THE INTERACTION OF BIG DATA, FLEXIBLE OPTIONS, AND NETWORKED ECOSYSTEMS IN AUGMENTED BUSINESS PLANNING

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1 author:

Roberto Moro visconti
Università Cattolica del Sacro Cuore

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Roberto Moro-Visconti*

* Department of Business Administration, Università Cattolica del Sacro Cuore, Milan, Italy.

Abstract

Traditional business planning follows a managerial top-down approach where forecasts are conceived within the firm and occasionally compared with market returns. The increasing availability of timely big data, sometimes fueled by the Internet of Things (IoT), allows receiving continuous feedbacks that can be conveniently used to refresh assumptions and forecasts, using a complementary bottom-up approach. Forecasting accuracy can be substantially improved by incorporating timely empirical evidence, with consequent mitigation of both information asymmetries and the risk of facing unexpected events. Network theory may constitute a further interpretation tool, considering the interaction of nodes represented by IoT and big data, mastering digital platforms, and physical stakeholders. Artificial intelligence, database interoperability, and data-validating blockchains are consistent with the networking interpretation of the interaction of physical and virtual nodes. Flexible real options represent a natural by-product of big data consideration in forecasting, representing an added value that improves Discounted Cash Flow metrics. The comprehensive interaction of big data within networked ecosystems eventually brings to Augmented Business Planning.

Keywords: Forecasting, Discounted Cash Flows, Real Options, Valuation Metrics, Stochastic Simulation, Revenue Model, Digital Platforms, Value At Risk.

1. Introduction

Business planning follows a typical managerial top-down approach where management-prepared forecasts and projections are conceived within the firm and occasionally compared with market returns. The increasing availability of timely big data, sometimes fueled by the Internet of Things (IoT) devices, allows receiving continuous feedbacks that can be conveniently used to refresh assumptions and forecasts, using a complementary bottom-up approach. Top-down and bottom-up are both strategies of information processing and knowledge ordering

Forecasting accuracy can be substantially improved by incorporating timely empirical evidence, with a consequent reduction of both information asymmetries and risk of facing unexpected events, concerning the magnitude of their impact. Since risk is represented by the difference between expected and real events, if occurrences are timely incorporated in expectations, this differential is minimized. This intuitive concept is well-known, but its practical implications are amplified by the unprecedented presence of big data.

Bottom-up feedbacks fed by IoT and big data can also readdress real-time strategies, incorporating in the business model forecast value-adding real options that increase its resilience.

The passage from deterministic to stochastic scenarios may also add up further flexibility, extending the probabilistic outcomes that may undergo periodical (ideally constant) updating.

Treatment of big data can be further improved using interoperable databases where information is stored in the cloud, processed with artificial intelligence and machine learning patterns, and if necessary,

validated with blockchains.

Valuation criteria of the project or investment are typically linked to business planning metrics, especially if they are based on Discounted Cash Flows (DCF). DCF forecasting can be greatly improved by timely big data feedbacks that positively affect the numerator, represented by growing cash flows (that incorporate real option flexibility), and decreasing discount rates (cost of capital) that reflect reduced risk. Value-adding strategies can conveniently reshape supply and value chains that embed information-driven resilience.

Network theory may constitute a further interpretation tool, considering the interaction of nodes represented by IoT and big data, mastering digital platforms, and physical stakeholders (shareholders, managers, clients, suppliers, lenders, etc.). Artificial intelligence, database interoperability, and blockchain applications are consistent with the networking interpretation of the interaction of physical and virtual nodes.

The interaction of big data with traditional budgeting patterns creates flexible (real) options nurtured by a networked digital ecosystem, eventually bringing to augmented business planning.

Augmented reality (AR) is the real-time use of information in the form of text, graphics, audio, and other virtual enhancements integrated with real-world objects. It is this "real world" element that differentiates AR from virtual reality. AR integrates and adds value to the user's interaction with the real world, versus a simulation (Gartner glossary).

Consistently with this background, **the research question of this study deals with the analysis of big data-driven input factors on business plan forecasting, showing that if incorporates value-adding growth options, it becomes "augmented".**

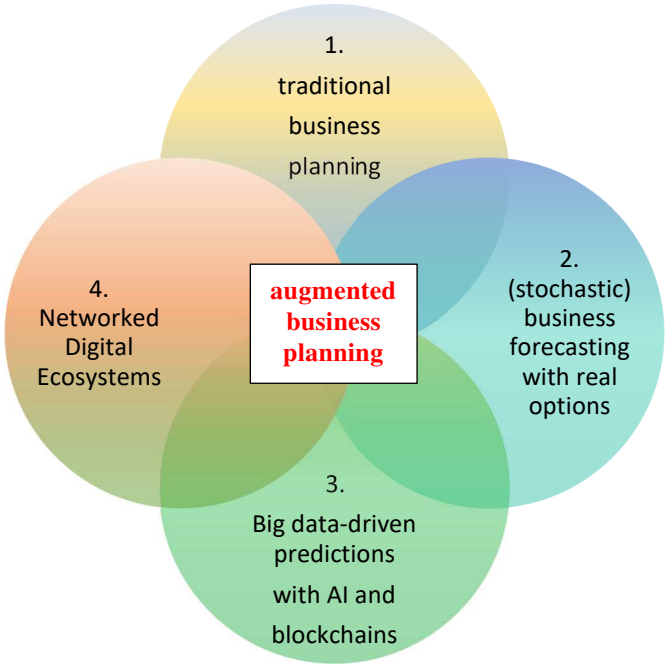
2. Literature Review

This topic is highly interdisciplinary as it concerns contiguous literature streams that have hardly been considered together, and may tentatively be represented by the following:

1. (traditional) business planning;
2. (advanced) business forecasting incorporating real options and stochastic modeling;
3. Big data-driven predictive analytics and advanced IT modeling (with artificial intelligence, blockchains, etc.);
4. Network theory ecosystems mastered by digital platforms.

Figure 1 synthesizes the main literature streams and their interaction.

Figure 1 – *Interacting Literature Streams*



1. Traditional business planning

The value of planning is driven by the possibility of evaluating alternative actions and being able to improve strategies. Before market entry, the main purpose of the evaluation is to pursue good and terminate bad business ideas (Chwolka & Raith, 2012). Planning is beneficial for performance (Brinckmann et al., 2010). Decision-making, however, remains a challenging task in the current age of forecasting (Asaduzzaman et al., 2014). As Razgaitis (2003) shows, prognosticators apply Monte Carlo Analysis to determine the likelihood and significance of a complete range of future outcomes; Real Options Analysis can then be employed to develop pricing structures, or options, for such outcomes.

Designing and creating a business model is crucial for a successful firm's operation in today's market in a complex and changing environment. A business model is a factor that differentiates one firm from another—it defines the distinctions of the firm, how the firm deals with the competition, the firms' partnerships, and customer relations (Koprivnjak & Peterka, 2020). Business modeling is increasingly focused on sustainability-orientation, extended value creation, systemic thinking, and stakeholder integration (Breuer et al., 2018).

Management-prepared forecasts and projections, collectively referred to as prospective financial information (PFI), serve as the critical foundation for discounted cash flow methods. Pro-forma information, often used in (traditional) business planning, is not prospective or forward-looking, but rather a restatement of historical information (Dufendach, 2020). Augmented business planning intends to go far beyond pro-forma top-down strategies. Interaction of top-down and bottom-up strategies is examined in Daradkah et al. (2018). According to Hutchison-Krupat J., Kavadias S., (2014), when senior managers make the critical decision of whether to assign resources to a strategic initiative, they have less precise initiative-specific information than project managers who execute such initiatives. Senior management chooses between a decision process that dictates the resource level (top-down) and one that delegates the resource decision and gives up control in favor of more precise information (bottom-up).

2. Stochastic business forecasting

Decisions are made based upon judgment that is influenced by analysis and instincts. Key to the analysis is the use of historical and current performance characteristics as a basis for forecasting future

performance, understanding that the future is difficult to predict. Consequently, the future might best be viewed in relation to statistically informed probabilities (Rubin and Patel, 2017). According to Scarpati (2017), a deterministic DCF uses deterministic forecasts which are driven by only one scenario of variables. Valuators normally analyze forecasts using three scenarios: optimist, pessimist, and mean or they use sensitivity analysis. However, such approaches do not work with multiple variables that change in time. Additionally, deterministic forecasts and valuations are not able to simulate volatilities and probabilities of the variables driving a business. The lack of probabilistic and volatile driven forecasts causes valuations to miss valuable information for decision making. Advanced valuations use stochastic or random processes which is a probability model used to describe business phenomena that evolve over time. More specifically, in probability theory, a stochastic process is a time sequence representing the evolution of business variables / drivers whose change is subject to a random variation (Models containing a random element, hence unpredictable and without a stable pattern or order). In contrast to deterministic planning, in stochastic forecasting, the input variables are modeled by their probability distributions rather than by their expected values to implement a realistic quantification of uncertainty (Dannenberg and Ehrenfeld, 2011).

3. *Big data predictions*

Big data help enterprises to make well-informed decisions (Al-Barznji & Atanassov, 2017), and can so be usefully incorporated in business planning and predictive analytics (Hazen et al., 2014; Moro Visconti et al., 2017). Big data analytics are also used in marketing (Xu et al., 2016), which is linked to sales forecasting, a crucial issue of business planning. Cognitive big data represent a powerful, albeit under-exploited, source of information for descriptive, prescriptive, and predictive analytics (Franks, 2014; Jumi et al., 2016; Tanner, 2014; Jin et al., 2015) supporting decisions especially in data-rich industries. Big data mining supports business analytics (Duan & Xiong, 2015). Recent studies have empirically shown how big data could significantly improve the accuracy of forecasting. See Moro Visconti et al., (2017), Lau et al. (2018). More specifically, social media and online communication can be relevant source of information in predicting sales dynamics (Xiaohui et al., 2012; Sonnier et al. 2011). Big data are also used in accounting (Vasarhelyi et al., 2015), which provides the basic input data for valuation. Big data mining can also reduce enterprise risk (Olson & Wu, 2017), with a positive impact on corporate valuation and governance concerns.

The volume of data is constantly increasing nowadays, thus businesses could benefit from analyzing existing data to make valuable predictions to develop a coherent business plan. Time series analysis enables companies to analyze data to extract meaningful characteristics and generate useful timely predictions. Mainly, time-series data consists of sequences of chronologically stored observations and are generated by recording, business metrics, monitoring sensors, observing network traffic, etc. (Rotuna et al., 2019).

4. *Digital platforms and ecosystems*

Digital ecosystems are founded on multisided platforms (Sussan and Acs, 2017), where digital platforms perform a pivoting role, acting as bridging nodes that are virtually connected with other vertices. Digital platforms represent bridging nodes that reshape the networked interaction of connected shareholders (Moro Visconti, 2020a). A literature review on digital platforms is contained in Asadullah, Faik & Kankanhalli (2019) and in Sutherland & Jarrahi (2018) that analyze sharing economy platforms. Platforms normally add value to the ecosystem, easing the exchange of (big) data and fostering transactions. Network Theory (Barabási, 2016) provides a sound mathematical interpretation of these interactions and is consistent with system theory that analyzes a cohesive conglomeration of interrelated and interdependent parts.

Traditional data analysis methods need to adapt in high-performance analytical systems running on

a distributed environment which provide scalability and flexibility (Khine & Nyunt, 2019). Big data are increasingly used for predictive purposes (Moro Visconti et al., 2017) and their monetization prospects are more and more scrutinized (Faroukhi et al., 2020).

This study represents an advance in this variegated literature, as it innovatively considers the application of big data and other scalability drivers to augmented business planning.

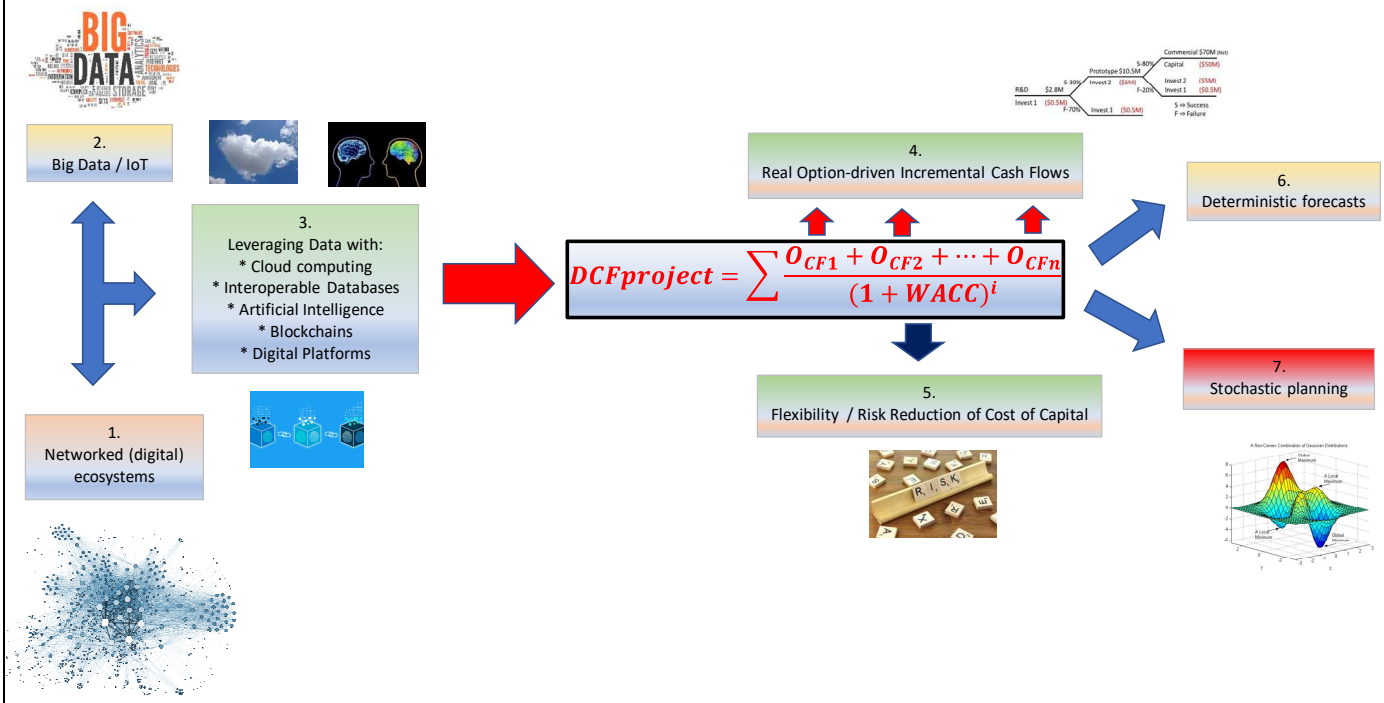
3. The Model

The flow chart of the sequential passages that start from bottom-up data and then impact on business planning, making it "augmented", is composed of these steps:

1. The empirical evidence that provides massive information is represented by the ecosystem - a network of interconnecting and interacting parts – where the firm is located. This networked ecosystem is levered by digitalization that transforms into IT data any useful information, fostering its use; the ecosystem is also consistent with personalization, for instance concerning ESG sustainability goals;
2. "Small" data, fueled by IoT or any other physical or digital source, are collected in the ecosystem, and their massive gathering makes them "big".
3. Data mastered by digital platforms and their networking properties are then stored in the cloud and fuel interoperable databases. Information is then interpreted with artificial intelligence (machine learning) algorithms and, if necessary, is validated through tailor-made blockchains. This process brings to "augmented information".
4. Augmented data are then timely incorporated in (traditional) business planning procedures (here exemplified by DCF metrics) bringing to flexible readjustments (real-time refreshing). This constant updating ideally produces incremental cash flows that can be interpreted with real option patterns that proxy flexibility;
5. The resilience and potential increase of the cash flows also reflects in the discount factor represented in the denominator of the DCF formula; the risk is reduced as a consequence of the shrinking difference between expected and real outcomes, due to the continuous refreshing of expectations that makes them closer to the ongoing ecosystem's evidence;
6. Timely reformulation of DCF metrics (current cash flows and their discount factors) impacts prospects within the time to maturity interval, bringing to a continuous updating of deterministic expectations;
7. The abovementioned updating may well fuel a stochastic scenario that adds further explanatory power to the standard deterministic outlook.

The model is graphically described in Figure 2.

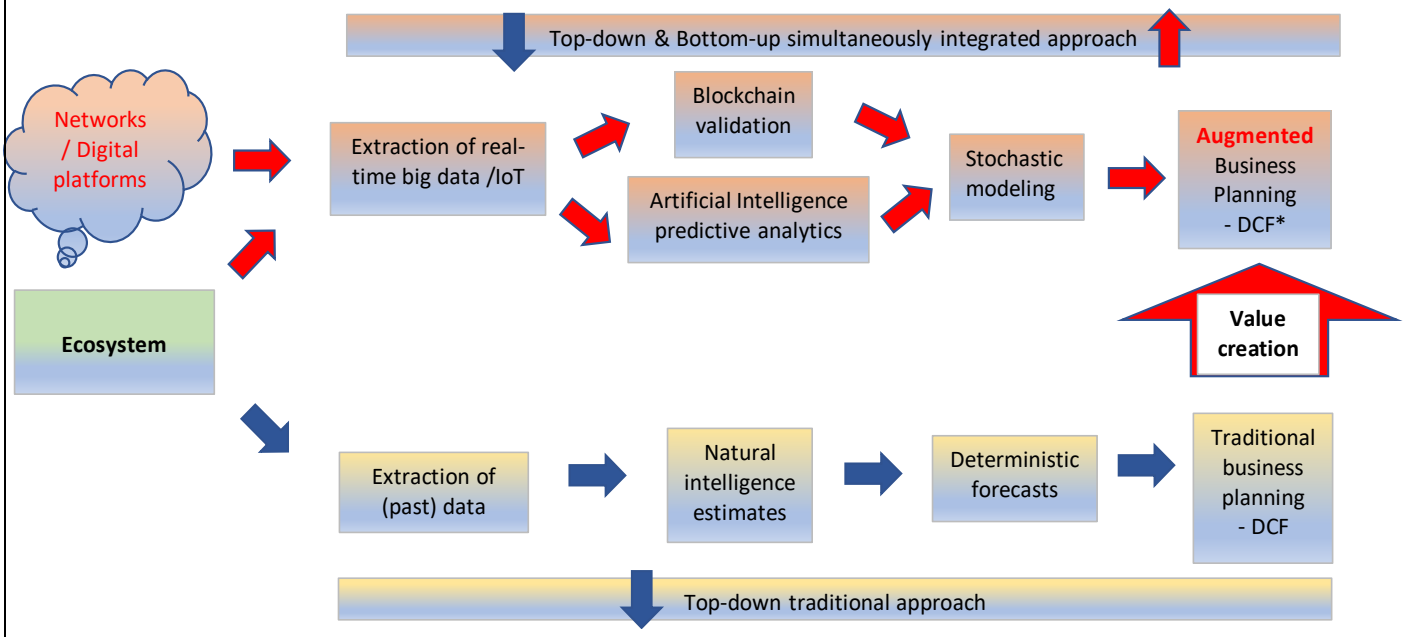
Figure 2 – *From Big Data-Driven Forecasting to Augmented Business Planning*



The methodology is consistent with the research question of this study, showing that business planning can become more valuable - augmented - if it incorporates big data's informative contents, validated by blockchains, and interpreted through artificial intelligence predictive patterns.

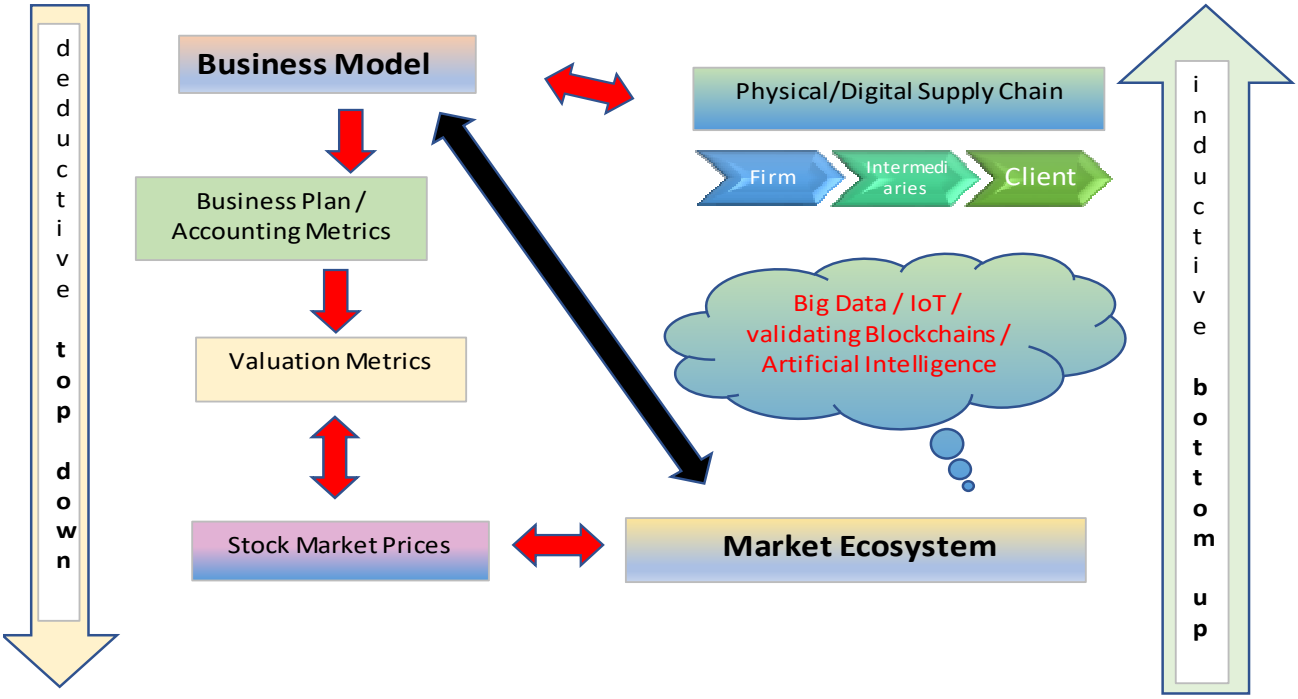
Figure 2 can be further developed, as shown in Figure 3, to express the added-value incorporated in augmented business planning.

Figure 3 – *Value Creation, from Traditional to Augmented Business Planning*



Interaction of top-down and bottom-up strategies can be synthesized in Figure 4.

Figure 4 – *Interaction of top-down and bottom-up strategies*



Section 4 describes how networks work and interact within the ecosystem, whereas section 5 illustrates the impact of artificial intelligence on "augmented" business planning. Section 6 contains some considerations about stochastic modeling. An empirical simulation will be conducted in section 7, followed by a discussion in section 8 and some concluding remarks in section 9.

4. Networking Ecosystems

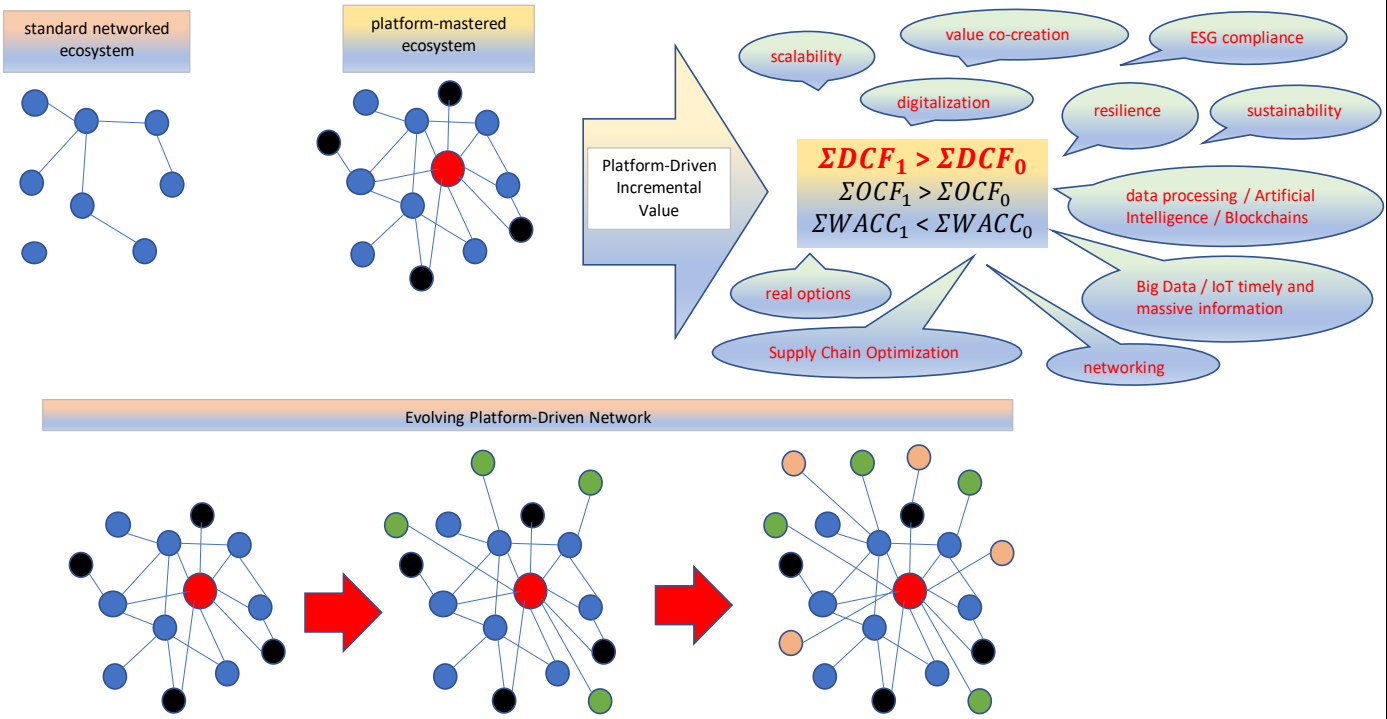
Network theory (Barabási, 2016) is the study of graphs as a representation of either symmetric relations or asymmetric relations between discrete objects. The networked ecosystem is the external source of information and represents the competitive environment where the firm is positioned. The standard ecosystem, inspected with the lens of network theory, can be rearranged including a pivoting node represented by the digital platform. This brings to an incremental (differential) value that positively affects the DCF, increasing the numerator, and softening the risk component embedded in the denominator.

Networks are, however, evolving, and their kinetic evolution brings to a continuous reshaping of the composition of the ecosystem, concerning its perimeter, internal links, and osmotic interaction with the outside world. Evolving networks change as a function of time, and they experiment with growth patterns since are added to the network over time and are more likely to link to other nodes with high distributions (like digital platforms that maximize the number of connections to other nodes). Nodes that dynamically increase their degree (number of edges connected to the node) intermediate more "traffic", from information (big data) to economic transactions, improving the overall value of the ecosystem.

The informative contents of the nodes depend on their features that continuously change over time and may be recalled in table 1A in the Appendix.

A comprehensive picture of the evolving network ecosystem, consistent with Figure 3, is shown in Figure 5.

Figure 5 – *Platform-Driven Evolving Networks*



The strategic drivers that impact the DCF formulation are recalled in Table 2.

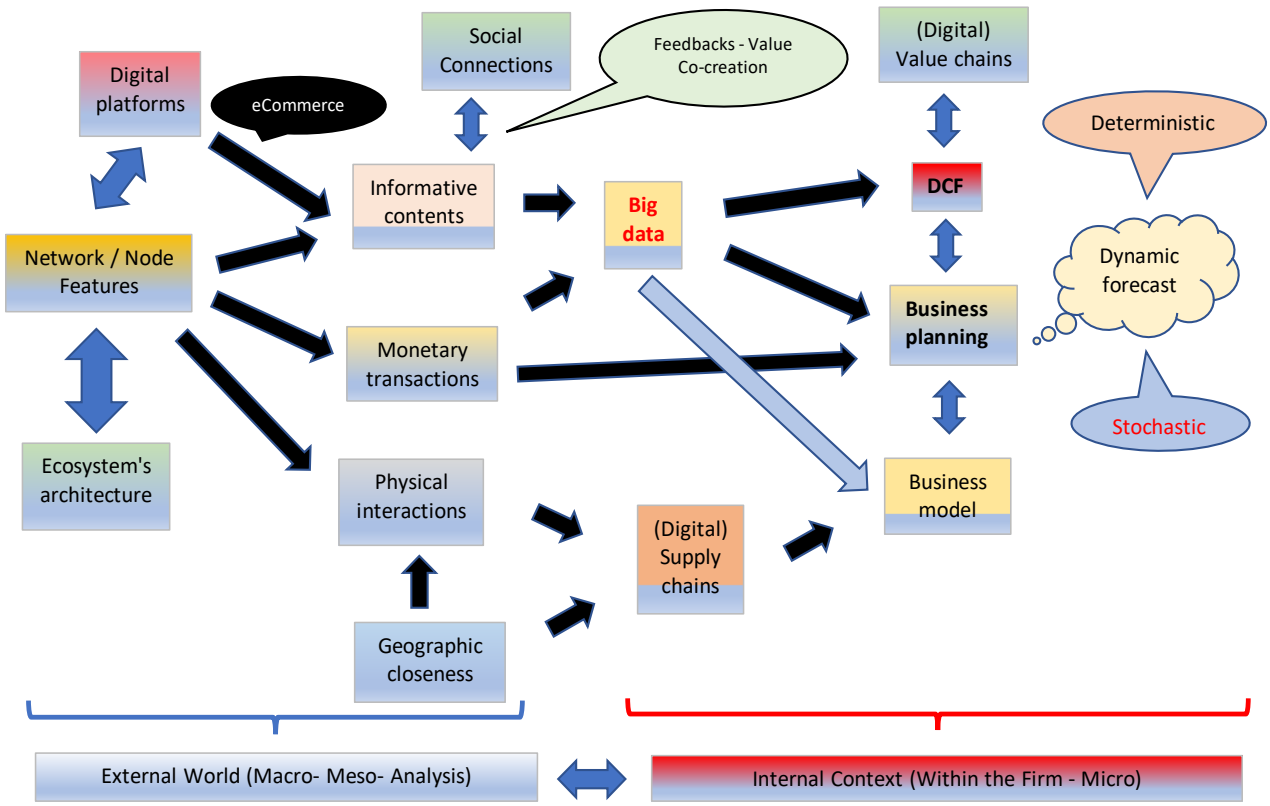
Table 2 – *Impact of the Strategic Drivers on the Discounted Cash Flows*

Strategic Driver	Impact on the Discounted Cash Flows
Scalability	A scalable firm can improve profit margins while sales volume increases. This positively affects the EBITDA and the operating and net cash flow.
Value co-creation	The joint creation of value by the firm and the customer with her feedbacks positively impacts economic and financial marginality, also improving customer loyalty, reducing the churn rate.
Digitalization	The process of converting information into a digital format increases the value of data making them accountable and manageable.
Resilience	It expresses the toughness or elasticity of a system, and its capacity to recover quickly from difficulties. Resilient cash flows mitigate risk incorporated in the discount factor
ESG compliance	Environmental, social, and governance (ESG) criteria are a set of standards for a company's operations that socially conscious investors use to screen potential investments. Their impact on DCF is mixed (Moro Visconti, 2020b).
Sustainability	Economic sustainability complements the social and environmental dimensions and consists of the ability of an economy to support a defined level of economic production indefinitely. Sustainable business models incorporate resilience and scalability, with a positive impact on DCF.

Data processing / Artificial Intelligence / Blockchains	Data processing and archiving in the cloud, together with artificial intelligence interpretation and blockchain validation, improve the value of information and may positively affect DCF.
Big Data / IoT	Big data and IoT nurture the business planning input factors with massive and timely information, improving the expected cash flows, and reducing their riskiness.
Networking	Networking, especially if mastered by digital platforms, is a scalability catalyzer that impacts DCF.
Supply chain optimization	Digital supply chains reduce intermediation costs, and improve resilience, with positive effects on cash flows.
Real options	Real options increase the resilience and scalability of forecasted cash flows.

The network interacts with business planning through digital and physical connections, and transactions. The sequential impact is dynamic and subject to continuous adjustments, due also to the feedbacks that fuel value co-creation, reshaping the supply and value chain. A representation is reported in Figure 6.

Figure 6 – *From Interacting Networks to Business Model and Planning*



5. Artificial Intelligence and Predictive Analytics

Artificial intelligence (AI) is normally referred to as the ability of a machine to learn from experience, unlike the natural intelligence displayed by humans. AI has been in existence for over six decades and has experienced winters and springs. The rise of super computing power and Big Data technologies appear to have empowered AI in recent years (Duan et al., 2019). AI technology is the catalyst of business

model innovation (Lee et al., 2019) that strongly impacts business planning. Disruptive innovation enables AI-led firms to potentially transform the global competitive landscape, with a landslide impact of the ecosystem illustrated in Figures 2, 3 and 4., fostering business model innovation (Valter et al., 2018).

AI-driven sales prediction, with its temporal granularity, is a key part of the planning process, as the revenue model is the basis for the forecast of cash flows. Tsoumakas (2019) shows that food sales prediction is concerned with estimating future sales of companies in the food industry. Accurate short-term sales prediction allows companies to minimize stocked and expired products inside stores and at the same time avoid missing sales.

AI is so fully consistent with the research scope of this study since it impacts on predictive analytics and it reshapes the flow-chart depicted in Figures 2, 3, 4 and 5. AI can ideally automize the value creation process illustrated in Figure 3, making it self-fulfilling and automatically increasing its potential with self-learning patterns that boost scalability and real options. The reality is, however, harder than these ideal targets, and AI setup needs careful tailor-made configuration, still characterized by limited applications. Digitalization is a pre-requisite for the usability of (preferably, numerical) big data that are then interpreted again following the patterns of Figure 3.

AI fosters data analytics (Askerkar, 2019) that impacts on cash flow forecasting, as shown in table 3 that represents just an example of the possible AI applications.

Table 3 - *Impact of Data Analytics on Cash Flow Forecasting*

Artificial Intelligence-Driven Data Analytics	Discounted Cash Flow Forecasting
Artificial Intelligence can improve the following processes, and in particular predictive analytics. • Descriptive Analytics illustrates what happened in the past and is widely used in traditional business planning. • Diagnostic Analytics helps to understand why something happened in the past. • Predictive Analytics uses data mining to predict what is most likely to happen in the future. • Prescriptive Analytics recommends actions to affect those outcomes.	Cash flow forecasts are nurtured by data analysis, a process of inspecting, cleansing, transforming, and modeling data with the goal of discovering useful information, informing conclusions, and supporting decision-making.
Customer analytics • Client profiling • Client experience / feedbacks • Market segmentation • Social Network analysis • Brand awareness • Marketing mix optimization	Client profiling eases cash flow forecasting, responses to unexpected positive or negative events (incorporating real options), experience sharing to foster value co-creation, viral networking through socials. Customer analytics mainly impacts on revenues, easing their prediction and leveraging the scalability of the business model that becomes more reactive and timelier.
Supply Chain analytics • Demand forecasting • Optimization of inventory • Pricing • Scheduling • Transportation and Storage • Human capital / Workforce analytics	Optimization of the supply chain improves demand forecasting and the stock turnover, providing useful insights for reactive pricing. Operating costs can be reduced, improving the efficiency and efficacy of used resources, and so productivity. Lower Operating expenditure (OPEX) increases the EBITDA, and optimizes Net Working Capital Management, with a positive impact on the

	Operating Cash Flows.
Risk analytics • Market risk • Operational risk • Credit scoring • Macroeconomic risk (interest rates, currency rates, country and political risk, inflation, GDP forecasts, etc.)	Improved forecasting of future events reduces risk, incorporated in the denominator of DCF metrics.

6. Stochastic Simulation

Stochastic simulations (depicted in point 7 of figure 2) represent a further research frontier, and they relate to random networks, where linking edges are random variables with a probability distribution.

Simulation models that contain no random variables are classified as deterministic. Deterministic models have a known set of inputs which will result in a unique set of outputs. A stochastic simulation model has one or more random variables as inputs. Random inputs lead to random outputs. Since outputs are random, they can be considered only as estimates of the true characteristics of a model. In a stochastic simulation, the output measures must be treated as statistical estimates of the true characteristics of the system. Monte Carlo simulations model the statistical probability and volatility of different outcomes in a probabilistic process that cannot easily be predicted due to random variables that are very common in business planning. They are used to assess the risk that an entity will default and to analyze derivatives such as real options (Scarpati, 2017).

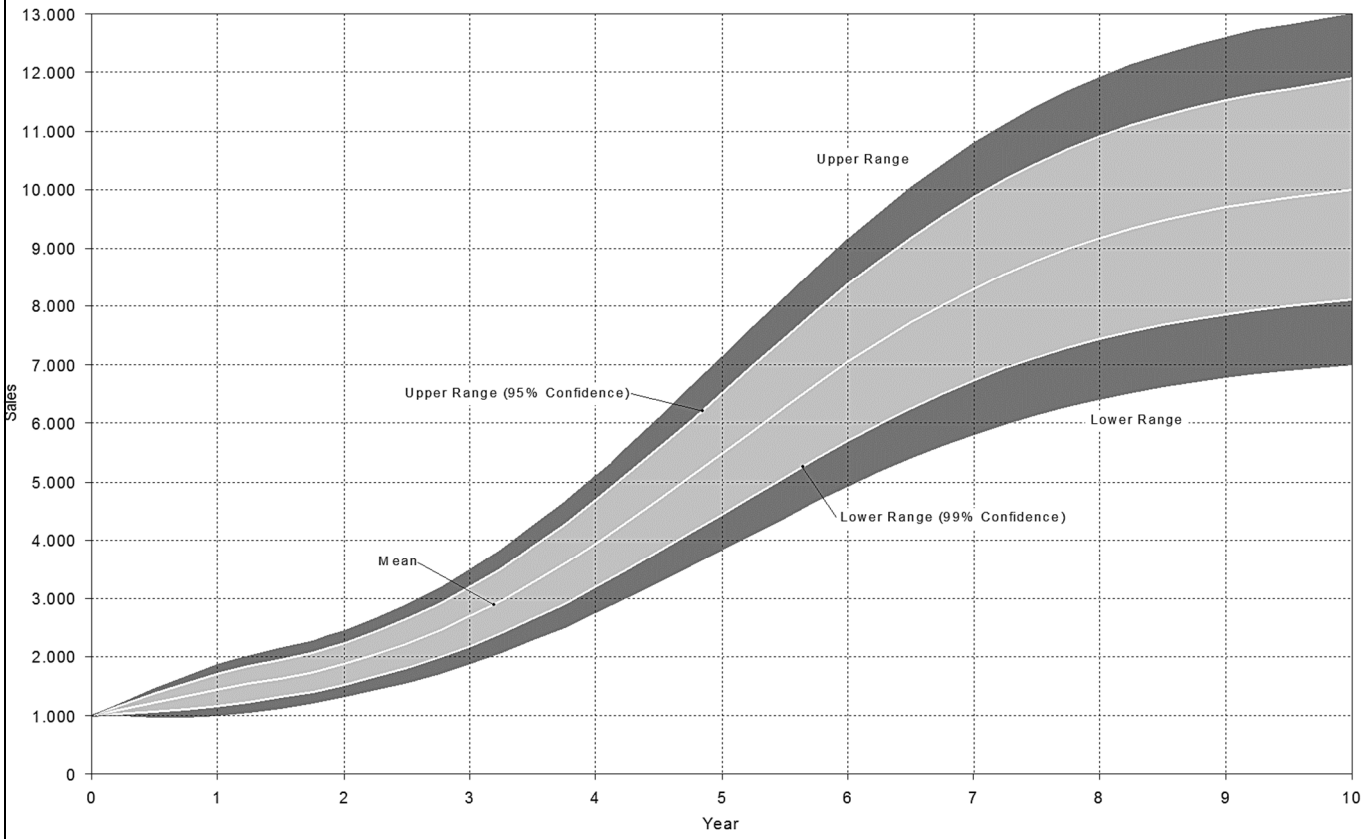
According to Moro Visconti et al., 2018, forecasting is increasingly difficult when the time horizon grows also because big data projections are limited to short-term budgeting purposes (within one year), such as setting the level of sales for the current fiscal year or adjusting the budget targeting for the next quarter. To make reasonable forecasts over the medium-long-term, we necessarily must recur to theoretical economic models, which somehow provide rational constraints to our forecasting process. Going beyond the short-term, the only "certain" benchmark for reasonable assumptions about the future evolution of the company's performances are a "starting point" based on the last historical available company's records; and a long-term "arrival point" at which the company should tend to converge, based on theoretical economic conditions of equilibrium and sustainability. In this context, forecasts should assume a trend of convergence towards an equilibrium level. Of course, due to the uncertain nature of the economic world we cannot exactly foretell year by year, how fast or slow or complete this convergence process will be; and that is why it makes no sense to develop deterministic projections. A stochastic approach to forecasting can so be helpful. Instead of making punctual projections, it is easier and more reasonable to manage them in a probabilistic term, considering for each driver a distribution function of possible forecast values for each year of the projection, and assuming an evolutionary pattern of its parameters (e.g., mean and standard deviation) through the years, simulating their convergence towards an equilibrium level.

The medium-long-term forecasting process could so be structured setting an evolutionary pattern of the two parameters that define the distribution function of the stochastic variable through the forecasting period, for example, the mean and the standard deviation. Typically, the mean pattern should follow an evolution related to the kind of economic relation described before, the kind of process (mean-reverting process, long-term equilibrium convergence, steady-state, etc.) with its speed depending on the kind of variable considered. The standard deviation should follow the principle that forecasts related to a more distant point in time should be associated with a higher risk.

Figure 4 shows an example of the evolutionary pattern of the sales distribution function. A logistic pattern for sales is represented, highlighting how the evolution related to the launch of a new business

line, typically characterized by three phases, can be stochastically modeled: a first one of slow growth when the new products/services enter the market; a second phase in which the demand grows exponentially and a final stage in which the market gets progressively saturated. The confidence interval is consistent with a probabilistic representation of optimistic / pessimistic ranges in business planning.

Figure 7. Sales evolutionary pattern: logistic growth (source: Moro Visconti et al., 2018)



7. The Impact of Business Planning and Productivity Gains on Market Value

Productivity - the periodic ratio of an aggregate output to a single input – is concerned with "doing more with less". Economists (e.g., Jones, 2015) today agree that the efficiency of the production of goods and services given levels of capital and labor in an economy—its technology-driven total factor productivity— is the key determinant of the pace of economic growth. Modern theories of economic growth have been elaborated, among others, by Solow (1956), Lucas (1988), Romer (1990), Aghion and Howitt (1992).

According to the Economist (2020), productivity is the magic elixir of economic growth. Increases in the size of the labour force or the stock of capital can raise output, but the effect of such contributions diminishes unless better ways are found to make use of those resources. Productivity growth—wringing more output from available resources—is the ultimate source of long-run increases in incomes. It's not everything, as Paul Krugman, a Nobel economics laureate, once noted, but in the long run it's almost everything.

A rise in total factor productivity—or the efficiency with which an economy uses its productive inputs—may require the discovery of new ways of producing goods and services, or the reallocation of scarce resources from low-productivity firms and places to high-productivity ones.

Sources of productivity growth include the following:

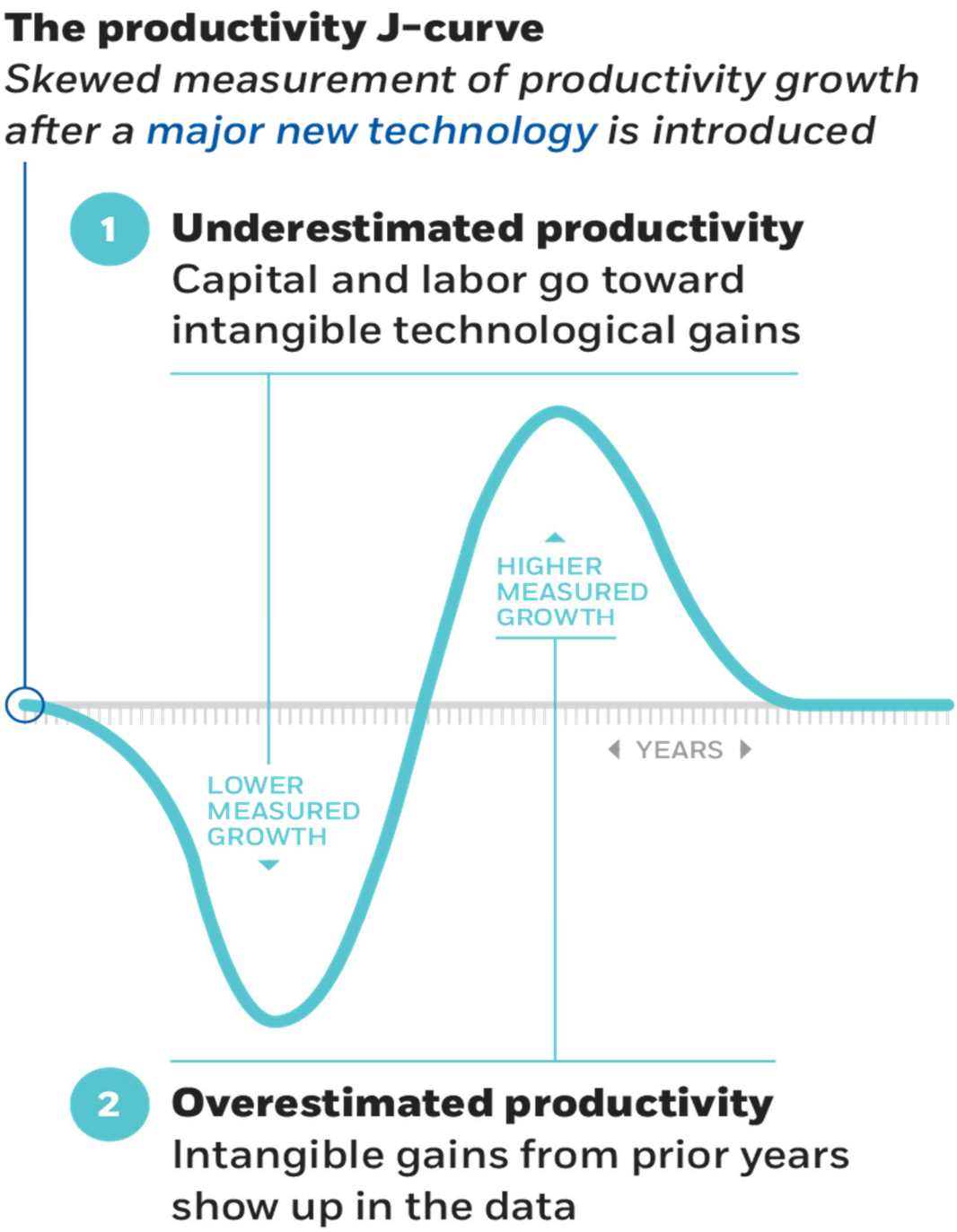
- Improvement in manufacturing techniques;

- Transformative (disruptive / world-changing) innovation, driven by general-purpose technology (innovative software; AI, improved robotics, cloud computing, video-conferencing ***) that can be adapted to specific applications;
- potential of the web to support an economy in which the constraints of distance do not bind;
- digital scalability;
- Better inventory management;
- Rationalization of logistics and production processes;
- Digitalization of firm records;
- Deployment of clever software;
- Disruptive events (e.g., pandemic) quicken the pace of technology adoption;
- Strong demand for goods and services.

According to The Office for National Statistics (https://www.ons.gov.uk/) five drivers interact to produce long-term productivity performance: investment, innovation, skills, enterprise, and competition.

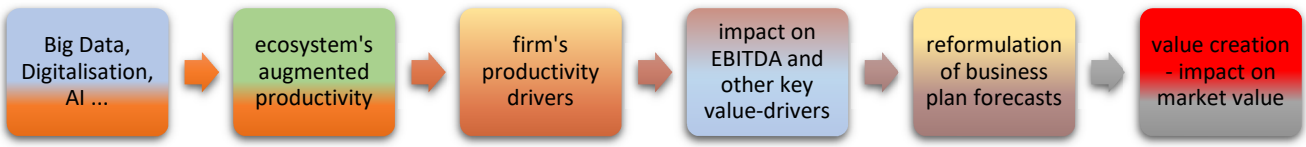
General purpose technologies such as AI enable and require significant complementary investments, including co-invention of new processes, products, business models and human capital. This pattern leads to a phenomenon they call the "productivity J-curve". As new technologies are first adopted, firms shift resources towards investment in intangibles: developing new business processes. This shift in resources means that firm output suffers in a way that cannot be fully explained by shifts in the measured use of labour and tangible capital, and which is thus interpreted as a decline in productivity growth. Later, as intangible investments bear fruit, measured productivity surges because output rockets upward in a manner unexplained by measured inputs of labour and tangible capital (Brynjolfsson et al., 2020). The pattern is shown in Figure 8.

Figure 8 – *The Productivity J-Curve* (taken from Brynjolfsson et al., 2020).



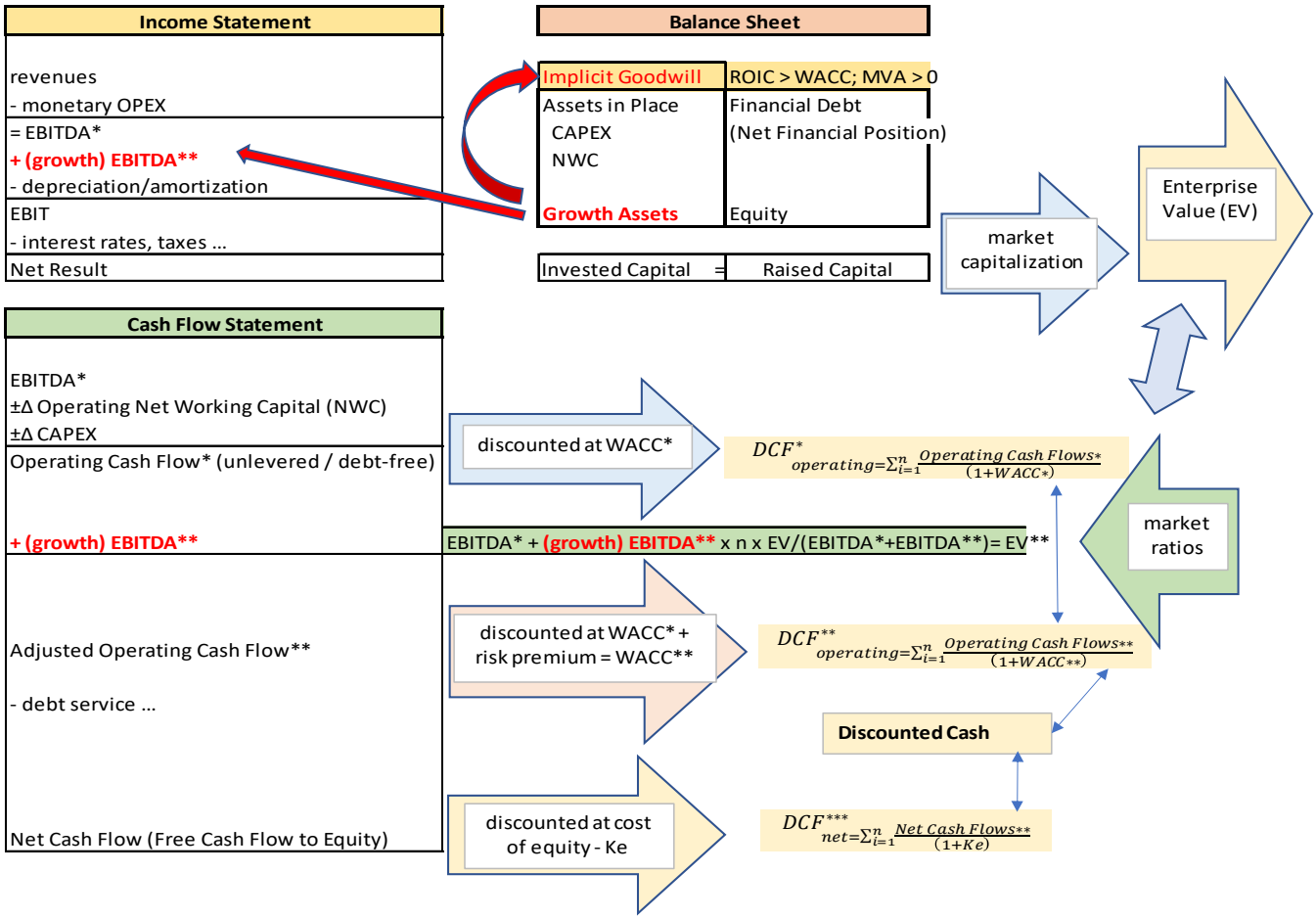
Productivity is incorporated in growth assets that impact the firm's EBITDA – a major driver of the valuation metrics. The sequential steps may be synthetized in Figure 9.

Figure 9 – *From Augmented Productivity to Value Creation*



Growth assets act as a "sponge" that absorbs productivity gains and releases them progressively. Figure 10 combines the perspective accounting framework (of interacting income statements with pro-forma balance sheets to generate forecast cash flow statements) with the valuation outputs that bring to the Enterprise Value estimate that derives from the two most commonly accepted appraisal approaches: Discounted Cash Flows (DCF) or market multipliers.

Figure 10. - *Impact of growth assets on valuation metrics*



The presence of growth assets in the balance sheet ignites excess returns and a positive Economic Value Added (EVA). EVA is a performance measure devised by Stewart (1991), based on the difference between the return and the cost of capital. It is obtained by subtracting the cost of capital employed from the operating result (= EBIT) normalized and after taxes (NOPAT):

$$EVA = NOPAT - WACC * Ic = (ROIC - WACC) * Ic \qquad (1)$$

where:

- NOPAT = normalized operating income after taxes;
- Ic = [adjusted] invested capital (shareholders' equity + financial debts + equity equivalents);
- ROIC = NOPAT / Ic = [adjusted] return on invested capital;
- WACC = weighted average cost of capital.

Cumulation of positive EVA across years produces a positive and growing Market Value Added (MVA). MVA is the difference between the market value and the invested capital, equivalent to the sum of the discounted future EVA:

MVA = market value – invested capital = present value of all future EVA = EVA1 / (WACC – g) = (economic profit of existing assets and growth opportunities) / WACC. (2)

The MVA is the measure of the value that a company has created in excess (goodwill) compared to the resources already bound to the company. This relates to the measure of the excess market value concerning the book value of the capital raised. When MVA > 0, Price / Book Value > 1.

The implicit (not recorded) goodwill occurs whenever ROIC > WACC (the market return on invested capital exceeds the weighted average cost of capital) and is a surrogate of EVA or the franchise Price/earnings factor determined by the difference between the return on the new business opportunity and the cost of equity.

These growth options embedded in the assets and depending on the innovative business model of the target FinTech are likely to produce excess economic returns that increase the EBITDA (EBITDA* + growth EBITDA**). A higher EBITDA** increases the liquidity produced within the income statement and positively affects the Operating Cash Flow (Operating Cash Flow* + growth EBITDA** = Adjusted Operating Cash Flow**). The Net Cash Flow, after debt service, is also positively affected by growth.

The valuation metrics, considering the DCF or the market multipliers, records the marginal impact of growth, whose riskier occurrence is, however, to be discounted at a higher rate. According to Damodaran [48, p. 5] "firms generate cash flows from multiple assets […] so the discount rates we use should be different for each set of cash flows". The scaling effect which drives the growth rate is difficult to be maintained in the long run, and forecasts of firms with little track-record are intrinsically riskier. Technological discontinuity also impacts on market risk, threatening the business of incumbent firms. For these very reasons, the discount rate should fairly incorporate this hardly predictable outlook that also reflects potential changes in risk over time. The value creed says rapid growth must eventually peter out.

8. An Empirical Simulation

The model described in the previous section is so innovative that it seems impossible, to the authors' best knowledge, to find an (already existing) empirical case that fits in. A simulation will so be carried on, starting from a generalized real case, and adapting it under the described model.

The following key aspects will be tested:

1. The impact of big data, borne within the networked ecosystem, and levered by Artificial Intelligence, on DCF metrics;
2. The consequential sensitivity of both cash flows and their discount factor (risky cost of capital);
3. The impact on deterministic and stochastic planning.

The simulation is inspired by a real business plan, duly generalized, composed of three main interacting documents: the pro forma balance sheets, the forecast income, and cash flow statements. The Discounted Cash flows (consistently with Figure 2) represent one of the main by-products. A dedicated repository, available upon request to the corresponding author, contains a comprehensive representation of the business plan. The case represents a long-term infrastructural investment in a healthcare facility that is adapted to accommodate the impact of big data and other scalability drivers on the DCF formulation. Such an impact involves both the cash flows in the numerator and the discount factor (the cost of capital) in the denominator.

The base case describes a standardized infrastructural investment of 3 years (project and construction) + 25 years of management, where key input data concern: the yearly revenues of the concessionaire (availability payment from the public procurer + hot/cold revenues); the investment amount, covered by the capital and the debt issued; the key macroeconomic/financial variables (inflation, interest rates, etc.).

There are four scenarios, with a sensitivity analysis that starts from the base case and foresees an increase in revenues with a corresponding decrease in operating expenditure (OPEX) that impact the numerator of the DCF formula (operating cash flow = revenues – OPEX = EBIT + amortization/depreciation = EBITDA ± Δ Operating Net Working Capital ± Δ Capital Expenditure [CAPEX]). There is also a decrease in the denominator, represented by the WACC and reflecting a trendy lower risk:

1.	Base case
2.	Revenues + 5%; OPEX – 5%; WACC- 10%
3.	Revenues + 10%; OPEX – 10%; WACC- 20%
4.	Revenues + 20%; OPEX – 20%; WACC- 30%

The results are synthesized in Table 4.

Table 4 – *Economic & Financial Plan Sensitivity Comparison*

[data in €/000]	Base case	Case I	Case II	Case III
Revenues	+/-0%	+5%	+10%	+20%
OPEX	+/-0%	-5%	-10%	-20%
WACC	+/-0%	-10%	-20%	-30%
Total operating revenues (3+25 years)	1.094.615	2.653.091	6.768.343	46.683.377
Total operating costs (3+25 years)	885.106	395.038	193.701	60.394
Total EBIT (3+25 years)	154.243	2.202.790	6.519.381	46.567.726
Total pre-tax result (3+25 years)	114.628	2.163.242	6.479.897	46.528.355
Total net result (3+25 years)	79.954	1.514.270	4.535.928	32.569.849
Cumulative EBITDA (3+25 years)	209.508	2.258.053	6.574.642	46.622.983
umulative unlevered cash flow (3+25 years)	113.234	2.166.014	6.502.849	46.831.588
Cumulative levered cash flow (3+25 years)	16.125	164.657	602.402	6.458.023
NPV equity	17.230	424.441	1.320.191	9.468.431
NPV project	30.034	650.068	2.004.788	14.266.705
Payback Period	2029	2023	2023	2023
Average Debt Service Cover Ratio	2,02	18,15	46,89	242,19
IRR equity	11,66%	37,54%	49,12%	65,88%
IRR project	10,91%	35,20%	49,42%	73,03%
Average EBITDA / financial charges	11,01	154,44	499,52	4.170,64

Table 1 can be synthetically interpreted as follows:

- The economic and financial margins and ratios are extremely sensitive to a joint

revenue increase + cost decrease + risk decrease; this also depends on the long time-horizon of the business plan (28 years); this is reflected in the cumulative EBITDA or cash flows (unlevered – before debt service; levered – after debt);

- the Net Present Value (NPV) of the project and the equity are always positive, even in the base case, showing that the investment is worth undertaking; anyway, they substantially grow under the progressively improving scenarios;
- the payback period shortens when margins improve;
- the debt service cover ratio (that compares incoming cash flows to outgoing liquidity to pay back debt) also substantially improves, reaching a comfort zone;

- the Internal Rate of Return (IRR) represents the discount rate that makes the NPV equal to zero, and also substantially grows;
- the EBITDA over financial charges - a multiplier of the liquidity inflows compared to the cash payout – also substantially improves.

The empirical simulation is consistent with tornado analysis to depict the sensitivity of a result of changes in selected variables (Borgonovo and Plishkhe, 2016). Business plans typically envisage an optimistic, intermediate, and pessimistic scenario that can be described with tornado sensitivity (https://wiki.analytica.com/index.php?title=Tornado_charts).

According to Dufendach (2020), the Expected Present Value Technique (EPVT) uses as a starting point a set of cash flows that, in theory, represents the probability-weighted average of all possible cash flows (expected cash flows). The resulting estimate is identical to the expected value, which, in statistical terms, is the weighted average of a discrete random variable's possible values where the respective probabilities are used as weights. Because all possible cash flows are probability-weighted, the resulting expected cash flow is not conditional upon the occurrence of any specified event (as are the cash flows used in the discount rate adjustment technique). EPVT can be consistent with a deterministic or stochastic scenario.

Whereas the impact of big data-driven scalability factors on the cash flows is direct, the discount factor in the denominator of the DCF formula is less affected. This is due to its intrinsic nature.

The WACC formulation shows that in the estimate of the cost of capital there is an internal and an external (systematic) component, both in the cost of debt and in the cost of equity:

a) in the cost of debt, the market interest rate (risk-free nominal interest rate = real interest rate + expected inflation) represents the systematic component, whereas the spread is the firm-specific parameter;

b) in the cost of equity, the systematic component is represented by the market premium (stock market return compared to the risk-free nominal interest rate), whereas the specific parameter is proxied by the firm's Beta (β):

$$ER_i = R_f + \beta_{i,m}(ER_m - R_f) \qquad [5]$$

where:

- ER_i = expected return of the investment;
- R_f = risk-free rate;
- $\beta_{i,m}$ = beta of the investment (sensitivity of the listed firm towards the stock market) =
  - cov (i, market) / σ^2 market;
- $(ER_m - R_f)$ = market risk premium.

If the cost of equity is proxied by the DDM, the discount rate r incorporates both the standard market discount rate and the specific firm risk:

$$P_0 = \frac{D_0(1+g)}{r-g} = \frac{D_1}{r-g}$$

Next dividend

Discount rate

Growing at (growth)

Where:

- P_0 is the current stock price
- g is the constant growth rate in perpetuity expected for the dividends.

- r is the constant cost of equity capital for that company.
- D_1 is the value of the next year's dividends (the model embeds constant growth that is a theoretical oversimplification of the real world).

Being the WACC mostly affected by external factors, the impact of big data-driven scalability is limited. It is so questionable that we can have a markable risk reduction. This is also due to the circumstance that growing cash flows in the numerator of the DCF formula may become more volatile, so incorporating a higher risk in their discount factor.

The case and its sensitivity simulations just consider the deterministic impact on the economic and financial forecasts.

9. Discussion

This study is very preliminary as it just considers a sensitivity impact of the big data and other related scalability drivers on traditional business plans that become "augmented".

A more comprehensive analysis may well consider a scenario analysis with dynamic and interdependent interaction among the key parameters (revenues, operating costs, and the risky cost of capital).

Continuous update of forecasts (up to an ideal instant refreshing, when the time span between one update and the following shortens, tending to zero) is ideally impacting the discount factor that incorporates a riskless time value of money plus a specific risk premium component, tailor-made for the firm. In formulae:

$$\text{Cost of capital} = WACC = k_i(1-t)\frac{D}{D+E} + k_e\frac{E}{D+E} =$$

$$= (\text{cost of debt} * \text{debt weights} + \text{cost of equity} * \text{equity weights})$$

The cost of debt (k_i), net of the tax effect (1-t), depends on several parameters (the financial leverage that expresses the ratio between financial debt, D, and equity, E; the credit quality of the firm and its rating, etc.) that are marginally impacted by forecasting improvements that reduce the difference between expected and real cash flows (represented in the numerator of the DCF formula, with a risk pattern reflected by the WACC in the denominator). The formula can be decomposed as follows:

$$cost\ of\ debt = \frac{negative\ interests}{financial\ debt}(1-t) = \frac{nominal\ interest\ rate + spread}{financial\ debt}(1-t)$$

The sensitive part of the cost of debt is represented by the firm-specific spread since the nominal interest rate (real rate + expected inflation) is fully market-driven.

Even the risk incorporated in the cost of equity can be mitigated by "instant" forecasting. Should the cost of equity be proxied by the Capital Asset Pricing Model formulation, we would have:

$$K_e = r_f + \beta(r_m - r_f)$$

r_f represents the risk-free rate (proxied by the expected return of long-term Government bonds), r_m the stock market return, (r_m-r_f) the market premium over the risk-free rate, and b the sensitivity of the firm towards its stock market. Both r_f and r_m are fully market-driven (and r_f is close to the nominal risk-free interest rate), whereas the b is firm-specific, and represents the sensitive part of the cost of equity.

Table 5 shows the primary impacts of big data on business planning issues.

Table 5. Impact of big data features on augmented business planning.

Big data dimensions	Impact on augmented business planning
Volume	Big volumes of data provide greater width and depth to bottom-up evidence.
Velocity	Data accumulate in real-time and rapidly. This helps the continuous refreshing of forecasts.
Variety	Evidence-based business planning combines and analyses a range of structured, semi-structured, and unstructured data to match strategies with outcomes.
Veracity	Key parameter, corresponding to data reliability. Increased variety and high velocity hinder the ability to cleanse data before analyzing it and making decisions, magnifying the issue of data "trust".
Validity	Data integrity is defined as the validity, accuracy, reliability, timeliness, and consistency of the data.
Variability	The way care is provided to any given patient depends on all kinds of factors—and the way the care is delivered, and data is captured may vary from time to time or place to place.
Virality	Measures the spread rate of data (sharing speed) across the networked ecosystem.
Visualization	Information visualization and visual analytics are connected to representation technologies that help users to understand data. The synthesis produced by data visualization tools is a crucial element to transform the information revealed by big data processing into accessible knowledge.
Viscosity	Characterizes the resistance to navigate in the dataset or complexity of data processing.
Value	Monetized value is the synthesis of big data V-dimensions, considering data as an asset to exploit to produce innovation and new information-sensitive products and services.

The business planning structure can conveniently follow an Introduction-Methodology-Results-and-Discussion (IMRAD) pattern (traditionally used for the outline of scientific papers), adjusted to comply with its specific targets, as shown in Table 6.

Table 6. Comparison between the IMRAD template and the business plan schedule

	Scientific Publication	Business Plan Template
Introduction	• Conceptual focus and problem statement • Why was the study undertaken? • What was the research question, the tested hypothesis or the purpose of the research?	• Pitch / executive summary • Outline of the plan
Method	• When, where, and how was the study done? • The steps of the scientific method are to: • Ask a Question • Do Background Research • Construct a Hypothesis	• How to conceive and prepare a business plan? • Which are the consequential steps? • How to be simultaneously effective and comprehensive?

	• Test Your Hypothesis by Doing an Experiment • Analyze Your Data and Draw a Conclusion • Communicate Your Results	• How to properly combine hard and soft skills? • Which are the milestones, goals, and objectives?
Results	• What answer was found to the research question? • what did the study find? • Was the tested hypothesis true?	• Proof of Concept – Pilot study • Forecasting of the income statement (budgeting), pro forma balance sheets, and cash flow statements
and		
Discussion	• What might the answer imply and why does it matter? • How does it fit in with what other researchers have found? • What are the perspectives for future research?	• Practical implications of the business plan. • SWOT analysis to assess and challenge the strategic positioning of the project.

10. Conclusion

This study has shown that bottom-up empirical facts, populated by big data and IoT sensors, can improve the informative set of managerial strategies with better and more timely evidence. This positively impacts the DCF metrics, affecting the numerator represented by cash flows that incorporate flexible options to expand or adapt the business. The denominator of the DCF formula reflects the Value at Risk (VaR) that continuously changes, incorporating timely information.

Forecasting is also influenced by real-time evidence, bringing to a constant reformulation of hypotheses that can favor instantaneous refreshing of business plan assumptions. Continuous feedbacks also fuel deterministic or stochastic (probabilistic) planning.

Further research may investigate the stochastic applications consistent with the random networking externalities driven by digital platforms that preside over the firm's competitive ecosystem. Such an ecosystem may well reflect ESG tendencies that again impact the long-term sustainability of strategic business planning.

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Table 1A - *Network (Node) Features and Impact on the Business Planning*

Network (node / edge) property	**explanation**	**Impact on business planning / DCF**
Network (un)directed links	A network is called directed (or digraph) if all its links are asymmetric, and cause-effect relationships are only one-way; it is called undirected if all its links are symmetric (one-to-one).	Most links within the network ecosystem are undirected. They have a greater potential impact on value.
Node degree	number of links to other nodes.	The higher, the bigger the "intensity" of the network and its potential value. The digital platform is a catalyzing node.
Edge - Physical links	pairs of nodes can be physically connected by a tangible link	Physical links coexist with digital ones, and their synergic impact can generate value.
Edge - Physical interactions	connection determined by a physical force	Physical interaction among physical (and digital) links impact on the supply chain
Edge - (intangible) connections	information or other immaterial links	Digital connections complement physical ones.
Geographic closeness between nodes	Geographic closeness between nodes	Physical proximity is an added value.
Social connections (friendship, collaboration, family ties, etc.)	Social connections (friendship, collaboration, family ties, etc.);	Social ties ease information spreading and transactions, generating value
Functional linking (actions that activate other activities)	Functional linking (actions that activate other activities).	Bridging nodes favor value-adding indirect links.