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A Data Valuation Model to Estimate the Investment Value of Platform Companies: Based on Discounted Cash Flow

Hyongmook Cheong [1], Boyoung Kim [1,]* and Ivan Ureta Vaquero [2]

[1] Seoul Business School, aSSIST University, Seoul 03767, Republic of Korea; hmcheong@stud.assist.ac.kr
[2] Department of Business Economics, Health and Social Care, The University of Applied Sciences and Arts of Southern Switzerland, 6928 Manno, Switzerland; ivan.uretavaquero@supsi.ch
* Correspondence: bykim2@assist.ac.kr; Tel.: +82-10-4046-2428

Abstract: As both investment attraction and mergers and acquisitions targeting information technology and platform companies are becoming more important in the digital-centric economic environment, interest in valuing corporate data assets is increasing. Accordingly, among the income approaches used in business valuation, this study presents a data valuation model based on discounted cash flow. This model is expected to be useful for corporate investment decision-making. The assumptions used in this study for the estimation of data income include intangible asset value, exclude net asset value, and data attribution is centered on technology, human resources, and market factors. In particular, data attribution accounts comprise ordinary data research and development, data labor costs, and data advertising expenses. Data costs were divided into those incurred during collection, storage, curation, analysis, and utilization. Financial statements and related data from a real estate information platform operator over three years were collected and used to simulate the data valuation model. The simulation reveals that the operator possesses KRW 472.6 billion in data assets. Ultimately, the data valuation model developed in this study can contribute to strengthening platform operators' investment attraction, guaranteeing financial sustainability, and transparency and data assetization.

Keywords: data valuation; intangible assets; data attribution; business valuation; investment attraction

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1. Introduction

Evaluating technology-related intangible assets is increasingly important as the global economy shifts from a tangible production facility-centered real economy to a knowledge-based economy focused on intangible technology. According to the International Valuation Standards and International Financial Reporting Standards, technology-related intangible assets encompass diverse data assets such as computer software, technology use, and processed data. In the modern digital environment, people generate big data, which drives digital technology development and leads to the creation of new businesses and systems (Rosamond 2002). Similar to capital and raw materials, data represent an asset that can generate economic added value in corporate digital business activities (Chen et al. 2012).

Accordingly, many investors actively invest or pursue mergers and acquisitions, focusing on high-quality data and highly valued companies with excellent data analysis capabilities (Kim et al. 2021). Ryu and Sung (2018) and Moody and Walsh (1999) argued that data, as part of a company's intangible assets, must be valued in monetary terms for various purposes, such as investments, loans, transfers and transactions, and investments in kind. Unlike goods or services valued by supply and demand, assessing the economic value of data as an intangible asset requires considering their inherent characteristics, such as non-depletability, currentness, reproducibility, and non-rivalry. Unlike labor or capital, data are non-depletable because their value does not decrease even if many people use them. Instead, their value tends to increase when used by many people. Furthermore, their value is at its highest when they are up-to-date and decreases over time. Additionally, even data that are not valuable independently tend to exponentially increase in value when combined or analyzed with other highly related data (Hjerpe and Linnér 2009; Golan et al. 1994; Cox and Tikvart 1990).

Previous studies have examined the value of data. For example, Pigni et al. (2016) addressed data access and scarcity that occur intermittently, in addition to data updates. Wang and Strong (1996) classified data quality and value into four upper-level attributes, intrinsic, contextual, representational, and accessible, to present the evaluation of data quality along with grading guidelines. Moreover, Reed (2007) argued that intangible assets should be evaluated to increase the accuracy of business valuations and discussed how, among those assets, a database (DB) containing information on customers and prospects should be defined, valued, and protected.

In particular, based on an examination of previous studies on the financial aspects of data valuation, Moody and Walsh (1999) recognized information, defined as being created through data collection, storage, processing, and maintenance, as one of the main corporate assets and studied methods to estimate its value that conformed to accepted accounting principles. They argued that not recognizing information in financial statements would be an error, especially in the changing business environment. Having demonstrated the significance of marketing and customer-related data assets among intellectual assets, King (2007) presented a hypothetical valuation scenario using financial information, based on the assumption that these assets create business value when developed as DBs.

However, these previous studies are limited in that they are conceptual and compare methodologies or introduce hypothetical scenarios. Thus, standardized models for evaluating and assessing the economic value of data as corporate assets are lacking (Kang and Byun 2019). In particular, the fact that investment decisions are made using general business valuations, without evaluating data as an intangible asset, is a limitation for platform companies seeking to attract investors. Similar to other intangible assets, data assets such as patents and brands should also be valued; there should be specific evaluation criteria and systems for this purpose (Kim 2011, 2014).

Therefore, this study aims to address this issue and proposes a data valuation model based on the income approach, which reflects the definition and characteristics of data revealed in previous studies, following an analysis of the value drivers of data. Based on how data create value in the market as an economic asset, various factors, such as sales, are estimated to analyze value drivers across all data activities. Therefore, this study proposes a data valuation model that addresses the limitations of existing valuation models. Ultimately, this data valuation model can be used by information technology (IT) and platform companies to attract investment, based on their data assets. It can also serve as a guideline for investors and financial companies when evaluating data assets and making investments.

2. Literature Review

2.1. Intangible Assets' Value

In contrast to tangible assets, intangible assets do not have specific material properties but provide the right to enjoy special benefits over a long period (Allee 2008). The most representative characteristics of an intangible asset are that it does not have physical substance and its future benefits are uncertain. Therefore, even if it is recognized as an asset, it is unclear how long its benefits will last and to what extent its cost should match (Lim et al. 2020; Shen et al. 2020). Nonetheless, intangible assets allow their owners to enjoy special benefits and exercise monopoly rights because they are vested with legal or economic rights.

Accordingly, in all member states of the Organization for Economic Co-operation and Development, investments in intangible corporate assets are increasing considerably; in some countries, such investments are larger than those in tangible assets. For example, according to Corrado and Hulten (2010), investments in intangible assets in the United

States exceeded those in tangible assets in the early 1990s, investments in intangible assets almost doubled. Comparing the scale of intangible asset investment in three areas, namely competitiveness, creative assets, and software and databases, Galbreath (2002) reported that investments in intangible assets in most developed countries accounted for 6–12% of gross domestic product. Brynjolfsson and Hitt (2000) pointed out that investments in tangible assets, such as computers and system integration should be accompanied by innovation in management processes, organizational innovations, and investments in intangible assets, to create complementary synergistic effects in increasing corporate productivity. They further showed that corporate investments in intangible assets are essential factors in short-term productivity growth, long-term competitiveness, and performance enhancement (Clark et al. 1979; Schultz 1980). Moreover, such investments complement other investments in tangible or intangible assets that contribute directly to performance.

Intangible assets belong only to a specific company; in other words, they are recognized as valuable assets of that company. Moreover, they are unidentifiable in a company's financial statements because they are non-financial and non-physical (Abhayawansa and Adams 2022). However, they help companies achieve their goals, providing them with a competitive edge. Despite difficulties in objectively valuing intangible assets, researchers are attempting to develop valuation methods given their importance (Cordazzo and Rossi 2020).

Soewarno and Tjahjadi (2020) classified knowledge and intangible assets into human, structural, and customer capital. Human capital includes employees' knowledge, skills, innovation, and abilities, as well as corporate culture, values, philosophy, and behavior. Structural capital includes hardware, software, data, organizational structure, patents, and trademarks. Customer capital includes customer satisfaction, brand awareness, and trademarks. Brennan and Connell (2000) divided intangible capital into human and structural capital. However, Kamukama et al. (2011) divided human capital into intellectual property and human-centered assets, while categorizing structural assets as infrastructure assets, and customer assets as market assets. Chavan (2009) divided intangible assets into customer assets, internal management and processes, learning, and growth. Hirschey and Weygandt (1985) presented the components of intangible assets by focusing on research and development (R&D), its costs, human resources, and advertising expenditure. Nellessen and Zuelch (2011) emphasized technology-related intangible assets, such as patents and software, dividing them into technological, human, and market capital.

Studies on the value of such intangible assets have mainly focused on the relationship between intangible asset expenditures and business value (Bublitz and Ettredge 1989; Chauvin and Hirschey 1993; Amir and Lev 1996; Klock and Megna 2000). However, most of these studies have focused on whether intangible assets affect corporate profits. Sougiannis (1994) reported an increase in corporate value, focusing on advertising and development costs, by regarding accounting profits as a variable in a company's R&D activities and examining the impact of tangible and intangible assets on a company's net profits. Bublitz and Ettredge (1989) explained that R&D and advertising expenditures affect earnings per share, whereas Chauvin and Hirschey's (1993) empirical study showed that R&D expenditures affected corporate profits.

2.2. Data Valuation

Although data are an "aggregate of electronic information that creates added value" in appearance, they inherently have special characteristics; they are "intangible, replicable, persistent, and combinable." Hence, data can be freely combined or separated from other data through unlimited and repetitive processing. In this process, added value may continuously increase or be created. In addition, because they are not amortized and do not perish, even if used in business activities for a long time, and their solid and permanent profit-generating abilities can be consistently utilized, they are fundamentally different from tangible or general intangible assets that depreciate or amortize over time and use (Steinmüller et al. 2019). Rowley (2007) noted that "data acquire value only after being transformed into knowledge and organizing and processing increase the relevance of the data to a specific purpose or context, making them useful while adding significance and value".

Generally, a company's data value chain can be divided into four stages such as collection, storage, analysis, and utilization. During the data collection stage, data are gathered or generated from various sources. For example, retailers, transportation companies, and service providers collect data directly through customer loyalty programs, or indirectly by recording the location information of third parties using mobile communication services. In the data storage stage, the data are stored and integrated. Traditional industries such as finance, retail, transportation, utilities, public sector companies, and service providers store and integrate data. Third, the data analysis stage provides customers with valuable results regarding a range of phenomena based on integrated and analyzed data from various sources. Finally, in the data utilization stage, data are used in the public and private sectors to improve customer service and increase efficiency (Teti et al. 2014). Ultimately, when data activities in these stages or business processes are strengthened, the data value of a business can be unleashed.

In addition, Côrte-Real et al. (2020) claimed that data value should be assessed by selecting a suitable model that considers data's specificity with regards to other intangible assets. First, data can be shared indefinitely and their value increases with usage. Second, the utilization period varies depending on the data type. Static data that do not change frequently, such as address and gender, have long service lives, whereas dynamic data that change in real time, such as customer purchase intentions and object sensors, have short lifespans. However, rather than using a data lifecycle approach, it may be more appropriate to consider the data retention period in a company's system when valuing corporate data. Third, the corresponding factors should be considered further because data value is affected by quality, as is the case for general products. Data quality should be considered from multiple perspectives, such as timeliness, accuracy, completeness, and accessibility. Fourth, the value of the data is multiplied when new information is created, and insights are derived by combining or converging them with other data. Fifth, because data value varies depending on the user's usage or ability, the valuation should include whether the data contributes to enhancing the capabilities of companies and users (Kim et al. 2021).

Although there are currently no data valuation models that consider the specific characteristics of data, methods to value intangible assets have been developed based on income, market, or cost-based approaches (Wilson and Stenson 2008; Rodov and Leliaert 2002). First, in the income-based approach, key variables, such as cash flow, economic life, discount rate, and data attribution must be determined for data valuations. The necessity of considering and determining various variables should also be addressed in an income-based approach to data valuation because each variable is determined through a reflection of the characteristics of the data, the latter can be valued objectively (Lopes 2011). Second, in market-based approaches, comparable transaction cases must be available for data valuation. In reality, the transaction system is complicated (Kleinow et al. 2017) because various discounts or premiums are offered, depending on the volume rates, flat rates, combinations of volume and flat-rate systems, and ranges and conditions of data usage. Finally, cost-based approaches commonly use the reproduction or replacement cost methods. The latter method must reflect the data value without omitting the input and direct labor costs. As such, specific activities related to the production and sales of DBs, such as preparing a detailed list of tasks and breaking down the labor, time, and equipment used as inputs for such tasks, have been segmented accurately (VanderMeer et al. 2012).

2.3. Business Valuation

In principle, platform operators are independent enterprises. However, because of the increasing interest in, and importance of platforms, many large companies are entering the market, and various types of platform operators have emerged with diverse capital investments (Altman and Sabato 2007). Darrough and Ye (2007) stated that any platform operators that survive long-term losses should be evaluated differently from traditional manufacturing businesses. Previous studies (Charumilind et al. 2006; Delcoure 2007) have shown that platform providers and IT startups have weak financial structures and require long-term investments. Notably, they claim that extraordinary expenses, R&D expenditures, growth rates, and fundraising abilities significantly affect success. For example, they can help loss-making platform providers achieve long-term success.

In particular, the ability to raise funds, success in attracting investments, greatly affects a company's sustainability (Lerner and Nanda 2020). Therefore, accurately evaluating and monetizing various company assets is critical. Hence, business valuation should be able to accurately estimate a company's intrinsic value in the investment process to determine whether its stock is undervalued or overvalued, enabling investors to make effective decisions (Jeon 2002). In this way, business valuation plays an important role in attracting investment. In business valuation, the share of cash flow of all economic entities of the company at each point in time is discounted as the cost of capital and aggregated. Business valuation follows the principles of deriving intrinsic values, such as each economic entity's corporate, shareholder, and debt values. Particularly, a company's cost of capital provides essential information for both companies and investors. Companies commonly use the weighted average cost of capital (WACC) as a criterion for investment decisions. This criterion is used because the target company's cost of capital, as the opportunity cost of an investment alternative, is essential when making decisions, setting a strategic direction for business restructuring, and evaluating investment performance. In addition, the cost of capital is essential when measuring economic value-added (EVA), which is considered an important performance indicator.

As Table 1 shows, business valuation methods can be classified into six groups (Fernández 2002). However, business valuations are generally represented by asset-, income-, and market-comparable transaction approaches (Kang 2003).

Table 1. Valuation methods and shareholder value creation.

Balance Sheet	Income Statement	Mixed (Goodwill)	Cash Flow Discounting	Value Creation	Options
- Book value - Adjusted book value - Liquidation value - Substantial value	- Multiples - PER - Sales - P/EBITDA - Other multiples	- Classic - Union of European - Accounting - - Experts - Abbreviated income Others	- Equity cash flow - Dividends - Free cash flow - Capital cash flow - APV	- EVA - Economic profit - Cash value added - CFROI	- Black and Scholes - Investment option - Expand the project - Delay the investment - Alternative uses

Source: Fernández (2002).

The International Valuation Standards Council (IVSC) defines the asset-based approach as "a means of estimating the value of a business or equity interest, using methods based on the market value of individual business assets minus liabilities" (Parker 2016). This approach finds its starting point in the information reported in financial statements. The book value method was the first applicable method for determining assets' net worth (Ghiță-Mitrescu and Duhnea 2016). The asset-based valuation method determines the value of a company by estimating the value of the asset. This method is traditionally used to say that a company's value is on its balance sheet. However, it does not take into account the possible future evolution of the company or the temporary value of its capital since it determines the value of a company from a static perspective (Fernández 2007).

Second, the income approach predicts future income, which is identical to the qualitative method used in the three traditional models. This method requires the individual analysis of cash flow, discount rate according to risk, and timing of receipt of income; the most common income-based methods are discounted cash flow (DCF) analysis and dividend discount analysis (Oliveira et al. 2010; Dyckman 1972). The most common method used in practice is DCF, which assesses whether a firm can generate positive cash flows in the future (Araz et al. 2020; Fernández 2002; Kishore 1996). Previous studies claim that the DCF analysis is the most conceptually correct among quantitative business valuation methods (Jennergren 2008; Jiménez and Pascual 2008; Fernández 2007). However, it is often cumbersome to use and sensitive to various assumptions (Lie and Lie 2002) and performing DCF analysis with sloppy hands makes it easy to manipulate the DCF to produce values independent of its intrinsic value (Damodaran 2006; Phung 1980).

Third, the market-comparable transaction approach is a valuation method that uses the value traded in the market. Specifically, it includes a market price approach, comparable company analysis, and comparable transaction analysis. For example, if a target company is listed, it is valued on the basis of its stock market price and number of shares. Therefore, the intangible assets of listed companies can be valued in a simple manner (Oliveira et al. 2010). However, it is difficult to collect information on similar cases, and it is not easy to apply due to difficulties in collecting information if there are few or no transaction cases. In addition, multiples use peer groups of companies with similar characteristics, and sometimes peer groups' means or median may not yield the best results (Marques 2017).

3. Data Valuation Modeling

3.1. Modeling

This study utilized DCF, the most common business valuation method. Platform companies may be difficult to evaluate with existing classification methods because platform companies have a large proportion of intangible assets that do not appear in their financial statements (Darrough and Ye 2007). Despite the need for several assumptions, DCF estimation is an alternative that can overcome the limitations of existing evaluation methods in evaluating data-based platform companies in the early stages of current uncertain growth (Arumugam 2007).

Although it has competed with the residual income model for several years, but has traditionally been dominant in practice (Lundholm and O'keefe 2001), DCF is becoming increasingly popular and can be evaluated as a financial asset because it analyzes a company (Fernández 2007). Applying the DCF method is a simple process that includes estimating cash flows for the following year and discounting them at a rate that reflects risk (Brealey et al. 2011).

DCF discounts a company's future cash flows through operating activities, at the rate of return demanded by shareholders and creditors. This process involves four stages: determination of a reasonable estimation period, measurement of expected cash flow, calculation of an appropriate discount rate, and calculation of corporate value. The corporate value calculated by DCF is determined by cash flow results and discount rates, all of which are related to financial information. In general, because *free cash flow (FCF),* or the cash flow of the entire company, is used as cash flow for corporate valuation, the WACC, which reflects shareholder and creditor risks, is used as the discount rate (Kang et al. 2017). Given the difficulty of predicting cash flows for all future periods, *FCF* is directly used only for an explicit forecast period (typically 5 to 10 years), and cash flows for periods beyond that are forecasted using the *terminal value (TV)* formula (Cheong et al. 2023).

$$V = \sum_{t=1}^{n} \frac{FCF_t}{\left(1+r\right)^t} + \frac{TV_n}{(1+r)^n}\left(provided, TV_n = \frac{FCF_{n+1}}{r-g} = \frac{FCF_n(1+g)}{r-g}\right)$$

FCF_t is the free cash flow at time t;
r is the WACC;
TV_n is the terminal value at time n;
FCF_{n+1} is the free cash flow at time n + 1;
FCF_n is the free cash flow at time n (final year);
g is the specific growth rate after time n.

The established model calculates the data value from the corporate value. In other words, data value is measured by reflecting the attribution of data to a company's intangible asset value. The corporate value was first calculated through *FCF* of DCF, among the income approaches, which are corporate value evaluation methods, and then the difference from net asset (assets minus liabilities) value in the financial statements was derived as intangible assets. Data attribution is calculated as the ratio of the sum of data assets to that of accounts related to data activities. The data contribution method calculates the ratio of data assets in accounts-related data activities, which is different from traditional corporate valuation approaches, such as asset-based approaches, income approaches, and market approaches.

In this study, the data attribution calculation method borrowed the concept of the technology attribution methodology for technology evaluation, announced by Marthandan and Tang (2010). Only technology development and related performance within the previous three years were recognized while calculating technology attribution. As such, the three-year cost was calculated, assuming that data from the preceding three years directly contributed to the current data-based business model for data valuation.

$$V_{data} = V_{intangible\ asset} \times C_{data}$$

V_{data} is the data value;
$V_{intangible\ asset}$ is the intangible asset value;
C_{data} is the data attribution.

In addition, assuming that a company's intangible asset value is composed of technological, human, and market factors, the logic of deriving target data from data activity-related accounts, which are components of intangible asset value, was applied (Zhao and Burke 2021).

Data collection/operation and platform value are technological factors, and ordinary R&D expenses, which include data collection expenses, server operation fees, and development outsourcing expenses. Human factors encompass the value of data scientists such as data engineers, data analysts, and machine learning task operators; they comprise labor costs. For market factors, such as brand value, advertising expenses were calculated as the corresponding account (see Table 2).

Table 2. Components of intangible asset value and related data activities.

Category	Title 2	Title 3
Technology factor	Data collection/operation, platform value	Ordinary R&D expenses (costs of data collection and server operation)
Human factor	Data scientists value	Labor costs (salaries + retirement benefits + other benefits)
Market factor	Brand value	Advertising expenses

Business value was estimated based on the average market capitalization of listed companies in the previous three months; the most recent estimated value was used for unlisted companies if they attracted investment. Ordinary R&D expenses, which are part of activity-related data accounts, were aggregated from FY18 Q3 to FY21 Q2 inclusive to reflect the three-year average. The labor costs of each department, as of September FY21, were aggregated to estimate annual labor costs. Owing to growth, which leads to reorganization and a rapid increase in the labor force, it was difficult to grasp the labor costs and trends for the three years prior to the valuation date. Thus, it was deemed more accurate to apply one-year labor costs. Advertising expenses were calculated by averaging the expenses from FY18 Q3 to FY21 Q2.

Data assets were calculated by averaging three-year ordinary data R&D expenses from ordinary R&D expenses. Data labor costs are based on the estimated labor costs, assuming that the estimated annual labor costs in September FY21 had not changed over the last three years. The ratio of activity-related salaries by group/department to the labor cost of each group/department was used to estimate salaries and retirement benefits. Welfare benefits were aggregated by applying the data activity-related man/hour (M/H) ratio to the entire staff's M/H, whereas data-related advertising expenses were obtained by averaging three-year advertising expenses to secure data contributors from the advertising account. The assumptions behind our calculations are summarized in Table 3 below.

Table 3. Key assumptions.

Category	Title of Account	Description
Accounts Related to Data Activities	Ordinary R&D expenses	The three-year average of ordinary R&D expenses from FY18 Q3 to FY21 Q2 was used.
	Labor costs	Labor costs by group/department were aggregated as of September FY21. Annual estimated labor costs remained unchanged for the preceding three years.
	Advertising expenses	The three-year average of advertising expenses from FY18 Q3 to FY21 Q2 was used.
Data Assets	Ordinary data R&D expenses	The three-year average of ordinary data R&D expenses was taken from the ordinary R&D expenses account.
	Data labor costs	Data activity-related salaries or an M/H ratio was used based on the estimated annual labor costs of each group/department.
	Data advertising expenses	The three-year average of advertising expenses for securing data contributors (application users) was taken from the advertising account.

3.2. *Definition of Data Activity and Method of Estimating Data as an Asset*

Data activities were divided into five types: collection, storage, curation, analysis, and utilization. Activities for collecting data, such as purchasing applications and devices, developing/operating data, scraping (crawling)/collecting data, and promoting applications, were categorized as data collection. Data storage refers to the accumulation and continuous management of collected data in storage; the main activities include the purchase/operation of DB/cloud servers and data security management. Data curation is an activity conducted to meet the requirements of effective data utilization and includes managing data quality and standards (dictionaries, annotation, etc.). Data analysis refers to data exploration, transformation, and modeling that is used to extract useful information from a business perspective, encompassing model development such as data mining, machine learning, deep learning, statistical analysis, and data testing. Finally, data utilization integrates data into businesses and includes data-based activities to improve internal operational efficiency, boost data-based sales, and create added value. These different stages and their relation to the costs and expenses are summarized in Table 4.

Table 4. Categories and accounts related to data activity.

Category	Title of Account	Classification				
		Collection	Storage	Curation	Analysis	Utilization
Direct Costs	Salaries	○ *	○	○	○	○
	Retirement benefits	○	○	○	○	○
Indirect Costs	Welfare benefits	△ *	△	△	△	△
Direct Costs	Ordinary R&D expenses	○	○	○	○	○
	Advertising expenses	○	△	- *	-	-

* Note: ○ (high), △ (medium), - (none).

The current organizational structure divides labor costs pertaining to salary and retirement benefits into data-direct and data-indirect departments. Considering salary information and evaluating the level of involvement in data activities by group/department, the ratio of remuneration related to data activity to total remuneration was calculated and applied to the corresponding accounts annually. Regarding welfare benefits, the level of participation in data activities by group/department was evaluated based on the current organizational structure, and the M/H ratio of data activities to all employees was calculated by considering the number of employees in each group/department. Data activity costs were aggregated into ordinary R&D and advertising expenses by checking each account's general ledger. This estimation method is summarized in Table 5.

Table 5. Data asset estimation method by direct and indirect costs.

Category	Title of Account	Estimation Method
Direct Labor Costs	Salaries Retirement benefits	Labor costs corresponding to salaries and retirement benefits were divided into data-direct and data-indirect departments. Then, considering the salary information by group/department and evaluating the level of involvement in data activities by group/department, the ratio of salaries related to data activity to total salaries, was calculated and applied to the corresponding account annually.
Indirect Labor Costs	Welfare benefits	The level of participation of group/department in data activities was evaluated; then, the data activity M/H ratio to the M/H of all employees was calculated by considering the number of employees in each group/department, and the rate was applied to the corresponding account annually.
Direct Costs	Ordinary R&D expenses Advertising expenses	Data activity costs were aggregated by checking each account's general ledger details (reflecting the whole amount).

4. Model Simulation Outcomes

4.1. Selecting the Valuation Target

Based on the Company database of the Korea Development Bank (KDB), Company A was selected as the simulation target for the application of the data valuation model, according to the designed business valuation approach. It was analyzed based on corporate investor relationship data as of September 2021, financial statements and financial information from 2016 to the first half of 2021, business plans from 2021 to 2024, and corporate organization chart and salary details as of September 2021.

First, it was checked whether the data-based industry was specified in the data-based business model, based on the 'Business Plan Writing Checklist', followed by the business and operations plans. Second, for marketability and growth, 'KDB's Standard Manual for Tech Credit' was applied as of December 2021, to determine whether one or more of the following three requirements were met: (1) it was listed on the stock market, (2) it attracted investments of KRW 10 billion or more within the last three years, or (3) the technology grade assigned by a Tech Bureau Credit-designated institution was T3 or higher. Third, the capability for data management was checked based on International Standard (IS) 8000-150 (Data management/Governance) and IS-Industry classification 25,010, 25,024 (data quality, 15 characteristics, and 62 detailed sub-characteristics) of the International Standard Index by verifying whether (1) there was a data management organization comprising data scientists within the company, (2) security policies and backup systems were established for data management, (3) work guidelines or manuals for efficient management and operation of data were formulated, and (4) periodic inspections to manage data quality were implemented and documented.

4.2. Results of Applying the Valuation Model

Company A primarily provides real estate and housing-related information. It dominates the real estate app service market with a brokerage app that searches for property-related information on smartphones and facilitates users' connection with the real estate market. In addition, it collects more than 600 sources from various contributors and stores and refines them in an operational DB and real-time data analysis processing system to search and visualize information based on data marts and other solutions. The company is valued at approximately KRW 1.1 trillion and has attracted investments from venture capitalists and others.

While calculating the company's business value, its FCF was directly predicted within an explicit forecast period of five years, the TV formula was used to calculate it for the subsequent period.

The growth rate assumption was evaluated as a two-stage growth rate interval. The first stage up to FY26 was evaluated through cash flow estimation, and the second stage after FY26 was evaluated assuming a zero-growth model (growth = 0%). From the second stage, it was conservatively assumed that additional growth would be limited. The WACC was 6.99% based on the assumption of 70% equity capital, 30% debt, and 22% corporate tax (average estimate by FY26), but the final 8% was used after additionally considering the risk to venture companies at approximately 1%.

The discount rate is WACC, assuming the same discount rate of 8%. In order to make a sophisticated estimate, there may be a method of applying a higher discount rate in the later period than in the initial period or conservatively considering the growth rate in consideration of cash flow uncertainty. However, in this model, the same discount rate was applied to simplify the assumptions, and the terminal growth rate in the latter period was applied as 0% instead. In the case of a multinational firm, it is necessary to additionally consider country risk and exchange rate risk depending on the degree of concentration in a specific country.

The resulting business value, which reflects the cash flow from operating activities and from TV, discounted at the end of FY26 at an 8% WACC, is described in Table 6. In general, venture companies or start-up companies show a negative free cash flow due to large initial investment and marketing costs, but after a certain point after the initial stage of business, the free cash flow changes to a positive flow and the corporate value can be calculated.

Table 6. Company A's business valuation results.

Category	FY22	FY23	FY24	FY25	FY26
Sales	144,500	253,100	416,700	574,700	764,700
Sales and administrative expenses	167,100	292,100	404,100	486,700	590,800
Operating income	(22,600)	(39,000)	12,600	88,000	173,900
Income taxes	0	0	2772	19,360	38,258
Operating income after income taxes	(22,600)	(39,000)	9828	68,640	135,642
Noncash profit/loss adjustment	12,800	21,600	21,900	21,400	21,400
Increase/decrease in invested capital	(94,243)	(13,900)	(13,093)	(29,521)	(44,884)
Free cash flow	(104,043)	(31,300)	18,635	60,519	112,158
Present value factor	0.9259	0.8573	0.7938	0.7350	0.6806
Present value	(96,336)	(26,835)	14,793	44,483	76,333
Terminal value			954,165		
Value of nonoperating assets/liabilities			141,512		
Business value			1,108,115		

Based on discounted cash flow: unit: KRW million.

The three-year average from FY18 Q3 to FY21 Q2 was applied to technology factor-related ordinary R&D expenses; it was estimated that the three-year average ordinary R&D expenses for the same period was KRW 6.3 billion, whereas the ordinary data R&D expenses were KRW 6 billion, as shown in Table 7.

Table 7. Calculation of data assets.

Category	FY18 Q3/Q4	FY19	FY20	FY21 Q1/Q2	Total Costs	3-Year Average
Ordinary R&D expenses	3072	6318	7903	1255	18,549	6183
Ordinary data R&D expenses	3019	6074	7649	1185	17,928	5976
Advertising Costs	11,795	24,062	17,560	10,124	63,543	21,181
Data Advertising Costs	5681	10,654	6354	2981	25,671	8557

Unit: KRW million.

The three-year average from FY18 Q3 to FY21 Q2 was applied to advertising expense accounts, related to market factors. During the same period, the average advertising expense was approximately KRW 21.2 billion, whereas the data advertising expense was approximately KRW 8.6 billion, as shown in Table 7.

For the labor cost account related to human factors, an annual estimation based on salaries in September FY21 was developed from the data provided by the target company. Data activity-related labor costs were aggregated by applying the data activity-based salary or M/H ratio to the labor costs by group/department. Labor costs were approximately KRW 27.5 billion, whereas data activity-related labor costs were approximately KRW 12.8 billion, as shown in Table 8 below.

Table 8. Calculation of data assets.

Category	Group/Department	No. of Personnel	No. of Data Personnel	M/H Ratio	Salary	Data-Related Salary	Salary Ratio
Direct Data Departments	Data Group	30	29.5	98	2587	2507	97
	Chief Technology Officer (CTO)	24	12	50	2202	1101	50
	Service Development Group	68	35.3	52	7218	3669	51
Indirect Data Departments	Product Owner (PO) Office	17	5.1	30	939	282	30
	Business Operation Group	121	12.1	10	5123	512	10
	Investment Development Group	31	20	65	1753	1050	60
	Communication Office	6	0.6	10	578	58	10
	Management Group	17	1.7	10	1076	108	10
	Design Office	15	6	40	1256	503	40
	Marketing Group	24	10.7	45	1186	536	45
	Subcontractor	1	1	100	1849	1849	100
(Data Activity) Total and Ratio		354	134	37.85	-	-	-
(Data Activity) Data labor costs: Total and Ratio		-	-	-	25,767	12,175	47.25 [1]
(Data Activity) Indirect labor costs: Total and Ratio		-	-	-	1727	653	37.85

Unit: number, KRW million, %. [1] The data activity ratios of 47.25% and 37.85% were applied to salaries and retirement benefits (direct labor costs) and welfare benefits (indirect labor costs), respectively.

The estimated data attribution rate was approximately 50%. The sum of data activity-related accounts (ordinary R&D expenses, labor costs, and advertising expenses) was KRW 54.858 billion, whereas the sum of data assets (ordinary data R&D expenses, data labor costs, and data advertising expenses) was KRW 27.361 billion, as shown in Table 9.

Table 9. Data attribution estimation.

Category			Amount
Data Attribution	Data activity-related accounts	Ordinary R&D expenses	6183
		Labor costs (salary + retirement benefits + welfare)	27,494
		Advertising expenses	21,181
		Subtotal	54,858
	Data assets	Ordinary data R&D expenses	5976
		Data labor costs	12,828
		Data advertising expenses	8557
		Subtotal	27,361
	Data assets/Data activity-related accounts (%)		49.9

Unit: KRW million.

From the business valuation results from FY18 Q3 to FY21 Q2, using DCF, the data value of the target company was estimated to be KRW 472.6 billion. The value of intangible assets, calculated by subtracting the net asset (assets-liabilities) value (KRW 160.6 billion) from the business value (approximately KRW 1.1 trillion) at the time of attracting investments, was KRW 947.6 billion. Data attribution is the ratio of data assets to data activity-related accounts (approximately 50%). Therefore, the final data value, which reflects the data attribution to the intangible asset value of KRW 947.6 billion, was estimated to be KRW 472.6 billion. Based on the data provided by the target company, the data value at the end of June FY21 was estimated, and the net asset value was calculated based on the effective evaluation standard in June FY21. This is summarized in Table 10.

Table 10. Data value estimation.

Category			Amount
Value of Intangible Assets	Business value	Market capitalization (average of the three most recent months)	-
		Investment value (most recent business valuation)	1,108,115
	Market capitalization for listed companies; investment value for those who attracted investments		1,108,115
	Net asset value (NAV, as of the end of the previous quarter)	Total assets	174,585
		Total liabilities	14,024
	Total assets minus total liabilities; NAV		160,561
	Business value minus net asset value in the financial statements		947,554
Data Attribution	Data activity-related accounts (average costs of the preceding three years [1])	Ordinary R&D expenses	6183
		Labor costs (salary + retirement benefits + welfare)	27,494
		Advertising expenses	21,181
		Subtotal	54,858
	Data assets (average costs of the preceding three years [2])	Ordinary data R&D expenses	5976
		Data labor costs	12,828
		Data advertising expenses	8557
		Subtotal	27,361
	Data Assets/Data activity-related accounts (%)		49.9
Data Value (intangible asset value × data attribution)			472,602

Unit: KRW million. [1] For labor costs, it was assumed that annual labor costs based on salaries in September FY21 had remained unchanged for the preceding three years. [2] In the case of the one-year labor cost estimate, the data activity-based salary or −M/H ratio were applied to labor costs by group/department.

5. Discussion and Conclusions

5.1. Discussion and Implications

This study proposes and verifies a data valuation model that can fully utilize the value of data to promote investments in companies that possess data. This study is significant because, in a business environment in which data are increasingly important as an intangible asset, it suggests a valuation model that can help investors' evaluation and decision-making processes. In particular, because the existing business or data valuation models are conceptual, they have limitations when calculating the specific monetary value of data as an intangible asset. However, this study derives the exact monetary value of intangible assets according to data attribution, using DCF to calculate the clear monetary value of the data.

Accordingly, the results of this study have the following implications. First, data valuation is performed by linking intangible asset values with data attribution. In particular, it is possible to calculate the unique economic value of data, using accounts that correspond to technological, human, and market factors among the total operating costs. This implies that companies and investors need to define data assets and specify account titles when developing or evaluating data valuation models because intangible assets should be valued in monetary terms. Each process has unique characteristics when estimating costs and executing data activities such as collection, storage, curation, analysis, and utilization; the clearer the enterprise-specific data activity process and system structure, the higher the valuation clarity. Following this model would make it easier for companies that consider data as an intangible or investment asset to realize its economic value; this is because the model systematizes different data-related processes and provides transparency in budgets and cost execution. Currently, most companies manage data only technically and focus on internal control systems. However, considering the financial value of data as an intangible asset as well as increasing, the possibility of corporate data protection and financial utilization through data valuation is necessary. In this context, promoting various approaches and institutional measures for data assetization and considering a structural system for protecting data rights and values is crucial.

Second, because data are emerging as key factors in corporate competitiveness for current data-based enterprises, such as platform operators and general enterprises, an increasing number of companies are attempting to utilize data as a resource for attracting investments. However, although data possess the advantage of generating high profits as an intangible asset, they have the disadvantages of low investment cost recovery and uncertainty in commercialization that considers both technology and market acceptance. Therefore, when a company performs data valuation to attract investments, it is necessary to consider factors that affect investments from various angles, such as the characteristics of the data as an intangible asset, market value of the data, investment payback period, and data value reliability. Most importantly, considering the design of accounting and financial systems that maintain objectivity in data collection, accumulation, and attribution evaluation factors is crucial. In addition, to strengthen the reliability of data valuation, it is imperative to provide continuous data management guidelines and solutions that can present valuation results corresponding to fluctuating trends through data accumulation.

Third, data form an intangible asset that cannot be treated as tangible under a company's resource utilization and expenditure standards. This study applied variables centered on ordinary data R&D expenses, data labor costs, and data advertising expenses for data attribution. In intangible asset investments, information asymmetry exists between management and investors. Such intangible assets are often vested in human capital, and related intangible asset types include R&D-related intellectual property. Therefore, intangible assets may be separated from their owners when they are used to attract investment, depreciating their value. Given the characteristics of human and technological data resources as intangible assets, the corporates must consider the value distribution or attribution rate of inward investment.

Fourth, when data as an intangible asset are reflected in the form of objective and reliable financial information, it improves corporate financial transparency and serves as a positive function for investors to reflect it as an indicator in investment decisions. This indicates that the motivation of companies to recognize intangible assets as major assets of companies and introduce them into financial information is more important. In addition, when data-related intangible expenditures such as current R&D expenses are assetized, as such, the management, measurement, and monetization of a company's intangible assets are important tools, so they can be linked to financial sustainability and have great meaning as continuous investment capital. If the relationship between intangible asset expenditure and financial sustainability is appropriately considered when evaluating corporate value, the reliability and relevance of financial information can be further enhanced.

Fifth, as the importance of data transactions increases and the scope of data utilization expands, this study measures the corporate value of data holding companies and develops a data value evaluation model for measuring intangible asset value, data contribution, and data value calculation. To this end, the purpose is to evaluate the data value of the actual platform company and to refine the model through simulation. This plays an important role in increasing the reliability of data valuation results, and it is expected that this model can be adjusted and applied to various businesses by analyzing cases for each business type.

Lastly, from an investor's point of view, FCF, discount rate, and estimation of forecast period are key factors when evaluating enterprise value using the DCF method. FCF, which is the net cash flow generated from sales, should be presented with objective data such as sales, expenses, and networking capital. In the case of venture companies with limitations on objective financial information, it can be used as the average financial data of the market. As for the discount rate, a discount rate that reflects the individual risk premium of the data holding company is applied. Depending on whether or not they are listed, WACC differential application is reviewed or, in the case of innovative companies, a relatively high risk premium is applied. For forecast periods in which cash flows are expected to be generated from businesses associated with held data, the period should be adjusted differently depending on the type of service (sales/leases) of the data or the actual terms of the contract (auto-extension contract). In addition, it is meaningful for companies to continue their business and secure competitiveness by expanding their ability to raise funds based on the data they possess based on the corporate value of the DCF method. Financial companies can expect the effect of promoting the vitalization of the financial data market by developing new investment products based on data and combining them with existing financial techniques to develop and activate various financial products.

5.2. Limitations and Future Research

Investment attraction and fundraising aided by data valuation are becoming increasingly important for companies that produce and use data in today's era of digitization and corporate resource development based on big data. Therefore, the data valuation model presented in this study holds significant value for companies' financial activity. Nevertheless, this study has several limitations.

First, this research conducted a simulation targeting a Korean online platform company to verify the designed data valuation model. Therefore, the simulated results do not prove that the model can be generalized. In future studies, conducting simulations that target many platform companies in various countries is required to raise the reliability and validity of the model and fully reflect the valuation process by accounting for the platform companies' characteristics and specificity at each stage. Additionally, advancing the data valuation model through comparative analyses according to platform company type, size, and qualitative/quantitative characteristics is required.

Second, our data valuation model was designed using the DCF approach; as DCF facilitates the calculation of the exact financial value, it can be the most suitable methodology for investment attraction. However, the data values can yield different results depending on the valuation situation and approach. Therefore, future studies should examine diversified approaches to data valuation methodologies, such as asset-, profit-, and market-based approaches.

Third, this study presents a data valuation model based on the financial statements provided by the target company, and information obtained through interviews and inquiries. Here, data disclosure, provided at the company's discretion, may be incomplete; the fact that this paper did not use objective data represents a limitation. Therefore, it is necessary to design a valuation model based on officially verified objective data.

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References

Abhayawansa, Subhash, and Carol Adams. 2022. Towards a conceptual framework for non-financial reporting inclusive of pandemic and climate risk reporting. *Meditari Accountancy Research* 30: 710–38. [CrossRef]

Allee, Verna. 2008. Value network analysis and value conversion of tangible and intangible assets. *Journal of Intellectual Capital* 9: 5–24. [CrossRef]

Altman, Edward I., and Gabriele Sabato. 2007. Modelling credit risk for SMEs: Evidence from the US market. *Abacus* 43: 332–57. [CrossRef]

Amir, Eli, and Baruch Lev. 1996. Value-relevance of nonfinancial information: The wireless communications industry. *Journal of Accounting and Economics* 22: 3–30. [CrossRef]

Araz, Ozgur M., Tsan-Ming Choi, David L. Olson, and F. Sibel Salman. 2020. Role of analytics for operational risk management in the era of big data. *Decision Sciences* 51: 1320–46. [CrossRef]

Arumugam, Thavamani Thevy. 2007. An Analysis of Discounted Cash Flow (DCF) Approach to Business Valuation in Sri Lanka. Ph.D. dissertation in Financial Management, St Clements University. Available online: http://stclements.edu/grad/gradarum.pdf (accessed on 27 April 2023).

Brealey, Richard A., Stewart C. Myers, and Franklin Allen. 2011. *Principles of Corporate Finance*. New York: McGraw-Hill/Irwin.

Brennan, Niamh, and Brenda Connell. 2000. Intellectual capital: Current issues and policy implications. *Journal of Intellectual Capital* 1: 206–40. [CrossRef]

Brynjolfsson, Erik, and Lorin M. Hitt. 2000. Beyond computation: Information technology, organizational transformation and business performance. *Journal of Economic Perspectives* 14: 23–48. [CrossRef]

Bublitz, Bruce, and Michael Ettredge. 1989. The information in discretionary outlays: Advertising, research, and development. *Accounting Review* 64: 108–24.

Charumilind, Chutatong, Raja Kali, and Yupana Wiwattanakantang. 2006. Connected lending: Thailand before the financial crisis. *The Journal of Business* 79: 181–218. [CrossRef]

Chauvin, Keith W., and Mark Hirschey. 1993. Advertising, R&D expenditures and the market value of the firm. *Financial Management* 22: 128–40.

Chavan, Meena. 2009. The balanced scorecard: A new challenge. *Journal of Management Development* 28: 393–406. [CrossRef]

Chen, Hsinchun, Roger H. L. Chiang, and Veda C. Storey. 2012. Business intelligence and analytics: From big data to big impact. *MIS Quarterly* 36: 1165–88. [CrossRef]

Cheong, Hyongmook, Boyoung Kim, and Ivan Ureta Vaquero. 2023. Data Valuation Model for Estimating Collateral Loans in Corporate Financial Transaction. *Journal of Risk and Financial Management* 16: 206. [CrossRef]

Clark, Peter, Alan Greenspan, Stephen Goldfeld, and Peter Clark. 1979. Investment in the 1970s: Theory, performance, and prediction. *Brookings Papers on Economic Activity* 1: 73–124. [CrossRef]

Cordazzo, Michela, and Paola Rossi. 2020. The influence of IFRS mandatory adoption on value relevance of intangible assets in Italy. *Journal of Applied Accounting Research* 21: 415–36. [CrossRef]

Corrado, Carol A., and Charles R. Hulten. 2010. How do you measure a "technological revolution"? *American Economic Review* 100: 99–104. [CrossRef]

Cox, William, and Joseph Tikvart. 1990. A statistical procedure for determining the best performing air quality simulation model. *Atmospheric Environment. Part A General Topics* 24: 2387–95. [CrossRef]

Côrte-Real, Nadine, Pedro Ruivo, and Tiago Oliveira. 2020. Leveraging internet of things and big data analytics initiatives in European and American firms: Is data quality a way to extract business value? *Information and Management* 57: 103141. [CrossRef]

Damodaran, Aswath. 2006. *Damodaran on Valuation: Security Analysis for Investment and Corporate Finance*. New York: John Willey & Sons, Inc.

Darrough, Masako, and Jianming Ye. 2007. Valuation of loss firms in a knowledge-based economy. *Review of Accounting Studies* 12: 61–93. [CrossRef]

Delcoure, Natalya. 2007. The determinants of capital structure in transitional economies. *International Review of Economics and Finance* 16: 400–15. [CrossRef]

Dyckman, Thomas. 1972. Discounted cash flows, price-level adjustments and expectations: A comment. *The Accounting Review* 47: 794–98.

Fernández, Pablo. 2002. *Valuation Methods and Shareholder Value Creation*. San Diego: Academic Press.

Fernández, Pablo. 2007. Company valuation methods: The most common errors in valuations. *IESE Business School* 449: 1–27. [CrossRef]

Galbreath, Jeremey. 2002. Twenty-first century management rules: The management of relationships as intangible assets. *Management Decision* 40: 116–26. [CrossRef]

Ghiță-Mitrescu, Silvia, and Cristina Duhnea. 2016. The adjusted net asset valuation method: Connecting the dots between theory and practice. *Ovidius University Annals, Economic Sciences Series* 16: 521–26.

Golan, Amos, George Judge, and Sherman Robinson. 1994. Recovering information from incomplete or partial multisectoral economic data. *The Review of Economics and Statistics* 76: 541–49. [CrossRef]

Hirschey, Mark, and Jerry J. Weygandt. 1985. Amortization policy for advertising and research and development expenditures. *Journal of Accounting Research* 23: 326–35. [CrossRef]
Hjerpe, Mattias, and Björn-Ola Linnér. 2009. Utopian and dystopian thought in climate change science and policy. *Futures* 41: 234–45. [CrossRef]
Jennergren, L. Peter. 2008. Continuing value in firm valuation by the discounted cash flow model. *European Journal of Operational Research* 185: 1548–63. [CrossRef]
Jeon, Sung Il. 2002. Value-relevance of intangible assets in KOSDAQ market. *Asia Pacific Journal of Small Business* 24: 247–69.
Jiménez, Luis González, and Luis Blanco Pascual. 2008. Multicriteria cash-flow modeling and project value-multiples for two-stage project valuation. *International Journal of Project Management* 26: 185–94. [CrossRef]
Kamukama, Nixon, Augustine Ahiauzu, and Joseph M. Ntayi. 2011. Competitive advantage: Mediator of intellectual capital and performance. *Journal of Intellectual Capital* 12: 152–64. [CrossRef]
Kang, Cheol Woong. 2003. Technology transactions and M&A-Regarding the enterprise value evaluation approach in M&A (I). *Venture Digest* 19: 9.
Kang, Ju Hyun, and Jeong Eun Byun. 2019. A study on value drivers for database valuation. *Journal of Information Technology Services* 18: 113–30.
Kang, Sang Wook, Young Seok Yang, and Soo Hee Yang. 2017. The study about developing more rational valuation model to the early stage companies. *Asia-Pacific Journal of Business Venturing and Entrepreneurship* 12: 15–24.
Kim, Jong Seo. 2014. Who should valuate fair value of an intangible asset. *Appraisal Studies* 13: 13–30.
Kim, Kwang Hee. 2011. Current status and challenges of technology finance. *Science and Technology Policy* 184: 51–71.
Kim, Ok Ki, Jung Park, Cheon Woong Park, and Wan Sup Cho. 2021. Data asset valuation model review. *The Journal of Bigdata* 6: 153–60.
King, Kelvin. 2007. A case study in the valuation of a database. *Journal of Database Marketing and Customer Strategy Management* 14: 110–19. [CrossRef]
Kishore, Rohit. 1996. Discounted cash flow analysis in property investment valuations. *Journal of Property Valuation and Investment* 14: 63–70. [CrossRef]
Kleinow, Jacob, Fernando Moreira, Sascha Strobl, and Sami Vähämaa. 2017. Measuring systemic risk: A comparison of alternative market-based approaches. *Finance Research Letters* 21: 40–46. [CrossRef]
Klock, Mark, and Pamela Megna. 2000. Measuring and valuing intangible capital in the wireless communications industry. *The Quarterly Review of Economics and Finance* 40: 519–32. [CrossRef]
Lerner, Josh, and Ramana Nanda. 2020. Venture capital's role in financing innovation: What we know and how much we still need to learn. *Journal of Economic Perspectives* 34: 237–61. [CrossRef]
Lie, Erik, and Heidi J. Lie. 2002. Multiples used to estimate corporate value. *Financial Analysts Journal* 58: 44–54. [CrossRef]
Lim, Steve C., Antonio J. Macias, and Thomas Moeller. 2020. Intangible assets and capital structure. *Journal of Banking and Finance* 118: 105873. [CrossRef]
Lopes, Ilídio Tomás. 2011. The boundaries of intellectual property valuation: Cost, market, income based approaches and innovation turnover. *Intelektinė ekonomika* 5: 99–116.
Lundholm, Russell, and Terry O'keefe. 2001. Reconciling value estimates from the discounted cash flow model and the residual income model. *Contemporary Accounting Research* 18: 311–35. [CrossRef]
Marques, Inês Sousa. 2017. Corporate Valuation: BNP Paribas Case Study. Ph.D. dissertation, ISCTE-Instituto Universitario de Lisboa, Lisbon, Portugal.
Marthandan, Govindan, and Chun Meng Tang. 2010. Information technology evaluation: Issues and challenges. *Journal of Systems and Information Technology* 12: 37–55. [CrossRef]
Moody, Daniel, and Peter Walsh. 1999. Measuring the value of information: An asset valuation approach. Paper presented at the Seventh European Conference on Information Systems (ECIS'99), Frederiksberg, Denmark, 23–25 June; pp. 496–512.
Nellessen, Thomas, and Henning Zuelch. 2011. The reliability of investment property fair values under IFRS. *Journal of Property Investment and Finance* 29: 59–73. [CrossRef]
Oliveira, Lídia, Lúcia Lima Rodrigues, and Russell Craig. 2010. Intangible assets and value relevance: Evidence from the Portuguese stock exchange. *The British Accounting Review* 42: 241–52. [CrossRef]
Parker, David. 2016. *International Valuation Standards: A Guide to the Valuation of Real Property Assets*. New York: John Wiley & Sons.
Phung, Doan. 1980. Cost comparison of energy projects: Discounted cash flow and revenue requirement methods. *Energy* 5: 1053–72. [CrossRef]
Pigni, Federico, Gabriele Piccoli, and Richard Watson. 2016. Digital data streams: Creating value from the real-time flow of big data. *California Management Review* 58: 5–25. [CrossRef]
Reed, David. 2007. Database valuation: Putting a price on your prime asset. *Journal of Database Marketing & Customer Strategy Management* 14: 104–9.
Rodov, Irena, and Philippe Leliaert. 2002. FiMIAM: Financial method of intangible assets measurement. *Journal of Intellectual Capital* 3: 323–36. [CrossRef]
Rosamond, Ben. 2002. Imagining the European economy: Competitiveness and the social construction of Europe as an economic space. *New Political Economy* 7: 157–77. [CrossRef]

Rowley, Jennifer. 2007. The wisdom hierarchy: Representations of the DIKW hierarchy. *Journal of Information Science* 33: 163–80. [CrossRef]

Ryu, Seung Mi, and Tae Eung Sung. 2018. A Study on public interest-based technology valuation models in water resources field. *Journal of Intelligence and Information Systems* 24: 177–98.

Schultz, Theodore. 1980. Investment in entrepreneurial ability. *The Scandinavian Journal of Economics* 82: 437–48. [CrossRef]

Shen, Na, Kevin Au, and Weiwen Li. 2020. Strategic alignment of intangible assets: The role of corporate social responsibility. *Asia Pacific Journal of Management* 37: 1119–39. [CrossRef]

Soewarno, Noorlailie, and Bambang Tjahjadi. 2020. Measures that matter: An empirical investigation of intellectual capital and financial performance of banking firms in Indonesia. *Journal of Intellectual Capital* 21: 1085–106. [CrossRef]

Sougiannis, Theodore. 1994. The accounting based valuation of corporate R&D. *Accounting Review* 69: 44–68.

Steinmüller, Elias, Georg U. Thunecke, and Georg Wamser. 2019. Corporate income taxes around the world: A survey on forward-looking tax measures and two applications. *International Tax and Public Finance* 26: 418–56. [CrossRef]

Teti, Emanuele, Francesco Perrini, and Linda Tirapelle. 2014. Competitive strategies and value creation: A twofold perspective analysis. *Journal of Management Development* 33: 949–76. [CrossRef]

VanderMeer, Debra, Kaushik Dutta, and Anindya Datta. 2012. A cost-based database request distribution technique for online e-commerce applications. *MIS Quarterly* 36: 479–507. [CrossRef]

Wang, Richard Y., and Diane M. Strong. 1996. Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems* 12: 5–33. [CrossRef]

Wilson, Richard M. S., and Joan A. Stenson. 2008. Valuation of information assets on the balance sheet: The recognition and approaches to the valuation of intangible assets. *Business Information Review* 25: 167–82. [CrossRef]

Zhao, Jingyuan, and Andrew F. Burke. 2021. Review on supercapacitors: Technologies and performance evaluation. *Journal of Energy Chemistry* 59: 276–91. [CrossRef]