

VALUING SOCIAL DATA

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Abstract

Social data production is a unique form of value creation that characterizes informational capitalism. Social data production also presents critical challenges for the various legal regimes that are encountering it. This Article provides legal scholars and policymakers with the tools to comprehend this new form of value creation through two descriptive contributions. First, it presents a theoretical account of social data, a mode of production which is cultivated and exploited for two distinct (albeit related) forms of value: prediction value and exchange value. Second, it creates and defends a taxonomy of three “scripts” that companies follow to build up and leverage prediction value and describes the normative and legal ramifications of these scripts.

The Article then applies these descriptive contributions to demonstrate how legal regimes are failing to effectively regulate social data value creation. Through the examples of tax law and data privacy law, it demonstrates these struggles in both legal regimes that have historically regulated value creation, like tax law, and legal regimes that have been newly tasked with regulating value creation by informational capitalism, like privacy and data protection law.

The Article argues that separately analyzing data’s prediction value and its exchange value may be helpful to understanding the challenges the law faces in governing social data production and the political economy surrounding such production. This improved understanding will equip legal scholars to better confront the harms of law’s failures in the face of informational capitalism, reduce legal arbitrage by powerful actors, and facilitate opportunities to maximize the beneficial potential of social data value.

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INTRODUCTION

Social data production is a form of value creation that is historically particular to, and defining of, informational capitalism. Recent technological transformations have contributed to the feasibility and utility of entities cultivating social data for prediction value. These technological changes have allowed entities to exploit for economic gain that which has long been true; that people are social beings, deeply knowable and materially influenced by our relations to one another. The widespread practice of cultivating social data to be stored, mined, and exploited for its value in apprehending, predicting, and influencing human behavior demarcates informational capitalism from its predecessors.

Social data as a value form has precipitated the business models that have come to typify informational capitalism. This (relatively) new form of value creation and its associated business models has challenged the diverse legal regimes that have encountered it. This Article aims to improve law's conceptual grasp of social data as a value form and the political economy of informational capitalism. This improved understanding will equip legal scholars and policymakers to better confront the harms and regulatory gaps stemming from law's failures in the face of informational capitalism, reduce legal arbitrage by powerful actors, and facilitate opportunities to maximize the potential benefits of social data and the prediction value it generates.

Before the argument proceeds any further, it is perhaps useful to briefly define social data and prediction value.¹ *Social data* is used to refer jointly to two interrelated categories of data. First, data that materializes and stores traces of human activity—information produced from the interaction between people living their lives and the digital devices that apprehend and store traces of them doing so.² Second, data that is used to apprehend, infer, or predict human activity.³ In contrast with the more commonplace term 'personal data', 'social data' nicely expresses the view (and a central focus of this Article) that data is useful—i.e., socially and economically valuable—not only for what it can tell us

¹ Both concepts are described at greater length in Part I below.

² This first category is adapted from the category of data that Julie E. Cohen refers to as of "central importance" to digital platforms. JULIE E. COHEN, *BETWEEN TRUTH AND POWER: THE LEGAL CONSTRUCTIONS OF INFORMATIONAL CAPITALISM* 42 (2019).

³ The difference between the two will be described in greater detail in Part I below. But for now, it is important to note that data used to infer or predict human activity need not always derive from data directly about human activity. For further discussion of the significance of the second category, see Alicia Solow-Niederman, *Information Privacy and the Inference Economy*, 117 NW. L. REV. (2022).

about any one person, but also, and especially, for what it can tell us about people.⁴

Prediction value refers to the specific value form produced from the cultivation and accumulation of social data. Social data assets are used by entities to provide insight into human behavior, guide predictions about behavior, and optimize strategies to intervene and modify behavior. Social data thus stores the value of being able to apprehend behavior and to infer and predict the likely future actions of people. This in turn provides the capacity to exert control over future behavior on the basis of this materialized insight.⁵ Prediction value is distinct from (and not always neatly transformed into) exchange value. Exchange value posits that the value of a thing is the value derived from its exchange, often expressed as its ‘fair market price’. In contrast, the value of social data lies in its capacity to apprehend and predict human behavior. Part I provides greater detail defending the descriptive and analytic virtues of cataloging this distinction.

This Article is not the first to clock the ontological, political-economic, or legal significance of contemporary social data production.⁶ Others, particularly political economists of communication and historians of science, have long identified and analyzed the role of informationalism in contemporary capitalist value formation as it emerged and took on growing importance.⁷ Previous work has established the centrality of social data as a vital, even paradigmatic, factor of production under informational capitalism,⁸ while others have identified the importance of behavioral monitoring and prediction to the

⁴ Salome Viljoen, *A Relational Theory of Data Governance*, 131 YALE L.J. 573 (2021).

⁵ DAVID GRAEBER & DAVID WENGROW, *THE DAWN OF EVERYTHING* 364-65 (2021) (arguing that ‘control of information’ is one of three bases of social power).

⁶ In 1951 Frank Knight remarked that “The very concept of a knowledge industry contains enough dynamite to blast traditional economics into orbit.” MARK A. LUTZ & KENNETH LUX, *HUMANISTIC ECONOMICS: THE NEW CHALLENGE* 179 (1988) (quoting Frank Knight). Fritz Machlup, was one of the first who systematically analyzed the production and distribution of commoditized knowledge. See generally FRITZ MACHLUP, *THE PRODUCTION AND DISTRIBUTION OF KNOWLEDGE IN THE UNITED STATES* (1962). In 1994, Robert E. Babe remarked on the curious need for mainstream economics to treat information as a commodity to make sense of it within the economic paradigm, a need that “obscures many essential properties of information, as well consequences of informational exchange.” Robert E. Babe, *The Place of Information in Economics*, in *INFORMATION AND COMMUNICATION IN ECONOMICS* 41, 42 (1994).

⁷ See generally MANUEL CASTELLS, *THE RISE OF THE NETWORK SOCIETY* (1996); S.M. AMADAE, *RATIONALIZING CAPITALIST DEMOCRACY* (2003); DAN SCHILLER, *HOW TO THINK ABOUT INFORMATION* (2007).

⁸ See generally COHEN, *supra* note 2; Jathan Sadowski, *When data is capital: Datafication, accumulation, and extraction*, 6 *BIG DATA & SOC’Y* 1 (2019); Nick Couldry & Ulises A. Mejias, *Data Colonialism: Rethinking Big Data’s Relation to the Contemporary Subject*, 20 *TELEVISION & NEWS MEDIA* 336 (2018).

governance capacities and challenges of the digital economy.⁹ Legal scholars have also explored the legal facilitations and fallouts of the informational turn.¹⁰

This Article builds upon these insights. It develops and defends an explanation of the conceptual and normative distinctiveness of social data as a value form, that in turn creates distinct challenges for the legal regimes tasked with governing it. It first provides two descriptive contributions to the literature: a theoretical account of social data as a distinct value form whose cultivation is a primary aim of digital firms, and a taxonomy of the business models and practices that this new factor of production has precipitated. It then uses those descriptive accounts as a basis to illustrate how and why legal regimes have misapprehended the value proposition of social data production and some of the failings and dangers that arise as a result.

This Article first presents its theoretical account of social data as a material store of prediction value. The capacity for social data to be stored, mined, and exploited for prediction value, and the hegemonic market pressure faced by companies to datafy, demarcates informational capitalism from its predecessors. It is this generalized competitive pressure to datafy that transforms social data into a key factor of production. This account also describes how prediction value departs from traditional views of value in the law. Prediction value does not always reduce quickly or neatly to exchange value (i.e. a monetary price), which is a problem because many areas of law do not register, apprehend, or consider significant forms of value production that predate and/or do not convert into exchange value.

Following this theoretical account, the Article introduces a taxonomy of the business strategies common to informational capitalism. This taxonomy divides the ways in which companies leverage prediction value to produce wealth and power for themselves and their investors into three scripts. The first script is direct and immediate conversion of social data's prediction value into exchange value through means such as targeted advertising. The second script is indirect, and often delayed in time, conversion of prediction value into exchange value through improving and developing new products and services, lowering costs, and expanding into new business lines and industries. The third

⁹ See generally KATHARINA PISTOR, *THE CODE OF CAPITAL* (2020); Marion Fourcade & Kieran Healy, *Seeing like a market*, 15 SOCIO-ECON. REV. 9 (2016); SHOSHANNA ZUBOFF, *THE AGE OF SURVEILLANCE CAPITALISM* (2019).

¹⁰ See generally COHEN, *supra* note 2; Amy Kapczynski, *The Law of Informational Capitalism*, 129 YALE L. J. 1460 (2020); Katharina Pistor, *Rule by Data: The End of Markets?*, 83 L. & CONTEMPORARY PROBLEMS 101 (2020); Kiel Brennan-Marquez & Daniel Susser, *Privacy, Autonomy, and the Dissolution of Markets*, Data & Democracy Series: Knight First Amendment Institute, Aug. 11, 2022, available at <https://knightcolumbia.org/content/privacy-autonomy-and-the-dissolution-of-markets>; Omri Marian, *Taxing Data* 47 B.Y.U. L. REV. 511 (2021).

script is leveraging prediction value to accrue power. After cataloging and describing these three scripts, the Article explores some specific business practices associated with following these scripts, each of which focus on growth and expansion. These practices include offering free and low-cost services, creating ecosystems of products and services, and embarking on aggressive merger and acquisition strategies. The Article shows how these strategies differ from traditional ones in ways that carry both legal and normative significance.

The Article then builds off these descriptive contributions to explore how, in light of its transformation into a key factor of production, diverse legal regimes are trying—but failing—to effectively govern entities’ cultivation and use of social data. It identifies two contexts or ways in which legal regimes are failing. In each of these contexts, the reason that the law is failing to effectively govern traces back to the misapprehension of social data as a new factor of production and prediction value as a value form distinct from exchange value. The first context is legal regimes that have historically been tasked with governing value creation. These areas of the law are now struggling to apply their existing regimes to informational capitalism’s new mode of value creation. The Article chronicles these struggles through the example of tax law. It explains how tax law’s attempts to govern prediction value creation using a legal regime that is built around exchange value has resulted in tax law failing to achieve its normative goals in the face of informational capitalism. The second context is legal regimes that have not historically understood themselves to have a primary aim of governing value creation but are now tasked with this role. Through the example of privacy and data protection law, the Article shows the conceptual and programmatic challenges that have emerged as these legal regimes are forced into this new role of governing value creation. It shows how privacy and data protection law’s focus on negative rights for data subjects has left the field poorly equipped to facilitate the production of prediction value for socially beneficial purposes.

The central goal of this Article is to provide through its descriptive contributions a comprehensive analytical base to launch a lively and productive discourse across legal disciplines on how the law can effectively respond to the challenges brought by informational capitalism. Its analysis has broad implications for other areas of the law that are struggling to adapt to informational capitalism. By developing a clear description of prediction value as a unique value form distinct from exchange value and explaining how prediction value is used by entities in informational capitalism, we provide legal scholars in other areas of the law a better understanding of how social data as a factor of production is meeting, challenging, and transforming legal forms. This understanding will be invaluable to legal fields that, like tax law, have historically been tasked with governing value creation but whose legal frameworks,

developed around the concept of exchange value, are not achieving their normative goals when applied to prediction value. Antitrust and financial regulation are prominent examples.¹¹ This understanding will also be invaluable to legal fields that, like privacy and data protection law, have not historically viewed themselves as being tasked with governing value creation and that, as a result, have not developed a positive agenda for regulating prediction value. First Amendment law is a prominent example.¹² This Article is providing legal scholars with the tools necessary to begin the essential work of adapting the law to meet the challenges (and nascent opportunities) of informational capitalism.

However, one should not mistake this Article’s project of clarity as one of uncritical acceptance of or endorsement of current modes of cultivating, accumulating, and using social data value. On the contrary, distinguishing the value of social data cultivation and accumulation from priced exchange value can help lay bare how much of alleged prediction value creation is mere puffery and speculation with little behind the curtain.¹³ As Aaron Shapiro notes in his excellent work on gig platforms, when it comes to understanding the way prediction value is capitalized by platforms into market valuation, there is a considerable “gap between what platforms do and what they say they do.”¹⁴ Clarifying the two modes of value production (and how they relate to each other) can help regulators and other observers evaluate when such claims are plausible, and when they are not.

Bringing this gap into legal view is particularly important for areas of law that manage and regulate value creation. Such regimes have an interest in

¹¹ Some legal scholars have identified and begun to address the failure of these types of legal regimes in the modern economy. For example, antitrust scholars within the New Brandeisian movement have highlighted how the Chicago school’s emphasis on short-term price effects fails to protect the public against the dangers of excessive private power, particularly within the context of digital companies. See generally Lina Khan, *Amazon’s Antitrust Paradox*, 126 YALE L. J. 710 (2017); Lina Khan, *The Separation of Platforms and Commerce*, 119 COLUM. L. REV. 937 (2019); TIM WU, *THE MASTER SWITCH: THE RISE AND FALL OF INFORMATION EMPIRES* (2010). This Article’s contributions can expand on this important work by providing one account of how that power accrues in the digital economy.

¹² Legal scholars have long called attention to the infrastructural role played by the First Amendment and free speech protections for facilitating the digital economy. More recently, scholars have directly linked the speech threats posed by digital platforms and the business models of such companies, premised, in this Article’s formulation, the cultivation of prediction value. See e.g., Jack M. Balkin, *The First Amendment in the Second Gilded Age*, 66 BUFF. L. REV. 979 (2018), Julie Cohen, *Infrastructuring the Digital Public Sphere* (unpublished manuscript) (on file with authors).

¹³ See I. Deborah Raji et al., *The Fallacy of AI Functionality*, PROCEEDINGS OF THE 2022 ACM CONF. ON FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY (2022); Angelina Wang et al., *Against Predictive Optimization*, Proceedings of the 2023 ACM Conf. on Fairness, Accountability, & Transparency (2023).

¹⁴ Aaron Shapiro, *Platform Sabotage*, J. CULTURAL ECON. 2 (Feb. 2023).

apprehending and distinguishing between speculative and productive activity, to channel social resources away from the former and towards the latter. But apprehending the distinction between these forms of value also matters for areas of law meant to mitigate the harms that may arise from such gaps, and the social disruptions that are left in the wake of entities pursuing growth based on dubious claims of value in either form. Confused and obscured claims of how these two forms of value relate in the digital economy are one way that speculative and harmful practices escape scrutiny and continue to flourish in the digital economy.

The Article proceeds in the following Parts. Part I develops the theoretical account of social data as a value form and prediction value as a central driver of value within informational capitalism. Part II develops a taxonomy of three ways in which companies leverage prediction value to create wealth and power. It also describes common business models associated with these means of wealth and power creation and their legal and normative significance. Part III uses the examples of tax law and privacy and data protection law to analyze how the law is colliding with informational capitalism in distinct ways. We conclude by highlighting how helpful it can be to disambiguate between prediction value and exchange value both for resolving current legal challenges and for developing policies to better regulate and direct prediction value towards socially useful ends.

I. PREDICTION VALUE AND THE DATA POLITICAL ECONOMY

Social data (i.e. data about people) production is a form of value production that is particular to, and defining of, informational capitalism. This Part lays out an account of data as a material store of prediction value. The aim is to sketch out a bit more about what is meant by the word ‘value’ and why it’s useful to think about in relation to social data production.

To do so, this Part will explore three questions. First, *what* is prediction value? What makes it ‘valuable’ and what makes it different from other kinds of value? Second, *why* do companies and governments cultivate and accumulate it? In other words, what is it good for, and how does it fit into current market behaviors and competitive practices? Third, if social data is so valuable, then where has it been all this time? Why are we only talking about it *now*?

A. *What Is ‘Value’?: A Quick Background*

Before the Article turns to prediction value, it is perhaps worth saying a few words about the concept of value more generally. Nowadays, talking about the ‘value’ of something refers to that thing’s *exchange value*: the priced, monetary value at which it can be (or could theoretically be) bought, sold, or exchanged

for something else on a market.¹⁵ This is the classic economic sense of ‘value’: the ‘market value’ of a house, or a painting, or a corporate merger, or a bushel of corn. Something’s value in a market is a subjective, relative, and contingent measure of that item’s desirability. It captures a specific or ‘average’ buyer’s ‘willingness to pay’ (WTP) for an additional (i.e. marginal) unit of said item. Willingness to pay in turn is determined by a combination of external, changing conditions (supply and demand) and internal, stable ones (the buyer’s particular reasons for wanting the item). Expressed as a priced market value, WTP also captures relative desirability between goods, since buyers have finite wealth and must prioritize among their desires (or most buyers must, anyway).

This is taken to be quite distinct from ‘values’ in an ethical or sociological sense: beliefs regarding the importance of certain things or actions that motivate individual or societal behavior. It is in this sense that one can speak of the ‘core values’ of an institution or that someone places a ‘high value on honesty.’ Indeed, much of what makes exchange value such a useful concept in economics (and beyond) is its stated neutrality on matters of ethical or sociological value: value is simply the price someone is willing to pay. One need not inquire into why people want what they do and whether those reasons are good or bad (i.e., as Smith endeavored to show, that the market rewards us justly for our labors). Such questions, to the extent they are answerable at all, lie outside the purview of economic theory.¹⁶

But economics began as an exploration of these exact questions. How do the individuals in a particular society put their limited time and resources towards productive activity? What does that say about what they value? What is the origin and nature of such value? Reflecting on these questions, observers distinguished exchange value from what they called ‘use’ value or ‘natural’ value: the value one gets from, say, *wearing* one’s favorite coat (i.e. using it as a coat), as opposed to the value that one or another would pay to obtain the coat.¹⁷ These

¹⁵ In classical political economy, exchange value (or *Tauschwert*) refers to only one attribute of a commodity: the proportion at which one commodity can be traded on the market for other commodities. In this understanding of the term, exchange-value isn’t *necessarily* money-price, although a market price will generally bear at least a rough correspondence to a commodity’s exchange-value. See KARL MARX, *CAPITAL* 138-139 (Ben Fowkes trans., Penguin Books 1990) (1867). However, the general adoption of marginalism in economic thought around the 1930s eliminated such distinctions: discussions of different value-attributes fell off, and value simply measured how much a potential buyer would desire an additional unit of said item, expressed in the form of a price.

¹⁶ David Graeber, *Value: Anthropological Theories of Value*, in *A HANDBOOK OF ECONOMIC ANTHROPOLOGY* 439, 443 (James G. Carrier ed., 2005).

¹⁷ The concepts of use value and exchange value are quite old. Marx quotes Aristotle on the subject: “For twofold is the use of every object...The one is peculiar to the object as such, the other is not, as a sandal which may be worn is also exchangeable. Both are uses of the sandal, for even he who exchanges the sandal for the money or food he is in need of, makes use

were not mere numerical differences, which continue to be widely observed today. For example, any economist will point out that the decision *not* to sell something—a home, a corporate asset, or one’s favorite coat—is simply a signal that one values that thing over its (current) market value. Behavioral economists have added to this observation the concept of ‘endowment effects’—that people systematically tend to overestimate the market value of something that they already have when compared with what they would pay to obtain that same thing (a testament to the notion that we grow attached to things we think of as our own).¹⁸ However, both of these accounts ground their explanations of such behavior in *numerical* difference in value—quantitative assessments of the priced value of a particular good.¹⁹

In contrast, early economists used the concept of use value to express a distinct *way* that a good could be valued, not simply differing degrees to which a good could be valued along the same dimension. Use value and exchange value captured distinct aspects of a good. The two concepts indexed different ways that people relate to and derive value from things, and different motivations they might have for making or obtaining things. The disaggregated notions of value thus corresponded to, or described, different aspects of ‘productive’ or economic activity. The two were related, of course, and much of early economic thought was devoted to developing distinct accounts for the origins of value and the relation between use value and exchange value.²⁰

There is widespread agreement that classical political economists’ preoccupation with developing some ‘true’, scientific, or systematic relationship between the different notions of value was destined for failure. The history of

of the sandal as a sandal. But not in its natural way. For it has not been made for the sake of being exchanged.” MARX, *supra* note 15, at 179 (quoting Aristotle, Republic, I, I, c.9). As David Graeber details, Smith’s famous ‘paradox of value’ is also much older than the eighteenth century: St. Augustine argued that ‘according to their own merits’ plants are clearly superior to stones, animals to plants, humans to animals, but because of our fallen nature, and thus endless physical needs and desires, we value things like bread and gold over animals like mice. To St. Augustine, this characterizes how we come to see things through our own needs (use value) rather than their absolute worth (their position along the Great Chain of Being). Graeber, *supra* note 16, at 441-42 (citing Augustine). Graeber draws on the work of Sasan Fayazmanesh. See Sasan Fayazmanesh, *The Magical, Mystical ‘Paradox of Value’*, 16 RSCH. IN THE HIST. OF ECON. THOUGHT & METHODOLOGY 123 (1998).

¹⁸ Daniel Kahneman et al., *Experimental Tests of the Endowment Effect and the Coase Theorem*, 98 J. OF POL. ECON. 1325 (1990).

¹⁹ Put another way, these are both instances where people are making an assessment of the current market price of such goods—deeming it lower than what they consider its exchange value.

²⁰ Mercantilists believed wealth originated from precious metals (gold, silver), physiocrats from nature, and hence, agriculture. The classical political economists believed value was a product of human labor, that it “emerged at the point where our minds became a physical force in nature.” Graeber, *supra* note 16, at 440.

economic thought is marked by non-exchange conceptions of value coming into conflict with and ultimately being (albeit imperfectly and partially) transfigured into exchange value. Over time, the value of an object “became increasingly indistinguishable from its price: how much potential buyers were willing to give up to acquire some product on the market.”²¹

Yet, in abandoning the study of distinct concepts of value, economics also lost its ability to express—and thus take seriously on their own terms—things (or uses of things) that are of high social or personal utility but that nonetheless have low exchange value. Or more accurately, economic thought moved on from puzzling deeply over such enduring ‘paradoxes’ of commercial activity, to providing a ready answer for resolving them. The standard line is that such things suffer from having high total utility but low marginal utility. Thus ‘undervaluation’ problems have, in theory, a simple solution. To properly value such things requires that we take the steps necessary to express their value *as* exchange value: in other words, to *create* a market (or if that isn’t possible, to simulate a market) in such goods.

Again, when thinking about value these days it can be hard to escape the exchange value sea we all swim in. Saying something has ‘economic value’ is necessarily taken to mean that this value *also* takes a particular form: exchange value within a market. But this Part endeavors to show that it can be worth returning to the old tradition of disambiguating forms of value—not to revive the old views entirely (this Article has no interest in wading into centuries’ old fights about value theory), but to take seriously the distinctions between different ways of cultivating and deriving productive value, and to take seriously the imperfect and messy task of transformation that occurs between forms of value.

B. *What is Prediction Value?*

Data is different. Social data production produces value from its capacity to materialize and store traces of human activity. This allows entities to catalog, analyze, aggregate and mine such traces for insight, and in turn, to use such insights to apprehend, predict and modify behavior. In other words, the value of social data lies in its capacity to apprehend and predict—and based on such apprehension and prediction, to manage—social behavior.²²

²¹ Graeber, *supra* note 16, at 440.

²² The value proposition here is that better prediction informs better strategies for action. The more an entity knows about a behavior or attribute and/or the effect of a proposed intervention on that behavior (or attribute), the more effectively it can convert prediction into a desired outcome (e.g. watching more Netflix, buying more products of the right kind on Amazon, driving longer hours on Lyft, being charged the highest price one is willing to pay in an ad exchange, etc). Increased efficacy can refer to a variety of comparative advantages in

We use the term *prediction value* for the value of being able to infer or predict likely future actions or effects. Value lies in the capacity to convert into actions of control: prediction value confers the capacity to exert a desired effect on future behavior based on prediction or inference. Social data is the material store (or medium) of prediction value. Its production materializes the latent predictive value of human activity for other human action so that it can be stored, used, reused, aggregated, and recombined with other data (i.e. other media of prediction value) across time and context, and mined for different kinds of insights and interventions.²³ Merging data with other data is a way to combine and compound prediction value.

Prediction value is derived from data's relational character. Because people are social beings who are like one another, who are the products of social formation and who construct their self-identity in dialogue with others, datafied traces of observed actions and behaviors of the many have something meaningfully predictive to say about any one.²⁴ Data stores represent a proto-asset that, stem-cell like, can be reapplied and specialized to predict behavior across a variety of settings.

The general observation that information produces social control, and this in turn can be exploited for commercial gain, is not novel, though what this Article calls prediction value goes by many other names. Aaron Shapiro identifies how platforms engage in worker surveillance to cultivate “calculative asymmetries,” which platforms exploit to manage worker behavior and maximize their own gain.²⁵ Kean Birch et al detail how platforms express value from personal data indirectly to investors and other market actors through ‘user metrics’.²⁶ Birch and others have written extensively on assetization and

modulating behavior towards a desired goal. Greater prediction value can produce interventions that are more accurate, more subtle, more widely deployed, more quickly deployed, etc. The particular usage of prediction value will depend on the setting in which it is being used and the desired goal.

²³ Cultivating data is less of a ‘harvesting’ process than it is a ‘manufacturing’ process. The ‘complete’ picture of human activity is not replicated like some digital twin or mirror. The process is more one of an engineered, synthetic distillation of human activity that reflects the goals of data production.

²⁴ Viljoen, *supra* note 4.

²⁵ Aaron Shapiro, *Between autonomy and control: Strategies of arbitrage in the ‘on-demand’ economy*, 20 NEW MEDIA & SOC’Y 2954 (2018). Shapiro develops the notion of asymmetries in his work on ‘platform sabotage’, a term he uses to describe platforms’ use of data and computation to derive value through strategically inserted inefficiencies in the market encounters they facilitate. *See* Shapiro, *supra* note 14.

²⁶ Kean Birch et al., *Data as asset? The measurement, governance, and valuation of digital personal data by Big Tech*, 8 BIG DATA & SOC’Y 1 (2021).

informational value²⁷ and Thomas Beauvisage and Kevin Mellet extend this assetization account to personal data.²⁸ Cecilia Rikap details the ‘intellectual monopolization’ of power among the world’s largest companies through the systematic concentration of knowledge and ‘planning capacity’ that, she argues, extends these companies’ power over the economy beyond their legally owned access.²⁹ Van Doorn and Badger discuss the ‘speculative valuation’ of gig platforms that configure data as a financial asset based on the expectation that data-driven analytics will later realize as efficiency gains.³⁰

Mainstream economic theory has taken a renewed interest in prediction value, though economists are decidedly mixed on whether prediction value is a good thing. Jean Tirole details how “managing the flow of information about individuals’ behavior” allows entities to “achieve social control,” which he argues can promote both prosocial behavior and “destroy the social fabric.”³¹ Glen Weyl and others argue that ‘free’ online services lead us to systematically under-incentivize and maldistribute data value; to correct these issues, they argue for treating the market for data like a labor market.³²

²⁷ See e.g., Kean Birch & Callum Ward, *Assetization and the ‘new asset geographies’*, DIALOGUES IN HUM. GEOGRAPHY (2022); Kean Birch & D.T. Cochrane, *Big Tech: Four Emerging Forms of Digital Rentiership*, 31 SCI. AS CULTURE 44 (2022), Kean Birch, *There Are No Markets Anymore*, TRANSNATIONAL INSTITUTE (2023), Kean Birch & Adediji ‘Damola, *Rethinking Canada’s Competition Policy in the Digital Economy*, Centre for International Governance Innovation, available at <https://www.cigionline.org/publications/rethinking-canadas-competition-policy-in-a-digital-economy/>. Birch and others distinguish the process of assetization from commodification: although they can be exchanged, assets are not produced for their exchange value (i.e. to be bought and sold) but instead to secure durable economic rents (investment and return) through the ownership and control of an asset. Kean Birch & Fabian Muniesa, *Introduction*, in ASSETIZATION: TURNING THINGS INTO ASSETS IN TECHNOSCIENTIFIC CAPITALISM, 1, 2-3, (Kean Birch & Fabian Muniesa, eds., 2020).

²⁸ Thomas Beauvisage & Kevin Mellet, *Datasets: Assetizing and Marketizing Personal Data*, in ASSETIZATION: TURNING THINGS INTO ASSETS IN TECHNOSCIENTIFIC CAPITALISM 75, 77 (Kean Birch & Fabian Muniesa, eds., 2020) (“We argue that the ability to capitalize personal data in the present is the result of a versatile and uncertain process of assetization.”)

²⁹ Cecilia Rikap, *From global value chains to corporate production and innovation systems: exploring the rise of intellectual monopoly capitalism*, 7 AREA DEVELOPMENT & POL’Y 147 (2022) [hereinafter Rikap, *From global value chains*]; Cecilia Rikap, *Capitalism as Usual?*, 139 NEW LEFT REVIEW 145 (2023) [hereinafter Rikap, *Capitalism as Usual?*].

³⁰ A transformation of prediction value into exchange value we discuss in greater detail in Part II. See generally Niels van Doorn & Adam Badger, *Platform capitalism’s hidden abode: producing data assets in the gig economy*, 52 ANTIPODE 1475 (2020).

³¹ Jean Tirole, *Digital Dystopias*, 111 AM. ECON. REV. 2007 (2021).

³² ERIC A. POSNER & E. GLEN WEYL, *RADICAL MARKETS: UPROOTING CAPITALISM AND DEMOCRACY FOR A JUST SOCIETY* (2018); Imanol Arrieta Ibarra, Leonard Goff, Jiménez Hernández, Jaron Lanier, E. Glen Weyl, *Should We Treat Data as Labor? Moving Beyond “Free”*, PAPERS & PROCEEDINGS OF THE AM. ECON. ASS’N. (2018).

Indeed, astute observers have been developing accounts of social data’s capacity to cultivate power and value for some time.³³ In her 1988 ethnography of computerizing workforces, Shoshanna Zuboff describes how these workplaces were deriving value not from automating, but from ‘informating’—datafying worker actions rather than simply automating workers away.³⁴ Oscar Gandy’s seminal 2000 work *The Panoptic Sort* details a ‘system of power’ developed from social data and used to “coordinate and control [people’s] access to the goods and services that define life in the modern capitalist economy.”³⁵ Gandy detailed how tracking institutions also enacted a distinct view of social life: they are concerned not with cataloging the self-conceptions of groups or individuals, but instead with identification—categorization for institutional utility—classification (“the panoptic sort is a difference machine”), and assessment.³⁶

1. Prediction Value Versus Exchange Value

Social data production materializes and stores value (and risk) in ways that are distinct and not always neatly transformed into—exchange value.³⁷ Robert Babe provided an impressively prescient distillation of the problem: money price states how much exchange value an informational commodity “contains” but is silent regarding what he calls its “quantity of information” (what we’d call its prediction value).³⁸

As he notes, for neoclassical economic theory (although not, importantly, older traditions) to make sense of informational value, it needs to be reduced to exchange value to index it and ‘count’ such value in economic terms. But social data “does not fulfill the definitional or conceptual requirements” of commodities as understood by economists of the time.³⁹ Moreover, attempts to translate or reduce information’s prediction value into

³³ Several older works are referenced in notes 6 and 7 above. James Beniger’s seminal work *The Control Revolution* came out in 1986.

³⁴ The authors thank Dan Greene et al., for pointing to this example, which is cited in Dan Greene et al., *The Visible Body and the Invisible Organization: Information Asymmetry and College Athletics Data*, 10 *BIG DATA & SOC’Y* 1 (2023).

³⁵ OSCAR GANDY, *THE PANOPTIC SORT* 29 (2000). *See also* Oscar Gandy, *Coming to terms with the panoptic sort*, in *COMPUTERS, SURVEILLANCE AND PRIVACY* (David Lyon & Elia Zureik eds., 1996).

³⁶ GANDY, *supra* note 35, at 29.

³⁷ Robert Babe provided an impressively prescient first foray into our argument: money price states how much exchange value an informational commodity ‘contains’ but is silent regarding its quantity of information. Babe, *supra* note 6.

³⁸ Babe, *supra* note 6, at 45.

³⁹ *Id.* at 42.

such terms “obscures many essential properties of information, as well as consequences of informational exchange.”⁴⁰

These distinct properties also suggest diverse applications where one kind of value enjoys a relative advantage over the other. Prediction value would be well spent, for example, in allocating goods for which priced market allocation might be independently wrongful.⁴¹ For example, one may think it wrong to affix a price to hearts for transplant, but this does not mean one would not value informational mechanisms to accurately identify which operating theaters need hearts and which may supply them. The same might be true in the reverse. For example, we may think the singular quality of artistic creativity and idiosyncrasy in aesthetic taste are intrinsically valuable, so we ought to resist allocating productive resources to artistic production based on predictive value.

In some ways, prediction value is *more* general than priced exchange value.⁴² Prediction value can be converted into exchange value, but it need not convert into wealth to exert power or control, or to drive decisions. Prediction value can exert social discipline on others and enact material outcomes or moral judgment that we do not currently express as market discipline (and perhaps could not express so even if we wanted to).⁴³

In other ways, prediction value is decidedly *less* general than exchange value. Prediction value of a given data point or dataset is contingent and unpredictable in ways that are unlike a more typical asset or commodity. Prediction value is not stable across contexts and, as data ages, or is combined with other data, or new analytic techniques or technical applications are developed, prediction value may shrink or grow. Prediction value is (in some general sense at least) nonrivalrous, but it's also not straightforwardly fungible, and thus not readily subject to traditional forms of transfer and redistribution. Marc Porat, an early information economist, said that information was, by nature, a “heterogenous commodity” that cannot be collapsed into one sector—like mining. For economists to make sense of it, he argued, they needed to think of the production, processing, and distribution of information goods and

⁴⁰ *Id.* at 42.

⁴¹ Salomé Viljoen, *Informationalism Beyond Managerialism* (unpublished manuscript) (draft on file with authors); Rahel Jaeggli, *What (If Anything) Is Wrong with Capitalism?*, 54 S. J. PHIL. 44 (2016).

⁴² As Kenneth Arrow explained: “the meaning of information is precisely a reduction in uncertainty.” Babe, *supra* note 6, at 42 (quoting Arrow)

⁴³ See Babe, *supra* note 6, at 42 (“[N]eoclassicists’ notions of ‘market,’ ‘price,’ ‘value,’ ‘commodity,’ ‘demand,’ ‘supply,’ and ‘exchange’ are but specialized instances of broader communicatory phenomena.”).

services as an *activity* rather than a product.⁴⁴ While a growing number of economists and studying prediction value, far more empirical work is needed.⁴⁵

2. Prediction Value into Exchange Value

As life becomes increasingly digital and datafied, prediction value takes on a greater economic and conceptual significance. Many of the largest companies in the world have, at least in part, gotten that way by accumulating and exploiting prediction value. This in turn puts general market pressure on *other* companies and entities to do the same thing to retain their market position against competitors.⁴⁶

As some of the scholarship reviewed above suggests, companies face pressure to transform prediction value into exchange value, or at the very least translate prediction value into exchange-value terms for investors and, to a lesser extent, regulators. Yet not all prediction value is readily reducible to exchange value, and there are several reasons, both practical and normative, to resist attempts to do so.

We explore in greater detail in Part II how well such transformation works: what is lost and entrenched in the process, what is the effect on the political economy of prediction value, and what are some legal issues that arise along the way. Prediction value confounds traditional approaches to regulating and apprehending value in law. This is a problem insofar as many areas of law (following the ‘if there’s no price, there’s no value’ view) do not register, apprehend, or count as significant forms of value production that do not readily convert into exchange value.⁴⁷ As we survey in Part II, many legally and normatively relevant decisions regarding the information economy and its effects on the social world occur well before prediction value converts into exchange value, if it ever converts at all.

⁴⁴ Marc Porat, *Definition and Measurement*, 1 *The Information Economy* (U.S. Government Printing Office 1977). As Babe and others note, focusing on the ‘inputs’ of information production alone (the activity) still only partially captures total prediction value. See Babe, *supra* note 6.

⁴⁵ See e.g., Alessandro Acquisti, *The Economics of Privacy at a Crossroads*, NBER (2022), available at <https://www.nber.org/system/files/chapters/c14785/c14785.pdf>; Alessandro Acquisti & Hal R. Varian, *Conditioning Prices on Purchase History*, 24 *MARKETING SCI.* 367 (2005).

⁴⁶ See Sadowski, *supra* note 8.

⁴⁷ Ronald Coase was a very astute observer of how a great deal of firm activity and production prefigured pricing. See generally Sanjukta Paul, *On Firms*, 90 *U. CHI. L. REV.* (forthcoming 2023).

C. *Why Datafy?*

Now we must address a possible objection from the other direction: If prediction value is not readily reducible to price, then perhaps the appropriate thing to study is not “prediction value” (which, the argument goes, still concedes too much to corporate claims that value is, indeed, being created from the datafication of social life), but instead to focus on the effects of the platform economy on autonomy and epistemic justice issues regarding “knowledge production”.

There is some merit to this view: this Article does not focus on the effects of datafication on social life, but instead on its cultivation as a media of prediction value.⁴⁸ Which is to say, it is not focused on ‘knowledge’ or ‘worldbuilding’ *per se*, but a particularly engineered form of insight. Prediction value reflects entities’ *capacity* to predict and manage behavior based on the knowledge-forms they have stored and cultivated. Capacity is not the same thing as using that capacity. Similar to power in the physical sense, prediction value is a stored *potential* to convert into an effect.

The concepts of social data value accumulation and knowledge economy distortion are related. After all, in the flurry of activity that accompanies the datafication of social life, companies *are* engaged in worldbuilding, creating a peculiar kind of knowledge of the social world that crowds out, destroys, and replaces others. What’s more, entities are acting on/enacting that knowledge back onto the world, in ways that are both inscrutable, and perhaps, worryingly, quite powerful.

The relation between knowledge production, profit accumulation, and power preoccupies several observers. For example, Zuboff is clearly concerned with issues of epistemic justice that arise from the walled gardens and skewed paths of platform knowledge formation.⁴⁹ Others raise concerns about the

⁴⁸ One of us does focus on this in other work; see Viljoen, *supra* note 4; Salome Viljoen *Data as Property?*, PHENOMENAL WORLD (2020).

⁴⁹ Shoshanna Zuboff, *The Coup We are Not Talking About*, N.Y. TIMES, Jan. 29, 2021 at <https://www.nytimes.com/2021/01/29/opinion/sunday/facebook-surveillance-society-technology.html> (“In an information civilization, societies are defined by questions of knowledge — how it is distributed, the authority that governs its distribution and the power that protects that authority. Who knows? Who decides who knows? Who decides who decides who knows? Surveillance capitalists now hold the answers to each question, though we never elected them to govern. This is the essence of the epistemic coup”); Lauren Jackson, *Shoshana Zuboff Explains Why You Should Care About Privacy*, N.Y. TIMES, May 21, 2021, <<https://www.nytimes.com/2021/05/21/technology/shoshana-zuboff-apple-google-privacy.html>> (“Instead of this being a golden age of the democratization of knowledge, it’s turned into something very different from what any of us expected. The last 20 years have seen, especially the last decade, the wholesale destruction of privacy.”)

challenges of cultivating self-knowledge and the capacity of self-formation in the shadow of such ‘surveillance empires.’⁵⁰ Still others (including one of us) consider the impact that the private curation of social knowledge forms has on public scientific inquiry and the future of social scientific work.⁵¹

These concerns, while important, are not the central focus here. We are more interested in the political economic factors *driving* these developments. Focusing on prediction value helps home in on two questions: first, *why* companies are using time and money and energy to collect data and produce these ‘knowledge artifacts’ to begin with. And second, if managing access to information has always been a source of power, why is it worth paying particular attention to prediction value, in the form of social data, *now*.

Social data does not exist in the ether. It costs money to collect and store and analyze. Data centers must be rented, staffed, and kept cool.⁵² Engineers and designers must be hired to design the technology environments in which data is collected, privacy managers retained to bring such environments into compliance.⁵³ Data scientists must be hired to make sense of data and use it. It is undoubtedly true that some amount of these costs invoiced against future prediction value are puffery and speculation.⁵⁴ So why are companies spending so much time and effort and money on social data? We think at least part of the answer is that companies are using time and energy and resources to collect and store and ‘produce’ this form of knowledge *because* it is indeed valuable to them, in some form or another. Companies are not, as a rule, engaged in ‘anti-democratic’ knowledge production for no reason, or due to conscious malevolence.⁵⁵ To understand those effects, it’s worth thinking deeply about their causes.

Entities looking to exert influence have long used the controlled management of information to engage in worldmaking, to understand and shape human behavior.⁵⁶ But only recently has it been economically feasible to mine,

⁵⁰ See generally ZUBOFF, *supra* note 9; BRETT FRISCHMANN & EVAN SELINGER, RE-ENGINEERING HUMANITY (2018).

⁵¹ Jathan Sadowski, Salomé Viljoen & Meredith Whittaker, *Everyone should decide how their digital data are used—not just tech companies*, NATURE, July 1, 2021; Christopher Morten, Gabriel Nicholas & Salomé Viljoen, *Researcher Access to Social Media Data: Lessons from Clinical Trial Data Sharing*, BERKELEY TECH. L. J. (forthcoming).

⁵² Dan Greene, *Landlords of the Internet: Big Data and Big Real Estate*, 52 SOC. STUD. OF SCI. (2022).

⁵³ ARI E. WALDMAN, INDUSTRY UNBOUND (2021)

⁵⁴ TIM HWANG, SUBPRIME ATTENTION CRISIS (2020).

⁵⁵ ZUBOFF, *supra* note 9.

⁵⁶ SARAH E. IGO, THE KNOWN CITIZEN: A HISTORY OF PRIVACY IN MODERN AMERICA (2018).

store, and generate prediction value at scale.⁵⁷ In other words, it takes a particular set of conditions for the accumulation of prediction value to become an imperative of commercial competitive success. These conditions include innovations in the cultivation, storage, transfer, aggregation, and combination of social data.⁵⁸ Improvements in microchip manufacturing and processing capacity, global supply chain optimization, the ubiquity of smart devices, and improvements in data science and machine learning techniques (to make sense of large-scale and continuous data flows), have all contributed to the feasibility and utility of exploiting social data for prediction value at scale.

These innovations in turn allow entities to exploit for economic value that which has long been true. People are social beings, deeply knowable and materially influenced by our relations to one another. This capacity for social data to be stored, mined, and exploited for prediction value, which in turn leads to hegemonic market pressure to datafy social life for exploitation and accumulation, is what demarcates informational capitalism from its predecessors.

We think separating out our study of data's prediction value and its exchange value may prove helpful to understanding some challenges law faces in governing social data production and the political economy organized around such production.

As an initial matter, distinguishing prediction and exchange value is helpful for diagnosing how and why entities go about cultivating, storing and exploiting social data for gain, and how these activities meet, challenge, and transform legal forms. This is the primary project of Parts II and III below. Clarifying the two modes of value production may also help index the chicanery that is, admittedly, rampant among certain corners of the digital economy, where overblown claims of how these two forms of value relate to one another may be used to obscure and befuddle. Understanding with greater specificity how prediction value is used, and how it may both be translated or transformed into exchange value and resist easy alchemy, is what we turn to in Part II below.

⁵⁷ Consider a simple analogy to energy. In its natural form, as water, lightning, sun and wind, energy has always existed and has long been known to be a useful source of power. But it was only over the course of the 19th century that people developed the techniques to store and transmit energy (and obtained the necessary economic conditions to make their adoption feasible). This is when energy's capacity or power to do work (i.e. generate heat and light) could play a transformative role in the political economy.

⁵⁸ Julie Cohen provides an in-depth review of the rise of these historical and technological conditions. See COHEN, *supra* note 2.

II. THE BUSINESS OF SOCIAL DATA

Social data as a value form has encouraged the growth of business models and corporate behaviors that leverage prediction value to produce both wealth and power for companies and their investors. These business models and behaviors have important normative and legal implications. The capacity of our existing law to grapple with those implications varies and is, in many cases, inadequate. This part begins by cataloging three scripts that companies take when leveraging prediction value. It then describes the business models and practices that have emerged as companies pursue these three scripts, models and practices which have important normative and legal implications.

A. The Three Scripts

This subpart catalogs three scripts that companies take when attempting to leverage prediction value and the business models and practices associated with those paths. These three scripts are not mutually exclusive. Companies may engage in different scripts at different points in their corporate lives. Some companies may never engage in some of the scripts. Some companies may engage in multiple scripts simultaneously. These companies may either engage in multiple scripts within a single business line or, perhaps more commonly, may operate in multiple business lines that are engaging in different scripts.

The first script is direct conversion of prediction value into exchange value. This direct conversion transforms data about people into money for companies through means such as targeted advertising. The second script is indirect conversion of prediction value into exchange value by leveraging prediction value to improve products and services, reduce costs, develop new products and services, and expand into different business lines and industries. The third script is not directly focused on converting prediction value into exchange value. Instead, in the third script, companies focus on transforming data about people into economic and political power, but not necessarily money, for companies.

1. Directly Converting Prediction Value into Exchange Value

There are three basic means through which companies can transform data about people into money for companies, thereby converting prediction value to exchange value.⁵⁹ They can sell or license social data. They can use social

⁵⁹ This discussion focuses on converting prediction value to exchange value at the company-level through business revenues and profits. As is discussed in more detail below, companies can also convert prediction value into exchange value at the investor-level to the extent that prediction value is reflected in the market valuation of the company. *See supra* notes 127 to 132 and accompanying text. Whether prediction value is realized as monetary exchange

data to predict and modify behavior. Or they can use social data to develop or improve products and services, earning profits through the eventual sale of these products or services.⁶⁰ The primary means through which direct conversion of prediction value into exchange value (the first script) are currently achieved by companies are either through the sale or license of social data or through targeted advertising, which is enabled by the use of social data to predict and modify behavior.⁶¹

Sale and license is the most obvious and legible way that companies can convert social data into money.⁶² The data brokerage industry has been valued at approximately \$200 billion.⁶³ Global revenues from data brokers were \$8.83 billion in 2022,⁶⁴ and annual global revenues for data brokers have been estimated to grow to \$34.04 billion by 2031.⁶⁵ The global market for location data alone was estimated to be \$14 billion in 2021, and that market has been predicted to grow at a mean annual rate of 15.6% through 2030.⁶⁶

While sale or license is the most apparent means of directly monetizing social data, it is not the most common means of direct monetization. The transformation of social data into an income-producing asset for companies can

value at the company- or investor-level has important ramifications for the effectiveness of legal regimes tasked with regulating value creation.

⁶⁰ David Stein, Presentation at the Privacy Research Group, NYU Law School (Feb. 26, 2020); David Stein, Presentation at the Information Law Institute, NYU Law School (July 15, 2020); Email from David Stein to Salomé Viljoen (Mar. 8, 2020) (on file with author).

⁶¹ As discussed in the following subpart, the ability to predict and modify behavior is also essential to pursuing the second script.

⁶² See DOUGLAS B. LANEY, *INFONOMICS: HOW TO MONETIZE, MANAGE, AND MEASURE INFORMATION AS AN ASSET FOR COMPETITIVE ADVANTAGE* 28 (2018). See also COHEN, *supra* note 2, at 48-74; BRUCE SCHNEIER, *DATA AND GOLIATH* 51-53 (2015). In addition to the sale or license of data, companies also use their data to barter with other businesses for goods and services. LANEY, *supra* note 62, at 29.

⁶³ David Lazarus *Shadowy Data Brokers Make the Most of Their Invisibility Cloaks*, L.A. TIMES, Nov. 5, 2019, <https://www.latimes.com/business/story/2019-11-05/column-data-brokers>. The global data brokerage industry does not exclusively trade in social data.

⁶⁴ Transparency Market Research, *Data Brokers Market, Global Industry Analysis, Size, Shares, Trends, and Forecasts, 2022-2031*, at 56 (July 2022).

⁶⁵ *Id.*

⁶⁶ Grand View Research, *Report Overview—Location Intelligence Market Size, Share & Trends Analysis Report By Application (Sales & Marketing Optimization, Remote Monitoring), By Service, By Vertical, By Region, And Segment Forecasts, 2022 - 2030*, available at <https://www.grandviewresearch.com/industry-analysis/location-intelligence-market> (last visited Sept. 27, 2022). See also Jon Keegan & Alfred Ng, *There's a Multibillion-Dollar Market for Your Phone's Location Data*, THE MARKUP, Sept. 30, 2021, <https://themarkup.org/privacy/2021/09/30/theres-a-multibillion-dollar-market-for-your-phones-location-data>.

take many forms other than a sale or license.⁶⁷ In reality, targeted advertising is the largest source of direct data monetization for companies.⁶⁸

Data about people allows companies to target their advertisements to the individuals who are most likely to be interested in the product.⁶⁹ Strollers are advertised to pregnant women but not teenage boys. Dutch ovens are advertised to avid cooks but not people who live on microwave dinners. Nicolas Negroponte presciently foresaw the potential of targeted advertising in the mid-1990s.⁷⁰ He presented the example of digital technology facilitating a person in the market for a car receiving nothing but car ads and, additionally, having those ads geographically tailored to include sales from local dealers.⁷¹ Social data collection by companies has enabled Negroponte's predictions to come to fruition. The social media platforms like TikTok collect data not only on their users activities on the platform but track their movements across hundreds of thousands of other websites, thus allowing them to gauge potential purchases and offer advertisers access to users with purchase intents that match the advertisers products.⁷²

Targeted advertising is a central way in which companies are able to take the prediction value that they draw from social data and turn it into exchange value. Companies can earn money by extracting social data, analyzing that data in order to divide people into categories based on salient features, and then auctioning ad space based on the premise that those ads are being properly targeted to the most relevant people.⁷³ For many tech companies, this means of leveraging prediction value constitutes the lion's share of their revenues. For example, more than eighty percent of Alphabet's revenues came from online

⁶⁷ See LANEY, *supra* note 62, at 28 ("Let's dispel the notion right away that information monetization . . . is just about selling your data. It's much broader than that."); Birch & Muniesa, *supra* note 27, at 2.

⁶⁸ See Beauvisage & Mellet, *supra* note 28; Viljoen, *supra* note 4, at 586-87; DUNCAN MCCANN, NEW ECONOMICS FOUNDATION, I-SPY: THE BILLION DOLLAR BUSINESS OF SURVEILLANCE ADVERTISING TO KIDS 6 (May 18, 2021), *available at* https://iapp.org/media/pdf/resource_center/i_spy_the_billion_dollar_business_of_surveillance_advertising_to_kids.pdf; ZUBOFF, *supra* note 9, at 27-196.

⁶⁹ See JOSEPH TUROW, THE DAILY YOU: HOW THE NEW ADVERTISING INDUSTRY IS DEFINING YOUR IDENTITY AND YOUR WORTH 74-76 (2011); SCHNEIER, *supra* note 62, at 53-54.

⁷⁰ NICOLAS NEGROPONTE, BEING DIGITAL 179-80 (1995).

⁷¹ *Id.* at 179-80.

⁷² Shoshana Wodinsky, *TikTok will use your data to fuel its multibillion-dollar shopping mall—whether you know it or not*, MARKETWATCH, Oct. 25, 2022, <https://www.marketwatch.com/story/tiktok-will-use-your-data-to-fuel-its-multibillion-dollar-shopping-mall-whether-you-know-it-or-not-11666653414>.

⁷³ See NICK SRNICEK, PLATFORM CAPITALISM 56-57 (2017); Hal R. Varian, *Online Ad Auctions*, 99 AM. ECON. REV. PAPERS & PROCEEDINGS 430 (2009); ZUBOFF, *supra* note 9, at 63-98.

advertising in 2021.⁷⁴ Even more stark is Meta, Inc. 97.5% of the company's revenues came from advertising in 2021.⁷⁵ Targeted advertising directly translates prediction value into exchange value for companies. They are essentially selling to advertisers their capacity to predict which products will be most salient to specific consumers.

2. Indirectly Converting Prediction Value into Exchange Value

Sale and license of data as well as targeted advertising are direct ways in which companies transform data about people into revenues. But these methods of direct conversion are not the only means by which companies convert data about people into company revenues. Prediction value stemming from social data is used by companies to both improve and expand their business operations. Companies are also able to use social data and the prediction value it creates to improve products and services, reduce costs, develop new products and services, or even enter into entirely new business lines. These improvements and expansions indirectly convert prediction value into exchange value through increased revenues and lowered costs. The ability to predict and modify people's behavior increases a company's bottom line.

By collecting and analyzing social data to predict customer behaviors and identify inefficiencies, companies are able to improve their existing products and services, thereby increasing sales and lowering costs.⁷⁶ As Erik Brynjolfsson & Andrew McAfee explained, “[t]he data revolution has turned customers into unwitting business consultants, as our purchases and searches are tracked to improve everything from websites to delivery routes.”⁷⁷

While this emphasis on data collection and analysis is most strongly associated with Big Tech,⁷⁸ the use of prediction value to improve business

⁷⁴ Alphabet, Inc., Annual Report 9 (Form 10-K) (Feb. 1, 2022).

⁷⁵ Meta, Inc., Annual Report 50, 54 (Form 10-K) (Feb. 2, 2022). The company acknowledges in its annual report that “[w]e generate substantially all of our revenue from advertising.” *Id.* at 14.

⁷⁶ See LANEY, *supra* note 62, at 13 (2018).

⁷⁷ Erik Brynjolfsson & Andrew McAfee, *The Big Data Boom Is the Innovation Story of Our Time*, THE ATLANTIC, Nov. 21, 2011, <https://www.theatlantic.com/business/archive/2011/11/the-big-data-boom-is-the-innovation-story-of-our-time/248215/>.

⁷⁸ See, e.g., Michael Schrage, *Rethinking Networks: Exploring Strategies for Making Users More Valuable*, MIT Initiative on the Digital Economy, Research Brief Vol 1, 2016 (quoting “media infopreneur” Tim O’Reilly, who coined the term “web 2.0” as stating that “[a] true Web 2.0 application is one that gets better than more people use it. . . . [Google] gets smarter every time someone clicks on an ad. And it immediately acts on that information to improve the experience for everyone else.”).

operations is not limited to tech companies but has expanded into other industries. For example, by consolidating and analyzing databases, retailer Dollar General discovered a pattern of customer purchases peaking near closing time.⁷⁹ The company inferred from this that later store hours would better accommodate customer needs and saw a 9.5 percent increase in sales within a year.⁸⁰ Data analysis has also been used to improve services and outcomes in the healthcare industry.⁸¹ For example, Intel recently partnered with a French hospital and used big data analytics to produce 15-day predictions of emergency visits and hospital admissions, which then allowed the hospital to plan their staffing to meet the anticipated needs.⁸² Internally collected data about customers can also be combined with “extraprise” data (data collected by a person other than the company) to strengthen the prediction potential of the data.⁸³ For example, a children’s clothing retailer might find data about fertility rates by geographic areas a useful predictor for product demand.

Collecting and analyzing social data can also allow companies to reduce costs and lower risk. Fintech is an important example of this means of monetizing prediction value. Fintech platforms leverage a wide array of social data and machine learning techniques to make consumer lending decisions.⁸⁴ The social data used by fintech companies moves beyond measures such as income and credit scores that have traditionally been used by financial institutions and incorporates alternative data into their lending decisions.⁸⁵ This alternative data can range from personal health information to data gleaned from social media activity.⁸⁶ The prediction value that comes from this data allows fintech companies to make better decisions regarding the future creditworthiness of potential borrowers.⁸⁷ This allows fintech companies to

⁷⁹ LANEY, *supra* note 62, at 40.

⁸⁰ *Id.* at 40.

⁸¹ See Sabyasachi Dash et al., *Big data in healthcare: management, analysis, and future prospects*, 6 J. BIG DATA 1, 1 (2019).

⁸² KYLE AMBERT ET AL., INTEL, WHITE PAPER: FRENCH HOSPITAL USES TRUSTED ANALYTICS PLATFORM TO PREDICT EMERGENCY DEPARTMENT VISITS AND HOSPITAL ADMISSIONS 1 (2016), <https://www.intel.com/content/dam/www/public/us/en/documents/white-papers/french-hospital-analytics-predict-admissions-paper.pdf>.

⁸³ THOMAS M. SIEBEL, DIGITAL TRANSFORMATION: SURVIVE AND THRIVE IN AN ERA OF MASS EXTINCTION 78 (2019).

⁸⁴ See Chris Odet, *Consumer Bitcredit and Fintech Lending*, 69 Ala. L. Rev. 100, 105-07 (2018).

⁸⁵ Marco Di Maggio et al., *Invisible Primes: Fintech Lending with Alternative Data*, Nat’l Bureau of Econ. Res. Working Paper No. 29840, at 1 (Mar. 2022), https://www.nber.org/system/files/working_papers/w29840/w29840.pdf.

⁸⁶ Odet, *supra* note 84, at 104.

⁸⁷ See Di Maggio et al., *supra* note 85, at 26 (analyzing data from a fintech lender and determining that alternative data used by the company “exhibits substantially more predictive power with respect to the likelihood of default than credit score).

extend credit to borrowers who might not qualify absent this additional social data and has been associated with higher returns for the fintech companies extending those loans.⁸⁸

In addition to garnering prediction value from observational social data, companies often stage experiments to manufacture and gather further data from their customers in order to improve their business operations.⁸⁹ Companies such as Microsoft, Amazon, and Google each run more than 10,000 controlled experiments each year.⁹⁰ As Hal Varian, chief economist at Google revealed: “[t]here are about 1,000 [experiments] running at any one time, and when you access Google you are in dozens of experiments.”⁹¹ The purpose of these experiments range from improving user interfaces to improving ranking algorithms.⁹² Pricing experiments are also common for companies—how much will demand shift with changes in price?⁹³ These pricing experiments not only improve companies’ bottom lines but also have important legal ramifications because they allow companies to engage in predatory pricing behaviors that potentially violate antitrust law.⁹⁴ As with analysis of observational social data, this practice of constant experimentation is not limited to Big Tech but has also spread to companies such as big box retailers and airlines.⁹⁵ The prediction value that stems from users and customers data allows companies to develop new products and services more quickly, at a lower cost, and with less risk than companies were able to prior to the explosion of informational capitalism.⁹⁶

Companies can leverage the prediction value of social data to create entirely new products and services.⁹⁷ Prediction value allows companies to

⁸⁸ *Id.* at 26.

⁸⁹ See DAVID L. ROGERS, *THE DIGITAL TRANSFORMATION PLAYBOOK: RETHINK YOUR BUSINESS FOR THE DIGITAL AGE*, chp. 5, Overview (2016).

⁹⁰ Ron Kohavi & Stefan Thomke, *The Surprising Power of Online Experiments*, HARV. BUS. REV. (Sept.-Oct. 2017), <https://hbr.org/2017/09/the-surprising-power-of-online-experiments>.

⁹¹ Hal R. Varian, *Beyond Big Data*, PROCEEDINGS OF NABE ANNUAL MEETING 7 (Sept. 2013), <https://people.ischool.berkeley.edu/~hal/Papers/2013/BeyondBigDataPaperFINAL.pdf>.

⁹² *Id.* at 7.

⁹³ *Id.* at 7 (citing company requests for pricing experiments as “one of the most common requests for big data analysts”).

⁹⁴ See Christopher R. Leslie, *Predatory Pricing Algorithms*, 98 N.Y.U. L. REV. 49 (2023) (arguing that “algorithmic pricing undermines all three major theoretical arguments that predatory pricing is not a credible route to monopoly”).

⁹⁵ See Kohavi & Thomke, *supra* note 90.

⁹⁶ See ROGERS, *supra* note 89, at chp. 5, overview.

⁹⁷ See MIT Technology Review Custom, *The Rise of Data Capital 2* (2016), http://files.technologyreview.com/whitepapers/MIT_Oracle+Report-The_Rise_of_Data_Capital.pdf; Sadowski, *supra* note 8, at 6; LANEY, *supra* note 62, at 68. See generally Yuanzhu Zhan et al., *Unlocking the power of big data in new product development*, 270 ANNALS OF OPERATIONS RES. 577 (2016).

determine which products and services will be most desirable and useful to customers and users by taking into account knowledge that they have on their preferences and needs from analyzing social data.⁹⁸ The prediction value derived from vast amounts of social data replaces traditional product development strategies that relied on expert intuition and smaller data gathering activities such as focus groups, leading to a lower risk and more efficient approach to product development.⁹⁹ This, in turn, indirectly creates exchange value for companies through lower costs and higher revenues.

An example of this can be seen in Netflix's foray into becoming a creator of entertainment content rather than simply a streaming service for third-party content. Netflix came into the world of content creation with the advantage of social data on the viewing habits of millions of subscribers. Through this social data, Netflix was able to predict factors that would lead to the success of newly-created shows, such as the appeal of different subject matters and actors.¹⁰⁰ Its first original series, *House of Cards*, debuted in 2013 to great success, and the company continues to leverage prediction value when creating original content.¹⁰¹

Prediction value from social data gathered in one industry can also be used by companies to gain a competitive advantage as they expand into other industries. For example, an airline has leveraged prediction value stemming from social data in its loyalty programs to expand into the insurance industry.¹⁰² TikTok and other social media companies have attempted to integrate shopping directly onto their platforms, using data on users to predict the products they are most likely to buy.¹⁰³ This business model is referred to as "social commerce." Verily, a life sciences company owned by Alphabet, Inc., Google's parent company, entered the data-driven life sciences space with the advantage of Google's data processing power¹⁰⁴ and has since used its data to expand into the health insurance market.¹⁰⁵ Using prediction value to gain competitive

⁹⁸ See Zhan et al., *supra* note 97, at 580.

⁹⁹ See ROGERS, *supra* note 89, at chp. 5, overview.

¹⁰⁰ Jon Markman, *Netflix Harnesses Big Data to Profit From Your Tastes*, FORBES (Feb. 25, 2019), <https://www.forbes.com/sites/jonmarkman/2019/02/25/netflix-harnesses-big-data-to-profit-from-your-tastes/?sh=1aa093d266f>.

¹⁰¹ *Id.* ("Netflix is quietly transforming the entertainment industry with data.")

¹⁰² Alex Koster & Konrad von Szczepanski, *Building a Business from Data Is Hard—Here's How the Winners Do It*, BOSTON CONSULTING GROUP (June 24, 2020), <https://www.bcg.com/publications/2020/how-winners-build-business-from-data>.

¹⁰³ Wodinsky, *supra* note 72.

¹⁰⁴ Sean Captain, *Google Life Sciences Rebrands As Verily, Uses Big Data To Figure Out Why We Get Sick*, FAST COMPANY, Dec. 7, 2015, <https://www.fastcompany.com/3054352/google-life-sciences-rebrands-as-verily-uses-big-data-to-figure-out-why-we-get-si>.

¹⁰⁵ Heather Landi, *Alphabet's Verily breaks into stop-loss health insurance market backed by Swiss Re*, FIERCE HEALTHCARE, Aug. 25, 2020,

advantage in other industries drives many of the aggressive merger and acquisition strategies that are discussed in more detail in Part II.b.3 below.

3. Converting Prediction Value to Economic and Political Power

The first two scripts of informational capitalism both involve social data being used to generate monetary exchange value for companies. They involve leveraging prediction value to achieve business profits, albeit in ways that are often different in normatively and legally relevant ways from the ways companies have earned money in the pre-informational capitalist world. The third script is different. In the third script, a company's focus is not to use social data to produce business profits. Instead, the company's focus is to use social data and prediction value to achieve economic and political power. This economic and political power might ultimately create monetary wealth for companies and their investors.¹⁰⁶ While monetary wealth might ultimately be achieved, the role of social data as a factor of production in the third script is to produce power.¹⁰⁷ Power is at the center of the third script.

The concept that mere control over a valuable resource brings with it power has been highlighted by legal scholars outside the context of informational capitalism. Within tax law, for example, this concept has colored debates around normative justifications for the consumption and wealth taxes as well as the corporate tax. Numerous tax scholars have argued that a person's consumption is the ideal tax base from both an efficiency and equity perspective.¹⁰⁸ But a frequent critique of using consumption as a tax base is that it ignores the power the mere possession of wealth brings with it, regardless of

<https://www.fiercehealthcare.com/payer/alphabet-s-verily-breaks-into-stop-loss-health-insurance-market-backed-by-swiss-re>.

¹⁰⁶ See *infra* notes 127 to 134 and accompanying text (discussing social data's impact on market capitalization and the possibility of supra-normal profits for companies that achieve certain levels of market concentration and power).

¹⁰⁷ Some readers may reject the assertion made by us and other scholars upon whose work we draw, see notes 108 to 126 and accompanying text, that the third script is distinct from the second script. They could argue that all companies ultimately exist to earn profits and any delay in converting prediction to exchange value is merely a strategy to achieve greater exchange value in the future. For the reasons articulated in this subpart, we contend that power alone is a driver of company behavior. However, our central argument—that various legal fields are failing to properly recognize social data as a value form and that these failures pose significant potential harms—holds even in the absence of the third script being a separate driver of company behavior.

¹⁰⁸ See generally William D. Andrews, *A Consumption-Type of Cash Flow Personal Income Tax*, 87 HARV. L. REV. 1113 (1974); Richard L. Doernberg, *A Workable Flat Rate Consumption Tax*, 70 IOWA L. REV. 425 (1985); Edward McCaffery, *The Uneasy Case for Wealth Transfer Tax*, 104 YALE L. J. 283 (1994).

whether that wealth is actually consumed.¹⁰⁹ More recently, this power stemming from the mere possession or control of something that is valuable has been cited as a rationale for imposing a wealth tax on individuals.¹¹⁰ Tempering the level of resources under the control of corporate management and the accompanying economic and political power that resource control brings has also been put forward as a justification for the corporate tax.¹¹¹ Legal scholars outside of tax law have likewise cited the link between concentrations of economic resources and power and the potentially negative ramifications for our democracy.¹¹²

The idea that control over something valuable brings with it power is not an unfamiliar concept in legal scholarship, nor is the idea that people or firms might accrue valuable resources for the sake of garnering power. But the conceptualizations discussed thus far still have a very clear connection to exchange value. The valuable thing, the wealth, is easily defined in terms of money, whether that be the cash in someone's bank account or a company's financial statements. With the advent of informational capitalism, this clear link to exchange value is broken.

In informational capitalism, power stems from the predictive capacities firms possess because of their control of social data. It is the control over prediction value that confers power onto firms. Scholars outside of the law have highlighted the power stemming from predictive power in the absence of money. For example, Castells, Schiller, Gandy, Mosco & Wasco all worked on the notion that social data confers a form of power, of governing capacity, onto its cultivators, and that the transformation of the activity of harvesting and exploiting this governance form into a market imperative is a key marker of capitalism's informational turn.¹¹³ Economist Joseph Stiglitz has also explored

¹⁰⁹ See, e.g., Anne L. Alstott, *The Uneasy Liberal Case Against Income and Wealth Transfer Taxation: A Response to Professor McCaffery*, 51 TAX L. REV. 363, 371 (1996); Barbara H. Fried, *Who Gets Utility from Bequests? The Distributive and Welfare Implications for a Consumption Tax*, 51 STAN. L. REV. 641 (1999); Edward D. Kleinbard, *Capital Taxation in an Age of Inequality*, 90 S. CAL. L. REV. 593, 640 (2017).

¹¹⁰ See, e.g., JEREMY BEARER-FRIEND, RESTORING DEMOCRACY THROUGH TAX POLICY 10-11 (Dec. 2018); Ari Glogower, *Taxing Inequality*, 93 N.Y.U. L. REV. 1421, 1422, 1445-50 (2018).

¹¹¹ See, e.g., Reuven Avi-Yonah, *Corporations, Society, and the State: A Defense of the Corporate Tax*, 90 VA. L. REV. 1193, 1233-41 (2004); BEARER-FRIEND, *supra* note 110, at 5.

¹¹² See generally Jedediah Britton-Purdy et al, *Building a Law-and-Political-Economy Framework: Beyond the Twentieth-Century Synthesis*, 129 YALE L. J. 1784 (2020); GANESH SITARAMAN, THE CRISIS OF THE MIDDLE-CLASS CONSTITUTION: WHY ECONOMIC EQUALITY THREATENS OUR REPUBLIC (2017).

¹¹³ See Part I *supra* for discussion of scholars in law as well as information and communication that have studied the power and control of information systems and their predictive capacity.

the negative implications of corporations deriving excess power and wealth based on their ability to exploit data.¹¹⁴ Cecilia Rikap has identified that the concentration of knowledge in a handful of companies through their possession of large quantities of data has created “intellectual monopolies” and has warned of the power implications of these monopolies.¹¹⁵

And legal scholars have also addressed the power of prediction value. For example, Katharina Pistor explores the relationship between prediction value and power in an article investigating the unexpected outcome of oligopothic power in the digital economy.¹¹⁶ Pistor’s work is particularly relevant to this Article’s account because it explores business outcomes in informational capitalism that do not align with what traditional economic analysis prescribes. Under a Coasean framework, the declining transaction costs in the digital economy should lead to the decline of the firm and a turn to markets.¹¹⁷ Instead, a small set of “Big Tech” firms have come to dominate the digital economy. Pistor highlights the power that Big Tech wields as a result of their control of data and that data’s predictive capacity in explaining the oligopolitic turn of the digital economy.¹¹⁸ She explains that:

[I]n the world of big data controlled by Big Tech, data are not primarily objects of exchange transactions; rather, they are both the source for and the means of *control* by Big Tech and their clients over others: consumers of goods and services, workers, voters, members in organizations, or whatever other targets they might choose.¹¹⁹

Pistor further explains that “[t]he worth of data does not lie in their exchange value but in the power they confer on data controllers”¹²⁰ and cites “creating asymmetries of power” as a defining characteristic of Big Tech.¹²¹ Informational capitalism transacts in power, that power stems from the

¹¹⁴ See generally JOSEPH E. STIGLITZ, *PEOPLE, POWER, AND PROFITS: PROGRESSIVE CAPITALISM FOR AN AGE OF DISCONTENT* (2019).

¹¹⁵ See Rikap, *Capitalism as Usual?*, *supra* note 29, at 159; Rikap, *From global value chains*, *supra* note 29, at 149.

¹¹⁶ See generally Pistor, *supra* note 10, at 101-04.

¹¹⁷ See *id.* at 101-04.

¹¹⁸ See *id.* at 105 (2020) (“In fact, power seems a better explanation for the rise of Big Tech than the standard transaction cost arguments.”).

¹¹⁹ *Id.* at 104 (emphasis added).

¹²⁰ *Id.* at 105.

¹²¹ See *id.* at 103.

Economist Jean Tirole reached similar conclusions to Pistor. He identifies the “soft control” that private companies, governments, and other organizations can achieve through control over social data. See Tirole, *supra* note 31.

prediction value of social data, and more social data leads to greater prediction value, leading to the rise of Big Tech oligopolies.

Other legal scholars have likewise explored the role of power in the digital economy. Julie Cohen constructs a forceful analysis of how technology, ideology, and the law have together produced power for informational capitalism's winners in her book *Between Truth and Power*.¹²² Cohen chronicles the ways in which the law has facilitated the rise of power within informational capitalism as well as the way those powerful interests are now attempting to use law to protect against countermovements to their rise in power.¹²³ In other work, Cohen has argued that the power wielded by some platform firms has potentially tipped into a form of sovereignty.¹²⁴ Frank Pasquale has highlighted the ways in which tech firms have used “obfuscation and secrecy to consolidate power and wealth.”¹²⁵ This scholarship demonstrates an understanding of the centrality of power in informational capitalism.¹²⁶

When a company leverages prediction value to amass power, this power can eventually result in exchange value at both the investor and company level. The forms that this exchange value takes for companies that have pursued the third script and amassed power have important legal ramifications. One way that the power achieved via the third script translates into exchange value is through increased market capitalization of a company. Increased market capitalization translates into exchange value for investors when they are able to sell their appreciated shares of company stock—it is investor-level, rather than firm-level, gain. Companies are able to frame their users and their users' data to investors as a measurable asset in a process that scholars have described as “techcraft.”¹²⁷ By presenting user metrics in a way that is legible to investors, companies transform social data and the prediction value it stores into an asset that investors take into account in the market valuation of a company.¹²⁸ The role of social data in rising market capitalizations of companies is clearly reflected in the

¹²² COHEN, *supra* note 2.

¹²³ See COHEN, *supra* note 2, at 11-13, 139-141.

¹²⁴ Julie E. Cohen, *Law for the Platform Economy*, 51 U.C. Davis L. Rev. 133, 199 (2017) (“Dominant platforms’ role in the international legal order increasingly resembles that of sovereign states. And even as they evade the obligations of domestic legal regimes, platform firms are actively participating in the ongoing construction of new transnational institutions and relationships that are more hospitable to their interests.”)

¹²⁵ FRANK PASQUALE, *THE BLACK BOX SOCIETY* 14 (2015).

¹²⁶ For further discussion in the legal academic literature of the relationship between data and power, see Kapczynski, *supra* note 10, at 1515; Marian, *supra* note 10, at 550-51; Maurice E. Stucke, *Should We Be Concerned About Data-Opolies?* 2 GEO. L. TECH. REV. 275, 312-323 (2018); Lina M. Khan, *Sources of Tech Platform Power*, 2 Geo. L. Tech. Rev. 325 (2018).

¹²⁷ See generally Birch et al., *supra* note 26.

¹²⁸ See *supra* notes 26 to 28 and accompanying text (discussing the process of assetization of data).

trend of many dominant companies achieving extremely high market values despite running losses. For example, when Microsoft acquired LinkedIn in 2016, the firm was a loss company.¹²⁹ But it had a network of 433 million users and an “enormous amount of data” on those users.¹³⁰ Microsoft paid \$26 billion to acquire the firm.¹³¹ And Amazon’s market capitalization rapidly rose even in periods when it was reporting regular losses.¹³² The fact that exchange value is realized at the investor level but not at the firm level, is an atypical result that presents important challenges for legal regimes trying to govern informational capitalism.

When a company amasses economic and political power, it may also translate to exchange value at the firm-level. Political power can bring with it the ability to secure favorable regulatory treatment, which can lower a company’s costs and improve their bottom-lines. A company that has amassed substantial power can also secure market dominance, which may put them in a position to demand supranormal profits. Kean Birch and D.T. Cochrane have identified this expectation of future high profits from digital firms that have achieved market dominance as a new form of rentiership that has emerged in informational capitalism, which they describe as “expected monopoly rents.”¹³³ And there is evidence that dominant digital firms have in many cases been able to command these very high profits after achieving market dominance.¹³⁴ In these ways, the power that social data produces for companies may ultimately lead to monetary gains if that power itself is leveraged into exchange value.

The three scripts that firms follow to leverage prediction value—directly converting prediction value to exchange value, indirectly converting prediction value to exchange value, and converting prediction value into economic and

¹²⁹ Kerry Flynn, *LinkedIn earnings are just fine ahead of Microsoft merger*, MASHABLE, Aug. 4, 2016, <https://mashable.com/article/linkedin-earnings-ahead-of-microsoft-merger> (reporting that LinkedIn posted losses of 89 cents per share in 2016 and 53 cents per share in 2015).

¹³⁰ Sarah McBride, *Microsoft to buy LinkedIn for \$26.2 billion in its largest deal*, Reuters, June 13, 2016, <https://www.reuters.com/article/us-linkedin-m-a-microsoft/microsoft-to-buy-linkedin-for-26-2-billion-in-its-largest-deal-idUSKCN0YZ1FP>.

¹³¹ *Id.*

¹³² See Khan, *supra* note 11, at 748-49.

¹³³ Birch & Cochrane, *supra* note 27, at 50-51.

¹³⁴ See, e.g. Shivaram Rajgopal et al., *Do Digital Technology Firms Earn Excess Profits?*, CA. MANAGEMENT REV., Nov. 19, 2020, <https://cmr.berkeley.edu/2020/11/do-digital-technology-firms-earn-excess-profits/> (finding digital firms to achieve large profit margins as compared to other industries); MAJORITY STAFF OF H. SUBCOMM. ON ANTITRUST, COMMERCIAL & ADMINISTRATIVE LAW, H. COMM. ON THE JUDICIARY, INVESTIGATION OF COMPETITION IN DIGITAL MARKETS 175 (Comm. Print 2020) (reporting that Google reported profit margins more than three times that of the average U.S. firm in 9 of the previous 10 years); PIERRE COLLIN & NICOLAS COLIN, TASK FORCE ON TAXATION OF THE DIGITAL ECONOMY 44 (Jan. 2013) (noting high profit margins for most Big Tech firms).

political power—have precipitated certain business models and strategies that have become prevalent in the wake of informational capitalism. The following subpart describes and analyzes those business models and practices.

B. The Business Models and Practices of Informational Capitalism

Many of the business models and practices of informational capitalism focus on growth and expansion.¹³⁵ Firms focus on growing their user and customer bases, increasing the amount of social data they are able to collect and fueling positive network effects. Firms also leverage prediction value to expand their product offerings, creating entire ecosystems to draw in users and customers, and to expand into entirely new industries. These growth and expansion strategies typically eschew profits (at least in the short or medium term) in favor of building up prediction value and access to streams of social data. The firms can then leverage that prediction value to achieve greater profits and power in the future. This subpart analyzes three business models and practices pursued by firms in informational capitalism. The first is offering free or low-cost services in order to build up user and customer bases, with the goal of achieving a dominant market status. The second is creating ecosystems of products and services that capture users and customers. The third is pursuing aggressive merger and acquisition strategies.

1. The Business of ‘Free’

Profits are not the central motivator for emerging firms in informational capitalism. These firms instead prioritize building up user and customer bases with the aim of achieving market dominance.¹³⁶ The role of social data as a mode of production is one reason for this. As discussed above,¹³⁷ the predictive power of social data relies on the ability to collect and analyze broad swaths of social data. Because “big” data requires systematic monitoring of large numbers of people, digital firms need to accrue large user and customer bases before they can fully realize the predictive capacity of social data. Building up a collection of data subjects is a necessary first step for firms to compete in an informational capitalist economy.

¹³⁵ The aim of this subpart is not to provide an exhaustive account of the business models and strategies seen within informational capitalism. Instead, the subpart highlights some key strategies that are both particularly prominent within informational capitalism and are significant for the legal regimes tasked with regulating these businesses.

¹³⁶ See Vijay Govindarajan et al., *Why Financial Statements Don’t Work for Digital Companies*, HARV. BUS. REV., Feb. 26, 2018 (describing “achieving market leadership” as “the most important aim” for digital firms); COLLIN & COLIN, *supra* note 134, at 28-29.

¹³⁷ See *supra* notes 22 to 30 and accompanying text.

Another reason that firms prioritize building up user and customer bases over profits has to do with the importance of platform business models within informational capitalism. Platform businesses use technology to connect users in a wide variety of value-creating interactions.¹³⁸ Platforms are key features of informational capitalism because they structurally facilitate tracking of users and data collection.¹³⁹ And platforms are also heavily reliant on network effects for the success of their businesses.¹⁴⁰ When a new platform is launched, there is little reason for a new user to join the platform because there is not an existing network of users with whom to interact. However, after a critical mass of users is reached, positive network effects begin to take over, which can lead to rapid growth of the platform and market dominance.¹⁴¹ At the point that market dominance is achieved, digital firms can, in theory, exploit their dominant market positions and begin to reap monetary profits.¹⁴² As Jathan Sadowski explains, “[T]he practice of acquiring data first—indeed, of designing things for the primary purpose of data extraction—and then (hopefully) figuring out how to valorise it later is now normal for organisations following the platform model.”¹⁴³

As a result, growing a network of users and customers is essential for digital firms, both to lock in access to flows of social data and to achieve the network effects necessary to achieve market dominance. In order to achieve this growth, digital firms eschew profits, often for very long periods of time. This method of eschewing profits is common amongst digital firms following all three of the scripts described above. One way they do this is by offering free services.¹⁴⁴ There is no fee to run a Google search, to post a photo to Instagram, or to stream music on Spotify. Firms offering free services will often still earn revenues in other ways, such as by selling targeted advertising¹⁴⁵ or charging a fee for premium versions of their services (known as the “freemium” business

¹³⁸ See generally GEOFFREY G. PARKER ET AL., PLATFORM REVOLUTION (2016).

¹³⁹ See Cohen, *supra* note 124, at 140-43 (describing the role of platforms in “the datafication of everyday life”); SRNICEK, *supra* note 73, at 42-43; Khan, *supra* note 126, at 329-30.

¹⁴⁰ See Stucke, *supra* note 126, at 281-83; CARL SHAPIRO & HAL R. VARIAN, INFORMATION RULES: A STRATEGIC GUIDE TO THE NETWORK ECONOMY 10-11 (1999); Michael L. Katz & Carl Shapiro, *Systems Competition and Network Effects*, J. OF ECON. PERSPECTIVES 93, 93-95 (1994).

¹⁴¹ See JEFFREY ROHLS, BANDWAGON EFFECTS IN HIGH-TECHNOLOGY INDUSTRIES 27-28 (2003). See generally WU, *supra* note 11.

¹⁴² See *supra* notes 127 to 134 and accompanying text.

¹⁴³ Jathan Sadowski, *The Internet of Landlords: Digital Platforms and New Mechanisms of Rentier Capitalism*, 52 ANTIPODE 562, 572 (2020).

¹⁴⁴ See Stucke, *supra* note 126, at 279; ZUBOFF, *supra* note 9, at 52-53. See generally CHRIS ANDERSON, FREE: THE FUTURE OF A RADICAL PRICE (2009).

¹⁴⁵ See *supra* notes 68 to 75 and accompanying text.

model).¹⁴⁶ Another strategy that allows firms to grow networks while still earning revenues is the use of predatory pricing algorithms to charge below market prices to competitors' customers and market prices to their own.¹⁴⁷ Despite the existence of these strategies, profit maximization is not the central goal for these digital firms—growth and its accompanying data collection is key.¹⁴⁸ For example, it is not until after its 2012 initial public offering (IPO) that Facebook began to expand its advertising sales.¹⁴⁹ The firm already had 800 million users at the time of the IPO.¹⁵⁰ This strategy of favoring growth over income can also be seen in acquisitions of digital firms where companies have sold for high market values despite not earning income.¹⁵¹ While providing free services can lower digital firms' bottom lines, it allows them to secure large networks and streams of social data from those network participants.

Other digital firms might not offer entirely free services to potential users and customers but will offer low-cost services designed to build up their network and data, often taking substantial losses in the process. Amazon's business strategy is a leading example of this. Amazon launched Amazon Prime in 2005.¹⁵² At an initial annual cost of \$79, the program offered free two-day shipping for customers and other features have been added onto the program over the years, such as streaming video services.¹⁵³ Lina Khan has written that “[t]he program has arguably been the retailer’s single biggest driver of growth,”¹⁵⁴ but “[a]s with its other ventures, Amazon lost money on Prime to gain buy-in.”¹⁵⁵ Khan cites an analyst who estimates that Amazon loses between \$1-2 billion per year through the Prime program.¹⁵⁶ This is part of a broader historical trend of Amazon eschewing profits in favor of growth for much of its corporate life.¹⁵⁷ It is only in recent years, after establishing market dominance,

¹⁴⁶ ANDERSON, *supra* note 144, at 26-27.

¹⁴⁷ See Leslie, *supra* note 94.

¹⁴⁸ SRNICEK, *supra* note 73, at 97 (“Unlike in manufacturing, in platforms competitiveness is not judged solely by the criterion of a maximal difference between costs and prices: data collection and analysis also contribute to how competitiveness is judged and ranked.”)

¹⁴⁹ Rebecca Greenfield, 2012: *The Year Facebook Finally Tried to Make Some Money*, THE ATLANTIC, Dec. 14, 2012, <https://www.theatlantic.com/technology/archive/2012/12/2012-year-facebook-finally-tried-make-some-money/320493/>; COLLIN & COLIN, *supra* note 134, at 28.

¹⁵⁰ Facebook, Inc., Registration Statement 1 (Form S-1) (Feb. 1, 2012).

¹⁵¹ See *supra* notes 129 to 132 and accompanying text.

¹⁵² Khan, *supra* note 11, at 750.

¹⁵³ *Id.* at 750.

¹⁵⁴ *Id.* at 750.

¹⁵⁵ *Id.* at 751.

¹⁵⁶ *Id.* at 751.

¹⁵⁷ *Id.* at 747-49.

that the firm has begun to report substantial profits.¹⁵⁸ Even then, the majority of those profits are derived from its cloud computing business line, with its other operations seeing lower margins or even losses.¹⁵⁹

The prevalence within informational capitalism of businesses choosing to not maximize their profits by offering free or low-cost services for extended periods of time is a result of the growing importance of social data as a factor of production and company's desire to build up this new value form. But this practice also defies many of the expectations of firm behavior, creating difficulties for legal regimes attempting to regulate these businesses.

2. Building Ecosystems

The building of ecosystems of products and services also typifies firm behavior within informational capitalism.¹⁶⁰ Google is not just a search engine. The firm has created an ecosystem that includes an email service (Gmail), an online word processing (Google Docs), a web browser (Chrome), a phone and accompanying mobile operating system (Android), among many, many other products and services.¹⁶¹ Apple's ecosystem ranges from hardware products like the iPhone and Apple Watches to services like iCloud storage and iMessaging to apps available via the Apple Store.¹⁶²

Ecosystem building serves many purposes. It is a mechanism for growth, allowing digital firms to build up user and customer bases, collect social data, and amass prediction value. Firms can create ecosystems in ways that lock-in users to that ecosystem, such as apps that are only compatible with the firm's operating system.¹⁶³ This lock-in guarantees flows of data.¹⁶⁴ Additionally, the more areas of a person's life a firm can collect data about, the more prediction

¹⁵⁸ See Amazon.com, Inc., Annual Report 38 (Form 10-k) (Feb. 3, 2022) (reporting net income of \$ 12 billion in 2019, \$21 billion in 2020, and \$33 billion in 2021).

¹⁵⁹ See *id.* at 24.

¹⁶⁰ See Birch & Cochrane, *supra* note 27, at 49-50; SRNICEK, *supra* note 73, at 95-96.

¹⁶¹ About Google, Browse All of Google's Products and Services, https://about.google/intl/en_us/products/ (last visited Dec. 16, 2022).

¹⁶² See, e.g., Thomas Ricker, *First Click: Apple's greatest innovation is its ecosystem*, THE VERGE, Sept. 7, 2016, <https://www.theverge.com/2016/9/7/12828846/apple-s-greatest-product-is-its-ecosystem>; Ian Sherr, *Apple's 'walled garden' walls will get even higher with iOS 14, iPadOS 14, and MacOS Big Sur*, CNET, July 2, 2020, <https://www.cnet.com/tech/mobile/apple-walled-garden-walls-will-get-even-higher-with-ios-14-ipados-14-macos-big-sur/>.

¹⁶³ Birch & Cochrane, *supra* note 27, at 49 (describing the approach of Big Tech companies "locking in users to their ecosystems, both legally (e.g. contractual agreements) and technically (e.g. interoperability restrictions)") (internal citations omitted).

¹⁶⁴ SRNICEK, *supra* note 73, at 96.

value the firm can amass.¹⁶⁵ For example, if Amazon has a map of your home, it can better anticipate what products you might be inclined to purchase for your home.¹⁶⁶ Ecosystem building provides access to both a greater quantity and greater variety of social data and fuels the positive feedback cycle of greater prediction power and further growth.

The greater prediction value drawn from ecosystems can be particularly useful for firms pursuing the second script—indirectly converting prediction value into exchange value by improving or developing new products and services. Having expansive ecosystems of products and services provides firms with the opportunities to use prediction value it has accrued in one part of its ecosystem and monetize it through another part of its ecosystem. As one tech entrepreneur explained: “[a]t large companies, sometimes we launch products not for the revenue, but for the data. We do that quite often . . . and we monetize the data through a different product.”¹⁶⁷ Because these products and services could be in different industries or different regions from those in which the social data was initially gathered, this business strategy presents important legal challenges.

The building of ecosystems can also be a useful tool for firms that follow the third script—leveraging prediction value to achieve power. Amazon’s creation of an ecosystem spanning broad arrays of business lines is reportedly part of founder Jeff Bezos’s vision to build the firm into a “‘utility’ that would become essential to commerce.”¹⁶⁸ Locking users into the ecosystem, closing out competitors and self-preferencing their own products, and controlling access to the data collected from the ecosystem, all contribute to firms consolidating economic as well as political power.¹⁶⁹

¹⁶⁵ See SRNICEK, *supra* note 73, at 95 (“[A]ccess to a multitude of data from different areas of our life makes prediction more useful, and this stimulates centralisation of data within one platform.”).

¹⁶⁶ See Ron Knox, *Amazon’s Dangerous New Acquisition*, THE ATLANTIC, Aug. 21, 2022, <https://www.theatlantic.com/ideas/archive/2022/08/amazon-roomba-irobot-acquisition-monopoly/671145/> (discussing Amazon’s purchase of the vacuum manufacturer iRobot and the implications of the data that Amazon could gather from smart vacuums for its retail business).

¹⁶⁷ Andrew Ng, *quoted in* Sadowski, *supra* note 143, at 572.

¹⁶⁸ Khan, *supra* note 11, at 754-55 (quoting Amazon employees).

¹⁶⁹ See ZUBOFF, *supra* note 9, at 179 (discussing the “unprecedented concentrations of knowledge and power” that companies like Google have achieved through ecosystem building); Birch et al., *supra* note 26, at 2 (describing the “social dominance” achieved by Big Tech firms through, among other factors, ecosystem governance and control over access to social data); U.N. CONFERENCE ON TRADE & DEVELOPMENT, POWER, PLATFORMS, AND THE FREE TRADE DELUSION vi-vii (2018), https://unctad.org/system/files/official-document/tdr2018_en.pdf (describing the concentration of market power through expansion of ecosystems).

3. Aggressive Acquisitions

Informational capitalism has brought with it an uptick in acquisitions. This can be seen particularly in the context of digital firms. Big Tech cash expenditures on acquisitions averaged \$23 billion in the period between 2010 and 2019—approximately three times the average for the top 200 global firms.¹⁷⁰ As of April 2021, since their respective foundings, Apple had acquired 123 companies, Amazon had acquired 111, Facebook had acquired 105, and Google had acquired 268.¹⁷¹

This business practice of aggressive acquisitions is part of the overall focus on growth and expansion within informational capitalism. Commentators have highlighted that many of these acquisitions have been primarily focused on acquiring data from the target company, so-called data-driven mergers.¹⁷² Facebook’s acquisition of WhatsApp has been cited as one example.¹⁷³ Google’s acquisition of Waze as another.¹⁷⁴ Building up prediction value is at the center of these transactions. Acquisitions by digital firms are often driven by the desire to acquire not only existing data but also user bases and future streams of data from those users. Acquiring other firms in order to gain access to their users is part of the growth strategy of leveraging network effects and building dominant market positions.¹⁷⁵ Microsoft’s 2016 acquisition of LinkedIn is an example of acquisition of a digital firm in order to gain access to a user base and their data. As discussed above,¹⁷⁶ LinkedIn was a loss company when Microsoft paid \$26 billion to acquire the company. But, as one analysis described, “[the acquisition was] a massive growth play for Microsoft.”¹⁷⁷ Microsoft highlighted the large customer base that the deal brought to them, as well as the potential for user data to improve their analytics and AI capacity.¹⁷⁸ Acquisitions can also be a method for digital firms to stamp out competition, making sure that they achieve and then maintain the dominant market positions that are necessary to preserve

¹⁷⁰ Birch et al., *supra* note 26, at 11.

¹⁷¹ Chris Alcantara et al., *How Big Tech got so big: Hundreds of Acquisitions*, THE WASHINGTON POST, April 21, 2021, <https://www.washingtonpost.com/technology/interactive/2021/amazon-apple-facebook-google-acquisitions/>.

¹⁷² See generally MAURICE E. STUCKE & ALLEN P. GRUNES, *BIG DATA AND COMPETITION POLICY* (2016).

¹⁷³ *Id.* at 124.

¹⁷⁴ *Id.* at 135.

¹⁷⁵ See Birch et al., *supra* note 26, at 11.

¹⁷⁶ See note 129 and accompanying text.

¹⁷⁷ McBride, *supra* note 130 (quoting analyst Ted Schadler).

¹⁷⁸ McBride, *supra* note 130.

and leverage their prediction value advantages.¹⁷⁹ As part of informational capitalism's overall focus on growth, aggressive acquisitions are an important business strategy for firms following all three of informational capitalism's scripts.

Another example of an acquisition that provided companies with access to a stream of social data (as well as expanding the company's ecosystem of services) is Google's acquisition of Fitbit. Google announced its intent to acquire Fitbit, a company that produces wearable fitness technology and had approximately 30 million active users and data on users' fitness and health spanning back a decade.¹⁸⁰ At the time, Google was attempting to pivot into the healthcare industry.¹⁸¹ The merger sparked concerns from antitrust authorities across the globe who were concerned about the implications of Google possessing that level of social data.¹⁸²

As the Google/Fitbit example illustrates, in addition to being a means to achieve growth and market dominance, acquisitions have also served as a means through which digital firms can expand into new business lines and build out ecosystems. Acquisitions are key for digital firms that follow the second script and use prediction value to develop and improve products and services. The majority of Big Tech's acquisitions have been acquisitions that expanded the firms outside of their original business lines and into new sectors. 78 percent of Apple's acquisitions, 64 percent of Amazon's acquisitions, 70 percent of Google's acquisitions, and 73 percent of Facebook's acquisitions have been of companies outside their original business lines.¹⁸³ Through these acquisitions,

¹⁷⁹ See MAJORITY STAFF OF H. SUBCOMM. ON ANTITRUST, COMMERCIAL & ADMINISTRATIVE LAW, H. COMM. ON THE JUDICIARY, INVESTIGATION OF COMPETITION IN DIGITAL MARKETS 11 (Comm. Print 2020). See generally C. Scott Hemphill & Tim Wu, *Nascent Competitors*, 168 U. PENN. L. REV. 1879 (2020).

¹⁸⁰ Lucas Griebeler Da Motta, *Why We Should Be Careful About Google's Promises in the Fitbit Deal*, PROMARKET, Aug. 21, 2020, <https://www.promarket.org/2020/08/21/why-we-should-be-careful-about-googles-promises-in-the-fitbit-deal/>.

¹⁸¹ See *supra* notes 104 to 105 and accompanying text.

¹⁸² See, e.g., Australian Competition & Consumer Commission, Statement of Issues: Google LLC-proposed acquisition of Fitbit Inc, para. 6, June 18, 2020, <https://www.accc.gov.au/system/files/public-registers/documents/Google%20Fitbit%20-%20Statement%20of%20Issues%20-%2018%20June%202020.pdf> ("The accumulation of additional, individual user data via this transaction in an entity which already benefits from substantial market power in multiple markets may contribute to reduced competitive outcomes in the future."); European Commission Press Release IP/20/1446, Mergers: Commission opens in-depth investigation into the proposed acquisition of Fitbit by Google (Aug. 4, 2020) ("The data collected via wrist-worn wearable devices appears, at this stage of the Commission's review of the transaction, to be an important advantage in the online advertising markets.").

¹⁸³ Alcantara et al., *supra* note 171. See also Khan, *supra* note 11, at 754.

firms are able to take the prediction value that they have built up through collecting social data in one context and apply it in another context.

Intuit's recent acquisition of Mailchimp is another useful example of this strategy. Intuit, a financial software firm, acquired Mailchimp, an email marketing platform in 2021 for \$12 billion.¹⁸⁴ Intuit's existing products included Credit Karma, Mint, and TurboTax, which provided the firm with data about individuals' personal finances and spending habits.¹⁸⁵ Quickbooks was another existing Intuit product, which provided the firm with customer sales data from small and mid-sized businesses.¹⁸⁶ Social data from Intuit's existing products on personal finance, spending habits, and customer sales could be used to predict and influence consumer behavior, and the firm can now use these insights in order to design more effective targeting of messages in an entirely new industry—email marketing.¹⁸⁷ As Intuit explained in an investor presentation on the acquisition, “[c]ustomer data and purchase data brought together creates actionable insights and opportunities for small business and mid-market growth.”¹⁸⁸ Acquisitions are a means through which digital firms can convert the prediction value that they accrue through one business activity into exchange value in an entirely new industry.

Informational capitalism has brought about seismic changes to our economy. As social data has emerged as a new mode of production, prediction value has emerged as a new value form. Firms have responded to these changes by following particular scripts and pursuing particular business models. As the next part will discuss, prediction value, these scripts and the business practices that have emerged run counter to many of the assumptions at the heart of a variety of legal regimes. As a result, various areas of the law are struggling to effectively govern informational capitalism.

¹⁸⁴ Press Release, Intuit, Inc., Intuit Completes Acquisition of Mailchimp (Nov. 1, 2021).

¹⁸⁵ Seeking Alpha, *Intuit: If Successfully Integrated, Credit Karma and Mailchimp Are Game Changers* (June 25, 2022), <https://seekingalpha.com/article/4520384-intuit-successfully-integrated-credit-karma-mailchimp-game-changers>.

¹⁸⁶ Gene Marks, *On CRM: How Intuit's Purchase of Mailchimp Will Kill Your Monthly Newsletter*, FORBES, Sept. 22, 2021, <https://www.forbes.com/sites/quickerbetteertech/2021/09/22/on-crm-how-intuits-purchase-of-mailchimp-will-kill-your-monthly-newsletter/?sh=337d85f5bdba>.

¹⁸⁷ See Seeking Alpha, *supra* note 185; Marks, *supra* note 186.

¹⁸⁸ INTUIT, INC. INVESTOR PRESENTATION: INTUIT'S ACQUISITION OF MAILCHIMP 11 (Sept. 13, 2021), *available at* https://s23.q4cdn.com/935127502/files/doc_presentations/2021/Intuit%27s-Acquisition-of-Mailchimp-Presentation.pdf.

III. LEGAL COLLISIONS

A. Two Camps of Legal Collisions

The challenges of grappling with social data and prediction value creates issues across several legal regimes. Below we focus on two: tax law and privacy and data protection law. These fields represent two “camps” of legal failings in the face of informational capitalism.

This first camp consists of fields of law that have historically been tasked with governing and regulating value creation. These fields are struggling to integrate value creation from social data into their existing regulatory regimes. The Article argues that these struggles stem from the failure to recognize prediction value as a distinct and separate value form that does not readily translate into exchange value. In addition to tax law, other legal fields included in this camp include antitrust law and financial regulation.

The second camp consists of fields of law that have not historically viewed themselves as having a role in governing and regulating value creation. This Article argues that the advent of social data as a factor of production and prediction value as a key and distinct mode of value creation has made regulating value creation an imperative for these fields. However, these fields are still grappling with their new role as primary governors of value creation under informational capitalism. As a result, while recent shifts in scholarly trends promise otherwise, these fields have not yet developed a positive agenda for regulating value creation. Recognizing prediction value as a form of value creation separate from exchange value can help inform this positive regulatory agenda. In addition to privacy and data governance law, other legal fields included in this camp include First Amendment law.

B. Taxing Prediction Value

Tax law is in the business of governing value creation. This business of governing value creation is in pursuit of three basic goals: to raise government revenues, to redistribute income and wealth, and to regulate private sector behavior.¹⁸⁹ In pursuit of these goals, the tax system strives to allocate burdens amongst taxpayers in a way that is equitable, efficient, and administrable.¹⁹⁰

¹⁸⁹ Reuven Avi-Yonah, *The Three Goals of Taxation*, 60 TAX L. REV. 1, 3 (2006).

¹⁹⁰ Avi-Yonah, *supra* note 189, at 26; Allison Christians, *Introduction to Tax Policy Theory*, Working Paper 10-11 (May 29, 2018), available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3186791.

Informational capitalism and the accompanying rise of prediction value as a dominant value form is colliding with tax law in two distinct ways. The first is a conceptual collision. Tax law scholars and policymakers are not recognizing and understanding prediction value as a new value form distinct from exchange value and, as a result, are inappropriately attempting to address tax law’s failures in the face of informational capitalism through an exchange value lens. The second collision relates not to prediction value itself but to informational capitalism’s scripts and resulting business practices. Our existing tax system produces results incongruent with the underlying goals of tax law when applied to these new and unfamiliar scripts and business practices.

1. A Conceptual Collision

Modern tax law is grounded in exchange value. At the end of the day, tens of thousands of pages of code and regulations, countless judicial and administrative decisions, and thousands of bilateral treaties boil down to numbers on a tax form, and these numbers represent the monetary value of income or, in the case of estate and gift taxation, wealth.¹⁹¹ The Internal Revenue Code does not contain a standard definition of “value.”¹⁹² But the hundreds of references to “value” in the code predominantly refer to fair market value—the price, or exchange value, that an asset would demand in an open market transaction.¹⁹³

Tax law’s conceptual equation of “value” with exchange value is stymying efforts to adapt tax law to informational capitalism. There is widespread agreement that tax law, particularly international tax law, is failing in the modern economy.¹⁹⁴ Assertions by politicians and governments that multinational corporations, particularly Big Tech companies, are not paying their “fair share” of taxes are common.¹⁹⁵ This concern over companies paying their

¹⁹¹ See Marian, *supra* note 10; Allison Christians & Laurens van Apeldoorn, *Taxing Income Where Value Is Created*, 22 FLA. TAX REV. 1, 10 (2018); CONGRESSIONAL BUDGET OFFICE, UNDERSTANDING FEDERAL ESTATE AND GIFT TAXES (June 2021), <https://www.cbo.gov/publication/57272>.

¹⁹² Shu-Yi Oei, *United States*, in TAXATION AND VALUE CREATION 669, 669 (Werner Haslehner & Marie Lamensch, eds. 2021) (“There is no singular coherent definition of value in the Code.”).

¹⁹³ *Id.* at 669.

¹⁹⁴ See, e.g., Mitchell Kane, *A Defense of Source Rules in International Taxation*, 32 YALE J. REG. 311, 311 (2015) (“The body of law generally labeled ‘international taxation’ is widely perceived to be in shambles.”); Lilian V. Faulhaber, *Taxing Tech: The Future of Digital Taxation*, 39 VA. TAX REV. 145, 149 (2019); COLLIN & COLIN, *supra* note 134, at 2.

¹⁹⁵ See, e.g., The Associated Press, *The G-7 Nations Agree To Make Big Tech Companies Pay Their Fair Share of Taxes*, NPR, June 5, 2021,

fair share is a matter not only of the total amount of tax paid but also to which countries those taxes are paid. The need to align the place of taxation with the place of “value creation” has been a frequent refrain amongst politicians and policymakers.¹⁹⁶

This political push to use the concept of value creation to determine which country gets to tax companies has been broadly criticized by academics.¹⁹⁷ The concept of value creation has been described as “a phrase that has no meaning in modern economics,”¹⁹⁸ an “unhelpful” and “fuzzy notion”¹⁹⁹ and “not even conceptually coherent as a theory.”²⁰⁰ The conversation surrounding aligning taxation with value creation exemplifies how exchange value continues to be at the center of tax policy discussions, despite the vital role of prediction value in the modern economy. It also exemplifies the harms caused by that continued focus. The concept of value creation is arguably unhelpful, fuzzy, and incoherent when value creation is viewed exclusively through the lens of exchange value. But, if academics and policymakers expand their notion of value creation to include prediction value, the move to align the place of taxation with the place of value creation would become more conceptually coherent.

<https://www.npr.org/2021/06/05/1003563505/the-g-7-nations-have-agreed-to-make-big-tech-companies-pay-their-fair-share-of-t> (quoting Rishi Sunak, then-British Treasury chief, as characterizing the G-7 agreement on international tax reform as “requiring the largest multinational tech giants to pay their fair share of tax in the UK.”); Richard Lough, *Explainer: Macron’s quest for an international tax on digital services*, Reuters (Aug. 22, 2019), <https://www.reuters.com/article/us-g7-summit-digital-tax-explainer/explainer-macrons-quest-for-an-international-tax-on-digital-services-idUSKCN1VC0VH> (describing frustration amongst political leaders regarding their inability to tax tech companies on profits they believe to be derived from business activities in their countries.).

¹⁹⁶ See, e.g. EUROPEAN COMMISSION, TIME TO ESTABLISH A MODERN, FAIR AND EFFICIENT TAXATION STANDARD FOR THE DIGITAL ECONOMY 4 (2018), https://eur-lex.europa.eu/resource.html?uri=cellar:2bafa0d9-2dde-11e8-b5fe-01aa75ed71a1.0017.02/DOC_1&format=PDF (explaining that a disconnect has emerged in the digital economy “between where the value is created, and where taxes are paid” and proposing reforms to correct this disconnect). See also Werner Haslehner & Marie Lamensch, *General Report on Value Creation and Taxation: Outlining the Debate in TAXATION AND VALUE CREATION* 3, 35 (Werner Haslehner & Marie Lamensch, eds. 2021); Andrew Hayashi & Young Ran (Christine) Kim, *Taxing Digital Platforms*, 26 VA. J. L. TECH. 1, 8 (2023).

¹⁹⁷ See Werner Haslehner, *Value Creation and Income Taxation: A Coherent Framework for Reform?* in *TAXATION AND VALUE CREATION* 3, 35 (Werner Haslehner & Marie Lamensch, eds. 2021).

¹⁹⁸ David Quentin, *Corporate Tax Reform & “Value Creation”*: Towards Unfettered Diagonal Re-allocation across the Global Inequality Chain, 7 ACCOUNT ECON. L. 1, 1 (2017).

¹⁹⁹ Wolfgang Schon, *Ten Questions About Why and How to Tax the Digitalized Economy* 22 (Max Planck Institute for Tax L. & Pub. Fin., Working Paper No. 2017-11).

²⁰⁰ Allison Christians, *Taxing According to Value Creation*, 90 TAX NOTES INT’L 1379, 1379 (June 18, 2018).

The problem is not that academics and policymakers are not recognizing the growing importance of social data in the economy. The unfairness of digital companies collecting and exploiting data from a country's residents without the company being subject to tax in those jurisdictions has been broadly cited.²⁰¹ This perceived unfairness has led to user participation proposals: reforms that would allocate taxing authority over digital companies' income to users' jurisdictions based on their contributions of data as well as content.²⁰² But, while the importance of social data is being recognized, the emergence of prediction value as a new value form is not. Conversations around reform are still trying to fit prediction value into the familiar exchange value mold. The difficulty of measuring and attributing income to users' data creation has been cited as a barrier to user participation proposals as well as taxing based on value creation more generally.²⁰³ That difficulty of measurement stems from the conceptual incoherence of trying to translate prediction value into monetary exchange value.

Outside of the "taxing where value is created" debate, much of the discussion in policy and academic circles surrounding the appropriate taxation of the data economy is seen through this same exchange value lens. Assigning an accurate market value to data in order to tax it is an oft-cited challenge,²⁰⁴ as is the "cash-less" nature of transactions between data subjects and data collectors.²⁰⁵ These discussions show a continued focus on fitting the square peg of prediction value into the round hole of our exchange-value based tax system.

²⁰¹ See, e.g., EUROPEAN COMMISSION, *supra* note 196, at 4; COLLIN & COLIN, *supra* note 134, at 53-54.

²⁰² See, e.g., OECD/G20 BASE EROSION & PROFIT SHIFTING PROJECT, PUBLIC CONSULTATION DOCUMENT, ADDRESSING THE TAX CHALLENGES OF THE DIGITALISATION OF THE ECONOMY 9 (2019), <https://www.oecd.org/tax/beps/public-consultation-document-addressing-the-tax-challenges-of-the-digitalisation-of-the-economy.pdf>; HER MAJESTY'S TREASURY, CORPORATE TAX AND THE DIGITAL ECONOMY: POSITION PAPER UPDATE 10-11 (2018), https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/689240/corporate_tax_and_the_digital_economy_update_web.pdf.

²⁰³ See, e.g., Christians, *supra* note 200, at 1381; Johannes Becker & Joachim Englisch, *Taxing Where Value Is Created: What's 'User Involvement' Got to Do with It?*, 47 INTERTAX 161, 168 (2019); Itai Grinberg, *User Participation in Value Creation*, 2018 BRITISH TAX REV. 407 (2018).

²⁰⁴ See, e.g., Aqib Aslam & Alpa Shah, *Tec(h)tonic Shifts: Taxing the "Digital Economy"* 51-54 (Int'l Monetary Fund, Working Paper No. 20/76, 2020); Adam B. Thimmesch, *Transacting in Data: Tax, Privacy, and the New Economy*, 94 DENV. L. REV. 145, 174 (2016).

²⁰⁵ The possibility of these exchanges being treated as taxable barter exchanges has been explored by commentators. See, e.g., Hillel Nadler, *Taxing Zero*, 26 FLA TAX REV. (forthcoming); Louise Fjord Kjærsgaard & Peter Koerver Schmidt, *Allocation of the Right To Tax Income from Digital Intermediary Platforms—Challenges and Possibilities for Taxation in the Jurisdiction of the User*, NORDIC J. COM. L. 146, 159-60 (2018); Thimmesch, *supra* note 204, at 162-63.

A notable exception to this focus comes from Professor Omri Marian.²⁰⁶ In a 2021 article, Marian proposes moving away from trying to fit the data economy to our existing income tax system by assigning monetary value to data because he argues doing so is “an insurmountable, if not logically incoherent task.”²⁰⁷ On the policy level, the New York State Senate has proposed a personal consumer data excise tax that would tax data collectors based on the number of residents from whom they collect data.²⁰⁸ These efforts to push our tax system out of the exchange value-based mold are commendable and exciting but unfortunately remain in the minority.

2. Colliding with Informational Capitalism’s Scripts

Beyond the conceptual challenge of integrating prediction value into a tax system centered around exchange value, informational capitalism’s script and associated business practices are also colliding with tax law. These scripts and practices were beyond the historical imagination of the original architects of the tax system, and many of the assumptions about business practices that these lawmakers held no longer hold true. As a result, our existing tax system, when applied to informational capitalism, precipitates tax outcomes that are inconsistent with the underlying norms and goals of taxation. This subpart briefly explores three examples of tax law failing in the informational capitalist environment. The first is the continued use of income as a tax base when companies focus on growth over profits. The second is the opportunity for advantageous tax deferral offered to companies who are not immediately converting prediction value into exchange value. The third is international tax implications of prediction value manifesting as exchange value via increase in company market capitalization versus company profits.

a. Income as a Tax Base

Firms are taxed on their income, not on the size of their user bases or the amount of social data and resulting prediction value they have amassed. Until this growth and expansion translates into exchange value, it exists outside our current tax system.²⁰⁹ As explained in Part II, they often do not earn income as they instead focus on growth through business practices such as freemium business models. Governments are unable to collect tax revenue from these

²⁰⁶ See generally Marian, *supra* note 10. See also Reuven Avi-Yonah, Young Ran (Christine) Kim, & Karen Sam, *A New Framework for Digital Taxation* 63 HARV. INT’L L. J. 279, 335-41 (2022).

²⁰⁷ Marian, *supra* note 10, at 561.

²⁰⁸ See Robert D. Plattner, *The Virtues of a Simple Excise Tax on Personal Consumer Data*, 108 TAX NOTES INT’L 1381, 1381 (Dec. 12, 2022) (describing the structure of the New York data excise tax).

²⁰⁹ Marian, *supra* note 10, at 561; Thimmesch, *supra* note 204, at 174.

digital firms despite the fact that they provide benefits and resources without which the firms would not be able to operate—benefits and resources that are funded by tax revenues. Digital firms’ focus on growth over income also frustrates tax law’s redistributive goals. The rise of Big Tech oligopolies has sparked concerns amongst various scholars, particularly the concentration of prediction value and the accompanying economic and political power it brings to those firms.²¹⁰ But prediction value is not part of our tax base; therefore, the tax system cannot redistribute prediction value and temper this concentration of economic and political power. Finally, the focus on growth over income frustrates the regulatory purpose of taxation. The deductions and credits offered by the tax code as a means to shape firm behavior are less effective when firms do not have significant income or tax liabilities to offset.

b. Tax Deferral Opportunities

A common dismissal of the concerns about the continued reliance on income as a tax base is arguing that all companies will *eventually* convert prediction value into exchange value. While social data as a factor of production tends to lead companies to defer short or medium profits in favor of building up greater prediction value, a company’s purpose is to earn profits for their shareholders, and they will eventually achieve this purpose. These profits might be earned through script one’s direct conversion of prediction value to exchange value through means such as targeted advertising revenues. Or these profits might be earned through indirectly converting prediction value into exchange value through profits earned from the new or improved products and services companies are able to offer as a result of the prediction value they have accrued. Why does it matter that the tax system is not capturing prediction value when it will eventually be converted to exchange value, which the tax system will capture?

This argument is flawed in a couple of ways. First, it ignores the existence of the third script—where companies never fully convert prediction value into exchange value but instead use prediction value as a means to gain power. Power which may or may not be used to create exchange value. As discussed in Part II.a.3 above, the power that stems from merely possessing something of value has been invoked to justify the taxation of wealth as well as income versus consumption, and this same rationale carries over to justify taxing companies pursuing the third script.²¹¹

However, even if one rejects the idea that any company would pursue the third script and never fully monetize prediction value, this argument ignores

²¹⁰ See *supra* notes 113 to 126 and accompanying text.

²¹¹ See *supra* notes 108 to 112 and accompanying text.

a foundational consideration for evaluating the effectiveness of a tax system: the value to the taxpayer of deferring tax liabilities. The benefit of tax deferral is a fundamental concept taught to students in basic tax law classes.²¹² If a taxpayer is able to push off their tax liability into some point in the future (either by deferring income inclusion, accelerating deductions or both), they are able to put the amount that they would have paid in taxes to productive use in the intervening period of time. This concept is known as the “time value of money.”²¹³ For example, if a taxpayer can expect a rate of return on investment of 7% annually, \$1 saved in taxes this year has a future value to the taxpayer of \$1.97 in 10 years.²¹⁴ This benefit of tax deferral is an essential driver of tax planning. Tax expenditure policies, such as defined contribution retirement plans, use the benefits of tax deferral as a carrot to encourage individuals to save for retirement.²¹⁵ Deferral is also a key feature of many tax shelters, which are designed to artificially accelerate the timing of deductions and defer the timing of income inclusion.²¹⁶ Because tax law conceptualizes “value” in terms of exchange value,²¹⁷ the benefit of tax deferral has historically been framed in monetary terms. But the same principle applies when a taxpayer is able to defer tax on prediction value. When a company is allowed to build up prediction value for extended periods without forcing any type of distributive mechanism, the company benefits by being able to accrue even greater levels of prediction value and its resulting economic and political power.

Companies not earning income for periods of time because they are building up and investing in their businesses and, as a consequence, deferring tax liabilities while simultaneously building economic value, is not a phenomenon unique to informational capitalism. But what is unique to informational capitalism is the extent of this deferral. Longer periods of tax deferrals produce greater advantages to the taxpayers and greater harms to the tax system. These lengthy tax deferrals are another way in which tax law is colliding with informational capitalism.

c. International Tax Implications

²¹² See, e.g. JOSEPH BANKMAN ET AL., FEDERAL INCOME TAXATION 191-92 (18th. ed. 2019) (introductory income tax casebook describing the importance of tax deferral and the time value of money); MICHAEL J. GRAETZ & ANNE L. ALSTOTT, FEDERAL INCOME TAXATION: PRINCIPLES AND POLICIES 297-303, 627 (9th ed. 2022) (same).

²¹³ BANKMAN ET AL., *supra* note 212, at 191-92.

²¹⁴ Future value = $(1+r)^n$.

²¹⁵ See GRAETZ & ALSTOTT, *supra* note 212, at 627-703.

²¹⁶ See Stanley S. Surrey, *The Tax Reform Act of 1969—Tax Deferral and Tax Shelters*, 12 B.C. L. REV. 307, 310 (1971); BANKMAN ET AL., *supra* note 212, at 504.

²¹⁷ See *supra* notes 191 to 193 and accompanying text.

Finally, the focus on growth over income within informational capitalism often leads to prediction value manifesting as an increase in the market valuation of a company.²¹⁸ To the extent that prediction value is reflected in the market value of a company, it is then converted into exchange value when an investor sells their shares and realizes capital gains income. The tax system is able to capture prediction value that manifests into exchange value in the form of increased market valuation of the company. This is beneficial because it allows the tax system to raise government revenues and accomplish redistributive goals. There are, however, troubling normative implications for tax law when prediction value is only taxed when it converts to exchange value in the form of capital gains income at the investor level.

One of these problems emerges in the context of international tax law, specifically the determination of *which* country will have taxing rights over informational capitalism's value creation. In order to prevent double taxation, international tax law divides taxing rights over cross-border income amongst countries based on a system of classification and assignment.²¹⁹ This classification and assignment system was first developed by members of the League of Nations in the 1920s and has remained largely unchanged since.²²⁰ The system generally grants taxing rights over active business income to the source country (the country in which the business operates) and taxing rights over passive investment income, including capital gains income, to the investor's residence country.²²¹

This choice in the 1920s to assign taxing rights over active business income to source countries and passive investment income to residence countries was influenced by tax law's underlying normative principles that continue to be influential today.²²² It was also influenced by assumptions about the nature of business activities that no longer apply in informational capitalism.²²³ One of these normative principles was the benefits principle,

²¹⁸ See *supra* notes 127 to 132 and accompanying text.

²¹⁹ See Steven A. Dean, *A Constitutional Moment in Cross-Border Taxation*, 1 J. FIN. DEVELOPMENT 1, 1-3 (2021).

²²⁰ See Michael J. Graetz & Michael M. O'Hear, *The "Original Intent" of U.S. International Taxation*, 46 DUKE L. J. 1021, 1023 (1997). For a thorough history of the development of these model treaties, see SUNITA JOGARAJAN, *DOUBLE TAXATION AND THE LEAGUE OF NATIONS* (2018).

²²¹ See Reuven Avi-Yonah, *All of a Piece Throughout: The Four Ages of U.S. International Taxation* 25 VA. TAX REV. 313, 322 (2005). See generally ORG. ECON. CO-OPERATION & DEV., *MODEL TAX CONVENTION ON INCOME AND ON CAPITAL* (2017); UNITED NATIONS, *MODEL DOUBLE TAXATION CONVENTION BETWEEN DEVELOPED AND DEVELOPING COUNTRIES* (2017).

²²² Amanda Parsons, *The Shifting Economic Allegiance of Capital Gains*, 26 FLA. TAX REV. [12-21, 25-28] (forthcoming 2023).

²²³ Parsons, *supra* note 222.

which justifies taxation based on the benefits and resources that a country provides to taxpayers.²²⁴ And one of these assumptions was that any firm that increased in market value would also earn business income.²²⁵ Under this assumption, even though only the residence country would be able to tax investors on capital gains income from the sale of shares of a successful company, the country in which the company was operating, the source country, would still be able to collect tax revenues from the company itself because that company would be earning active business income, which is generally taxed in the source country.²²⁶ Therefore, the source country would be compensated for the resources and benefits that they provided to the company, and the benefits principle would be satisfied.

As explained in Part II above, this assumption that an increase in the value of a company would always be accompanied by income no longer holds in informational capitalism under the growth and expansion focused business strategies of digital firms. As a result, the benefits principle goes unfilled. Countries can provide digital companies with benefits and resources that the firms rely on to achieve growth, such as infrastructure and the education of users. But, without company-level income, the source countries are unable to collect tax revenues, even when that growth is translated into exchange value when investors sell their appreciated shares. For example, Company A could have millions and millions of users in Argentina, building out its network, providing the firm with a steady stream of social data, and, in turn, contributing to a rise in the firm's market value. However, when a U.S. investor in Company A goes to sell their appreciated shares, only the United States (the residence country) is able to tax that income.²²⁷ Argentina does not get a bite at the tax apple unless Company A earns income, which it often does not under the prominent business models of informational capitalism that eschew income in the short or medium term in favor of growth. This growth without income phenomenon and business model was beyond the historical imaginations of the original designers of the international tax system in the 1920s.²²⁸ The business model is clashing with existing international tax law, leading to outcomes that

²²⁴ Parsons, *supra* note 222 at 12-21.

²²⁵ In a seminal report commissioned by the League of Nations during the 1920s negotiations (the recommendations of which were largely followed by the original designers of the international tax system), the authors stated in their analysis of which country should be granted taxing rights over capital gains income, “[c]orporate shares would, indeed, be worth nothing if the company had no earnings . . .” See *Fin. Comm., Report on Double Taxation*, League of Nations Doc. E.F.S.73.F.19, at 36 (1923).

²²⁶ See ORG. ECON. CO-OPERATION & DEV., *supra* note 221 at art. 7. See also Avi-Yonah, *supra* note 221, at 322.

²²⁷ See ORG. ECON. CO-OPERATION & DEV., *supra* note 221 at art. 13. See also Avi-Yonah, *supra* note 221, at 322.

²²⁸ Parsons, *supra* note 222, at 20-21.

violate the normative goals of international tax law, and contributing to a broad sentiment that the current international tax system is unfair.²²⁹

This subpart explores the conceptual disconnect of tax law scholars and policymakers failing to recognize prediction value as a new and distinct form of value creation and then explains a few of the ways in which the unfamiliar and unexpected business practices associated with informational capitalism have collided with existing tax law. These collisions have resulted in tax law's failing to achieve its underlying goals of revenue-raising, redistribution, and regulation and have raised questions about the effectiveness of tax law in the modern economy. Both a conceptual understanding of prediction value as a value form that is distinct from, and does not always translate neatly into, exchange value and an understanding of the types of business activities that prediction value has precipitated are an essential first step for tax law to adequately respond to the challenges presented by informational capitalism.

C. *Governing Social Data Value*

Data privacy (and the related field of data protection law)²³⁰ is the legal field historically focused on the project of governing social data. Data privacy law not only guards against privacy violations, but also governs the economic production of datafied social relations.²³¹

As a result, data privacy law has, in many respects, been carefully attuned to the growing significance of social data in the information economy. Given that data privacy law is the primary regime that regulates how data about people is collected, processed, and used, it also serves as one, if not *the*, primary legal regime currently regulating social data value creation, accumulation, and use. But

²²⁹ Parsons, *supra* note 222, at 51.

²³⁰ Note that much of what is called “data privacy” or “information privacy” in the United States also includes elements of data protection law. In the EU, these are separate, though related, legal regimes. In the Article, ‘data privacy law’ will generally be used to refer to the broader category of both related regimes. For a discussion of the differences between privacy and data protection (and the tendency of U.S. law to favor the former), see Anupam Chander et al., *Catalyzing Privacy Law*, 105 MINN. L. REV. 1733, 1747-49 (2021).

²³¹ Whether data privacy law governs economic production of datafied social relations depends on one’s account of privacy interests and privacy law. Privacy is a “big tent” concept experiencing a high point of concept pluralism as the past decade has seen the expansion of informational wrongs characterized within the language of privacy law wrongs. See María P. Angel & Ryan Calo, *Distinguishing Privacy Law: A Critique of Privacy as Social Taxonomy*, 123 COL. L. REV. (forthcoming); María P. Angel, *Privacy’s Algorithmic Turn: An Intellectual History* (unpublished manuscript) (draft on file with authors), Ryan Calo, *The Boundaries of Privacy Harm*, 86 IND. L. J. 1131, 1139-42 (2011).

data privacy law has not traditionally understood its primary aim as that of governing and managing value creation.²³²

In short, data governance law faces the “mirror image” of tax law’s challenges discussed in Part III.b. The problem is not that data privacy laws are indexing prediction value as exchange value. Instead, existing data privacy laws are not designed with the task of regulating value creation, of any kind, in mind. However, as social data value emerges as a primary goal of production under informational capitalism, data privacy finds itself thrust into—and grappling with—the role of regulating this value creation. This introduces both conceptual and programmatic challenges. Conceptually, data governance law has primarily developed negative rights for data subjects against personal data being collected against their will or used for purposes that thwart certain inalienable data subject rights. This leaves privacy law poorly equipped to respond programmatically to the systematic pressures placed on privacy in a surveillance-fueled economy, and to develop a positive agenda for how to manage the social stakes of prediction value.

Yet data privacy law is also comparatively well positioned among legal regimes to meet this challenge. Over the past several years, scholarly work in privacy law has begun to systematically respond to these conceptual and programmatic challenges. This Part argues that distinguishing between prediction value and exchange value can provide a helpful way to translate recent pioneering work in privacy law into legal action. Thinking of the relevant tasks of data privacy law in the language of exchange value and prediction value can both identify and regulate harmful practices of prediction value production, as well as foster and facilitate socially beneficial uses of social data value.

1. Privacy Law Background

While the concept of privacy itself is considerably older, U.S. digital privacy law began in the 1970’s, as Congress passed a rash of bills in response to the early wave of computerization and digitalization in both the government and the private sectors.²³³ The highly influential Fair Information Practice Principles (FIPPS), first laid out in a 1973 report, while never directly made law, canonized best principles regarding information processing and deeply

²³² Viljoen, *supra* note 4.

²³³ Several experts consider the year 1974 a turning point in U.S. privacy law, when Congress passed The Privacy Act. For a general overview of this history, see Daniel Solove & Paul Schwartz, An Overview of Privacy Law, *in* PRIVACY LAW FUNDAMENTALS 42 (2015).

informed the privacy statutes of the U.S. as well as those of organizations and states around the world.²³⁴

These principles, as enacted in agency policies and laws, focus on proper data hygiene, data subject consent, and preventing privacy harms to individuals from which data is collected.²³⁵ While the specifics of how the FIPPs were operationalized vary from law to law, the standard package of privacy protections they provide includes two aspects. First, negative individual rights *against* overreaches in data collection, accompanied at times by narrowly tailored inalienable data subject rights against downstream misuses of their data.²³⁶ These elements grant data subjects their privacy rights, ensuring data is collected with their consent, and that certain decisions regarding how their data is used are not undertaken (typically, without first obtaining additional consent).²³⁷ Second, privacy laws may also include provisions that can be understood as data protection requirements.²³⁸ These elements impose proper processing obligations onto businesses that collect and handle data, to ensure that data requests are tailored to the purposes for which data is being collected, honor the intentions of the data subject in any further sharing of their data, and impose protocols to enhance the security of data resources.

In practice, much of actual privacy management (and regulation) occurs not via courts or regulators, but in the private actions of entities that develop internal compliance systems in the shadow of these rarely enforced laws.²³⁹ Internal managerial processes result in terms of service entities then present to users. Users in turn are burdened with the task of legitimizing these privacy practices via the routine act of click-through consent, a legal approach Daniel Solove refers to as ‘privacy self-management’.²⁴⁰

²³⁴ Department of Health, Education, and Welfare Advisory Committee, “Records, Computers, and the Rights of Citizens,” (1973).

²³⁵ For an overview of the FIPPs, see Federal Privacy Council, “Fair Information Practice Principles” <https://www.fpc.gov/resources/fipps/>.

²³⁶ For example, the Fair Credit Reporting Act (FCRA) prohibits credit score decisions on the basis of incorrect or out of date information. 15 U.S.C. § 1681 (2018).

²³⁷ Margot Kaminski, *The Case for Data Privacy Rights (or ‘Please, a Little Optimism’)*, 97 NOTRE DAME L. REV. 385 (2022).

²³⁸ For example, the Health Insurance Portability and Accountability Act, 45 C.F.R. §§ 160, 162, 164 (2020); Children’s Online Privacy Protection Act, 15 U.S.C. §§ 6501–6506. *See also* Chander et al., *supra* note 231, at 1747-49.

²³⁹ Waldman, *supra* note 53.

²⁴⁰ Daniel J. Solove, *Privacy Self-Management and the Consent Dilemma*, 126 HARV. L. REV. 1880 (2013).

2. Data Privacy Is a Value Regulation Regime

As written, none of the privacy rules canvassed above bear on the economic motivations for collecting data, or account for the market imperatives of informational capitalism that place growing pressure on privacy law's system of individual rights and corporate compliance. In short, they are poorly attuned to the reasons *why* entities violate privacy and misuse data—namely, in the pursuit of prediction value.

Several scholars have criticized US privacy law as overly focused on individual privacy rights—what can be considered the “supply” side of the social data market.²⁴¹ In response, lawmakers have (understandably) enacted solutions that strengthen existing approaches: higher standards of consent, more expansive lists of data subject rights covering a greater swathe of downstream uses of their data, and more robust enforcement mechanisms.²⁴² This approach, while admirable, falls short of the steps required to transform data privacy law into an effective regulator of prediction value.

In other words, these laws lack an explicit focus on creating ‘demand side’ checks on the social data market—which would focus on the motivations that drive companies to cultivate social data. The lack of demand-side controls on entities cultivating social data value results in (arguably artificially) low costs and risks associated with surveillant practices. Entities can cultivate maximum prediction value all while externalizing the current costs and future risks of doing so.

Which isn't to say that privacy and data protection law does not in fact serve as a that demand-side regulation—data privacy law is necessarily a regime engaged in the regulation of social data value creation. The issue is that privacy and data governance law isn't traditionally conceived of this way. One result is

²⁴¹ Sebastian Benthall & Salome Viljoen, *Data Market Discipline*, J. INT'L & COMPAR. L. (2021) (introducing the concept of ‘supply side’ and ‘demand side’ data market regulation). The shortcomings of current individual consent-based laws has been comprehensively covered by privacy scholars. See e.g., Neil M. Richards & Woodrow Hartzog, *The Pathologies of Digital Consent*, 96 WASH. U. L. REV. 1461 (2019), Elettra Bietti, *Consent as a Free Pass: Platform Power and the Limits of the Informational Turn*, 40 PACE L. REV. 307 (2020), Katherine J. Strandburg, *Free Fall: The Online Market's Consumer Preference Disconnect*, 2013 U. CHI. LEGAL FORUM 95.

²⁴² For example, the California Consumer Protection Act (CCPA) is considered a more robust consumer-protection style U.S. privacy law. It retains the basic package of rights, but expands the scope of actions and data covered by these rights, strengthens the usual individual rights beyond consent and access to information, and imposes higher and more frequent consent requirements. Cal. Civ. Code § 1798. For a discussion and overview of the CCPA provisions, see Chander et al., *supra* note 231, 1747-49. For an analysis of how these provisions compare to existing FIPPs-style law, see Katherine Strandburg et al., *The Great Regulatory Dodge*, HARV. J. L. & TECH. (forthcoming).

that great pressure is placed on the existing data privacy system; a legal regime tasked with protecting individuals from surveillance in an economic system that rewards—indeed depends on—the very same thing.²⁴³ Digital privacy law suffers from the collective erosion of privacy that necessarily results from informational capitalism, but it lacks the conceptual and legal tools to go beyond the (privacy-loss) symptoms to their wider, social data value extraction causes.

In *Beyond Truth and Power*, Julie Cohen uses the excellent analogy of corn production, which will be borrowed and expanded on to illustrate the basic point: what data privacy law currently offers is roughly akin to a set of rules ensuring that corn is properly and ethically planted, grown and harvested.²⁴⁴ While this is, in and of itself, a perfectly legitimate set of goals, such rules would be wholly inadequate to govern and regulate the commodity derivatives and futures markets that assetize corn at scale to produce billions of dollars in downstream value.²⁴⁵ Moreover, such rules would be inadequate to manage the effects that such processes of accumulation have on the general landscape of corn production: the transformational market pressures of industrial scale production and engineered modification to make corn-as-commodity more predictable and stable to grow, harvest, store, transport, and refine. Such modifications make corn well suited to its role as a key input in maximizing derivatives exchange value but leave corn decidedly less suited to certain (previously central) use values: namely, as a food.²⁴⁶

3. Promising Horizons for Regulating Social Data Value in Data Privacy (and Beyond?)

In his excellent synthesis of recent trends in data privacy, Daniel Susser notes that while the policy response to imperatives to cultivate prediction value have been uneven, several shifts in the general tenor of data privacy scholarship

²⁴³ COHEN, *supra* note 2, at 40 (noting that digital platforms are designed fundamentally for “data-based surplus value extraction.”)

²⁴⁴ COHEN, *supra* note 2.

²⁴⁵ The corn derivatives market was valued at over \$75 billion as of 2022. See GLOBAL MARKET INSIGHTS, INDUSTRY ANALYSIS: CORN AND CORN STARCH DERIVATIVES, <https://www.gminsights.com/industry-analysis/corn-and-corn-starch-derivatives-market#>.

²⁴⁶ Only one percent of corn planted in the United States is sweet corn, the kind grown to be eaten as a vegetable by people. The rest of U.S. corn is a grain, primarily used for livestock feed, ethanol production, and manufactured goods (which does not include the small portion of grain corn used for human consumption as cereal, corn starch, corn oil, and corn syrup). In Iowa, the state that produces the most corn, 57 percent of corn goes to ethanol production. See IOWA CORN PROMOTION BOARD, CORN FACTS, <https://www.iowacorn.org/media-page/corn-facts#:~:text=While%20a%20small%20portion%20of,frozen%20or%20canned%20for%20eating>.

signal growing attention to privacy law's role as a value-regulating legal regime.²⁴⁷ In particular, he notes two relevant shifts. First, from privacy as an individual interest, and privacy law's role taken to be to strengthen that interest, to the social and relational nature of privacy and the need for structural approaches to secure privacy for everyone. Second, from a primary focus on public actors and a rights-based model against public overreach, to growing concerns over the surveillance practices of private firms that incorporate a political economy perspective.²⁴⁸

Each of these trends facilitate the conceptual work needed to take up the task of directly regulating prediction value. Taking the second trend first, data privacy scholars that focus on the business models and scripts canvassed in Part II, *supra*, take as their object of inquiry the economic causes of privacy erosion—namely, the market imperative to cultivate prediction value.²⁴⁹ Transforming market imperatives to cultivate, accumulate and exploit prediction value also takes as its central focus the other trend canvassed by Susser; the move from individual privacy rights to structural and systemic solutions.

Distinguishing between social data's prediction value and exchange value can lend clarity to the task of evaluating this market imperative and its systematic privacy-eroding effects. Distinguishing prediction value from exchange value can explain broad trends in what aspects of life are datafied. Social data whose prediction value is more convertible into exchange value under scripts one and two, such as data subjects' clicks on relevant advertisements or expressions of purchasing preferences, may be more extensively produced than social data whose prediction value is not as readily converted into exchange value. While this may seem rather obvious, it suggests that shifting trends in datafication may in turn hint at shifting technological capacities and business strategies to transform prediction value into exchange value.

The distinction can be particularly helpful in charting a path towards a positive agenda for prediction value regulation. At least some under-cultivated social data (not readily convertible into exchange value under any script) may nevertheless be of great predictive value for certain applications. Data privacy

²⁴⁷ Daniel Susser, *From Procedural Rights to Political Economy: New Horizons for Regulating Online Privacy*, in THE ROUTLEDGE HANDBOOK ON PRIVACY AND SOCIAL MEDIA 281 (Sabine Trepte and Philipp Masur eds., 2023).

²⁴⁸ *Id.* at 282.

²⁴⁹ See e.g., COHEN, *supra* note 2; SRNICEK, *supra* note 73; ZUBOFF, *supra* note 9, at 10 (“Surveillance capitalism’s products and services are not the objects of a value exchange [...] they do not establish constructive producer-consumer reciprocities. Instead they are ‘hooks’ that lure users into their extractive operations in which our personal experiences are scraped and packaged as the means to others’ ends.”)

scholars are necessarily attuned the harms of surveillance overreach, where excessive datafication creates personal and social disruption. It is thus not surprising that data privacy scholars and activists commonly diagnose (albeit often implicitly) the problem of the digital economy as one of too much datafication.²⁵⁰

But this is perhaps not exactly right. It is true that there is almost certainly too much datafication of consumptive choices. But there is also almost certainly too little datafication of local climate data.²⁵¹ Distinguishing exchange and prediction value can home in on the maldistribution of social data resources here: one's shoe purchasing preferences are readily transformed into script one or script two-style exchange value, while this is less clear of citizen-collected rainwater data. Nevertheless, detailed real-time rainwater data is of profound predictive value for understanding climate effects.

Data privacy scholars are increasingly interested in distinguishing the good from the bad when it comes to scholarly accounts of datafication.²⁵² Distinguishing exchange and prediction can aid the conceptual and programmatic agenda of this shift; describing current practices, and identifying gaps in the task of regulating prediction value. Namely, it can help not only to prevent problems of speculative and excessive social data production—which result in excessively risky or ill-gotten prediction value production—but also to identify areas that actually suffer from an under-production of prediction value.

CONCLUSION

This Article shows how separately analyzing data's prediction value and its exchange value may prove helpful to understanding the challenges law faces in governing social data production and the political economy organized around such production.

Part I lays out the theoretical account of social data as a materialized store of prediction value, and describes how this value form diverges from how

²⁵⁰ Daniel Susser, *Data and the Good?* 20 SURVEILLANCE & SOC'Y 297 (2022).

²⁵¹ Christopher Flavelle & Rick Rojas, *Vermont Floods Show Limits of America's Efforts to Adapt to Climate Change*, N.Y. TIMES, June 11, 2023 (detailing how the US lacks a comprehensive current precipitation database that could help assess flood risk) Local rainfall data is also an excellent example of how non-human data—this is data about rain, after all—can still be social data, insofar as such data is used to inform how and where people may safely live.

²⁵² See e.g., Solow-Niederman, *supra* note 3 (arguing to reframe privacy governance as a network of organizational relationships to manage—not merely dataflows to constrain); Susser, *supra* note 250 (calling for surveillance scholars to move past critique and put forward alternative conceptions of a good digital society); Birch, *supra* note 27 (considering the role of data in replacing markets and neoliberalism).

value is traditionally conceived of in law and beyond. Part II develops the case for the legal (and normative) relevance of this conceptual gap. As this Article shows in Part II, distinguishing prediction and exchange value is helpful in capturing with greater precision how and why entities go about cultivating, storing and exploiting social data for gain. Part III considers how social data value fares under current legal regimes. As it shows, both areas of law that are not typically considered regimes of value regulation (like data privacy / data protection law) and those that squarely focus on regulating value struggle with social data value, albeit in different ways. Part III considers how the cultivation and accumulation of social data value meets, challenges, and transforms legal forms.

While the Article focuses on data privacy law and tax law, this analytic approach should prove fruitful in other areas of law as well; notably for free expression and first amendment law, antitrust and financial regulation. These areas are similarly grappling with the changes to economic activity that derive from the cultivation and accumulation of prediction value. The Article's analytic separation of prediction value and exchange value is helpful in other ways, too.

First, distinguishing the value of social data cultivation and accumulation from priced exchange value helps lay bare how much of alleged prediction value creation is mere puffery and speculation with little behind the curtain. As Aaron Shapiro notes, when it comes to understanding the way prediction value is capitalized by platforms into market valuation, there is a considerable "gap between what platforms do and what they say they do."²⁵³ Clarifying the two modes of value production (and how they relate to each other) thus helps regulators or other observers assess when such claims are plausible, and when they are not.

Second, while it is not this Article's aim to develop a normative account of how social data production should be regulated, this Article's work to distinguish prediction and exchange value is helpful for such work. The Article does not engage in a normative evaluation of when (under what conditions) and why (for what reasons) the use of prediction value may be wrongful. But this is not to say that prediction value is not cultivated, hoarded, or used in wrongful ways, nor indeed, that certain wrongful actions are not widespread among corners of the digital economy. Holding the cultivation of prediction value apart from its transformation into exchange value can further clarify distinct normative critiques lodged against social data production.

²⁵³ Shapiro, *supra* note 14.

Some accounts appear to critique data production insofar as it is directed by exchange value; they take issue with the commodification of social data. Certain things are considered degraded or violated by being reduced to exchange value. For example, Rahel Jaegghi points out that our conception of what makes child labor wrong is not the risk that children’s labor is likely to be systematically undervalued by the market (a ‘quantitative harm’) but that making a labor market for children is itself violative (a ‘qualitative harm’).²⁵⁴ Similarly, critics argue that a priced market in adoptions, or organs, would be wrongful even if such markets might increase allocative efficiency.²⁵⁵ Some feminists make a similar point about sex, and use this normative diagnosis to argue against sex work.²⁵⁶ Is assigning a priced value to social data, or certain sub-classes or uses of social data, wrong in the same way? The recent FTC proposal to ban Meta from monetizing children’s data suggests such a theory.²⁵⁷

Other accounts appear to take issue with data production in virtue of it serving as a material store of prediction value. In other words, some argue there is something particular to the cultivation of prediction value that is, or can be, wrongful. Zuboff, both in her early work on ‘informating’ and in her later work on surveillance capitalism, suggests such a diagnosis. Philip Agre diagnosed informational harm as a process of ‘capture’, whereby greater portions of human activity are forced into market competition with other humans through the collective project of institutions measuring them against one another.²⁵⁸ Gandy’s panoptic sort is a ‘disciplinary’ system of power that, if left unchecked, can result in amplifying loops of growing mistrust and amplified surveillance where “each cycle pushes us further from the democratic ideal.”²⁵⁹ Is the cultivation of material stores of predictive value independently wrongful? Legal reforms to ban outright certain forms of surveillance, such as facial recognition and other forms of biometric surveillance, suggest such a theory.²⁶⁰

²⁵⁴ Jaegghi, *supra* note 41.

²⁵⁵ For a famous example defending the allocative efficiency of non-priced markets in altruistic goods, see RICHARD TITMUS, *THE GIFT RELATIONSHIP: FROM HUMAN BLOOD TO SOCIAL POLICY* (1970).

²⁵⁶ See, e.g. Andrea Dworkin, *Prostitution and Male Supremacy*, 1 MICH. J. GENDER & L. 1,3 (1993) (“Prostitution in and of itself is abuse of a woman’s body”).

²⁵⁷ FTC Proposes Blanket Prohibition Preventing Facebook from Monetizing Youth Data, FTC Press Release, May 3, 2023, <https://www.ftc.gov/news-events/news/press-releases/2023/05/ftc-proposes-blanket-prohibition-preventing-facebook-monetizing-youth-data>

²⁵⁸ Philip E. Agre, *Surveillance and capture: Two models of privacy*, 10 INFORMATION SOC’Y (1994).

²⁵⁹ GANDY, *supra* note 35, at 260.

²⁶⁰ In 2020, the city of Boston enacted a local ban on the use of facial recognition technology, becoming the tenth U.S. city to do so. See Boston City Council, Docket #0683, ordinance banning facial recognition technology in Boston, <https://www.boston.gov/sites/default/files/file/2021/02/Boston-City-Council-face->

Different observers may come to different conclusions. But disambiguating the two aspects of data value makes distinguishing such critiques, and the relation they bear to one another, clearer.

Informational capitalism has reshaped and remade both our social lives and the laws that structure them. The business models and tactics of accumulation pursued for social data value have produced significant wealth and power, as well as significant social disruption. The primary ambition of this Article is to provide conceptual language better equipped to understand the specificities of how information produces value, to in turn better equip the various legal regimes tasked with regulating that value and enacting our social goals regarding the direction and shape of the information economy.

surveillance-ban.pdf. In 2021, Massachusetts restricted the use of facial recognition by police but did not ban it. Mass. Gen. Laws ch. 110I (enacting bill H.117, 192nd (2021-22)).