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Data as asset? The measurement, governance, and valuation of digital personal data by Big Tech

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Abstract

Digital personal data is increasingly framed as the basis of contemporary economies, representing an important new asset class. Control over these data assets seems to explain the emergence and dominance of so-called "Big Tech" firms, consisting of Apple, Microsoft, Amazon, Google/Alphabet, and Facebook. These US-based firms are some of the largest in the world by market capitalization, a position that they retain despite growing policy and public condemnation—or "techlash"—of their market power based on their monopolistic control of personal data. We analyse the transformation of personal data into an asset in order to explore how personal data is accounted for, governed, and valued by Big Tech firms and other political-economic actors (e.g., investors). However, our findings show that Big Tech firms turn "users" and "user engagement" into assets through the performative measurement, governance, and valuation of user metrics (e.g., user numbers, user engagement), rather than extending ownership and control rights over personal data per se. We conceptualize this strategy as a form of "techcraft" to center attention on the means and mechanisms that Big Tech firms deploy to make users and user data measurable and legible as future revenue streams.

Keywords

Personal data, user metrics, assetization, Big Tech, data governance, techcraft

Introduction

> "It was the 'Wizard of Oz' in digital format as the four titans of Big Tech testified via video before the House Antitrust Subcommittee. Just like in the movie, what the subcommittee saw was controlled by a force hidden from view. The wizard in this case – the reason these four companies are so powerful – is the math that takes our private information and turns it into their corporate asset."[1]
>
> —Tom Wheeler, ex-Chairman of US Federal Communications Commission (2013–2017)

Digital personal data is often described as *the* resource of the future, even as a "new asset class" according to the World Economic Forum, which argued that a massively increased amount of personal data "is generating a new wave of opportunity for economic and societal value creation" (WEF, 2011: 5). The importance of personal data is evident in the rise of so-called "Big Tech" as the dominant firms in our societies today. As Prainsack (2019) notes, these Big Tech firms have inserted themselves as key social and economic intermediaries, providing often essential services, products, and infrastructures in exchange for our personal data (also Fourcade and Kluttz, 2020). Personal data appear to be a key asset for Big Tech and other digital technology firms, providing an important new measure for investors to evaluate future revenues and earnings expectations (Ciuriak, 2018; OECD, 2019; The Economist, 2020). For example, an article in the MIT Sloan Management Review extols business readers to ask, "What's your data worth?" (Short and Todd, 2017). Other examples abound of the increasing political-economic emphasis on personal data as the asset of the 21st century.

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With their ascendance to positions of societal dominance, Big Tech has increasingly come under the glare of regulatory spotlight. In October 2020, the US Congress ended a nearly two-year investigation into Big Tech with the release of a highly critical report on "competition in digital markets" (US House of Representatives, 2020). The report highlights the various ways that Big Tech firms have been exploiting their control over digital ecosystems and data to entrench their market power. Shortly afterwards, the US Department of Justice announced they would be suing "the monopolist Google for violating antitrust laws",[2] potentially launching a new era in antitrust. Similar antitrust suits are being considered in Canada against Amazon. These cases result from a growing concern in public and policy circles with the data monopolies Big Tech has created through network effects, ecosystem governance, and market power derived from control over access to their user base (see Foroohar, 2019; Prainsack, 2019).

The political-economic framing of personal data as a critical resource of the future alongside the importance of data monopolies goes some way to explain the massive growth in valuations of Big Tech. Even the rising public and policy backlash—dubbed the "techlash" (Foroohar, 2019)—has not dented the valuation of Big Tech; their market capitalization rose by 52% between February 2019 and February 2020, for example, increasing by almost US$2 trillion in one year (The Economist, 2020: 11). And these valuations have only increased throughout 2020 and the COVID-19 pandemic. According to many scholars, the reason why is simple: investors are counting on Big Tech to keep accumulating more personal data from which they can extract monopoly rents (e.g., Birch et al., 2020; Li et al., 2019; Mazzucato, 2018; Srnicek, 2016; Zuboff, 2019). This would suggest that it is important to understand how Big Tech firms and their investors measure, govern, and value personal data as an asset: how do they understand and frame personal data? And how do they govern and value personal data as an asset?

We ask these questions to unpack the political-economic framings of personal data as an emerging asset class for Big Tech firms. Although the five Big Tech firms are not homogenous, as we discuss below, it is analytically and politically useful to focus on them collectively because of the similarities in their market power, which is (purportedly) derived from the collection, use, and exploitation of personal data. We need to understand how Big Tech firms—and other relevant political-economic actors—measure, govern, and value personal data in order to explain their market dominance, and the concept of *assetization* provides the analytical tools to do so. Assetization is a concept developed at the interface of science and technology studies and political economy (Birch and Muniesa, 2020), and highlights the contingent transformation of a resource (e.g., data) into capitalized property. As such, we understand assetization as a mode of techno-economic ordering that helps to explain how the measurement, governance, and valuation practices used by political-economic actors transform personal data into future revenue streams.

However, rather than confirming existing analyses of Big Tech and fears about personal data monopolies, our findings illustrate something different. They show that it is "users", "user engagement", and "access to users" that are turned into assets through the performative transformation of personal data into user metrics that are measurable and legible to Big Tech and other political-economic actors (e.g., investors). This does not entail the extension of ownership rights over personal data, but rather the deployment of a range of practices, which we define as "techcraft", that convert personal data into user metrics. This process is evident in the emergence of new metrics of political-economic performance—for example, "daily average user" (DAU) and "monthly average user" (MAU)—that reflect the growing importance of enrolling users and encouraging user engagement across different digital ecosystems. Drawing on Scott (1998), we therefore argue that to understand the relationship between Big Tech, market power, and personal data we need to pay particular attention to their techcraft. Before we get to that point, we first outline our conception of techcraft, drawing on insights from the assetization literature. We then analyze the asset base of the five Big Tech firms to track changes over time. Based on current debates (e.g., Ciuriak, 2018; Mazzucato, 2018; WEF, 2011), we expected to see a significant rise in intangible assets (including goodwill) reflecting the measurement of personal data they collect. Instead we found a diverse shift in the asset base of Big Tech, including lower proportions of intangible assets than other Top 200 firms. We therefore examined how Big Tech firms govern personal data by analyzing the earnings calls between executives, financial investors, and analysts. Here, we found almost no discussion of personal data; instead, they focus on "users" as key assets. Finally, we examined how Big Tech value personal data by analyzing their financial reports. Again, we found very limited discussion of personal data and more focus on users and "user engagement". We conclude the paper by considering the implications of these findings.

Techcraft and the assetization of personal data?

Our analytical objective is to examine how personal data is being turned into an asset. That is, we want to understand its *assetization*, which is a concept used to analyze the logics, devices, and practices that construct something as capitalized property (Birch, 2017; Birch and Muniesa, 2020; Muniesa et al., 2017). A growing literature on assetization has emerged over the last few years that helps us to do this theoretical work (Birch, 2017; Birch and Muniesa, 2020; Muniesa et al., 2017), including previous studies on the assetization of personal and health data (e.g., Beauvisage and Mellet, 2020; Birch et al., 2020; Geiger and Gross, 2021; Prainsack, 2020). Assetization focuses our attention on the contingent techno-economic measurements, processes, and practices that social actors perform to order and configure their worlds—e.g. identify an asset boundary, create monetization strategies, and so on. Using the concept of assetization helps us to understand the attempts to construct a new asset class out of personal data, while our introduction of the concept of *techcraft* helps us understand how Big Tech makes "user" data measurable and legible as this asset.

Personal data can be defined as "any information relating to an identified or identifiable natural person" (Edwards, 2018: 81). The collection, use, and exploitation of personal data has a long history, including the credit scoring activities of data brokers like Experian and Axciom (Pasquale, 2015). However, digital personal data is different, as others have noted, and not just in terms of "volume, velocity, variety and value" (Prainsack, 2019: 1). Personal data is now collected through digital processes that enable mass collection, use, and exploitation of data with the imposition of new technical objectives and structures of collection (e.g., patterns of online "attention"), as well as new logics of use (e.g., inferential predictions) (Cohen, 2019; OECD, 2019; Viljoen, 2020; Zuboff, 2019). As such, mass digital personal data—"Big Data"—entails different dynamics than earlier credit scoring, most obviously in terms of the inherently collective nature of its algorithmic applications and the network effects that arise; for example, using personal data from thousands or millions of people to predict individual or group behaviors (Viljoen, 2020). Personal data are differentiated into "identifiable", "anonymous", and "pseudonymous" with the difference largely relating to how it is collected: identifiable being voluntary and knowingly given; anonymous being collected by data processors, often involuntarily and unknowingly, using supposedly anonymous identifiers; and pseudonymous being obtained from third parties. However, it is increasingly evident that it is possible to track back from anonymous and pseudonymous data to a person's identifiable personal data (Edwards, 2018). Consequently, we treat the three categories as largely similar.

Echoing the WEF (2011), scholars like Zuboff (2019: 52) have called personal data a "new asset class", where "every casual search, like, and click was claimed as an asset" (see also Arvidsson and Colleoni, 2012; Pasquale, 2015; Sadowski, 2019). Others have sought to identify how to assign legal claims to personal data, whether through direct property rights or labor rights: for example, Lanier (2014) argues that personal data should be governed by individual property rights, while Posner and Weyl (2019) argue that personal data is better governed through labor relations. At present, these propositions are largely theoretical: personal data cannot be owned because names, addresses, relationships, etc. are facts and not creative outputs (Cohen, 2019). Even if they could be treated as property, it would be conceptually and methodologically difficult to identify what facts belonged to whom; for example, Doctorow (2020) discusses whether the fact of being someone's child should belong to you, your parent, or both of you. Despite these issues, the mass collection of personal data remains critical to Big Tech firms. And the concept of assetization helps us examine the techno-economic knowledge claims, instruments, devices, and mechanisms deployed by Big Tech in the transformation of personal data into a future revenue stream through techcraft.

Understanding personal data as an asset requires an unpacking of the accounting concepts used to define the asset base of Big Tech firms. In accounting, digital resources (e.g., databases, software) and intellectual resources (e.g., copyright, patents, trademarks) are defined as intangible assets (OECD, 2019). The International Accounting Standards (IAS) define intangible assets as "an identifiable non-monetary asset without physical substance" [IAS 38]. Intangible assets are increasingly considered to be the driver of economic performance for most contemporary firms (e.g., Lev, 2019), or the main mechanism to secure profitability through intellectual property claims (e.g., Durand and Millberg, 2020; Rikap, 2020; Schwartz, 2020). Another important, yet distinct, intangible asset is "goodwill", which can be defined as the net price paid for an acquisition after accounting for the "fair value" of the acquired firm's identifiable assets and liabilities (including contractual rights) (Lev, 2019); as such, goodwill includes all assets that cannot be separated or distinguished from the firm itself (Nitzan and Bichler, 2009). While it would seem logical to treat personal data as an intangible asset, it is not clear whether it can be measured and valued as a distinct resource, or if it is better thought of as a component of goodwill. Either way, its measurement and value is an accounting artifact of market capitalization (Lev, 2019; Philippon, 2019) wherein the gap between tangible asset values and capitalization is used to explain the value (and importance) of intangible assets. But this is tautological: the departure of capitalization from tangible asset values is claimed as evidence of value of intangible assets, while the value of intangibles (e.g., data) is evidenced by the gap between capitalization and asset values. This creates a conceptual problem, since reading the value of personal data off market sentiment does not provide the analytical means to understand *how* personal data is measured, governed, or valued by Big Tech.

Our argument is that Big Tech makes personal data measurable and legible as an asset through "techcraft". This concept corresponds to Scott's (1998) notion of statecraft and contributes to our analysis in the following ways. First, like intangible assets, it is difficult to measure personal data. Google's chief economist, Hal Varian (2018), notes that only data that has been sold or licensed can be clearly identified and measured. He argues that personal data are not "sold"; rather, access to personal data is "licensed" through contractual arrangements (also see Fourcade and Kluttz, 2020; Li et al., 2019). Consequently, Big Tech firms have to identify something that can be measured. Drawing on Scott's (1998) work, Fourcade and Healy (2017) argue that the monetary calculation and measurement of data depends on the tracking and ranking of users. Similarly, Hwang (2020) argues that the technological architecture of digital platforms and ecosystems enables firms to standardize their users in order to measure them; for example, he outlines how "attention assets" are constructed through the "standardized concept of a 'viewable impression'" defined by the need for 50% of an online advert to occupy a browser's viewable space for more than one second (Hwang, 2020: 51). Such user metrics and standards depend on techcraft as a way both to understand and to perform "data" as a measurable asset. Moreover, techcraft not only includes the metrics and standards—i.e. the "Tech"-side—it also expresses the market power embodied by monopoly and market concentration—i.e. the "Big"-side; having scale enables these firms to assert their metrics as industry and even economy-wide standards.

Second, the notion of techcraft makes it problematic to frame the governance of personal data as an asset in terms of property rights. According to Lev (2019: 724), not only is there a "virtual absence of markets" for intangibles like data—although see Wichowski (2020) for a discussion of data brokers—but personal data itself is not ownable per se, being a "fact" (Cohen, 2017; Laney, 2018). Although many scholars are currently trying to theorize personal data as property in one form or another (e.g., Brynjolfsson and Collis, 2019; Lanier, 2014; Li et al., 2019; Posner and Weyl, 2019), these discussions miss a key aspect of the assetization process already at play. Returning to Scott (1998), it is important to understand how personal data is made legible to political-economic actors as a specifically techno-economic object. This does not happen organically or automatically; personal data has to be made legible through techcraft, just as it has been made measurable. It is made legible through the definition of "users" *and* control of access to those users as a resource, which explains the emphasis that investors put on user monetization rather than personal data (Arvidsson and Colleoni, 2012; Wu et al., 2020). Users are made legible as an asset through their monetization as "attention" or "impressions", articulated via metrics like DAU or MAU. Here, Big Tech derives its power from control over access to users (Pistor, 2020), extending this control through techcraft developments that maintain and augment active use of their platforms—for example, auto-play, constant scrolling, etc. (Kang and McAllister, 2011; Wu et al., 2020)—which then comes to define *what* a "user" is.

Finally, it is important to understand what is being made valuable, as much as being made legible and measurable; it is users, not "personal data". A user is a specific measurement of a person's time, activeness, regularity, and repetitiveness in "using" an ecosystem (i.e. "engagement") (Arvidsson and Colleoni, 2012). Techcraft makes a user legible to Big Tech as that user's use of a platform or device, and use is made measurable through techno-economic standardization like "viewable impressions" (Hwang, 2020). User engagement represents both a way of valuing information about people and a way of transforming people and their subjectivities into techno-economic objects through online engagement architecture (Wu et al., 2020). In turn, the user is made legible to investors via Big Tech's metrics in order to explain how users are, or will be, monetized. Like Scott (1998) argues with regards to the state, making a person legible and measurable as a user through focusing on their engagement activities makes that person *only* legible and measurable to Big Tech as those specific techno-economic activities (e.g., searching, scrolling, viewing); people's online activities are configured by Big Tech in this way. Users become their use, or their time and effort spent on a platform or in an ecosystem. Here, then, we are building on Zuboff's (2019: 129) argument that Big Tech are in the business of making "prediction products" by surveilling and changing behavior, although our point is that techcraft entails a recursive and performative transformation of users into measurable and legible techno-economic objects that constitute claims on future revenues, whether or not this transformation actually changes individual behavior to make it predictable.

Materials and methods

Personal data promises new means and methods of capital accumulation as the key resource of future digital economies (Sadowski, 2019). We want to understand how Big Tech firms—and other political-economic actors—understand, govern, and value personal data through the concept of techcraft introduced above. Frequently defined by acronyms like "GAFAM" (e.g., Foroohar, 2019; The Economist, 2020), Big Tech represents the five largest technology firms in the world by market capitalization: Apple, Amazon, Facebook, Google/Alphabet, and Microsoft. Other firms have been associated with the label of "Big Tech"; for example, Netflix is the next largest member in the S&P500, yet it is only one-third the size of Facebook, the smallest member of GAFAM. Our interest is in the largest technology firms who dominate personal data collection, so we do not include others in the analysis here. The five largest Big Tech firms are also all US firms, so we specifically focus on North America in this paper. To analyze Big Tech, we use a mixed methodology approach drawing on qualitative interviews with policymakers, financial data from Compustat, transcriptions of quarterly earnings calls in the Seeking Alpha database, and annual reports produced by Big Tech firms.

First, in 2019 and 2020 we interviewed policymakers in the USA and Canada ($n = 21$) to explore the emerging concerns about data monopolies and the rise of Big Tech; all interviews followed an institutional ethics review and included informed consent. We use this material to contextualize our other empirical material within ongoing political-economic debates about personal data. Second, we collected financial data from Compustat to identify the reported asset base of Big Tech and other firms; our analysis compares the balance sheets of Big Tech firms with those of the Top 200 US firms by capitalization (i.e. debt plus equity). We do so to explore the quantitative measurement of personal data as an asset. And finally, we collected and analyzed information from earnings calls (2010–2019) and financial reports (e.g., SEC-mandated 10-Q and 10-K disclosures) of Big Tech firms to identify how investors and Big Tech firms understand, govern, and value personal data in their own reporting; we undertook a quantitative textual analysis of these earnings calls and a qualitative discourse analysis of the annual reports. This methodological approach enabled us to see how investors monitor corporations, which are mandated to disclose their underlying financial situation, and how executives represent their firms.

Our rationale for taking this multi-methods approach is twofold. First, the US Financial Accounting Standards Board, which maintains the Generalized Agreement on Accounting Principles (GAAP) that standardize corporate accounting practices, does not currently allow digital personal data to be treated as an asset on balance sheets. Given this, we wanted to see where the value of personal data is reflected—if at all—through a quantitative analysis of Big Tech's balance sheets. Second, if personal data does not appear on Big Tech's balance sheets, we wanted to examine what data (e.g., user metrics) are deemed important to a firm's operations, revenues, and profits by examining their earnings calls and financial reports. Due to the importance of financial disclosure to shareholders, we surmised that the measurement, governance, and valuation of data would likely be qualitatively reflected within these materials if not in the Compustat statistics.

Big Tech in North America

Before we turn to the measurement, governance, and valuation of personal data in the next sections, we outline the context of the rise of Big Tech in North America and subsequent fears about data monopolies. Big Tech firms are increasingly central players in North American economies and societies. Recently, they have been the focus of significant policy and public critique and condemnation (e.g., US House of Representatives, 2020), especially in light of their innovation and business strategies driven by the accumulation of user data as a new asset class of personal data.

The rise of Big Tech

Big Tech is generally associated with the emergence of digital platforms and ecosystems that act as techno-economic intermediaries, connecting buyers and sellers in multisided markets (Khan, 2017; Nieborg and Poell, 2018; Srnicek, 2016). As many interviewees noted, there are self-reinforcing advantages for large players and first movers in such markets, creating "winner-takes-all" dynamics. Intermediation relies on network effects—how a service's usefulness is enhanced as more users are connected—with a large network providing economies of scale and scope, connecting more transactions in terms of volume and function. This is enabled by control over digital data to tailor services, respond to, anticipate, and create demand (Khan, 2017). One interviewee argued that this model is similar to traditional "big network" infrastructure, but highlighted the new role of data:

> . . . what is more unique to digital platforms is that the nature of the enterprise has been data gathering, which is - can be monetised through advertising. And monetised through increased, I'll say, understanding of human behavioural patterns and preferences that can be monetised in enhanced algorithms, artificial intelligence. (ex-Federal Ministry A, USA, 2019)

While there are parallels with existing databrokers (Pasquale, 2015), Big Tech is also unique due to a combination of regulatory deficit and the natural monopoly dynamics of network effects. This led interviewees to highlight Big Tech's role as a market-maker, using their scale and control over data to become market infrastructural actors: "What we have is competition to control markets instead of competition within markets, and that's because we didn't put any public rules on the use of data" (Think Tank A, USA, 2019). Consequently, Big Tech firms have often been willing to accept low revenues in the short- to medium-term with the longer term goal of capturing markets and monopoly rents through their expected future control over data (Foroohar, 2019; Khan, 2017). In the context of cheap credit since the 2008 global financial crisis, Big Tech became a popular investment option as the prospect of unregulated monopolies looked like a safe bet—even creating a self-fulfilling prophecy as cheap financing made it possible for Big Tech firms to outgrow or absorb less well-financed rivals (Galloway, 2018; Srnicek, 2016). As illustrated in Figure 1, the market capitalization of Big Tech had risen to nearly 25% of the S&P500 total capitalization by mid-2020. The expansion of Big Tech's domination accelerated during the COVID-19 pandemic as digital platforms have become increasingly important for everyday life.

Big Tech and the post-2018 techlash

The market outperformance of Big Tech has continued apace despite policy and public condemnation. This so-called "techlash" has its origin in the breakdown of public and policy trust in Big Tech firms starting with the 2016 US Presidential Election (Foroohar, 2019) and exacerbated by the 2018 revelations about Cambridge Analytica and Facebook (Zuboff, 2019). There has been a growing expectation that regulatory interest in digital market power would lead to a shift in market sentiment against Big Tech. So, while Silicon Valley was perceived to be favored in the Obama era—as one interviewee noted (Academic Lawyer A, USA, 2020)—public opinion has increasingly driven policy and political momentum towards greater regulation of the collection and use of personal data. Big Tech became the focus of antitrust reform in the USA (Crane, 2018), with Senator Elizabeth Warren articulating the radical edge of the techlash in her proposals to "break up big tech". More recent policy and public concern about Big Tech's data monopolies is evident in the US Congressional Hearings about market power and Big Tech in 2019 and 2020.[3]

Longer term concerns with the distinct dynamics of digital platforms exposed the fissures in existing antitrust legislation in North America (Crane, 2018; Khan, 2017). The dominant consumer welfare principle—emerging out of the Chicago School in the 1970s—holds that monopoly power only matters if it has a negative material effect on consumers (i.e. short-term price rises), ignoring the structural market power that Big Tech has amassed through their control of data (Khan, 2017). As an interviewee noted:

> ...whether you're anticompetitive right now is based on competition law statutes that are based on sort of industrial age thinking...But none of those factors apply to

Figure 1. Big Tech's share of S&P500 total capitalization, 2013–2020.
Note: Series calculated by authors with data from Barchart, Global Financial Data, and Yahoo Finance. Series begins 23 December 2013, the day of Facebook's inclusion in the index.

> digital, intangible assets [which] . . . can be replicated infinitely. So regulators have a hard time . . . they feel something's wrong with the scale and pervasiveness of [Big Tech]. They don't like it, but they don't know why . . . (Private Lawyer A, Canada, 2020)

However, despite all this, the techlash does not appear to have impaired the growth of Big Tech (see Figure 1), even though US and Canadian regulators are now taking more robust antitrust stances and introducing new data protection policies. In a broader political context increasingly concerned with fears about data monopolies, then, how Big Tech measures, governs, and values personal data matters.

How do Big Tech firms measure, govern, and value digital data?

Where is personal data in the Big Tech asset base?

Our empirical starting point is a statistical analysis of Big Tech firms to identify their asset base relative to that of the Top 200 US corporations, defined by capitalization. Our aim is to examine how personal data is measured by Big Tech and other market actors (e.g., investors). As noted above, although personal data cannot be booked directly as an asset, we expected it to be implicitly valued through other intangible assets, including goodwill.

The rise of intangible assets. We start by trying to measure the personal data held by Big Tech firms. Figure 2 shows the asset base of the Top 200 US corporations, stacked from most to least "liquid" assets. It shows a significant decline in property, plant, and equipment (PPENT) and rise in intangibles between 1950 and 2020.[4] In the early 1980s, PPENT represented nearly 60% of total corporate assets, but by 1999 this fell to less than 30% and remained there; the intangibles share rose from less than 1% in 1983 to more than 20% in 2005, and by 2016 intangibles had surpassed PPENT. We can explain part of this trend by pointing to changes in accounting practices, as well as increasing acquisitions and industrial transformation. It seems a reasonable assumption that at least a portion of the increase in intangibles can be implicitly attributable to personal data; but that does not seem to be the case when we examine each Big Tech firms individually (see Figure 3).

Despite the rise in intangibles in the corporate asset base, these findings contrast with claims that intangibles are driving contemporary capitalism (e.g., Ciuriak, 2018; Durand and Millberg, 2020; Lev, 2019; Philippon, 2019; Short and Todd, 2017). Moreover, there seems to be some confusion between the market value and accounting value of personal data, where the latter is not identifiable while the former is imputed from the expansion of intangibles, but mainly assumed to be represented by goodwill (see below). Rather, these

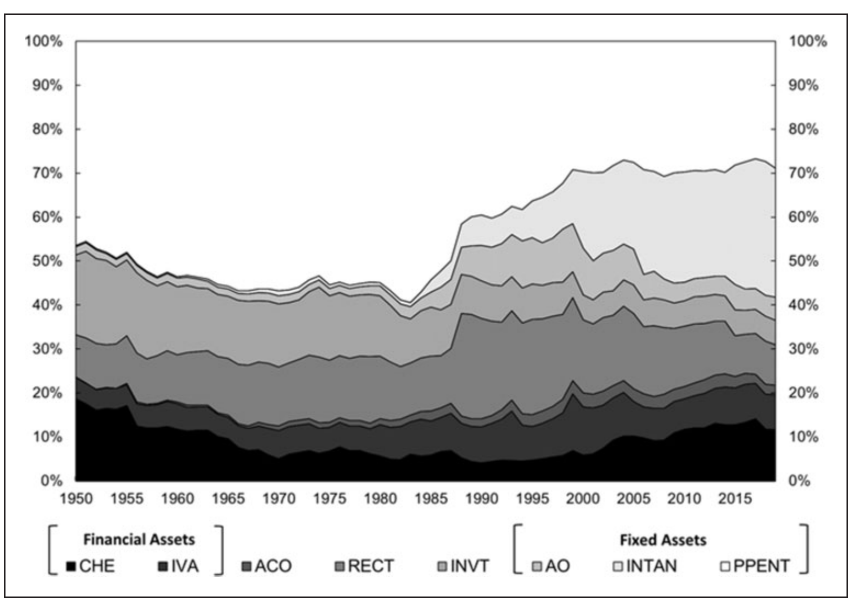

Figure 2. Distribution of total assets, Top 200 US Corporations 1950–2019.
Note: Calculated by authors; data from Compustat via Wharton Research Data Service. Series aggregate reported values for Top 200 US Corporations, ranked by capitalization (debt plus equity), excluding public utilities and federally backed financial institutions. CHE: cash and equivalents; IVA: investments & advances; ACO: other current assets; RECT: receivables; INVT: inventories; AO: other assets; INTAN: intangibles; PPENT: total property, plant, and equipment. We have labeled noncurrent assets as "fixed assets" to acknowledge their greater role in the valuation of the companies.

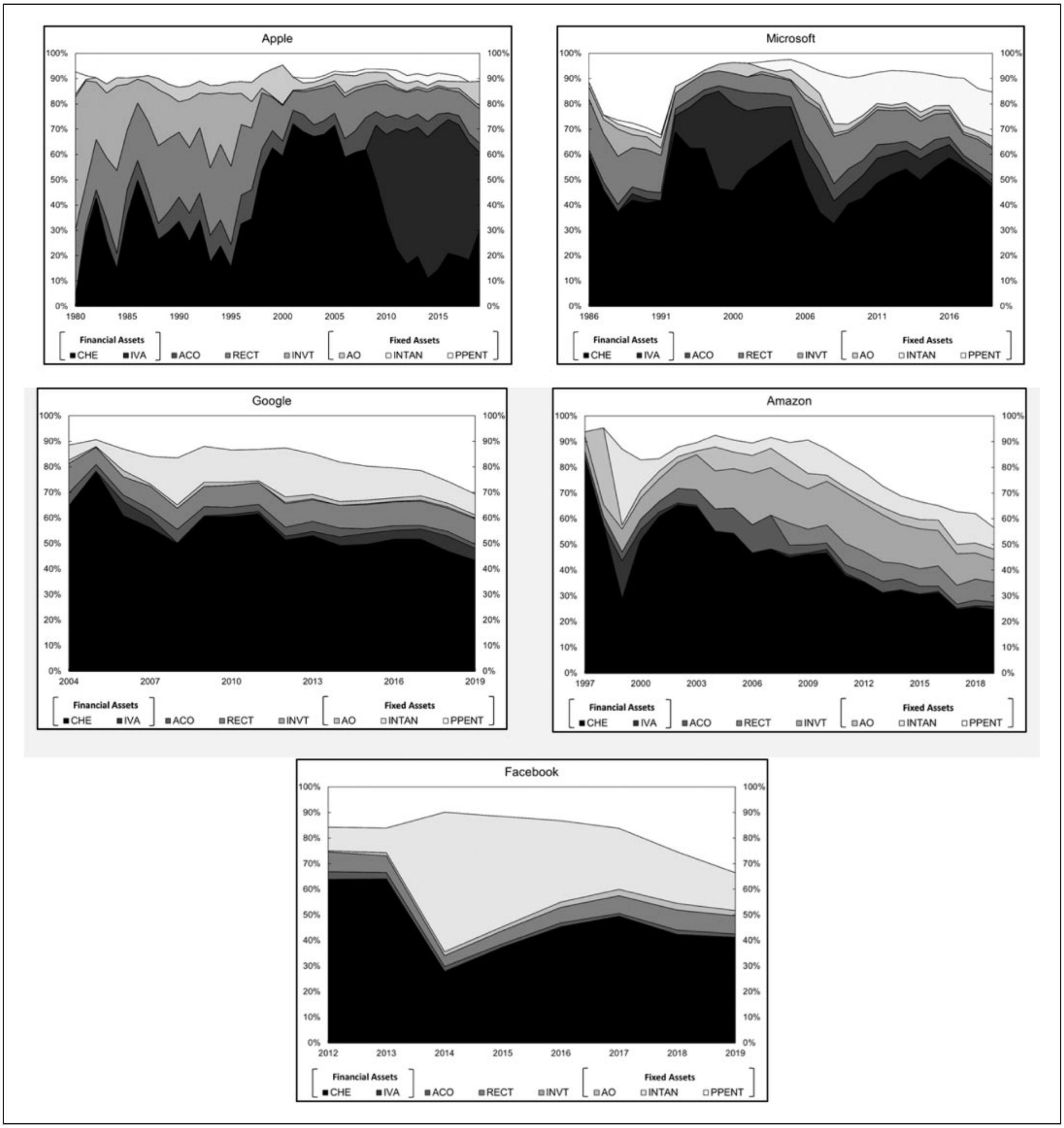

Figure 3. Breakdown of Big Tech total assets: Apple, Microsoft, Google, Amazon, Facebook.
Note: Calculated by authors; data from Compustat via Wharton Research Data Service. CHE: cash and equivalents; IVA: investments and advances; ACO: other current assets; RECT: receivables; INVT: inventories; PPENT: total property, plant, and equipment; INTAN: intangibles; AO: other assets.

findings reflect the argument that the value of intangibles exceeds what is recorded on balance sheets. This value is implied by the growth of market capitalization relative to the accounting value of intangible assets, including personal data presumably, rather than reflecting recorded assets (see Figure 3).

Intangible assets, personal data, and Big Tech. We now turn to the measurement of personal data in the five Big Tech firms; see Figure 3 for a breakdown of assets of each Big Tech firm. There is limited uniformity amongst these firms, which contrasts with the discourse that often treats Big Tech as similar (e.g., Wichowski, 2020). These statistical differences stem from differences in both the structure and accounting of their assets (Birch and Muniesa, 2020). Although there are SEC-mandated disclosure requirements each firm should adhere to, corporations still retain considerable latitude in what financial data they report, as well as how they classify assets. Perhaps the clearest example of this discretion is the disappearance of intangible assets from Apple's balance sheet in 2018.[5]

Despite the heterogeneity in Big Tech, there seems to be a more notable difference between Big Tech firms and other firms in the Top 200 (see Figure 2). Amazon, Google, and Facebook are moving against the Top 200's trend of a stable share of PPENT and a growing share of intangibles. Since their IPOs, all three have more than doubled the share of *tangible* assets in their asset base. As of 2019, Google and Facebook both had a slightly higher proportion of tangible assets than the average Top 200 firm. Intangibles is an even starker contrast: while the Top 200 have about 30% of their assets in intangibles, Amazon and Google's intangibles comprise less than 10% of their assets, with Facebook's intangibles at 15%. Obviously, then, these findings contrast with the expectation that Big Tech invest more proportionally in intangibles, or that such investment is their main competitive strategy (e.g., Philippon, 2019); it even contrasts with arguments about the importance of intangibles in contemporary capitalism more generally (e.g., Lev, 2019). To understand these findings, we must sort out the ambiguities around the valuation of Big Tech as an effect of personal data holdings, supposedly captured by intangible assets on their balance sheets. Since we cannot identify where those "data assets" sit in accounting terms (including goodwill), we must approach the question via investor assessment of the market value of those personal data holdings, which we do in the next section.

Is personal data an intangible asset?. Overall, Big Tech firms have a lower proportion of intangible assets than the Top 200 firms and higher tangible investments. Our explanation for this goes back to the GAAP accounting principles that mean personal data cannot be included on a firm's balance sheet; hence, personal data cannot be treated as either a distinct intangible asset or imputed as goodwill (Laney, 2018). As Varian (2018) argues, since personal data cannot be owned per se, it is the *access rights* to personal data collected by Big Tech that can be turned into an asset. This suggests that the value of granting access depends on the enclosure of user data as an asset (e.g., Foroohar, 2019; Posner and Weyl, 2019), but such data is not simply waiting to be claimed. It is always formatted in the process of collection and transformation into an asset; it must be made measurable and legible through techcraft (Scott, 1998). While there have been several attempts to theorize the measurement of personal data (e.g., Brynjolfsson and Collis, 2019; Laney, 2018; Li et al., 2019), they do not provide a means to get at current practices. Understanding *how* Big Tech firms make user data measurable and legible as a new asset class of personal data to investors is a critical issue for ongoing analyses of our digital economies.

How do Big Tech firms govern personal data?

We now examine how Big Tech govern the personal data they collect. To understand how Big Tech firms govern personal data, we analyze their quarterly earnings calls with financial actors (e.g., analysts, investors) so that we can then unpack how user data is made measurable and legible as an asset for these firms and investors (Fourcade and Healy, 2017).

Typically, an earnings call consists of a presentation by a corporate executive (e.g., CEO, CFO) that is then followed by a question and answer (Q&A) session where analysts can ask about recent financial results and future plans. Until 2020, Amazon was an exception to this structure, foregoing the presentation and opting to share a press release in advance and reserving the call for the Q&A. If personal data is seen as an important, although unaccounted, asset for Big Tech, then we expected analysts to ask for information about it to work out how it is being managed and valued by the firms. However, our analysis of the earnings calls shows that there was almost no expressed interest in personal data per se. Table 1 shows our quantitative textual analysis of these earnings calls, and it shows that "personal data" was only mentioned two times in nearly a decade of earnings calls across five Big Tech firms. Rather than personal data, the immediate concern of the analysts was "monetization", and the preferred techno-economic object of monetization was "users" (see Table 1). Here, users are framed as part of a broader techno-economic assemblage—identified as an "ecosystem"—capable of generating revenues, if properly monetized.

Despite the heterogeneity of Big Tech, this concern with users is not only relevant for those firms whose innovation and business strategies reliant on advertising (e.g., Google, Facebook, and now Amazon), but

Table 1. Number of mentions of terms in Big Tech Earning Calls (2010–2019).

	"Personal data"	"Privacy"	"User"	"Monetize"
Amazon	0	11	26	8
Apple	2	54	257	17
Facebook	0	220	430	230
Google	0	47	1050	244
Microsoft	0	54	271	85

Each search term includes relevant forms and variations (e.g., "Privacy" includes "private" and "privately"). Count for Amazon is from just the Q&A. Count for Facebook is for 2012–2019.

also for firms like Apple and Microsoft. For example, from the 2015Q1 earnings call onwards, Apple executives consistently refer to active devices as its "installed base" with terminological slippage between "installed base of devices" and "installed base of users", especially in 2019 earnings calls. Apple executives speak about their efforts to generate future revenues from this "installed base", especially by monetizing the techno-economic ecosystem, as one executive pointed out:

> Paid subscriptions is another target, is important to us. It's an important way for us to *monetize our ecosystem*. We set a target of surpassing 0.5 billion paid subscriptions on the ecosystem during 2020. We're already at 420 million now. So, we feel confident there. (2019Q3 – our emphasis)

Framing users as an asset in this way has led to concerns with privacy following the techlash (Foroohar, 2019), which can be clearly seen in Figure 4 where we break down mentions of "privacy" over time. Before 2018 there was limited discussion of privacy in earnings calls, but in 2018 and 2019 there was a significant jump in interest, especially for Facebook and Google. During Facebook's 2018Q2 Q&A, an analyst from Citigroup specifically asked if "giving people more control over their privacy and data" would have a negative impact on Facebook's earnings. A Facebook executive downplayed the impact but still affirmed that it would have one. Interestingly, Apple CEO Tim Cook spelled out an important difference between Apple and other Big Tech firms in their treatment of personal data. Asked by an analyst from RBC about Apple's vocal advocacy for more privacy protection, Cook responded, "If you look at our model, if we can convince you to buy an iPhone or an iPad, we'll make a bit of money. *You're not our product*" (our emphasis). In other words, greater privacy protection would harm some of Apple's Big Tech rivals to a greater degree than it would harm Apple.

As this empirical material illustrates, it is users that are understood as assets, which entails specific forms of governance predicated on the monetization of user data and "ecosystems". This is because Big Tech cannot own personal data as an asset as illustrated by the near absence of mentions of personal data in earnings calls. Instead, assetization involves: (1) the deployment of standards and digital architectures to measure and delineate users and usage; (2) the configuration of users within an ecosystem; (3) the contractual (i.e. terms of service) and technical (i.e. interoperability restrictions) enclosure of user and usage metrics for different purposes (e.g., training algorithms, data analytics); and (4) capitalizing future revenues derived from different monetization mechanisms, including locking-in users to digital ecosystems (e.g., Apple), offering subscription services (e.g., Microsoft), selling access to users and user data (e.g., Facebook, Google), or collecting a range of fees for use of a platform (e.g., Amazon) (Arvidsson and Colleoni, 2012; Cohen, 2019; Wu et al., 2020; Zuboff, 2019). Despite their heterogeneity, Big Tech firms seek to entrench their dominance

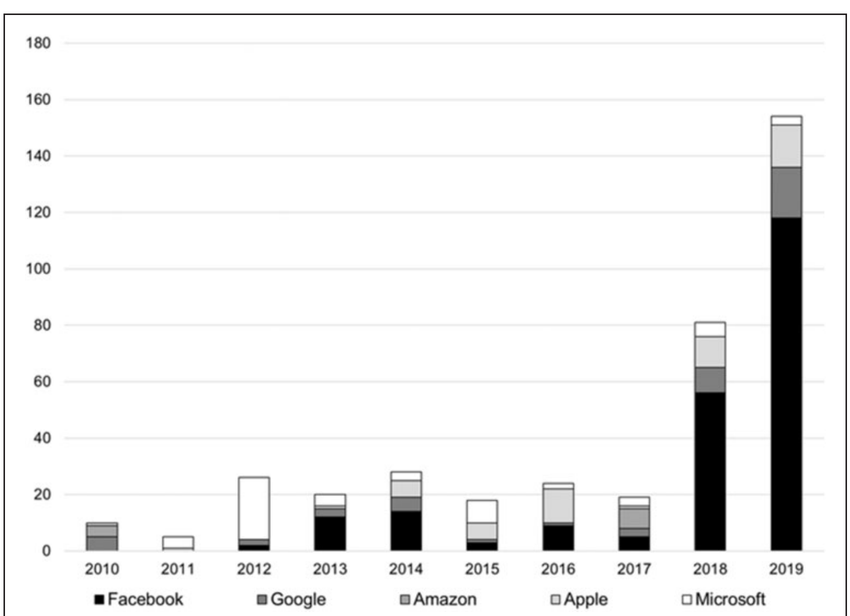

Figure 4. Mentions of privacy, private, privately in Big Tech Earning Calls, 2010–2019.
Note: Count for Amazon is from just the Q&A and count for Facebook is for 2012–2019.

by extending their data-gathering activities, as one interviewee explained:

> ...the business model usually in these platforms, has been to sell advertising based on that information. And what that - when you add that to the network effects and the economies of scale, you then also get scope economies. Because then the more things I can sell out of that network, or the more functions I can provide... the more diverse data I can get about the users, which enhances the predictability of behavioural patterns and predilections and inclinations. (Think Tank A, USA, 2019)

As such, Big Tech firms deploy techcraft to convert personal data into user metrics through "artifacts of the design of datafication" (Cohen, 2017: 160); these artefacts are designed and configured to attract attention, to generate activity, and to stimulate further interaction, engendering more data about users (Arvidsson and Colleoni, 2012; Kang and McAllister, 2011; Wu et al., 2020; Zuboff, 2019). Here, "users", "usage", and "access to users" end up as the legible techno-economic objects that Big Tech can value as future revenue streams through different monetization strategies.

How do Big Tech firms value personal data?

Next, we analyze the valuation of personal data by examining the treatment of acquisitions by Big Tech firms, drawing on their financial reports (and earnings calls). From 2010 to 2019, Big Tech firms spent an average of $23 billion in cash on acquisitions, much more than the average firm in the Top 200, which spent $8.4 billion.[6] According to Wichowski (2020: 63–64), Big Tech has made 1227 investments or acquisitions between 1998 and 2018. Given their heterogenous business models, there are variations among Big Tech firms when it comes to acquisitions, although the core commonality of their business model is that they seek to strengthen their monopoly of users, user engagement, and access to users.

At the low end for acquisition spending is Facebook with cash expenditures of $7.5 billion over the last 10 years, less than the average Top 200 firm. More than two-thirds of that spending was in 2014 when Facebook acquired WhatsApp for $4.6 billion in cash plus $15 billion in shares. Two-years earlier, Facebook acquired Instagram for $1 billion, specifically because "user engagement" on Instagram—not just user numbers—had surpassed other social media sites (Galloway, 2018). As Facebook's 2012 10-Q report notes: "[Instagram] is expected to enhance our photos product offerings and to enable users to increase their levels of mobile engagement and photo sharing" (p.9); the value ascribed to "goodwill" in the transaction was $435 million. Notably, personal data is not mentioned in this report, while "user engagement" is referenced 15 times, including the statement that "our business performance will become increasingly dependent on our ability to increase user engagement and monetization in current and new markets" (p.35).

At the high-end for acquisitions is Microsoft, which has spent $52.2 billion over the last ten years, including $25.9 billion in 2017 primarily on acquiring LinkedIn. Consequently, Microsoft is responsible for almost half of the cash-funded acquisitions by Big Tech since 2010. The pace of acquisitions by Microsoft helps explain why it is alone among Big Tech firms with a growing share of intangible assets, although at 17.4% it remains well below the average Top 200 firm. This is because almost half of Microsoft's assets are financial, as are most of the members of Big Tech. The purchase of LinkedIn is again related to the desire to increase user engagement, spelled out in Microsoft's 2017 10-K:

> Growth will depend on our ability to increase the number of LinkedIn members and our ability to continue offering services that provide value for our members and increases their engagement. (p.7)

Although Microsoft's 2016 10-K does not mention 'user engagement' at all, its 2018 10-K does and specifically in relation to reaching "new customers and increase usage and engagement with existing customers" (p.4). Unlike Facebook's earlier report, Microsoft's 2017 annual report does reference personal data, but only in terms of legal privacy and regulatory concerns; for example, that EU regulations "may impede the adoption of our services" (p.22).

As mentioned earlier (e.g., Laney, 2018), accounting rules currently prevent firms from valuing and accounting for personal data on their balance sheets. Consequently, the value of personal data might show up in the valuation of 'goodwill'. Since the early 2000s goodwill has trended at around 60% of the Top 200's intangible value. For Big Tech firms, however, goodwill has averaged about 80% of intangible value. As a reminder, goodwill captures the difference between the price of an acquisition and the so-called "fair value" of its assets and liabilities (Lev, 2019); for example, Alphabet's 2019 10-K puts the value of goodwill from the acquisition of Looker that year at $1.9 billion compared with $290 million for intangible assets (p.76). Again, Alphabet's annual report highlights the importance of user engagement, primarily relating to the "use of monetization metrics" (e.g., paid clicks) (p.30). It is not clear, then, that goodwill reflects the valuation of personal data—again, seen as a regulatory or reputational issue in Alphabet's 2019 annual report. Big Tech firms do not value personal data as goodwill in the annual reports we examined; instead, user engagement and undefined "synergies" justify the valuation of goodwill. It seems that the contractual arrangements (e.g., terms and conditions) between firms and users is important in ensuring that user data are measurable and legible as an asset, since contracts can be separated and distinguished from the firms themselves and are not part of the undifferentiated mass reflected in goodwill (Lev, 2019).

Again, Big Tech are not valuing personal data per se, even as goodwill. Rather, users and user metrics are valued through tracking and recording of user engagement with/in a firm's ecosystem (Fourcade and Healy, 2017). Techcraft involves a valuation of user data, measured as users and their legible engagement as future revenue streams (Scott, 1998). Users need to be governed for user engagement to be monetized (Hwang, 2020). Acquisitions provide a snapshot of this assetization process, where innovation and business strategies are specifically valued based on user numbers, user engagement, user clicks, click-through rates, and so on (Lubian and Esteves, 2017); users *and* user engagement are the thing being valued as assets by Big Tech firms and market actors. Monetization of user engagement is based on selling access to user decisions, actions, and behaviors (Zuboff, 2019). Access to users is controlled via the legal rights that users sign over to firms and the techno-economic configuration of user engagement through technological capture (e.g., Like buttons, cookies, etc.) (Pistor, 2019). User engagement is valuable because it drives an extraction-as-service or subscription-based business model, entailing repeat revenue streams rather than one-off earnings (Perzanowski and Schultz, 2016; Sadowski, 2020). Of particular importance is that users indefinitely sign away their legal rights in ubiquitous terms and conditions contracts that can be amended at will by Big Tech (Obar and Oeldorf-Hirsch, 2020), as well as indirectly signing away their friends and families' rights through third-party permissions embedded in numerous apps (Lai and Flensburg, 2020). Fourcade and Kluttz (2020: 6) call this a "Maussian bargain", in which supposedly reciprocal exchanges "lock users into a perpetually renewed transactional cycle in which consent is assumed 'forever'".

Discussion: Assetization, techcraft, and Big Tech

Big Tech is engaged in the assetization of users, user engagement, and access to users, specifically bounded by an ecosystem or enclave. This reflects earlier arguments by Arvidsson and Colleoni (2012: 144), although they place emphasis on "affective attention and engagement" rather than on access to users. Our findings show that Big Tech places particular stress on governing and valuing access to users via techcraft that makes users and user engagement (i.e. user data) measurable and legible as an asset. For example, the report from the 2020 US Congressional Hearing outlines the various techno-economic mechanisms that Big Tech firms deploy to control access to users on their digital platforms or ecosystems, which includes setting quasi-market rules for other digital firms who want to access those users to grow their businesses (US House of Representatives, 2020). The report states, for example, that Facebook "selectively enforced its platform policies based on whether it perceived other companies as competitive threats" (US House of Representatives, 2020: 166). It also includes details of how Google pays significant sums to Apple "to secure the search default across iOS devices" (US House of Representatives, 2020: 178), thereby extending its user base. The number of users is important as it has become a measure of Big Tech's power.

Measures like DAU, MAU, or "user base" are key metrics for these firms and their investors. Users are not the product—a pithy, yet incorrect aphorism—since users are not sold, nor can their information be sold without losing control over access rights; they are, instead, a new asset class of personal data through which Big Tech firms can generate continuing revenue streams. However, a "user" is a techno-economic object, rather than a person. The user is constituted through a series of technological and socio-legal choices (e.g., contract rights, technical limits to interoperability) that shape, constrain, and facilitate activity within digital platforms or ecosystems, thereby making them legible and measurable to both Big Tech firms and their investors (Fourcade and Healy, 2017; Scott, 1998; Wu et al., 2020). As Hwang (2020) outlines, a "user" is only legible (to Big Tech) as someone who pays attention—or from whom you are "getting another minute" to quote a Facebook product manager (US House of Representatives, 2020)—and they are measurable in this way. For example, Hwang argues that the standardization of "the attention asset" in digital platforms has emerged through the construction of attention standards like "viewable impression". This measurement of users and use reflects the techcraft that both creates *and* controls user data.

As these sorts of standard imply, someone who is not making viewable impressions—by using an ad blocker, for example—is not legible or measurable as a "user". Here, "use" matters; a user must engage in *particular* techno-economic ways with the digital technology to matter to Big Tech, meaning that user data is as much a construction of digital platforms or ecosystems as the user. "Use" can be seen as the performative construction of legible and measurable uses, as understood by Big Tech, through the development of digital technologies—like constant scrolling, autoplay, ecosystem lock-in, etc.—that specifically generate users who make viewable impressions. This feeds into the Big Tech concern with regular user engagement, measured as DAU or MAU, and the revenues that this generates, measured as "average revenue per user". Hence, it is not that personal data per se is turned into an asset, but rather that techcraft makes users and user engagement legible and measurable as an asset in ways that reinforce and perpetuate the market power Big Tech derives from their control of access to user data and the technological developments that maintain and augment the active use of Big Tech's digital platforms and ecosystems.

Conclusion

Our objective was to unpack how personal data is measured, governed, and valued by Big Tech firms, starting from the premise found in academic, policy, and business debates that personal data is a valuable resource or asset held by Big Tech firms, especially as a data monopoly. In unpacking this framing, we adopted assetization as our analytical lens to examine the transformation of personal data into an asset by Big Tech. We positioned our analysis within the broader context of the backlash against Big Tech presaged by revelations about the use and abuse of personal data. In contrast to our starting premise, however, our empirical analysis showed that personal data has not been incorporated into Big Tech balance sheets. We therefore explored Big Tech's governance and valuation practices—which we defined as "techcraft"—to identify how they reconfigure personal data as a techno-economic object (i.e. user metrics) that can be turned into an asset. Our argument is that Big Tech assetizes users and user engagement (i.e. user data) by making them measurable, legible, and monetizable, such as through subscriptions or selling access.

Big Tech's focus on user data is reflected in the market sentiment of investors. Control over users depends on acquiring contractual rights to collect and use personal data, as well as limiting access through further contractual arrangements and technological restrictions (e.g., limiting interoperability). As Big Tech increase the collection and monetization of user data, they can extend perpetual contractual agreements through legal alterations to those contracts. As such, techcraft creates a recursive feedback where users are (re)configured as techno-economic objects of governance and valuation, while data monopolies enable the techno-economic configuration of users and user engagement. The power of Big Tech is vested in this process of assetizing users rather than from the "ownership" of personal data.

Despite the power of Big Tech, there is a real threat to their dominance arising from their data governance practices. People are not users, yet they are reconfigured as these techno-economic objects; and personal data is not user engagement, yet it is treated as measurable and legible as such (Hwang, 2020; Scott, 1998). In building on claims made by Zuboff (2019) about surveillance capitalism, especially her notion of "prediction products", we would argue that the reconfiguring of people and personal data as users and user engagement makes these entities measurable and legible *only* in these terms, without a requirement that they translate into actual changed behavior (e.g., changing spending behavior). Consequently, the simulation of "users" and "user engagement" can disrupt and distort the very measurement, governance, and valuation on which Big Tech relies; for example, bots, click farms, and other automated processes simulating user activity undermines trust in Big Tech's supposedly key assets (Birch, 2020; Hwang, 2020). This represents an important agenda for further research, especially as Big Tech still benefits tremendously from these automated processes.

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Notes

1. https://www.brookings.edu/blog/techtank/2020/07/31/big-tech-and-antitrust-pay-attention-to-the-math-behind-the-curtain/
2. https://www.justice.gov/opa/pr/justice-department-sues-monopolist-google-violating-antitrust-laws

3. https://judiciary.house.gov/calendar/eventsingle.aspx?EventID = 3113
4. Note that the sudden jump in receivables in 1988 is due to an accounting change that moved the receivables of majority-owned subsidiaries onto the consolidated balance sheet of the parent companies
5. This appears to be an accounting change, although there is no explanation for the change in either the annual 10-K, or quarterly 10-Qs for 2017/8. The matter is not raised by the analysts on Apple's earnings calls.
6. A shortcoming of the Compustat database is that recorded value for acquisitions is just the cash portion.

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