concentration is correlated with higher per-capita innovation and faster productivity growth, suggesting that the rising market share of a small number of leading firms were largely a result of them producing superior products and services. However, it does not rule out the possibility that these dominant market positions—initially attained due to their higher productivity—could allow firms to maintain or even expand their market shares without necessarily being consistently better at serving their customers' needs. The true concern is over whether the market dominance is permanent or transient.

Concerns about abuse of market power is not limited to the data economy, and certainly not new, tracing its origin back to at least ancient Roman time (Hawk, 2003). However, a case can be made that the unique nature of the data economy has made it even more difficult for smaller firms to effectively contest their dominant competitors. Notably, the increasing returns to scale feature of data economy gives substantial advantages to

first-movers and larger firms that can quickly amass, and act on, the rapid inflow of information. Whereas in a market of decreasing returns to scale potential entrants could see openings for entry since marginal cost of an incumbent's productive activity is expected to increase with output and eventually exceed the marginal value, such opportunities are much slimmer in the case of increasing return to scale, which is associated with decreasing marginal cost.[10]

While firms should be rewarded to some extent for their ability to obtain data and extract useful information out of it earlier and more efficiently than others, the increasing returns to scale feature does makes it difficult for newer and smaller firms to compete in the long run. It creates the possibility that larger and more powerful participants in the data value chain could potentially maintain their market position by the mere virtue of having entered the market earlier or being larger than others, not because they are better. This development is changing the nature of competition in high-technology and traditional sectors alike.

The cost structure of firms in data economy also contributes to the tendency for high market concentration to emerge. Data firms typically incur large, upfront fixed cost associated with development of technologies for collecting, storing and analyzing data. In contrast, once the operation starts, the marginal cost of maintaining or expanding the operation are relatively insignificant. The large initial sunk cost—irrecoverable even in the case of bankruptcy—creates a barrier to market entry, as prospective firms might find it uneconomical to enter a market. Compared to the typically more static traditional sectors, the fast-changing trends in the data economy add additional uncertainty to the commercial prospects of any initiative, which makes significant upfront investment even riskier and more potent as a barrier to entry. Another entry to market barrier is the massive trove of data that incumbents have collected. As data can be made excludable, prospective firms would have to collect data themselves in order to compete, which can be considered too costly, time-consuming and difficult, especially given data subjects are often "locked into" certain providers of digital services, such as e-mail and social media.

Possession of massive amount of data and the equally important ability to process them has also put leading firms of the data economy in a position to be able to more aggressively prevent rivals from competing effectively once they enter the market. First, the possession of massive trove of detailed personal data and the existence of network effects have made it difficult for customers to switch to other firms.[11] This puts latecomers in a disadvantageous position to fairly compete. Second, and this is a case more specific to firms that own major digital platforms, these platform firms—with control of algorithms that determine customer exposure to different apps on their respective platforms—could unfairly favor its own apps over rival apps. Moreover, with real-time access to data of transactions over their platforms, they could also quickly identify newer and smaller firms with significant commercial potentials and buy them up before they emerge as efficient rivals.

Besides hampering innovation and productivity growth, reduced competition could also have implications for consumer welfare and labor market outcomes. Fewer firms mean fewer products or services options for consumers, which limit the bargaining power of the latter for better features, including lower prices or better privacy protection. Similarly, there is also a possibility, albeit a seemingly distant one at the moment, that fewer employment options in a data economy sector will limit the bargaining power of workers with sector-specific skills in negotiating wages.[12] Should this possibility materialize, a monopoly could also begin to exercise monopsony power.

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[10] See footnote 5 for explanation.

[11] As previously discussed, network effect exists when the value of a product or service is influenced by the extent to which it is also adopted by others (e.g. one directly benefits more from a social media platform if more friends are also using the platform).

[12] It must be noted that tech sector, typically data-intensive, is among the sectors with highest pay in the US (Serkez & Francis,

III.3   Power asymmetry between firms and governments

From a political economy perspective, higher concentration of market power increases the likelihood of "regulatory capture"—a situation where policymakers or enforcement agencies are in a constant state of being influenced by powerful firms, rather than by an argument's merits (Hempling, 2014).[13] The recent ramp-up of major technology companies' spending on lobbying has raised concerns that these firms might seek to gain unfair advantages over smaller competitors or potential entrants through political means. In 2018, the largest US technology companies spent a record-high amount of money on lobbying (Stacey, 2019). The top 5 spenders—Google, Amazon, Facebook, Apple and Microsoft—collectively spent $64 million on lobbying—10 per cent more than what they spent in 2017. Google alone spent $21.2 million.

Beside holding concentrated market power that is typically translated into significant political clout, major technology firms have tight control of the relevant data that shelter them from intense public scrutiny to some extent (McCarty et al., 2019). The complex and opaque algorithms that they employ also make it much difficult to be properly regulated. Furthermore, social media firms—with access to extensive personal datasets—are transforming the interaction between governments and their constituents as well as playing an intermediary role in public debates and acting as "quasi media" that could shape political outcomes. All these serve as another avenue for powerful tech companies to exert their influence over governments.

This asymmetric balance of power between corporate and the State could further exacerbate the imbalance of power among firms, as larger firms could use their political influence to tilt the competition landscape further towards them. It is also likely that the efforts to strengthen such regulatory capture is going to be more intense as the data economy expands and become more integrated in the broader economy, meaning the stakes are becoming greater and dominant firms in data economy could capture more wealth through gaining and exercising more political power.

One must note that the balance of power between the State and corporates depends on the political-economy structure of each country. An opposite case to regulatory capture is one in which the State have significance influence over private firms. In this scenario, possession of sizeable amount of data by private firms could become susceptible to government overreach, as governments could seek to gain access to the massive personal data trove through policy and regulatory means or even by circumventing these firms' privacy protections.

The unfavorable prospects of either a few dominant firms or the government having access to the massive personal data trove are underpinned by the eminent downside risk of allowing any single or a few entities to gain control of a lot of data that can be translated into undue influence over the society.

IV   Permanence of monopolies—the case of Myspace and Facebook

While the previous sections contend that there is a monopolistic tendency in data economy, the permanence of monopolies—once they emerge—is however uncertain. The history of competition landscape is laden with examples of companies that at different periods in time displayed such dominance that it was almost unthinkable that their leading status could be challenged. Time and time again, superior value propositions entered the market and toppled the reign of the leading product (Bourne, 2019). Episodes of market dominance in tech industry exhibited by firms or products such as Kodak, Nokia, and Microsoft's Internet Explorer should make one skeptical of fear about persistent market power.

2019). In particular, Facebook employees earned a median pay package of more than $240,000 in 2017, second highest among 325 companies in the S&P 500 index that disclosed their salary data (Seetharaman, 2018).

13 The issue of regulatory capture has been explored since 1960s, starting from Olson (1965) and Stigler (1971).

Specifically, in data-driven industries, discussions concerning durability of market dominance cannot be complete without addressing the case of Myspace, which has often been used to illustrate the vulnerability of seemingly invincible giants in these industries. Indeed, it was not a very long time ago that Myspace's dominance was unquestionable. Founded in 2003, Myspace became the most visited website in the US within three years' time, overtaking Google Search in 2006. In the same year, it signed a landmark $900 million advertising deal with Google. The meteoric rise of Myspace was however disrupted by Facebook very shortly after, when the latter overtook the former as the most visited social network website in 2007. Srinivasan (2019) documented that Facebook successfully differentiated itself from Myspace by initially focusing on privacy, at a time when public concern over social media began to grow.[14] Others have suggested the firm's controlled growth approach of gradually building a robust and reliable technology infrastructure, relentless efforts to copy best features of actual and potential competitors, cleaner interface, and shrewd public relations, among others, have allowed the firm to reach dominance that supersedes that of Myspace (Kellenher, 2010; Press, 2018). While there is no clear consensus on specifically why Facebook has flourished, most seem to agree that Facebook has dominated because it has so far provided a better product and that access to large amount of personal data is likely not the only factor that contributes to lasting market power.

If the rise of Facebook—by dethroning the once-leading social network Myspace—demonstrates the difficulty to establish enduring market dominance, what has transpired since illustrates the harm a dominant firm could cause to competition and consumers. After competitive threats from other social network firms largely languished, it was documented that Facebook started in around 2014 the gradual procession of degrading privacy to levels that would not have been sustainable in the earlier competitive market when firms must strive to meet privacy-related demands from users. The Cambridge Analytica-Facebook data breach provides a clear illustration of the social network firm's insufficient regard for data privacy. Also, the firm has been actively acquiring smaller-size companies—most of them in the tech industry, tallying up to over 70 companies during the 14-year span from August 2005 to June 2019 (A V, 2019). Notably, Facebook made the high-profile acquisition of Instagram and WhatsApp—two global social media platforms with tens of millions of users. The acquisition of the latter eventually led the European Commission (EC) to fine Facebook 110 million euros in 2017, as it was determined that the firm misled the EC to believe it was unable to establish "reliable automated matching between Facebook users' accounts and WhatsApp users' accounts."[15]

The possibility to link user data from Facebook and WhatsApp highlights a critical source of dominance for data monopolies, which is the ability to have a comprehensive view of data subject's digital footprints that reveal their preferences. Nowadays, with its extraordinary code presence on third-party applications, Facebook—unlike Myspace even at its peak—is so entrenched in people's digital life that it can track and store data about name, gender, date of birth, email or mobile number, every ad that users click on, every friend in the network, and users' behavior and preference on third-party apps that could be logged in through a Facebook account, among others.[16] [17] Data monopolies—such as Facebook and Google—become de-facto monopolies of information. The vast knowledge they possess give them immense power to influence people's behavior—from consumption to political participation. The announcement of Facebook to launch its own

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14 Initially, Facebook was only available to those with e-mail address of certain universities and the default privacy setting was that only one's university classmates or friends could see one's profile. The social network firm also quickly hired a chief privacy officer and provided users with a concise privacy policy that emphasized the firm's commitment to put privacy at the center of the user experience. For a detail account of Facebook's evolving privacy policy, see Srinivasan (2019).

15 The decision of the European Commission can be found here: https://europa.eu/rapid/press-release_IP-17-1369_en.htm.

16 Excluding mobile apps, Facebook plugins that allow online tracking are installed in about 30 per cent of the top 1 million of the most-visited websites as of January 2016 (Englehardt & Narayanan, 2016).

17 For a detailed discussion on what data Facebook collects, please refer to Korosec (2018).

global digital currency Libra only intensifies the concern that the company is steadfastly expanding its influence—rivalled only be few—to an increasing number of spheres of people's daily life. It is not hard to see why those who are concerned often invoke the fictional character "Big Brother" in George Orwell's 1984—an entity that has eyes everywhere and maintains constant surveillance of the public at all time, thanks to the ubiquitous "telescreen", a big-screen device that acts as both information conveyor and surveillance device at the same time.

V   Policy discussions

One key point the discussion on power asymmetries brings out is how market power concentration is central in reinforcing other asymmetric balances of power (see figure VII). Insufficient viable alternatives in digital markets put data subjects in a disadvantageous position in advocating and bargaining for their consumer rights vis-à-vis corporates. Rising political influence of firms—results from their dominance of the data economy that is only going to expand further and entrench the whole economy even more—has made it more difficult for governments to regulate corporates effectively. Seeing it as perhaps the most effective first step in creating a more equitable data economy and limiting the possibility of an Orwellian society under far-reaching influence of monopolies of information, this section will focus its discussion on how to improve market competition in data economy.

V.1   How to deal with data monopolies

Broadly speaking, the literature discusses five types of proposals for dealing with data monopolies—defined as firms that have access to significant amount of data and exercise monopoly power in the data-driven economy.

First, break up data monopolies once they reach certain thresholds of market power concentration. Second, instead of breaking them up, nationalize data monopolies. Third, strengthen regulation to ensure that data monopolies do not act against the interest of the public. This could include public utility-style regulation that regulate firms' price-setting or outputs. Fourth, ensure a fair competition landscape—which minimizes the chances of monopolies emerging—by strengthening antitrust regulations and their enforcement. Fifth, strengthen data subjects' control of their own data, rebalancing the ownership of data in favor of data subjects. The variety of proposals to strengthen data ownership include elements such as giving data subjects the ability to have an overview of what personal data is being collected—in the form of a dashboard—and to opt it or opt out of data collection.[18]

Each of these approaches have their pros and cons, and are not necessarily mutually exclusive of each other. This section will not weigh on each of these approaches in detail, but will discuss how understanding of data properties could shed lights on the feasibility and effectiveness of some of these approaches.

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[18] A more sophisticated version of this personal data dashboard is a "personal data store" that advises individuals on how to set up personal data privacy policy, which governs how personal data is being distributed or stored on different servers (Tranberg, 2019). Privacy arrangement can be set such that firms have to obtain consent for accessing data in real time and provides expiration dates for access to personal data. Data subjects can activate personal data only when they want to use a new service. Actualizing this level of data ownership would likely require some significant changes to the technologies and organizational structures used for managing data. For example, cryptography technology could be utilized to enable data subjects to sell anonymized data on blockchain data marketplaces (Jackson, 2018); or data union that control the aggregate flow of personal data to firms, which gives data subjects the ability to collectively bargain with firms regarding payments for their inputs to productive activities (Arrieta-Ibarra et al., 2018).

Figure VII
How unbalances of power among actors in data economy can reinforce each other
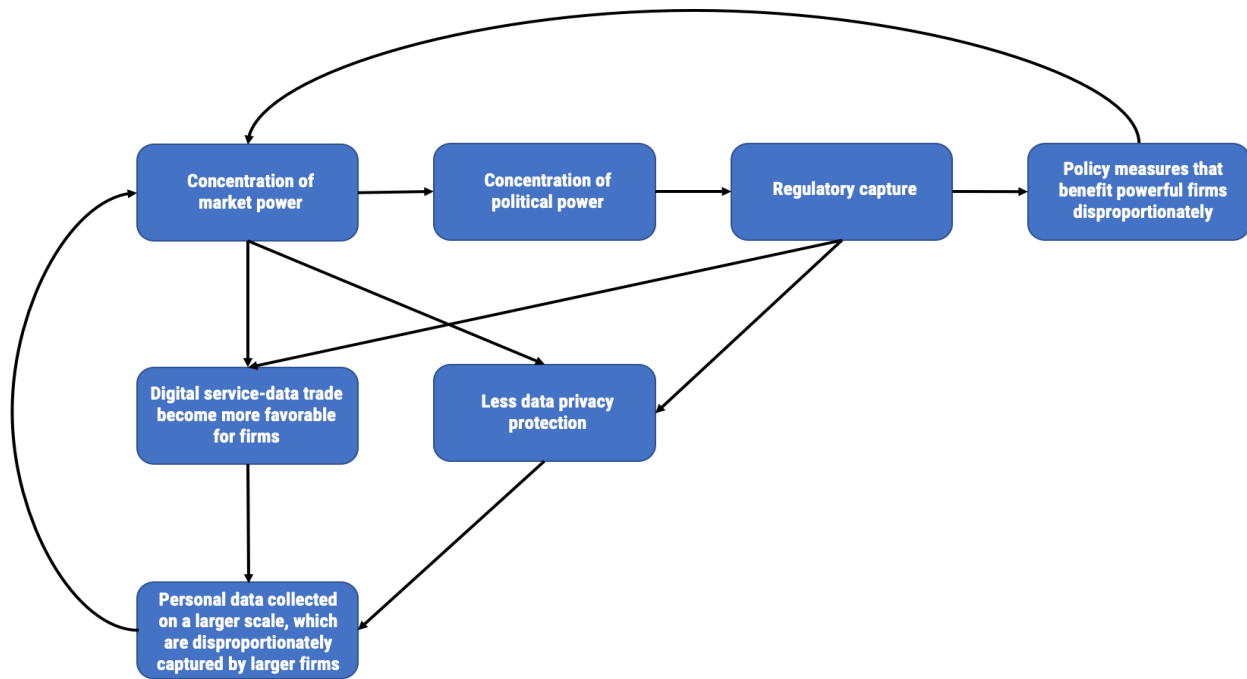
Source: Author.

First, the increasing returns to scale feature of data-driven activities means breaking up data monopolies would likely be less effective at preventing the rise of market power concentration than in the past. Previous monopolies such as Standard Oil and different iterations of AT&T gained their dominance through a variety of means, such as denying competitors from assessing "essential facilities" that they possessed or aggressively buying out smaller competitors during trough of the business cycles—but an essential, common factor was their ability to invent or utilize pioneering technologies of the time that give them competitive advantages over their competitors. Once such technologies become accessible to competitors, breaking up monopolies could have a longer-term effect on ensuring reasonable levels of competition in the specific industries. In contrast, increasing returns to scale allow firms to gain monopoly-like status quickly and without necessarily having better technologies. Comparing to a world of decreasing returns to scale, breaking up existing data monopolies—without other supporting measures—is likely only means paving ways for new data monopolies to emerge later in a data economy.

Second, a certain level of excludability is important for incentivizing firms to collect data, but high excludability of data allows firms with a massive trove of data to gain advantage over the latecomers that prevent fair competition. In ensuring data would not be used as effective barriers to market entry or means to increase consumers' switching costs, governments should consider—as has already been done in the EU—introducing a right to data portability, which gives a data subject the right to receive his or her personal data initially collected by a controller and transfer those data to another controller without hindrance from the former.[19]

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[19] An earlier example of data portability is mobile number portability (MNP), which allows consumers to keep their phone number when they change wireless service provider. Analyzing 15 EU countries, Cho, Ferreira, & Telang (2016) have shown that the introduction of MNP in early 2000s have led to decrease in market price of wireless service by at least 4.15 per cent and increase in consumer welfare by at least 2.15 euros per person per quarter on average during their period of analysis.

Implemented in 2018, the EU General Data Protection Regulation includes the right to data portability, with the expectation that it would improve interoperability of platforms and foster competition of digital services. An even more proactive approach, and specific to social network firms, is to have the dominant firms share with their competitors the so-called social graphs, i.e. data on users' network connections with their social contacts (Zingales & Rolnik, 2017). Mayer-Schönberger & Ramge (2018) proposed a "progressive data sharing" mechanism, in which the amount of data sharing by a firm is linked to its market share. A firm is required to start sharing a randomly-chosen portion of its data with any competitor that requests it once its market share reaches a certain threshold. As a firm becomes more dominant, this random portion of data required to be shared would become larger, which helps to create a more level playing field.

Third, the fact that data is a non-rivalrous, experience good with limited fungibility—making it difficult to be valuated—poses a fundamental challenge to any proposal that seeks to give digital subjects sufficient control of their data and allow them to be adequately compensated while giving up their data. Non-rivalry of data means firms that collect personal data could be sharing or even selling it to as many buyers as possible without the consent of data subjects. Current lack of consensus on how to valuate data means that data subjects would not be able to determine if they are properly compensated for their own data when they are paid in monetary payment or in exchange of services. Meanwhile, data that captures people's behaviors and preferences continue to be generated and collected every day. In one single day, 4 petabytes of data are created in Facebook alone, which include 350 million photos and 100 million hours of video watch time; 5 billion of searches are made on search engines; and 500 million tweets are sent.[20] In effect, data subjects are on a daily basis trading away tremendous amount of personal data for services that the data firms provide, with the possibility that they are getting the short end of the stick in the exchange. High priority must therefore be put on creating mechanisms that can properly determine actual values of data as well as micropayment systems that can process the transactions between digital subjects and firms. For certain data-driven activities such as development of ML algorithms, estimating marginal effect of new data on predictions could be a potential approach for pricing data (Arrieta-Ibarra et al., 2018). However, valuating data used for other economic activities that have less clear production function and performance measurement would be more challenging.

V.2   Do not forget the algorithms

Dominance of big tech firms depends not only on possession of a significant amount of data alone, but also on their ability to possess and turn them into structured data that can be used to inform business decision-making.[21] Firms should be properly rewarded for the values these algorithms create for the society, but there are concerns that the prowess of algorithms have also enabled firms to engage in anticompetitive behaviours, including facilitation of collusion (through, for example, enabling real-time monitoring of all firms' behaviors in the market and stabilization of price competition) or—in the case of platform firms that host a digital ecosystem where other firms operate in—detection and elimination of nascent competitive threats.

In view of how the combination of powerful algorithms and large amount of data can be used to erode the competition landscape, regulatory interventions seeking to improve competition should aim to make algorithms more transparent and accountable for their effects (Organization for Economic Cooperation and Development, 2017). In practice, it would require tackling daunting challenges such as making complex algorithms—sometimes developed by ML systems that are not instructed by any human—comprehensible to

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20 Source: https://www.visualcapitalist.com/wp-content/uploads/2019/04/data-generated-each-day-full.html.

21 Lambrecht & Tucker (2017) provided a careful assessment of how big data alone is not sufficient to create profit-enhancing opportunities.

public. It also requires multiple government agencies to collaborate in reviewing and supervising algorithms, as companies that use algorithms extensively very often operate at the interface of a range of existing laws, including privacy law, transparency law, data protection, intellectual property right, consumer protection and competition law.

Governments could also take one step closer to the source of the challenge and introduce rules that govern algorithm design. For example, regulations could be introduced to restrain algorithms from adjusting to certain changes in market variables that are essential to sustain tacit collusion. Specifically, algorithms could be designed not to react to price changes made by individual companies, but rather to changes in average prices across the industry. Another example is to mandate a reduction of the speed and frequency that algorithm can adjust to prices, as high speed and frequency of price adjustment facilitates collusion (Ezrachi & Stucke, 2016). However, this feature could lead to suboptimal results, as speed restriction on price changes could create unjustified benefits for the first firm that lowers price when other competitors are not able to adjust prices immediately.

V.3   Striking a balance between competition, innovation and consumer protection

Ultimately, concern about competition—while paramount—must also be considered together with other issues that are central to the achievement of sustainable development. Chief among these issues is innovation. Schumpeter (1934) brought attention to the linkage between innovation and market structure, hypothesizing that for firms to be incentivized to innovate they must be allowed to increase their market shares and to attain temporary monopolistic status. It is the same logic that provided the primary justification for patent systems, which effectively give patent applicants a defined period of monopoly power that allows them to recoup their investment in the innovation processes. This school of thought has continued to enjoy popularity up to today: Thiel & Masters (2014) gave a modern rendition of this view in the context of tech industry, enthusiastically embracing monopoly, with the reasoning that cutthroat competition limits long-term, creative vision and encourages obsessive hostility among firms.

In the context of data economy, there is a belief that access to a large amount of data for analyses, such as deep learning, is crucial for advancing innovation and improving productivity growth (Manyika et al., 2011). In this view, while restricting firms from collecting personal data on a massive scale could help to prevent the rise of data monopolies, it could also end up hampering technological progress. Another supportive argument for acquiescing to the existence of data monopolies is the possible social optimality of having only one firm providing certain digital services to the entire population. This argument for allowing the existence of so-called natural monopolies is based on the assertion that—due to structural reasons, such as high-cost infrastructure—the entire societal demand for a service can be satisfied at the lowest cost by one firm, rather than by two or more (Posner, 1969). Indeed, some such as prominent investor Warren Buffett have argued that Google's search engine business is effectively a natural monopoly (Oyedele, 2017). It might be less costly overall for a society to have one search engine that processes all search requests, recognizes the trends of users' demands and evolves to provide better search results, rather than having two or more search engines carrying out the same task and dividing up data on search requests (consequently, making each separate effort of improving search results less effective).

Driven by cost efficiency consideration, traditional approaches to handling natural monopolies have been nationalization or stringent price regulation and/or quality regulation (Kim & Horn, 1999). While these approaches might work well for traditional natural monopoly such as utilities (electricity, water, gas and oil, etc)

and transportation (railways and airlines, etc.) where the technologies are already relatively mature, adopting the same approaches toward data-driven industries could have unintended effects of slowing innovation. The important roles that governments play in creating an enabling environment for innovation and in guiding the direction of technological advances are undeniable, but it is also indisputable that many private firms in the data economy are currently leading the efforts of making advances at the technological frontier. Any measure that could possibly sap that dynamism and consequently hamper innovation would need to be carefully assessed.

Given innovation in data economy relies to a great extent on access to large amount of personal data, tension could also arise between innovation and consumer protection. There might be a possible trade-off between collecting massive amount of personal data—which could be very useful in generating innovation and insights about human behavior—on one hand, and protecting customer—particularly their privacy—on the other. For example, the recognition of the right to privacy and the right to data protection as inalienable, as in the European Union, has direct and significant implications for the practices concerning data collection, storage and analysis, hence innovation. The adoption of the privacy principle of data minimization under EU's GDPR means data handling should only involve the minimum amount of personal data that is required to accomplish a legal purpose. It also means that data collected for such purpose is not to be reused for other purposes, without consent from data subjects. In other words, enshrining of the principle puts considerable limitation on what firms operating in the EU can do with the data they collected, which could lead to very different outcomes in their development when compared to other firms that are not subject to the same restriction.

Ultimately, the optimal balance between innovation and consumer protection—likely different for each country or region—would require obtaining good grasp of how much people value privacy of their personal data. In assessing the value people place on privacy, a main challenge to tackle is the so-called privacy paradox. The paradox describes the phenomenon that while survey results show online users around the world place high priority on privacy of personal data, most users make minimal effort to actively protect this data and in fact often give it away voluntarily. In a randomized experiment setting, Athey, Catalini, & Tucker (2017) have found that small incentives, small navigation cost or reassuring, even if irrelevant, information about privacy protection can make people safeguard their data less when facing a "notice and choice" process.[22][23] They also found that people quickly abandon a technology with greater privacy protection if it comes at the cost of extra effort or a less smooth user experience. It suggests that policymakers would need to be careful with introducing privacy policy that could inadvertently drive users away from certain technologies, consequently hindering innovation.

There could also be interactions between some aspects of consumer protection and competition. Data privacy laws that are intended to protect consumer might end up unintentionally hurting competition, as smaller firms have less resources (e.g. software engineers and compliance lawyers) to ensure full compliance. Moreover,

[22] As pointed out by the authors, the discrepancy between the stated and revealed preferences could have two possible policy interpretations. First, when formulating privacy policy, policymakers might question the validity of stated preference that places high value on privacy protection. Second, and in contrast to the first interpretation, policymakers that have firm belief in data privacy might want to pursue more comprehensive and stringent privacy policy, protecting people from giving up their data when being enticed by relatively small incentives.

[23] Another possible explanation of the privacy paradox could be that even though data subjects do not want to give up their personal information, they are resigned to do so under the belief that loss of control over their personal information is inevitable. In their survey of 1,506 Americans, Turow et al. (2015) found evidence that suggest a large percentage of Americans consent to giving up their personal data for discounts not because they consider the commercial benefits are worth the costs, but rather because they are resigned to the inevitability of surveillance.

challenging the influential Chicago School of Antitrust that put consumer welfare—typically assessed by price or supply changes—at the center of competition policy, there is a growing call for competition law to consider factors beyond quantitative measures of consumer welfare. The call urges regulators to consider taking a broader view of the harms that anticompetitive behaviors can bring. Beside quantifiable variables such as price and supply, this view holds that firms could also compete on other features of the products and services they provide, including the extent of privacy protection (Stucke & Grunes, 2016). For example, if there is no strong competition, dominant platform companies could be negligent in protecting user data privacy, without having to worry competitive threats that could cut into their market share. Full recognition of both quantifiable and non-quantifiable harms that anticompetitive behaviors can bring help regulators to better assess the urgency in limiting such behaviors. Indeed, some recent competition cases in Europe have shown that European competition authorities are considering the link between data protection and competition. For example, in February 2019, the German Competition Authority (Bundeskartellamt) issued a decision that imposes far-reaching restrictions on how Facebook can collect and process user data, asserting that the social network firm has unlawfully gained a competitive advantage over its competitors through inappropriately processing user data, thereby infringing users' data privacy right.[24]

There has been an ongoing, rigorous debate concerning the scope of competition law and whether competition policy should go beyond the traditional, relatively narrow focus on consumer welfare.[25] Weighing on this debate would be beyond the scope of this paper, but the discussion in this section suggests that the issues of competition, innovation and consumer protection must be considered jointly. At the very least, regulators in these areas should coordinate and consult with each other while pushing for regulatory changes in their respective policy spheres.

A more forward idea is for governments to set up a Digital Authority (DA)—as proposed by the Committee on Digital Platform convened by the University of Chicago Stigler Center. Reflecting new understanding of market dynamics in the data economy, the proposed regulatory entity will have multiple functions, which include complementing the existing competition authorities in limiting or even preempting competitive harm in the digital markets (which might require lower burden of proof—relative to traditional antitrust laws—from the regulator, ensuring more effective antitrust enforcement). With enhanced arrangement for coordination with other agencies, the DA will also be tasked with non-competition goals, such as those in the areas of privacy, media, data-use restrictions, and consumer protection. In order to carry out these tasks effectively, the DA must have regular access to market transaction data of data-driven firms that fall within its regulatory scope, which can include samples of search queries, samples of activities on social media platforms, and samples of queries followed by purchases on particular sites, etc. Also, the DA is to adopt a forward-looking regulatory approach that is expected to increase stability of business environment by making clear what conducts are allowed and how enforcement efforts are implemented. Rightfully, critics are concerned of a far-reaching regulatory entity's susceptibility to issues such as crony capitalism and over-regulation. Independence of corporate influence, accountability to the public, and careful research must therefore be the cornerstones of the DA, which could be a viable option for responding to the rising demand for policy efforts to check the power of dominant data firms.

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[24] The ruling was however suspended by Düsseldorf Higher Regional Court later in August 2019, casting uncertainty over whether it will hold at the end. The original decision of the Bundeskartellamt can be found here: https://www.bundeskartellamt.de/SharedDocs/Meldung/EN/Pressemitteilungen/2019/07_02_2019_Facebook.html. The suspension by the regional court is reported here: https://www.lexology.com/library/detail.aspx?g=eb62ca02-bc17-4757-8ede-0dc8af0ec8b7.

[25] For a brief overview of the debate, please refer to Walter-Warner & Hatch (2018).

VI   Conclusion

High economic inequality has become a key policy concern around the world. While the focus in public discourse has been on how trade, financial development, advances of specific frontier technologies such as robotics and artificial intelligence, and economic and social policies have contributed to the emergence of the increasingly unequal world, analysis presented in this paper suggests that the rise of data economy could be another unequalizing force.

This paper has discussed how certain properties of data that make up its economic identity as a factor of production have engendered the tendency for monopolies to rise in data-driven sectors, creating persistent asymmetries of power among actors in the data economy. If such asymmetries are not addressed, the path to data economy—a transformative development that could drastically improve many aspects of societal wellbeing—could be undermined by persistent policy failures as those with power leverage their influence to capture oversized gains generated by the data economy, rather than serving the common interests of different actors. Such exclusion is a recipe for persistent inequality.

Given the growing power that data monopolies could exercise over societies worldwide, it is only reasonable that their powers are to be kept in check. Analyses presented in this paper have shown that breaking up data monopolies is likely to be only a temporary solution and nationalization could have highly uncertain consequences for innovation. Strengthening people's control of their own data is crucial, but challenges with proper data valuation need to be overcome in ensuring fairer distribution of gains generated from data. More stringent regulation on data privacy and security is needed, and so are more proactive competition policy and its enforcement. An independent, accountable and forward-looking Digital Authority that has both competition and non-competition goals, with access to samples of a wide range of data on market transactions and equipped with updated understanding of market forces in data economy from careful research could become an effective option for reining in the unwieldly influence of powerful firms.

Still, some are concerned about the unintended effects of more aggressive regulation and competition policy on innovation, often emphasizing the tremendous benefits that innovation powered by data have brought to people and the futility of looking forward in the context of competition policy. In response to that, even if imperfectly, let us recall that similar arguments for favoring a less proactive regulation—on the premise that it could foster more innovation and do more good to the society—was also made about financial deregulation. Decades of financial deregulation did contribute greatly to financial innovation, but it also resulted in one of the worst economic and financial crises in history as inappropriate implementation of innovation became detrimental (Bernanke, 2009). If the global financial crisis and the built-up to it can be of any guidance, a key lesson would be that there should be appropriate governance and control procedures over innovation, and, if the effects of innovation are not all benign, that there should be appropriate monitoring of such innovations, including the processes that led to their creation. Policymakers in data economy would be best served to keep this hard-earned lesson in mind.

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