Centre for International
Governance Innovation

CIGI Paper No. 327 — July 2025

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Dan is also a senior fellow with the C. D. Howe Institute, a distinguished fellow with the Asia Pacific Foundation of Canada, a fellow with the Balsillie School of International Affairs and an associate with Munich-based BKP Economic Advisors GmbH. Previously, he had a 31-year career with Canada's civil service, retiring as Deputy Chief Economist at the Department of Foreign Affairs and International Trade (now Global Affairs Canada).

Acronyms and Abbreviations

AI	artificial intelligence
DOGE	Department of Government Efficiency
IP	intellectual property
LLM	large language model
LTV	labour theory of value
MFP	multifactor productivity
OECD	Organisation for Economic Co-operation and Development
R&D	research and development
S&P 500	Standard and Poor's 500
SNA	System of National Accounts

Executive Summary

Data is widely acknowledged as the essential capital asset of the modern economy, yet its value remains largely invisible in corporate balance sheets and understated in national economic accounts. This paper argues that conventional valuation approaches — particularly those based on the costs of datafication — capture only part of the story. While expenditures on datafication enter GDP as investment in intangible assets, they do not reflect the substantial economic rents generated by the effective use of data within firms. These rents arise from data's distinctive economic characteristics, including non-rivalry and combinatorial scalability, and its role in creating information asymmetries that give data-rich firms a competitive advantage. As a result, data contributes to enterprise value not through direct transactions, but by enhancing profitability, accelerating innovation through machine learning, and enabling the creation of machine knowledge capital. Drawing on trends in the US economy, the paper estimates that data rents alone account for more than two percent of GDP — representing a layer of value in addition to the investment flows currently captured in GDP. This has profound implications for national accounting methodologies, which underestimate the value contribution of data. It also flags risks for economic policy in small open economies that lack the scale to effectively capture data rents, since investing in datafication at less than critical scale may not recover costs and may result in negative productivity outcomes.

Introduction

Economists have famously been pilloried for knowing the price of everything and the value of nothing. In the case of data, economists know neither the price nor the value. That is a problem for a market-based economic framework that depends on the discovery of prices through market exchange to determine the value of things. In particular, while data is often said to be the most valuable commodity of our age — the essential capital of the modern data-driven economy and the source of instruction for artificial intelligence (AI), whose rapid evolution is ushering in the age of machine knowledge capital — it remains largely invisible on the balance sheets of companies, and largely unmeasured in our national economic and trade accounts.

Unlike other productive assets that served as the essential capital asset of their age (land, in the agrarian age; the machinery of mass production, in the industrial age; and traditional intellectual property [IP], in the knowledge-based economy), data is "captured," rather than acquired in market transactions for which there are invoices and receipts. This bypasses the market frameworks developed since the Marginal Revolution for attributing a price to an asset — no marginal cost, no marginal price, no inference as to market value.

At the same time, while data can be bought and sold in secondary markets (once assembled into databases owned by companies), "ownership" of the data itself is not possible. There is no limit to the number of companies that can stake a claim in the same data (for example, the information flowing over the internet) yet claim a monopoly on their own data set. Moreover, while some insights into the value of data might be obtained from secondary market transactions in curated databases, the large pools of data that define the data-driven economy (that is, those assembled by the superstar platform firms) are not traded. They are akin in this sense to the "dark pools" of capital in equity markets that allow private exchange without influencing market prices through transparent bids.

A third critical feature of "big data" is that unlike the data that was mobilized for business and analytical purposes historically, big data delivers information that is, almost by definition, beyond what the human mind can access — in a sense, there is an opacity threshold that is passed, which creates pervasive information asymmetry. Information asymmetry is a source of market failure. Exploitation of information asymmetry for commercial advantage is at the heart of the business model of the data-driven economy. In other words, data empowers a business model that bases the development of markets *explicitly* on market failure. This too raises unprecedented conundrums, since information asymmetry is something that regulation and markets seek to "correct" — in other words, to annihilate. At the same time, information asymmetry is instrumental in driving enterprise value, which, of course, no one wants to annihilate.

Finally, the data-driven economy greatly amplifies the feedback effects of data-driven analysis on the social and economic structure that generated it in the first place and in not necessarily good ways. The negative externalities of data are many and significant — this is data as the new plutonium rather than the new oil. This challenges a market-oriented valuation framework that traditionally ignored negative externalities. Whether the risks can continue to be treated mostly as caveats while concrete valuation continues to be on monetary value (see, for example, Organisation for Economic Co-operation Development [OECD] 2013) is an open question.

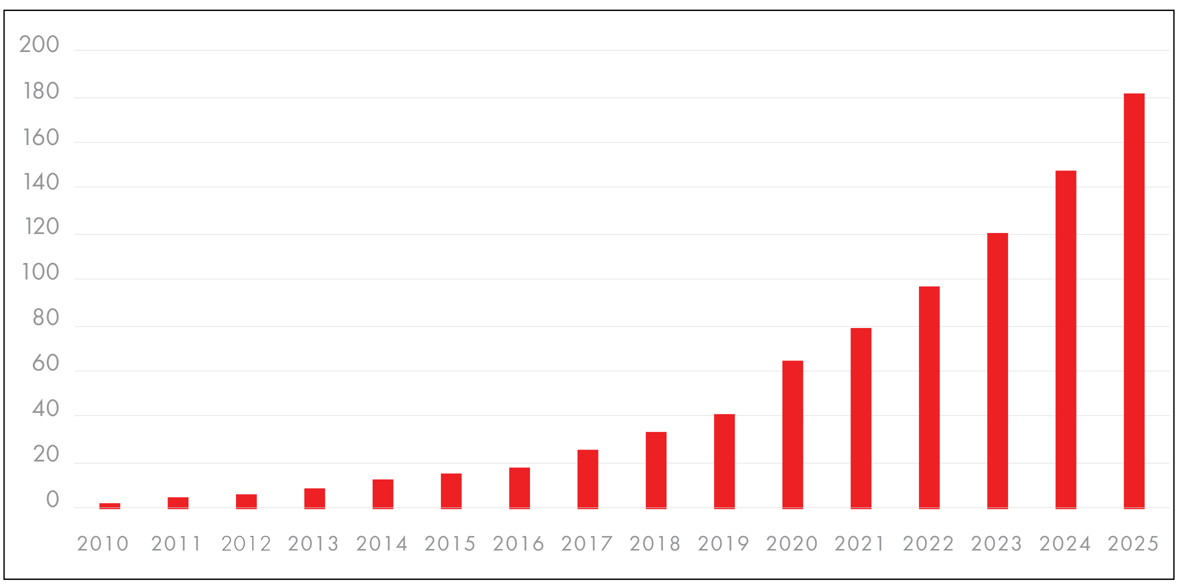
The estimates of the value of data have tended to place a rather small value on it — on the order of one to three percent of GDP (Sargent and Denniston 2023; Nakamura, Samuels and Soloveichik 2018). This is, in prima facie terms, incongruous with the astronomical amounts of data captured over the course of the short life of the data-driven economy (Figure 1) and with the transformative impact that data is having on our economy and society, not least as the key input into training AI. We are experiencing an earthquake and measuring a tremor. The thesis advanced in this paper is that this incongruity is attributable to the conundrums listed above.

The rest of this paper is organized as follows. The second section discusses the conundrums raised by trying to fit a capital asset that does not fit the paradigm around which market economies are organized into a market accounting framework. It draws a distinction between the process of "datafication" — the capture and curation of data — and the economic value of data, which comes from its use. In the absence of direct measures of the value of data, indirect approaches based on the costs associated with datafication have been adopted as a proxy; the weakness of this approach as a proxy for the value of data is discussed.

The third section argues that the value of data in commercial terms is internal to the enterprise, noting the various ways identified in which data improves the functioning of firms, as a complementary productive asset to their other capital assets. These include, *inter alia*,

- → optimizing business processes;
- → capturing consumer surplus;
- → allowing firms to exploit information asymmetry for market advantage;
- → shifting innovation into machine-learning space, which in effect permits the industrialization of learning, accelerating the process of innovation and providing a speed advantage to firms that are able to harness this element; and

Figure 1: Data Generated During the Data-Driven Economy Era (zettabytes/year)



Source: Duarte (2023).

- creating machine knowledge capital as a new factor of production.

The final section discusses the implications of a firm-centred approach to assessing the value of data and, by extension, value creation in the data-driven economy, and draws tentative conclusions.

The Conundrums

No Micro Foundations to the Value of Data

The ur-problem of data as an economic asset stems from the fact that it is not acquired in a market transaction for which there are invoices and receipts.

Markets are reducible to transactions. Data, not so.

To take one analogy of non-reducibility, Georges Seurat's famous pointillist painting *A Sunday Afternoon on the Island of La Grande Jatte* consists of approximately 220,000 dots (Goldstein 2019). Knowing that — and even knowing the distribution of the colours of the dots across the spectrum (Seurat used virtually every one of the 72 colours on Michel-Eugène Chevreul's colour wheel, the creation of which in 1839 was an inspiration for his work [ibid.]) — tells us nothing about what we see in the painting or even the colours that we perceive. Notably, all colours are interpretations that we place on wavelengths of light, but some colours do not even exist in nature as a discrete part of the spectrum; they are, to some extent, optical "illusions." Just as the "meaning" of Seurat's dots is not an intrinsic property of the dots themselves but an emergent property of their arrangement, so the value of data is not intrinsic to the individual datums but rather to the patterns that emerge from their assembly.

In short, an individual datum or observation is not traded, nor does it have economic value absent a context (that is, a set of correlations with other datums or observations). If sufficiently large, a collection of such observations — data — has enormous value, but there are no micro foundations to this value — it cannot be traced back to individual observations for which values are established by markets and aggregated to yield the value it has.

Accordingly, the valuation of data has to be pursued indirectly, which places great importance on the *choice* of indirect method.

Measuring Datafication Cost, Not Data Value

The source of value is not a new problem for economics; in grappling with the value of data, we are going back in time. The classical economists, including Adam Smith, David Ricardo and Karl Marx, tried to attribute the value of a product to the amount of labour that went into its creation (Marx added "surplus value" as an early recognition of the returns to capital). The labour theory of value (LTV) didn't succeed — although, interestingly, horsepower is used to measure the power of automobile engines, which is somewhat analogous to LTV.

Another train of thought introduced the abstract but seemingly intuitive concept of utility as the unit of value. While in the absolute sense advanced by Jeremy Bentham and John Stuart Mill this didn't succeed either, the Marginal Revolution led by William Stanley Jevons, Carl Menger and Léon Walras linked value, in a context of scarcity, to the *marginal* utility of a product, which led directly to marginal cost and marginal price establishing the value of things in a transactions-based market economy. The result of this evolution gives rise to what might be called the "product theory of the value of labour," which stands LTV — or better, what might be called the "labour theory of the value of products" — on its head, since the value of labour is determined by the value of the product created, rather than vice versa.

In the absence of reducibility of data to transactions, adopting a framework that values data based on the expenditures to acquire it — the process of datafication — confronts all the issues that caused LTV to fail. This is a problem, because, as Tim Sargent and Laura Denniston (2023) report, statistical agencies, including the Canadian, Dutch and US authorities, have all tried to value the economic contribution of data-related assets in the System of National Accounts (SNA) by using a "sum of costs" approach, which values an asset or a service on the basis of the expenditures incurred in its production.

This follows the approach to establishing the value of government services in the national accounts because of an analogous problem, the absence of a direct price signal. The value proposition with government services is in the externalities — public safety, the control of contagious diseases, the spillover benefits of education and so forth. With government services, this can result in misallocation of a nation's resources through under-provision of services that have public-good characteristics, with long-term deleterious consequences for a nation's competitiveness and, indeed, viability.[1]

With data, valuation based on the cost of datafication can lead to a similar problem: underinvestment due to a lack of appreciation of the true economic value. However, it can lead to another, still more serious problem: lack of insight into the business model required to benefit from data, an issue discussed further below in the discussion of data rents and enterprise value.

Implicit Exchange Values

An alternative to the sum-of-costs approach to establishing a value for data is to estimate the value of, say, free internet services that households obtain in exchange for the data that their online activity generates (see, for example, Nakamura, Samuels and Soloveichik 2018). This approach substitutes the challenges of measuring one non-market-transactions-based activity (the benefit of free services) for another (the value of data). Further, it measures the value of atomized data to consumers rather than the value of concentrated data to the main users, which can be very, very different orders of magnitude.

The Data Rush

Back in the day when money was dug out of the ground (the metallic standards era), the rapid growth of industrial economies put a premium on expanding the money supply to avoid deflation and all the ills that go with that. And so there were gold rushes. Miners would claim "stakes" and, given the lack of supporting paper-based legal infrastructure, literally split a wooden stake several ways, with each person holding a splinter being a "stakeholder," denoting ownership. The key point is there was unique ownership of the stake, which gave traction to markets.

Today we are having a "data rush," given the voracious appetite of AI systems for data. However, no one can claim ownership of the data itself. For example, even when data is generated by market transactions, numerous parties have access to the information content of the transaction, from the purchaser of a product, the vendor of the product, the credit card company that processes the payment, the banks of the purchaser and the vendor, the telecommunications provider, and any number of commercial apps and government agencies that monitor traffic on the internet (see, for example, OECD 2013, 12). In the digital age of surveillance capitalism and national security surveillance, there is no expectation of privacy for any communication over a telecommunications network or anything done in public. Moreover, unlike in the pre-digital age, when most information had the half-life of a firefly, the datafication of information means that it now lives on indefinitely and may be subject to any amount of analysis and re-analysis by any number of parties, including data brokers who monetize it by selling it onward, both in real time, as the observations are captured (for example, by Google with its real-time advertising push), and with an indefinite lag, as the data is incorporated into curated databases by others.[2] There can be no presumption of either ownership or control of our datums. By extension, there is no ownership of data.

What is interesting in this context is that any number of stakeholders can claim a stake in more or less the same data. Kevin Kelly (2017) recounts a conversation he had with Larry Page, one of the co-founders of Google, at a Silicon Valley party in 2002. Kelly asked Page how Google was planning to make money off a free search engine. Page answered that they were building an AI.

And Google did, capitalizing on the data generated by its search engine. Google's Bard (since replaced by Gemini) read almost everything on the internet in creating a model of what

1 As a digression, the United States, with its Department of Government Efficiency, or DOGE, is conducting a natural experiment of eliminating or sharply scaling back the provision of various government services for ideological reasons. Since externalities are not directly measured, the United States is facing a case of "you don't know what you've got till it's gone." The catastrophic decline in economic welfare in failed states testifies to the value of good governance.

2 On the distinction between "observations" and "data," see Sargent and Denniston (2023, 2). In the age of mobile, it is both possible and lucrative to monetize observations. For example, if someone is visiting Barcelona, searching restaurants at the dinner hour, and their search history shows a proclivity for sushi, Google is able to put that information in front of them in real time, including if they're on the move in an Uber, using geolocation to identify those restaurants close by.

language looks like (Pelley 2023). Of course, so did ChatGPT, OpenAI's large language model (LLM).

The scholastics debated questions satirized as "how many angels can dance on the head of a pin"; we could have a similar discussion today about how many stakeholders can hold a stake in the same data.

Before the data era, forms of capital had characteristics that allowed unique ownership rights to be staked out. Even intangible assets such as traditional IP and trade secrets allowed legal ownership regimes to be applied, albeit with substantially greater work for legal systems in determining infringement. With data, that is no longer the case. That is unusual and implies potentially different behaviour of the data-driven economy, raising many issues not directly related to the main one under discussion here.[3]

Data, Combinatorial Expansion and the Matthew Principle

The major breakthroughs that have been made recently in improving AI models, in particular, LLMs, came from scaling the power of AI systems: the size of specialized AI computer chips broke through the trillion-transistor level, the size of LLMs soared past the trillion-parameter level, the power of training methods increased by orders of magnitude, and the power consumption of AI chips was improved by orders of magnitude, pushing back the limits on scaling.

For deep-learning models, recent experience with the improvements of LLMs testifies that the larger the data set, the better the trained AI is in understanding context, interpreting out-of-sample data, capturing outliers, and handling nuances and variations in language.

In this regard, a distinctive economic property of data is that its value scales not just with volume but with combinatorial potential. Unlike conventional economies of scale, where unit costs fall with output, the aggregation of data exhibits a "power of scale": each additional data point increases the total value of the data set by expanding the number of potential correlations and inferences that can be drawn from the whole. This generates returns to scope within a single data domain and even more so across domains when data sets are linked.

This property is foundational to understanding the rise of superstar firms in the data-driven economy. The more data a firm has, the better its AI models perform; the better the models, the more compelling the user experience; the more users, the more behavioural data is generated — creating a self-reinforcing loop. This dynamic — a data-specific version of the Matthew principle ("to those who have, more shall be given") — can lead to a runaway concentration of market power in the hands of firms with first-mover data advantages.

Two-sided markets in which one side faces a zero monetary price — typically, users — have become a defining institutional architecture for this loop. While pre-digital analogues existed (for example, ad-supported television), digital platforms have taken the model to a new level. By offering free services to users, platforms rapidly scale their user base, harvest detailed behavioural data, and leverage that data to improve service quality and target advertisers more effectively. The result is an intensification of network effects that reinforce the dominance of incumbent firms and make market entry increasingly difficult for rivals lacking comparable data assets.

Summary

The technological revolutions that have culminated in the modern data-driven economy emerged in a market economy in which the productive capital assets had ownership rights with prices established in market transactions, allowing straightforward aggregation of the value of a nation's capital assets in its economic accounts. By extension, GDP could serve as an intermediate target for economic management. While there were sources of potential market failure, they were far from predominant, and the mature industrial era economy of the late

3 Ownership of data appears to bear mainly on the question of who owns the library costs of capture, classification and curation. In the modern digital context, besides the costs associated with archival hosting, library costs include the costs associated with access management and use/breach-based liability coverage. The generation of economic value from use of data can be based on proprietary or open data (in the latter case, avoiding many of the ownership-related costs, although not necessarily all). The exercise of usage rights creates obligations related to "ownership," although the exact extent is not settled, as there are open questions about whether owning a copy and exercising valid, limited use rights should be viewed as only part of an umbrella "ownership" of representations of a common fact (all the data pertaining to the same fact), or whether each representation attaches the whole universe of usage rights, and therefore constitutes independent ownership. Clearly, since a data-driven company can be bought and sold, de facto ownership of data as a capital asset (even if not in its raw form) is established and can be transferred.

twentieth century featured broadly competitive market conditions that were ideal for the emergence of a rules-based economic governance system in which governments had little incentive to intervene (Ciuriak 2024). The data-driven economy does not fit this mould. The characteristics of data are at the root of the problem, and trying to shoehorn data into the economic accounts and governance systems developed for an earlier age is not likely to be feasible or effective. Accordingly, we must return to first principles.

Enterprise Value

There are good reasons to believe that there are large economic rents generated by data, which implies that the cost of datafication — collecting, cleaning, classifying and curating data — falls well short of its value. For example, Carol Corrado, Jonathan Haskel and Cecilia Jona-Lasinio (2021, 436) calculate that capitalizing all the research and development (R&D) conducted by the major data firms since their birth yields a capitalized value of their R&D capital of $53 billion for Alphabet, $85 billion for Microsoft and $14 billion for Facebook, far short of these companies' value and, by extension, their data assets. Meanwhile, although there is some data that is traded in the market in the form of databases or subscriptions thereto, the large proprietary databases of the superstar firms, the "dark pools" that are the signature feature of the data-driven economy, are not traded. This leaves only enterprise value as a primary source to draw on to estimate the commercial value of data, since enterprise value includes data rents.

The Basic Intuition

Businesses have always used data for analytics, decision making, forecasting, and so forth. Data has thus always been central to enterprise value. For example, the banking business is based on understanding creditworthiness; the insurance business, on understanding risk; the restaurant business, on how much of what foods to buy on what schedule. In this regard, nothing has changed with the data-driven economy — data just got bigger and more powerful.

It is also instructive that there were analogues for the market concentration issues that have flared in the data-driven economy. For example, German insurance regulators require insurers with dominant market positions to share their risk data with their competitors to maintain competitive market conditions. This practice recognizes the information asymmetry issue inherent to data as a productive asset. And it is also from a context in which the value of data was not recognized separately as a line item in the capital structure of the firm.

This intuition can be sharpened by recalling one of the best-known tag lines developed by a company — BASF's "We don't make a lot of the products you buy. We make a lot of the products you buy better" (Deutsch 2004). Thinking about data in this sense suggests it is a complementary form of capital asset that makes other capital assets that are more conventionally valued on a transactions basis more efficient. This efficiency would manifest itself in an increase in profits that implicitly are data rents. To illustrate the point, the next section briefly runs through some, but by no means all, of the ways in which data performs this function.

Monetizing Data

The literature has identified numerous ways in which data increases the efficiency and profitability of firms.

Optimization of Processes

Sector by sector, company by company, leveraging data enables firms to improve business processes, reduce costs and increase operating margins. While the scope for potential gains varies by sector, and many firms have struggled to become data-driven enterprises (Bean 2023), the successes recorded by industry leaders has placed competitive pressure on firms to use data analytics to optimize their processes (Weill et al. 2024; Ma, Yang and Li 2024; Adaga et al. 2023; Hu, Li and Zheng 2022).

Capture of Consumer Surplus

Big data on consumer preferences and habits enables companies to apply first-degree price discrimination. This form of price discrimination involves a firm charging a different price for every unit consumed, based on the individual consumer's reservation price. With perfect price discrimination, the firm captures all the consumer surplus. This is the business model of, for example, Uber.

Exploiting Information Asymmetry

The information advantage conferred by command of big data can be likened to a sixth sense — but an industrial-strength sixth sense. Information asymmetry adds another source of potential market failure to the economy built on big data, joining economies of scale (inherent in the investments required to capture, classify and curate); economies of scope (reflected in the increase in value of data when it can be cross-referenced with other types of data); and, in many cases, network externalities (especially in platform markets). All of these effects tend to promote market concentration (and thus market-share capture for the leading firms).

Importantly, market mechanisms emerge to address information asymmetries in the normal course (as in "the market for 'lemons'" [Akerlof 1970]). But the information asymmetry inherent in big data seems irreducible — there are no market solutions to correct for this information asymmetry. This is the "original sin" of the data-driven economy (Ciuriak 2018).

We expect information asymmetry to lead to market failure, and indeed observe it in the emergence of superstar firms and the rising concentration in the leading data-driven economies. In the most intensively data-driven sectors, we see global near-monopolies. This reality reflects the exploitation of, and thus the monetization of, information asymmetry.

Shift of Innovation into Machine Space — Acceleration of Product Development

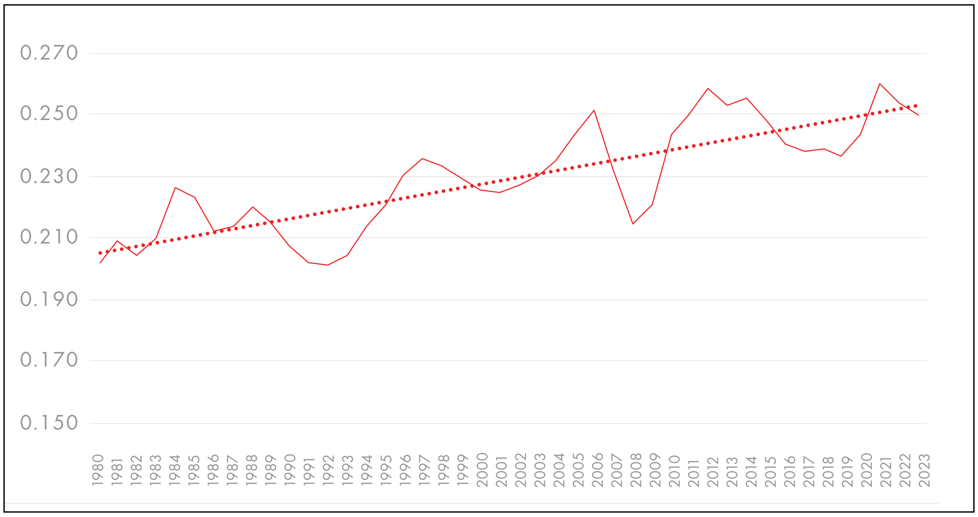
In the modern innovation-intensive economy, a major source of value in big data is that it enables machine learning. Machine learning can be understood as the industrialization of learning: it scales, accelerates, and automates pattern recognition and inference generation across massive data sets. This allows the acceleration of the process of innovation, providing a speed advantage to firms that are able to harness it. While we are still in the early phases of widespread machine learning deployment, the market increasingly rewards firms that can make a credible claim to an advantage in this area.

Training AI and the Creation of Machine Knowledge Capital

Data is the main feedstock in developing AI systems. The enormous strides in scaling AI systems in the late 2010s and early 2020s (Ciuriak 2023) led to the sensational breakthroughs in LLMs with text- and image-generation capabilities, which made "generative AI" the new buzzword. From an economic perspective, a more insightful term is "machine knowledge capital," as it points to how AI fits into the array of productive capital assets. Machine knowledge capital is to human capital what robots are to physical labour. However, where robots are large, expensive and difficult to deploy, machine knowledge capital can be reproduced at essentially zero marginal cost and distributed globally with frictionless ease. Moreover, machine knowledge capital can be integrated into robots to make them more flexible and to greatly extend the tasks they can perform, including in the service industries.

From the perspective of monetization of data at the firm level, the key observation is that the ability to create machine knowledge capital will enable market-share capture: this follows from the economics of superstars, whereby even a small quality advantage will lead to dominance in market share and substantial rent capture (Rosen 1981). From the perspective of national accounting, it implies a rising share of national income flowing to capital, as reflected in a rising profit share of national income.

Figure 2: US Profit Share of GDP, 1980–2022



Data source: https://apps.bea.gov/; author's calculations.

Some Evidence for the US Economy

The foregoing discussion suggests that the emergence of a major new form of capital that enhances firm profitability should be reflected in the economy in several ways.

First, the profit share in national income should be rising. Given the steep asymmetries in the ability to capture data rents, the overall contribution of data would be greater than the observed rise in the aggregate profit share, since some of this would be, in effect, cannibalized from pre-existing profits of corporations unable to use data.

Second, the share of income flowing to traditional legacy IP assets should be flattening, due to (creative) value destruction in an accelerated innovation context. Meanwhile, the share of IP accounted for by trade secrets, the form of IP protection of choice in the data-driven economy, should be rising.

Third, markets would recognize the value of data by bidding up the market capitalization of data-rich firms, which would rise on the leaderboards. Among the leaders, the share of assets accounted for by intangibles would be rising, and the share accounted for by physical assets, declining.

Fourth, the pace of innovation should be accelerating, and the pace of patenting of the main derivative product of data — AI systems — should be creating the next "hockey stick" spike in growth.

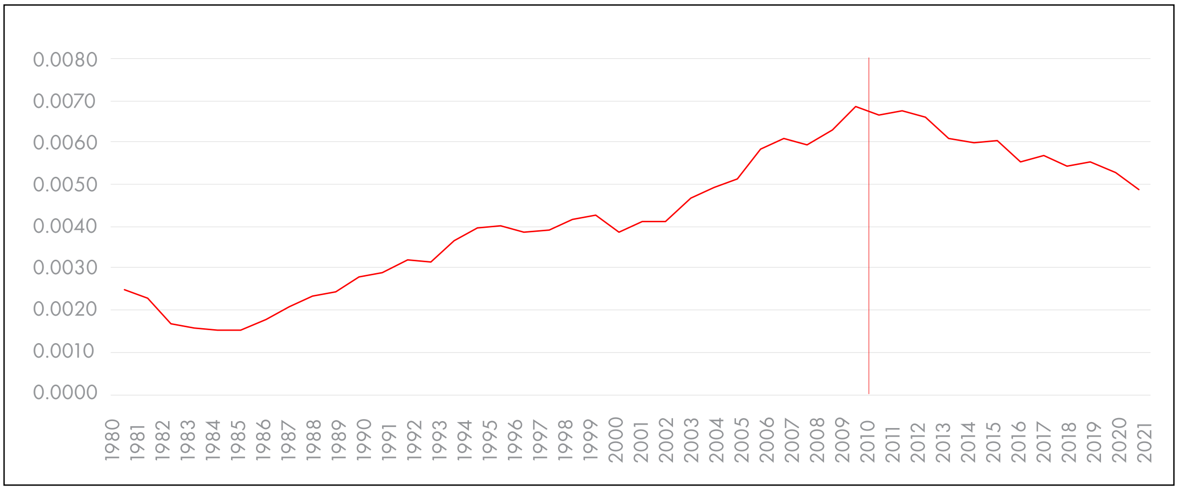
There is evidence for all these effects. It is useful to focus first on the United States, as the leading data-driven economy.

The US profit share of GDP has risen on trend since 1980, which is the beginning of the knowledge-based economy era (Figure 2). That trend continued in the post-2010 era as the economy transitioned into one driven by data. Recalling that the pre-1980 economy was characterized by Nicholas Kaldor's "facts" (Kaldor 1961), including a constant labour share of income and constant returns to scale in industry, the rise in the profit share post-1980 is to be attributed to IP.

While the profit share of income continued to increase after 2010, US international receipts on traditional IP flattened out in value terms and fell as a share of GDP (Figure 3). There is a reasonable inference that this was mirrored in overall returns to traditional IP in the US economy and that the continued rise in the overall profit share was due to data and algorithms.

The rising importance of trade secrets in firms' IP strategies (the form of IP for data and algorithms) is evidenced by the adoption of substantially elaborated and strengthened trade secrets

Figure 3: US International IP Receipts as Percentage of GDP



Data source: https://data.worldbank.org/indicator/BX.GSR.ROYL.CD.

laws in all the major jurisdictions in the mid-2010s as awareness of the value of data and the data-driven economy started to dawn.[4]

The acceleration in the pace of innovation is starkly illustrated by the success of Google's machine-learning model AlphaFold in predicting the three-dimensional structure of a protein from a given amino acid sequence, facilitating the design of molecules for pharmaceutical development (Nourmohammad, Pun and Visani 2022).

The share of intangible assets in the Standard and Poor's 500 (S&P 500) has risen from 16 percent in 1976 to as much as 90 percent or $52 trillion (Table 1). Five of the six most valuable companies on the S&P 500 (by exchange-traded fund ranking) are data-rich companies and the sixth is Nvidia, which supplies the key hardware for the data-driven economy. Their combined current market capitalization as of May 3, 2025, is about $11.8 trillion. Their tangible assets have been estimated at only around five percent of their total value.

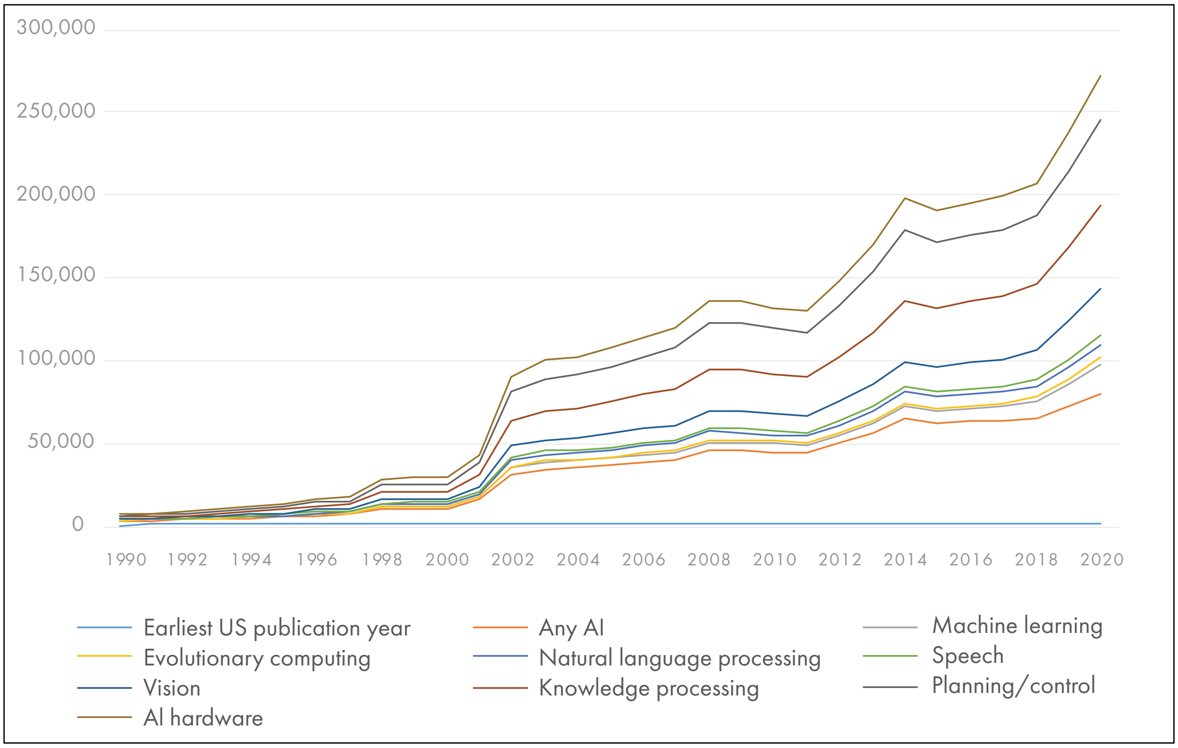
Table 1: Market Capitalization of Leading Data-Driven Firms

Company	Market Capitalization
Microsoft	3,235
Apple	3,084
Amazon	2,016
Alphabet	2,001
Facebook	1,507
Total	**11,843**
Memo: Nvidia	2,793
Memo: S&P 500	58,088
Of which intangibles	52,279

Data source: https://companiesmarketcap.com/usd/usa/largest-companies-in-the-usa-by-market-cap/ (accessed May 3, 2025); intangible share: https://oceantomo.com/intangible-asset-market-value-study/.

4 These included the US Defend Trade Secrets Act, enacted on May 11, 2016; the EU Directive 2016/943 on the protection of undisclosed know-how and business information (trade secrets) against their unlawful acquisition, use and disclosure, adopted on June 8, 2016; and a strengthening of China's trade secret laws with a revision of the Anti-Unfair Competition Law on January 1, 2018. See O'Connell (2018).

Figure 4: US AI Patent Applications Issued in the United States, 1990–2020



Source: Pairolero (2022, 8).

The major share of the market value of these firms is comprised of IP and data — with data arguably comprising a dominant share as these companies became superstars in the age of data. The sixth member of the top group is Nvidia, whose rise, as noted, has been jet-fuelled by its leading position in making computer chips for AI use.

Finally, there was a clear upturn in the pace of AI patent applications in the United States after 2010. There has been a further steep upturn since around 2019, reflecting the extraordinary advances in the power of AI systems since then (Figure 4).

If one were to hazard a back-of-the-envelope guess as to the order of magnitude of the value of data to the US economy based on the premises outlined above, one could make the following calculation. Net operating surplus in the United States expressed as a ratio to nominal GDP rose from 20.2 percent in 1980 to 25 percent in 2023. However, US international receipts on IP as a share of GDP fell by close to four-fifths of their gain during the knowledge-based era. Using this to adjust the trend share of GDP of traditional IP in 2022 yields an estimate of the trend share attributable to data. This translates into a flow value of $610 billion in 2023 and an asset value on the order of $6.1 trillion, assuming a 10 percent return on investment (Table 2).

In 2023, US net worth was estimated by the Federal Reserve to be on the order of $135 trillion (Simko and Smith 2023). The value of US domestic businesses was estimated at $55 trillion, while IP and "other" similar assets, treated as a separate line item, had a value estimated at $2.3 trillion (ibid.).

If we consider the value of data to be part of the value of US enterprises, the back-of-the-envelope figure of $6.1 trillion in data rents would account for about 11 percent of total enterprise value. Expressed as a share of the intangibles in the S&P 500, data rents would be 11.7 percent of the total. If we consider the value of the top five data-intensive corporations and assume, consistent with an 80–20 rule, that they account for 80 percent of the total data returns in the US economy, these figures would suggest that data rents accounted for nearly 50 percent of the value of these superstar corporations. Finally, considered as a contribution

Table 2: Back-of-the-Envelope Estimate of the Value of Data in the United States, 2022

	1980	2010	2023	Change 2010–2023
Profit Share of GDP	0.202	0.244	0.250	0.006
Trend share of GDP	0.205	0.239	0.253	0.014
Trend share less data share	0.205	0.239	0.231	–0.008
Data share				0.022
Memo				
Data value as flow ($ billions)			610	
Data value as asset ($ billions)			6,099	

Source: Calculations by the author. See this paper's appendix for a detailed derivation.

to GDP, the addition of 2.2 percent of data rents as a share of GDP to the approximately 0.7 percent of investment in data assets arrived at by the sum of costs approach (Calderón and Rassier 2022) yields a more respectable contribution to US GDP of close to three percent.

There are obvious risks to this calculation. In the first instance, the decline in US international IP receipts in the 2010s was in part due to tax avoidance schemes as US multinationals parked their IP assets in tax havens (Ireland in particular), which reduced the flow to the United States. As well, the calculation assigns the entire wedge to the value of data, whereas other parts of the data-driven value chain — such as the generation of algorithms, which are also measured on a sum-of-costs basis — are likely responsible for part of the rent capture. At the same time, it is likely that other factors of production are being assigned increased value because of the way data works to make other production inputs more efficient (recall the BASF analogy outlined earlier). In short, this is the beginning of a journey to arrive at a robust valuation of data, not an attempt to provide a definitive estimate.

Evidence for Other Economies

The critical role of scale in the data-driven economy warns that data might have very different value to different countries, depending on their ability to scale firms. As Andrew McAfee has shown graphically in his "Visualization of Europe's Non-Bubbly Economy," the European Union has not been successful at scaling up firms during the digital era (see McAfee 2024). Canada would be in a similar situation to the European Union, while China would compare more favourably to the United States.

It is of interest to compare the extent of investment in data assets by the United States, the European Union and Canada (Table 3). Rupert Allen, Wulong Gu and Ryan Macdonald (2025) provide a decomposition of the sources of labour productivity growth in the three economies. In the United States, there is intangible capital deepening in the form of data assets and there is measured MFP (multifactor productivity) growth, consistent with the evidence above for the United States. For Europe and Canada, which have not been successful in scaling data-driven firms, there was investment in data assets but not an evident payoff in MFP growth. Scaling firms matters in the data-driven economy and an inability to scale firms permits an inference of failure to generate value from data assets.

Discussion and Conclusions

The digital transformation enabled the emergence of a data-driven economy, in which data became the new essential form of capital that could enable firms to capture economic rents. But data did not fit the conventional paradigm of being a traded good with a market price that would allow the aggregation of individual transactions into national accounts with market-determined values.

Table 3: Sources of Business Sector Labour Productivity Growth in the United States, Europe and Canada

	United States	Europe	Canada
Labour composition	0.27	0.26	0.23
Tangible capital deepening	0.50	0.42	0.59
Intangible capital deepening: non-data	0.42	0.25	0.17
Intangible capital deepening: data	0.35	0.22	0.06
MFP growth	0.35	-0.10	-0.05
Total	**1.90**	**1.05**	**1.00**

Data source: Allen, Gu and Macdonald (2025, Chart 7).

Challenges to National Accounting Frameworks

In confronting this conundrum, national statistical authorities are resorting to a "sum of costs" approach to establishing the value of data assets, following the practice established for other intangible assets and for non-market sectors such as government services. This approach necessarily excludes the economic rents captured by data. The analysis in this paper leads to two important conclusions.

First, *insofar as data assets are being effectively exploited by firms*, this approach potentially understates the value of data.

Second, in the data-driven era, the scale at which data becomes valuable in capturing the economic rents that underpin measured productivity appears to be extraordinarily large. This makes the distribution of investment in data assets across firms important. Simply put, if a billion dollars' worth of investment in data assets falls short of what is required to capture economic rents, then 100 billion dollars spread over 100 companies could result in negative productivity outcomes, whereas 100 billion concentrated in one firm could generate positive economic returns. It goes without saying that this is an extraordinary problem for small open economies such as Canada.

These conclusions present an equally extraordinary problem for constructing national accounts, since measured activity might be generating value for some countries but not for others. The conventional inference that benefits can be constructed, with reasonable margins of error, indirectly on the basis of costs of datafication does not work in this economy.

In constructing national accounting frameworks, these considerations force us to stop looking *through* the firm to the underlying assets of those firms, and to look *at* the firms, recognizing their heterogeneity and their role in value creation, productivity and innovation.

Prior to 1980 or so, the economy was characterized by the "Kaldor facts" — constant returns to scale and a constant labour share of income (and by corollary, a constant profit share of income) (Kaldor 1961). In this context, even though each industry featured a heterogenous mix of firms, the composition of firms in terms of size distribution could be safely ignored because, from an economic accounting perspective, the composition was effectively invariant over time. That is no longer true.

Challenges to Economic Policy in Small Open Economies

Beyond national accounting, these considerations have important implications for policy, particularly for small open economies. With the data-driven economy post-2010, understanding the changes in the composition of firm populations became essential to understanding the differences in economic performances across countries and within countries over time.

First, the data-driven era witnessed the rise of superstar firms that dominated their sectors at the global level (Autor et al. 2020). Regions that were not home to the digital superstar firms appear to have missed out on the data-driven economy. Canada is one of those. On the positive side, Canada's minimal amount of investment in data assets meant that Canada did not fritter away its capital on investments in data at a scale that would likely have failed to generate returns in any event. That is a silver lining to be sure, but there is a black cloud there as well.

Second, the data-driven economy witnessed the emergence of a new class of firms — the unicorns. This term was coined in 2013, early in the data-driven era. It was chosen to underscore the rarity of such firms. Such firms subsequently proliferated as the data-driven era proceeded; by one count, as of January 2025, they numbered 1,260 worldwide with an estimated value of $4.4 trillion (CB Insights 2025). At the beginning of 2025, Canada is assessed by CB Insights as having 21 unicorns worth a combined US$56 billion (ibid.). These figures are, respectively, three percent and two percent of the US totals (690 firms worth $2.6 trillion), well below the traditional 10 percent ratio for Canadian scale relative to the United States. For Canada, there is no silver lining to this black cloud.

Policy frameworks, meticulously refined in application to a traditional industrial economy, are not appropriate for this economy. The policy focus has to shift to firms: the metric for success is whether Canada is generating superstar firms and a large number of unicorns that represent the feedstock for future superstar firms.

The Value of Data

This paper establishes that enterprise value is critical to establishing the value of data. In the leading technological economies, both the knowledge-based economy and the data-driven economy have featured an increasing profit share of GDP. Joel Stiebale, Jens Suedekum and Nicole Woessner (2020) show that this dynamic was present prior to the data-driven economy, as technologically leading firms exploited technological advances to capture market share from laggards and to increase their markups. In the data-driven economy era, a handful of superstar firms made disproportionately large investments in what has been termed "digital capital" — "cumulative investment in skills training, new decision-making structures within the firm, management practices, and software customization" (Tambe et al. 2020). These investments were, arguably, consequential to the capture of data as a capital asset. While there is a return to be attributed to these investments, the major part of the return must be attributed to the scarce asset, data. Accordingly, it is intuitively sound to attribute the continued rise in the profit share of GDP in the United States during the data-driven economy era to the data itself as a productive asset.

The societal benefits of innovation unlocked by data (for example, AI systems that implicitly have learned the as-yet-unknown physics of protein folding) and the AI applications that are now being deployed and developed are, at this point, beyond our capability to value. However, it is likely that they are substantially greater than the private commercial benefits captured by firms. Support for innovation has long been the key industrial policy in the advanced countries and such support is now fully justified for data-driven innovation. The fact that we do not have adequate measures of the value of data in terms of enterprise value, let alone in terms of positive externalities, means that we are almost certainly underinvesting.

The Negative Externalities

The negative externalities are also massive. The digital transformation made data the "new plutonium" when applied in social and political contexts, including through ushering in the age of disinformation (Ciuriak 2025). The toxicity of social media is now the daily bread of commentary. Similarly, data-driven innovation that enables discovery of new medicines that address disease while minimizing toxicity to humans can be tweaked to maximize toxicity to humans. In one experiment, such a simple tweak allowed the AI to discover VX or "venomous X," a neurotoxic chemical warfare agent, and other lethal compounds (Calma 2022).

And, of course, there are the incalculable risks associated with increasingly powerful AI that operates beyond human capability, especially when it is empowered with agency, as is increasingly being done, including in drone warfare.

Accordingly, while ignoring externalities was excusable when they were understood to be a marginal knock-on effect to the main economic results, it is not defensible when the externalities might well be much greater than the direct commercial value.

The Bottom Line

If the value of data continues to be established by the sum-of-costs methodology, data's contribution to GDP growth will be understated significantly and, by the same token, its place in policy priorities will fall off the radar. Policy makers will be overlooking the elephant in the room.

As established above, the sum-of-costs methodology does not capture data rents, which represent a meaningful share of returns to capital in the modern data-driven economy. At the same time, for small open economies, it is critical to realize that investing in data assets at less than some critical threshold may be worse than useless. As data and AI redefine global economic leadership, policy makers and firms must recognize that the ability to scale, monetize and govern data will be the key determinant of economic power in the twenty-first century. And establishing where that critical threshold lies is surely the research question of the hour.

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Appendix

A Back-of-the-Envelope Estimate of Data Rents in the US Economy in 2023

The basis for this calculation is the continued rise in the US profit share of GDP over the period of 1980–2023, which spans both the knowledge-based economy era (1980–2010), when traditional IP was responsible for a growing share of national income, and the data-driven economy era (2010–2022), when data was capturing a growing share of national income. US international IP receipts turned down during the data-driven economy era, which allows an inference that traditional IP was also capturing a declining share of national income. Applying the percentage decline in international IP receipts to US profits then generates a wedge between the total profit share of GDP and the share assignable to traditional IP. This wedge then is identified as data rents.

Row 1 shows US international annual IP receipts growth in US dollar terms between 1980 and 2010. The increase was about $88 billion. Over the same period, US corporate profits grew by almost $5.2 trillion. Both figures are in nominal US dollars. Row 3 expresses the growth in international IP receipts over the period 1980–2010 as a share of US GDP over that period as a point of reference. As can be seen, this ratio was about 1.7 percent.

Rows 4 and 5 show the change in international IP receipts expressed as a share of GDP over the period 1980–2010 (when the ratio increased by 0.0038) and over the period 2010–2023 (when it fell by -0.0015). Row 6 shows that international IP (expressed as a share of GDP) gave up about 38 percent of its increase over the period 1980–2010 in the more recent period when receipts started to decline while profits continued to surge. Assuming that there was a commensurate decline in the domestic capture of profit by traditional IP allows a straightforward calculation of the wedge that can be attributed to data rents, which works out to 2.2 percent of GDP and $610 billion.

	Item	$/%
1	US international IP receipts change 1980–2010 ($ billions)	88
2	US corporate profits change 1980–2010 ($ billions)	5,166
3	International IP share in profit growth 1980–2010	0.017014
4	Change in international IP receipts as share of GDP 1980–2010	0.0038
5	Change in international IP receipts as share of GDP 2010–2023	-0.0015
6	Percentage decline in international IP receipts as a share of GDP 2010–2023 vs. 1980–2010	-0.38113
7	Change in trend profit share of GDP 1980–2010	0.042
8	Change in non-data profit share 2010–2023	-0.01602
9	Profit share of GDP ex data share in 2023	0.228
10	Data rent share of GDP in 2023	0.022
11	Data rent flow value in GDP in 2023 ($ billions)	610

Data sources: US corporate profits are sourced from the Bureau of Economic Analysis, Table 1.16: https://apps.bea.gov/. US GDP is sourced from the International Monetary Fund World Economic Outlook database, April 2025: www.imf.org/en/Publications/WEO/weo-database/2025/april. US international IP receipts are from the World Bank: https://data.worldbank.org/indicator/BX.GSR.ROYL.CD.

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