Alternative ESG Data for Investment Decision Making

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What is environmental social and governance (ESG) data and how do we evaluate its quality? Previous literature describes intrinsic properties of ESG data (i.e., multifaceted and context dependent), recognizing an unavoidable trade-off between the validity and reliability, which is often tied to the lack of theoretical foundations and dearth of the actual ESG data. Encouragingly, new data technology has improved accessibility, availability and transparency, but we still do not have an agreed theoretical framework to evaluate ESG data quality. This paper seeks to fill this theoretical gap by proposing a "user-oriented" approach to evaluate ESG data. In this framework, we consider ESG data to be a "continuous concept with limitless boundaries" and characterize it in terms of its width and depth. We adopt a user-oriented approach because it is the users who decide the width and depth of ESG data as well as evaluate its quality. We identify six dimensions of ESG data quality (i.e., reliability, granularity, freshness, comprehensiveness, actionability, and scarcity), and six dominant variables that are used by investors in their decision-making (i.e., risk, performance, cost, construction, commitment, and influence). We then demonstrate that each of the six properties has a distinct level of relevance to the six key investment decision variables.

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1 Introduction

Investors have shown increasing interest in environmental, social and governance (ESG) factors in their investment decisions. So far, however, the rise of ESG has been hamstrung by a widespread belief that ESG criteria are extra-financial and that explicitly managing these risks could reduce investment returns. At the same time, a growing number of investors have shown interest in, and ramped up their acquisitions of, alternative data. The boom in alternative data, which refers to the novel and unconventional data sets emerging out of digital sensors, satellites and even smartphones, has been catalyzed by the belief that it can help investors better manage risks and maximize long-term investment returns. In short, where ESG data has been seen as a potential drag on returns, alternative data is often perceived as a way of driving higher risk-adjusted performance. We find this phenomenon particularly interesting because according to our definition, ESG data is alternative data. And the only reason one or the other has a different connotation in the eyes of investors stems from the provenance of the concept; ESG emerges out of sustainability initiatives, while alternative data emerges out of the world of hedge funds. Beyond that, the data is, by and large, the same.

Alternative data refers to data from factors that are not conventionally used for investment decision-making, yet these unconventional factors have a special role in corporate profits and sustainability. For instance, in addition to analyzing historical revenue and revenue forecast, investors today evaluate corporate reputation and future revenue streams through social media presence. Alternative data has its unique value because it is consistently and closely correlated to investment outperformance, which cannot be fully explained by traditional financial data. For this reason, alternative data can also be considered "innovative data." And this form of innovation is something that business leaders and investors are naturally interested in as a driver of profits. Accordingly, it comes as no surprise to us that academic research shows that corporate environmental improvement can be a source of competitiveness (Schmidheiny, 1992; Porter and van der Linde, 1995), and the impact of ESG factors can be seen in higher investment returns (In et al., 2018; Starks et al., 2018). In this respect, innovation, alternative data, and ESG all share the same characteristic in that they do not necessarily show up in a company's quarterly or annual financial reports, but they all still have material long-term implications for value. In short, much of alternative data is ESG data, and much of ESG data is alternative. And yet, many people see the two types of data as coming from different extremes of investing; one focused on more than returns, while the other is purely about investment outperformance.

Significantly, the Principles for Responsible Investment (PRI) seek to define ESG as being more akin to alternative data. Indeed, it has argued that ESG data integration demands "the explicit and systematic inclusion of ESG issues in investment analysis and investment decisions," and distinguishes it from considering ESG issues as extra-financial. In fact, the PRI has suggested that the key to successful and sustainable implementation of ESG is ultimately a function of whether ESG performance can be linked with business, finance and investment performance. Similarly, we have found in our research that a lack of ESG integration and implementation is most often due to the lack of understanding of the link between a firm's environmental performance (EP) and its financial performance (FP). While a growing number of empirical studies have found a positive relationship between EP and FP (In et al., 2018; Eccles et al., 2014; Khan et al., 2016; Clark et al., 2015), many investors still question whether this outperformance can be replicated and persistent in a long-term is still outstanding.

Wood (2010) points out the lack of theoretical foundation and progress in measurement of corporate social performance as a critical reason of such mixed evidence.[1] Prior studies illustrate that the empirical relationship between EP and FP can vary depending on how the study measures EP (Chatterji et al., 2009; Sharfman, 1996; Szwajkowski and Figlewicz, 1999; Orlitzky et al., 2003; Dixon-Fowler et al., 2013). Thus, the most significant barrier to ESG integration today is the lack of standards for ESG and how it is used. Part of the problem is the inaccessibility, both apparent and actual, of good ESG data. Eccles et al. (2017) found, by conducting a global survey with 582 institutional investors, that sixty percent of respondents identified the lack of common standards for measuring ESG performance as their dominant concern.

Global initiatives have been launched to address some of the barriers preventing ESG integration. For example, corporate disclosure on ESG issues has steadily improved since the launch of the Global Reporting Initiative (GRI) in 2000. Today, 80% of the world's largest corporations use GRI standards. The Sustainable Stock Exchange Initiative (SSEI), supported by United Nations Conference on Trade and Development (UNCTAD), launched in 2006 with a mandate to enhance corporate transparency on ESG issues and encourage ESG investing. SSEI is now mandating ESG disclosure for listed companies or providing guidance on how to report on ESG issues. Still, most of reporting practices are voluntary and companies have incentives for manipulating its EP by providing selective and biased information (In, 2018).

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[1] Wood (2010, 1995) used the term corporate social performance (CSP)–she also listed its sister concepts such as corporate social responsibility, corporate social responsiveness, corporate citizenship–as a broader term that contains a firm's social and environmental impact.

Over the same time period as ESG data has come into the mainstream, the financial industry has readily embraced alternative data and new data technologies, as it tries to enhance investment performance. These advanced data technologies can help investors to conduct deeper analyses and to create investable insights. New fin-tech companies have emerged that evaluate companies' performance based on alternative data sources (e.g. satellites) and alternative analysis techniques (e.g. artificial intelligence [AI] and machine learning). APG, the large Dutch fund, for instance, turned to data science and advanced analytic technology by acquiring a topnotch analytics team from Deloitte, which has become a unit called "ENTIS." APG aims to enhance its investment performance while meeting its required contribution to the achievement of the United Nations Sustainable Development Goals (SGDs). As such, the use of this type of alternative data has spiked as new technologies have expanded data availability and processing capabilities while significantly bringing down costs. Therefore, these new tools further devalue conventional financial datasets, making alternative data even more appealing to investors.

Although the rise of new data technologies has enabled easier access to and promoted use of this alternative data, there is an outstanding gap between ESG integration and new data technologies. Similarly, there may be an over-exuberance surrounding alternative data integration, as some investors press ahead without thinking through all the potential consequences.

- First, it is extremely hard to establish universally agreed criteria of ESG evaluation. ESG data is intrinsically multifaceted and context-dependent–unlike traditional financial data that is structured and quantitative, most ESG data is unstructured, qualitative, scattered, and incomplete. These special characteristics of ESG data and the lack of theoretical foundation have hampered the implementation of ESG strategies for most investors.

- Second, new tools of data collection and analytics are not effectively used by investors. Some organizations that are well equipped for using ESG and alternative data to improve net returns remain largely unconvinced as of today. They are concerned that costs for getting ESG data, especially for developing in-house capability, are relatively high compare to realizable returns today. Enhanced ESG data and its analytics without addressing this gap will likely accelerate an arms race in data-driven investing, which intensifies competition without any defined endpoints.

Technological advancement contributes to enhancing the volume and depth of ESG datasets. Yet, if the usage of ESG data is dominantly driven by short-termism not completely reflecting the true preferences of diverse investor groups, its value proposition will accelerate an arms race in data-driven investing, which intensifies competition without any defined endpoints.

In this paper, we review how previous studies set criteria to evaluate a firm's ESG performance and criteria to evaluate the quality of ESG data. We then investigate why, at this time, ESG data cannot be defined and evaluated by the previously established criteria. For instance, today's ESG ratings are inconsistent and incomparable as they are not relying on shared theoretical foundations nor sharing the common reporting standards. We identify traditional challenges to ESG data, such as accessing transparency and reliability data or data representing environmental aspects, and investigate they have been gradually surmounted due to the advanced data technologies. Next, we identify new or remaining challenges to ESG data. We see ESG data as no longer being defined by discrete dimensions, sources, or types–nor can it be evaluated by reliability and validity qualities.

Alternatively, we consider ESG data as a "continuous concept with limitless boundaries" and characterize it in terms of its width and depth. In this regard, we propose a "user-oriented" approach to evaluate ESG and alternative data. Under this framework, it is the users who decide the width and depth of innovative data and evaluate the data quality based on individual users' unique investment preference. More specifically, we identify six dimensions of ESG data quality (i.e., reliability, granularity, freshness, comprehensiveness, actionability, and scarcity), and six dominant variables that are used by investors in their decision-making (i.e., risk, performance, cost, construction, commitment, and influence). We then demonstrate that each of the six properties of ESG data has a distinct level of relevance to the six key investment decision variables. We provide implications on how to enhance innovative data quality and usage by leveraging advanced data technologies available today.

The article is organized as follows: In the next section, we present an overview of the theoretical foundation of EP measures that have been used to evaluate corporate environmental performance. Then we examine the confronted challenges with using ESG data and testing its quality. This is followed by a discussion of the major research challenges concerning the use of new data technologies in addressing these challenges, highlighting areas where they can improve the quality of ESG data. We then develop new properties of ESG data, which have been extended due to the advancement in data collection and analytics, and identify main drivers in making ESG investment decisions. Finally, we discuss which property of ESG data is the most critical in delivering the investment outcome set by an individual investor. The final section presents conclusions and recommendations for further development in the use of new data technologies in ESG integration.

2 Understanding ESG Data: Characteristics and Challenges

2.1 Perceived Structure of ESG Data

Empirical studies that examine the relationship between EP and FP assess EP in quantitative units. To quantify EP, researchers first identify criteria based on single or multiple conceptual frameworks that define distinct environmental impacts. Second, they collect and verify data points that are consolidated into a EP measure. With the EP measure, they evaluate a firm's performance in the criteria they have built. The results of prior studies are mixed mostly because they do not agree on what and how to measure EP. Therefore, previous literature has built EP measure as a set of structural categories that can be identified, described and measured (see, for example, Kang and Wood, 1995; Mitnick 1993, 1995, 2000; Swanson, 1995, 1999; Wood, 1991, 2010). One approach is to define EP measure as a single dimensional construct that has a strong representation power such as strong correlation of a firm's FP and so on. The other approach is to consider EP as a multidimensional construct. Under this approach, FP is considered as one variable among many others that are relevant (Wood, 2010; Peloza and Papania, 2008). It seeks measures that are relevant to multiple conceptual frameworks, but it does not necessarily draw a single measure that captures all the components. For instance, there can a firm that performs good in one key component (e.g., carbon emission reduction) but at the same time underperforms in the other components (e.g. social responsibility).[2]

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[2] Some studies explain difference between single- and multi-dimensional approach from stakeholder perspectives (see Delmas & Blass [2010] for instance). The performance is defined as the extent to which companies achieve their principals' target. If one believes there are multiple environmental stakeholders of a firm, the construct to defines its EP should be multiple as well.

Studies with a single dimensional approach often use quantifiable performance indicators, such as emissions, penalty amounts, oil spills, and number of environmental management system. This approach has been widely used because these EP indicators are measurable and easily understood by members of a community. Early empirical studies use toxic chemical emissions data from the Environmental Protection Agency (EPA)'s Toxic Release Inventory (TRI), which reports annual quantities (in pounds) of over 650 toxic chemicals released from a facility to the environment, managed by the facility as waste, transferred from the facility to another facility for release or other waste management. Hart and Ahuja (1996) use TRI data and examine whether emission reduction enhances corporate performance (such as return on sales [ROS], return on assets [ROA], return on equity [ROE]). King and Lenox (2002) take a similar approach using TRI data, firm's ROA and Tobin's *q*, but further distinguish waste management methods so that they can better explain where the source of profit (or loss) lies.

This single dimensional approach is often limited because single-dimensional EP measures do not encompass diverse aspects of a firm's EP, which may mislead the relationship between EP and FP. For instance, Dixon-Fowler et al. (2013) point out that TRI data is primarily a measure of chemical emissions, not a comprehensive indicator of a firm's EP. Moreover, most of single dimensional EP measures only able to capture a firm's exposure to environmental risks in a short term. For instance, a firm's oil spill event can explain immediate increase in capital and operating expenses, but it does not provide what causes this event, whether and how frequent it would happen, or what effects the event would bring to a firm's overall performance in a long-term. Clarkson et al. (2013, p. 411) claim that companies' impacts (such as TRI emissions) could capture partial dimension of a firm's risk, but "do not necessarily reflect a firm's current environmental strategy and commitment to future environmental protection."

Researchers who emphasize multifaceted properties of ESG data define EP measure as a multidimensional construct. Wood (1991), based upon Wartick and Cochran (1985) and Caroll (1979), introduces three dimensions of corporate social performance (CSP), which include motivation, process and outcome. She also emphasizes to consider interconnectedness among multiple constructs: the outcome may indicate immediate social impact of a firm but may not be able to capture the firm's motivations (i.e., institutional, organizational, and individual principles) and process (i.e., environmental assessment, stakeholder management, and issues management), which however can determine future outcomes and impact. Wood (1991) argue that considering interactions among these three dimensions, not separating from business performance itself, can allow to identify possible reverse causality and enables comprehensive assessment of CSP.

Schultze and Trommer (2012), based on Wood (1991), Jung et al. (2001) and Günther (2004), suggest alternative set of multidimensional categories by filtering the indicators that directly correspond to a firm's EP and by categorizing them into strategic and operational kinds. They develop five sub-categories: the operational category further separated into four casually linked sub-categories: input, process, output, outcome, and the strategic category addresses a firm's attitudes and objectives regarding environmental responsibility as well as environmental management structures and processes. The authors suggest that operational input and output are closely related to incurrence of environmental impact, but these indicators are retrospective and thus are not very useful in predicting future outcomes. Whereas the strategic indicators are more useful in this part. Adopting from Schultze and Trommer (2012), Semenova and Hassel (2015) build EP measure with performance- and risk-based indicators. The performance component focuses on a firm's actions to reduce its environmental impacts while the risk component reflects the environmental impacts of the firm's operations and external consequences. As such, each dimension of EP construct is designed to represent a distinct, causally linked construct.

At the same time, however, researchers recognize that some EP information cannot be quantified nor be assigned to a single category. This information cannot be categorized under one specific dimension but rather they are interconnected throughout multiple categories. The use of these multi-category indicators is based on the conclusion that relying on single indicators does not cover the complex EP construct sufficiently. For example, Christmann (2000) evaluates "best practices" of environmental management by the use of pollution-prevention technologies, the innovation of proprietary pollution-prevention technologies and an early timing of environmental strategies. Brammer and Pavelin (2006) use data on environmental policies, systems, reporting, and impacts to measure environmental related issues. Schultze and Trommer (2012), in addition to operational and strategic ones, include self-calculated EP scores, perceived performance, environmental ratings, environmental funds, and environmental related events.

Combined with the data science advancement and investors' interest in ESG, ESG rating organizations like MSCI, ASSET 4, Trucost attempt to develop their own rating criteria and methodologies. For instance, MSCI generally provide a univariate index of "environmental strength" and "environmental concern." MSCI sets eight sub-categories to evaluate firm's environmental strength and concern, and each reported as a binary indicator that reflects whether the firm meets the particular criteria or not. Then MSCI sums up those binary indicators to get the environmental strength and concern scores. Trucost (now merged to S&P Global Index) provides firm-level carbon intensity data, which covers a firm's GHG emissions from the all three sources of GHG emissions (i.e., Scope 1, 2, and 3 defined by the GHG Protocol).[3] As the emission data comprehensively monitors from direct emissions to indirect emissions throughout the firm's supply chains, it represents how the firm manage its emission activities. Rating organizations take advantage of new data technologies. For example, Tomson Reuter provides ESG data entitled ASSET4, which monitors a firm's management commitment to three environmental criteria: emission reduction, product innovation, resource reduction. The main variable is an equal-weighted rating by combining three sub-scores. It collects over 250 key performance indicators (KPIs) and 750 separate data points from multiple sources, including company reports, company filings, company websites, NGO websites, CSR Reports, and established and reputable media outlets.[4]

2.2 Assessing and Describing the Quality of ESG Data

According to measurement theory, a good measure should satisfy two main requirements: validity and reliability (Mitnick, 2000). A measure is valid if it measures what it is supposed to measure (i.e., "measures the right things"), and a measure is reliable if it delivers an accurate and stable picture of EP ("measures the things right"). A related strand of empirical studies therefore tests validity and reliability of EP measures. Studies suggest that a valid EP measure should be

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[3] Carbon intensity is defined by Trucost as the absolute GHG emissions divided by one million USD of revenue. It is thus estimated in metric units of (tCO2e/$million), allowing us to compare firm-level carbon efficiency in all firm sizes and across industries.

[4] ASSET4 makes all data quantitative. It scores every company in a given year from 0 to 1 for each pillar, which is called "raw data." The raw data is normalized and adjusted for skewness and the differential between the mean and the median, then fitted to a bell curve to derive "ratings" between 0 and 100 for each company. Based on a company's raw scores as defined above, "percentile ranks" are calculated for all companies screened.

based on sound theoretical foundations (Carroll, 2000) and be able to cover relevant constructs correctly and completely (Bartolomeo, 1995). Reliable measurement requires objective data (Tyteca, 2002), consistent measurement terms with units or with a reference value (Wagner, 2005), and data availability (Schultze and Trommer, 2012).

But due to the heterogeneous nature of EP, testing the quality of EP measure by validity and reliability because it is extremely hard to obtain a measure that represents a complete picture of a firm's actual EP. Alternatively, researchers develop EP measures that can be the best proxy of a firm's EP, and test validity and reliability in relative terms. For instance, Chatterji et al. (2009) tested the validity and reliability of Kinder, Lydenberg, Domini Research & Analytics (KLD, now MSCI)'s ESG data, the most frequently used database, by regressing it with historical toxic chemical emissions, environmental penalties and fines, oil spills, and permit denials. But again, testing validity depends on how to define the actual EP – or more broadly, how to define the best quality of EP measure.

The growing presence of these multi-category indicators makes assessing the quality of ESG data even more critical. Today, there is no common properties (previously, validity and reliability) to evaluate the overall quality of ESG data. Moreover, ESG metrics are not comparable and highly contextual. Semenova and Hassel (2015) rather test convergence across different ESG metrics and investigate the extent to which the environmental construct converges. Hesstrom et al. (2011) compare environmental rank-orders of seven sustainability analyst organizations on the same set of companies, and evidence significant divergences. The authors also investigate the reliability of these ratings by testing convergence across the seven organizations' rank-orders. Similarly, Semenova and Hassel (2015) investigate the convergent validity of environmental ratings of three major global agencies, KLD, ASSET4, and Global

Engagement Services (GES), and find that those ratings have common dimensions, but on aggregate they do not converge.

2.3 Current ESG Data Assessment Practices

In previous studies, the choice of EP measures and way to collection information are mainly driven by practical feasibility without theoretical consideration. This approach may not be able to fully understand how and why some EP measures are causally connected because they are not directly related to outcomes (Günther et al., 2004; Weber, 2008; Orlitzky et al., 2011). Delmas and Blass (2010) demonstrate that there are trade-offs between the different metrics chosen, and thus rating organizations should be transparent about their choices such as the theoretical foundations and data sources. For instance, most studies that identify and define multi-category indicators to better represent the important environmental component, collect the relevant data from company surveys. These surveys partly gather objective facts but also often ask personal views, for instance asking to rate the level of EP relative to businesses' competitors (Günther et al., 2004). Similarly, Schultze and Trommer (2012) argue that having one generic EP measure for large-scale studies should come with a loss in validity.

As different definitions encompass the elements of the underlying construct differently, ESG measures have inevitably become incomparable (Griffin and Mahon, 1997; Wolfe and Aupperle, 1991; Wood and Jones, 1995). But, users do not know which one they should use. Previous literature finds that various ESG rating metrics are not consistent one another. In addition, it also finds that, due to the lack of understanding of what aspect of corporate sustainability that individual ESG rating represents, users cannot imply from such observed discrepancies. Chatterji et al. (2009) test the reliability of KLD's environmental rating by examining how accurately it fits with empirical EP, to measure which the authors use toxic chemical emissions, regulatory penalties and environmental accidents. They find KLD's "environmental concern" to be fairly good summaries of past EP, but "environmental strengths" do not accurately predict future EP. But their basic premise is that the measure is considered reliable if it can explain or predict a firms past or future pollution levels and compliance violations. When In (2018) compare these KLD measures to firm's GHG emissions, they find that KLD environmental concern and strength both are positively correlated with a firm's GHG emissions. Nonetheless, it has been common practice in many studies to simply sum KLD's environmental concern and strength to obtain one single EP score, by regarding them as environmental harms and benefits respectively (In et al., 2018).

However, data processing and consolidating data points are not based on sufficient empirical and theoretical justification. It is common practice to combine or weight multiple components of EP into one single EP measure are often criticized because they select and aggregate evaluation criteria without sufficient empirical and theoretical justification. Each dimension of EP construct is designed to represent a distinct, causally linked construct. Neglecting this causes inconclusive discussions on clarifying the dynamics between EP and FP (Cerin and Dobers, 2001; Rowley and Berman, 2000; Sethi, 2005). For example, it is a common practice to subtract the scores of concerns or weaknesses from those of strengths to arrive at a single net environmental score (e.g., Graves and Waddock, 1994; Griffin and Mahon, 1997; Johnson and Greening, 1999; Ruf et al., 2001; Waddock and Graves, 1997). But the aggregation process may drop important information because each score may represent distinct constructs (Mattingly and Berman, 2006).

Analysis of data should also understand how multiple but distinct EP construct are linked to stakeholders' environmental expectations according to their relevance. It is common practice to merge environmental indicators with other social and governance related indicators into one single measure or generic ESG score, but this merging process might fail to capture the complexity of firm's ESG decision making and the relevance of corporate environmental activities for corporate sustainability. Explicit consideration of environmental aspects in the sustainability can also be seen as a challenge to the idea that business and environment are opposites. Environmental activities, which play a fundamental role in marketing corporate image, are in consequence partly responsible for the construction of a profit-dependent notion of business. Therefore, it would also be as difficult to separate business and environment. The idea of some connection and interdependence between business and environment and between business themselves, in recognizing intrinsic value to environmental activities, is a powerful instrument with normative implications.

3 Technology and Quality of ESG Data

The foregoing underscores a fundamental tension between (1) the inherently multidimensional character of ESG data and (2) the present lack of agreement on what dimensions of ESG-relevant behavior by corporations is material for investment decision-making. This tension creates a self-reinforcing bottleneck that impedes progress, because:

- The complex impacts of corporate ESG behavior, and difficulty of acquiring suitable data on them, perpetuates the lack of convergence on ESG metrics (Ruggie and Middleton, 2019); and
- Lack of convergence inhibits collection of suitable data at larger scales, as well as hinders more unified application of that data to better understand the complex ramifications of corporate ESG behavior (see, e.g., Eccles and Stroehle, 2018).

This tension is also unlikely to fully disappear. Although consensus may strengthen on the materiality of some dimensions of corporations' ESG performance, the deep heterogeneity of investors cannot be overcome (Ryan and Schneider, 2003). They each approach portfolio construction and management with a diverse set of resources, constraints (e.g., time horizons), and risk appetites (Clark, 2018). Indeed, it is this heterogeneity that permits markets to function in the first place (see, e.g., Rubinstein, 2006). Consequently, it is improbable that investors will ever reach perfect agreement about "the right things to measure" regarding ESG performance.

It may instead be more pragmatic to reframe issues of convergence in ESG measurement around trade-offs between *depth and width* of ESG data. Depth of ESG data can be understood as scale, in terms of both the volume of ESG data that is available on a company or other asset, as well as the number of companies (or assets) for which ESG data is accessible. Width of ESG data, meanwhile, reflects the variety of different types and sources of ESG data available for a specific investment. Increasing either depth or width can paint a more comprehensive picture on ESG performance – so long as such additional data (be it deeper or wider) is of acceptable quality.

And it is with respect to quality that trade-offs between depth and width in ESG data often occur. Scarcity of resources for collecting and verifying the accuracy of ESG data necessarily forces investors to make decisions on whether to accumulate and assess more of the same type of data, or additional types of data. Favoring width over depth (or vice versa) has historically restricted the overall quality of ESG data, because both width and depth contribute to quality.

Various emerging technologies, however, offer the possibility of mitigating the need for such trade-offs. That is, these technologies may simultaneously be able to improve depth and width of available ESG data in ways that were not previously feasible. Consequently, they could significantly shape how investors evaluate ESG performance. Such technologies are divisible into *collection* and *analytic* technologies. We discuss applicability and examples of each below.

First, however, it is crucial to address the question of how to characterize data quality, which is itself multifaceted and context dependent. There are multiple features of any dataset that contribute to its usefulness for decision-making (e.g., accuracy, granularity, recency) and these collectively contribute to its total quality (see Monk et al. [2019]).[5] The specific importance of any one feature to an ESG dataset's total quality is dictated by the investment decisions that are informed by that dataset. Characterizing the quality of a dataset therefore involves accounting for the value of decisions it can enable. Thus, given that different investors face and make distinct decisions, and that the importance of those decisions varies across investors, ESG data quality is perhaps best understood in relative terms that adopt the user's perspective and assumed utility: that is, the most helpful approach to assess ESG data's quality may be a user-oriented approach.

In supporting a user-oriented approach, collection and analytic technologies have complementary roles in augmenting the quality of ESG data. Analytic technologies can enhance the extractable insights from a dataset, and thereby amplify the value of decisions that can be made from it. Meanwhile, collection technologies can permit gathering new forms, volumes, and attributes of data that allow for richer analytics. We now cover each of these classes of technology in turn.

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[5] For instance, a dataset that is only 80% inaccurate may be unacceptable to many investors. Yet, to a fund running a high-frequency trading strategy, such a dataset may be deemed "high quality" if it has sufficiently low latency (i.e., it can be accessed within a very short window after it is generated).

Collection Technologies

Collection technologies – which include a broad array of devices, protocols, and platforms for gathering data – can increase the quality of obtainable ESG data by expanding both the scope of data provided (in terms of more detailed, less error-prone/biased datasets) and the scales at which it is gathered (e.g., supplying data with higher granularity and coverage, as well as frequency). Collection technologies can be further subdivided as: (1) technologies that capture data, such as remotely connected sensors; and (2) new technologies to securely convey and store data, such as blockchain-enabled tracking, encryption tools, and new types of database architectures.

The rise of capture technologies for ESG data is closely tied to the growing importance of the internet-of-things (IoT): the increasing fraction of machines and infrastructure that connect to the internet (or other networked communications systems, such as GPS) means that ever larger amounts of data can be harvested from commercial and social systems – including on how they interact with the natural environment. Much of this data bears on ESG considerations (if only indirectly in some cases), as nearly all of it relates in some way to energy or natural-resource consumption (or disposal) – e.g., delivery or production of manufactured goods, operation of farming equipment, or temperature control for buildings. Together, such capture technologies produce enormous troves of ESG-relevant data that can (and is) providing investors with a fuller picture of the activities of companies, in terms of not just their direct operations but the impacts of their products and services. A chief consideration related to capture technologies concerns the ownership of the capturing device (be it a smart thermostat, drone, RFID chip, or satellite), along with who is entitled to access the data it generates: such technologies are of little value in raising the quality of ESG data if their outputs never reach investment decision-makers, or else there is the potential for those outputs to be corrupted or manipulated along their way to reaching them.

It is for this reason that secure transmission and storage technologies have a significant part in elevating the quality of ESG data. For instance, immutable, publicly auditable digital ledgers (of which blockchain is one type) can help enforce the integrity of data by automatically logging it and providing immediate indication when it has been tampered. Some ESG-relevant data, however, may be considered by companies to be too sensitive to be publicly distributable (e.g., it might be linked to competitive knowledge). In such situations, advanced encryption technologies (e.g., with homomorphic algorithms) can help keep such data safe, but still allow trustworthy parties – like regulators, watchdogs, or private investors – to access and analyze it.

But security is not the only concern when it comes to transferring and storing data; scale is also a major worry. The vast volumes of data produced by capture technology must be retained (at least temporarily) if they are to be analyzed. Luckily, a plethora of new storage architectures has arisen (and is rapidly evolving) to solve this problem. Such solutions include cloud storage, specialized infrastructure for hosting unstructured datasets (e.g., "data lakes" which can be used for large collections of text, images, and practically any other data type), and many more.

Analytic Technologies

Simply collecting more or different data, however, does not necessarily translate immediately to enhancement of ESG data quality. In most cases, there is an additional need to suitably analyze that data for either its quality to be ascertained, or for higher-value decisions to be derived from it (or both). Advanced analytic technologies – primarily in the form of more accessible and/or sophisticated inference algorithms, such as machine learning – are becoming instrumental to that end. These technologies are better equipped to handle the nuanced structure (or absence of it) and content of datasets produced by advanced collection technology. For instance, conventional statistical software would mostly fail in attempting to process large collections of satellite images that showed the activity of tanker ships or machinery at pit mines. But this task is largely trivial for certain advanced inference tools (specifically a type of machine-learning algorithm called a convolutional neural network).

But new analytic tools are useful for more than just processing data; in some situations, they can also *synthesize* it. For example, even with cutting-edge collection technologies, some forms of ESG data are not readily obtainable. In some of these cases, analytic technologies, such as deep-learning algorithms, can help in identifying more appropriate proxy variables that can substitute for direct measurements (or even more accurately interpolate missing or corrupted values). Corporations the world over are widely adopting advanced analytics to transform their businesses. It is entirely feasible, however, for investors to use those same analytics to steer that transformation toward sounder ESG practices.

Calibrating Optimism

Still, enthusiasm for new technology's potential to remedy problems related to ESG data must be appropriately calibrated. "Data science" has recently been touted across the corporate world as a cure-all for many of the inherent ambiguities of business (see, e.g., Monk et al., 2019, and references therein). Undoubtedly, decision-making that is rooted in better data and analytics can greatly benefit a business – such as more individualized understanding of customer sentiment, sharper forecasts, and improved visibility into internal operations. But many nascent data-science efforts in the corporate world fall short of the steep expectations placed on them because businesses are unwilling or unable to act on the insights that these efforts deliver. Institutional, behavioral, and cultural frictions have all be identified as contributors to this blunted responsiveness. Notably, misunderstanding and distrust of the newer methods for gathering and analyzing data have been cited as major impediments to businesses taking fuller advantage of the capabilities of data science.

These experiences offer a cautionary lesson in the domain of ESG data. Technology may be able to bridge many gaps in data availability and quality, as well as offer powerful tools for cutting through some of the complexity of ESG data. Yet, it is no panacea. Improvements to data technology must be attended by other systemic changes – notably: regulatory requirements for corporate reporting and disclosure; the language used in communicating ESG data (which, at present, is itself considerably complex and inconsistent); and the mechanisms by which investors can signal to and interact with corporate leadership (beyond just buy-sell decisions). Furthermore, sharper characterization is needed for the connections between attributes of ESG data and the variables that underpin investors' decision-making at the portfolio level. It is to this characterization that we next turn.

4 Characterization System

4.1 Properties of ESG Data

Many distinct (and not necessarily compatible) schemas for characterizing ESG data are plausible in a universal sense – that is, if one is considering domains beyond the realm of investing. But such universal characterizations may not be viable for the global community of investors: they generally require clarity on the specific ways that ESG data brings value to their investment decisions. But, as stated earlier, the variables that different investors prioritize in decision-making vary with their individual situations – including their strategies, resources, timelines, and clientele. Any fit-for-purpose characterization schema for classifying and judging the quality of an ESG dataset must therefore map identifiable data properties onto drivers of value in investment decision-making.

This situation is practically identical to that for alternative data (that is, data that is "non-standard" in investment decision-making). Diversity of investors' needs and processes in decision-making means that any candidate system for characterizing alternative data must be sensitive to investors' use cases if it is to be applicable for them. Monk et al. (2019) study existing characterization systems for alternative data and find that none fulfill that requirement. Consequently, they devise a six-part schema that reflects investors' heterogeneous uses for alternative data (as a function of their diverse contexts). The strongly analogous situations of alternative data and ESG data make that schema relevant for characterizing the properties of ESG data in terms of how these contribute value to investors' decision-making. We briefly review the six dimensions of that schema below (and refer readers to Monk et al. (2019) for more extensive discussion), and then link these dimensions to dominant variables that are used by investors in their decision-making.

Monk et al. (2019) propose characterizing alternative data along six dimensions: reliability, granularity, freshness, comprehensiveness, actionability, and scarcity. They observe that any given dataset (whether alternative or otherwise) is unlikely to score highly on all these dimensions. The more likely case is that – beyond some threshold – improvements along one dimension will demand some sacrifices along other dimensions. That said, there are also instances in which dimensions can be complementary, whereby an improvement along one translates to bettering others. A succinct description of each of these dimensions and its relevance to investment decision-making appears below.

- *Reliability* concerns the accuracy, precision, and verifiability of data. Practically, a dataset being reliable means it is "error-free, unbiased, and checkable". Reliability essentially captures the need for data to be trustworthy for supporting confident decision-making by investors.

- *Granularity* pertains to the coverage or "scale" of individual elements of a dataset – for example, does the dataset provide figures at the company or industry level? Granularity reflects the degree to which investors can make focused (versus generic) decisions based on a dataset.
- *Freshness* involves the age of a dataset relative to the relevance of phenomena that it reflects. Freshness is not simply equivalent to how old a dataset is: a dataset may have been produced many years ago and still be "fresh" if it pertains to events of relevance. E.g., decades-old records on environmental litigation may be understood as fresh if they relate to the most recent court proceedings against a company for its pollution activities; whereas data on the dividends paid by that company at the same time may no longer be relevant to decisions, and therefore not fresh.[6]
- *Comprehensiveness* entails how "complete" a dataset is, in terms of how exhaustively it covers a domain of interest. For example, a dataset that covers the emissions of companies in only one or two states is less comprehensive than a dataset that does so for

[6] "Freshness" subsumes a variety of temporal concepts. Perhaps the idea closest to freshness is *latency*: the lag between the occurrence of an event and the time-point of availability for data on that event. Data that is low-latency is thus inherently fresh. Somewhat confusingly, the notion of "high-frequency" data is often treated synonymously with low-latency data in finance. The frequency or regularity with which specific data-points become available to investors is surely important in some cases. Yet it is unclear that the regularity with which data is generated should be *a priori* more important than the speed with which generated data becomes available for use, regardless of its periodicity. Freshness, therefore, seems a more universally applicable parent concept.

all fifty states in the United States. Comprehensiveness matters for investment decision-making because it facilitates a more global perspective.

- *Actionability* involves the extent to which material actions can be taken as a direct consequence of possessing and analyzing the dataset in question. From an investor's standpoint, a dataset that cannot be translated into activity (e.g., buying, selling, or communication with corporate leaders) is of lower value and quality than one that can.
- *Scarcity* relates to availability of a dataset. From an investor's standpoint, possessing data that others do not can confer competitive advantages. The value of scarce data to investors therefore creates some potential tension with widespread sentiment that ESG data should be widely and freely available.

Collectively, these six dimensions comprise a theory-grounded starting point for determining how an ESG dataset's properties contribute to its value proposition for investment decision-making. The exact weights placed on each of these dimensions are, however, case-specific, and strongly driven by what variables a given investor emphasizes in the decisions it makes based on the ESG dataset in question.

4.2 Investment Decision-making Variables

The world of long-term investors has innumerable use cases for data that reflect the above characteristics. By and large, we can think about investors wanting more insight into the dynamic behavior of: (1) assets they hold in order to gain exposure to certain risk factors that drive returns; (2) the products they buy to facilitate access to these assets and risk factors; (3) the portfolios of diversified assets and products they hold to achieve some total-fund return objective; and (4) the metrics associated with assets, products and portfolios that can offer a long-term investor insight as to whether they are moving in the right direction. Investor activities that stem from these four layers of investment activity tend to consistently hinge on several high-level decision variables–namely:

- *Risk*: investment returns have no meaning if they are not communicated in the context of investment risks. Traditionally, volatility has been the measurement of risk in financial markets, and, at least for long-term investors, skew and kurtosis often also matter. But these can be hard to capture in small datasets of returns when there may be non-stationarity, which means that exploring other dimensions of risk (not just in price/volume info) can be a backdoor to characterizing an asset, product or portfolio's true riskiness.
- *Outperformance*: investors are looking to beat markets and generate "alpha". Today, most investors turn to high cost managers to help them in this regard. As alternative and ESG data become more pervasive, the data sources will become increasingly bespoke and tailored to a given investor. This data will help to unearth relevant risk factors to a certain investor; that they may be better equipped to manage effectively. This data will be mined from internal and private sources and provide the investor about their portfolios and the world that are, quite literally, unavailable to the rest of the world. In this way, alpha will be achieved on the back of new data, new information, new products and new strategies that are far more aligned with long-term investors than, say, a hedge fund is today.
- *Cost*: many people would say that net risk-adjusted returns are all that matter in the investment business. But the cost of producing investment performance – especially outperformance – is required to judge whether the return per unit of risk is being acquired efficiently. More to the point, detailed cost metrics can help a long-term investor just

whether they should pursue an innovation designed towards accessing an asset in a more effective manner; such as through internal teams or seeding new managers or products.

- *Construction*: there are many ways for an investor to combine their organizational inputs (people, process and information) with available assets and products to form a portfolio. Pension plans in Canada create portfolios that are profoundly different from American endowments, but they all seek to maximize risk adjusted return in a professional manner. As the information in inputs change, so too will the portfolios and the manner in which they constructed. ESG data will offer new sources of information, which, in turn, will lead to new product options for a growing number of investible assets.
- *Commitment*: for many asset owner investors, such as pension funds or sovereign funds, “time” can be a key comparative advantage in global financial markets. Put simply, a long-term investor can invest in assets that short-term investors cannot, and they can invest in all the assets available to short-term investors. By simple financial logic, this implies that long-term investors have a risk-return advantage over short-term investors. In order to help investors be long term – and partner with long-term managers and service providers – ESG and alternative data will be crucial to find those partners that are truly long term.
- *Influence*: some investors are willing and able to add value to portfolios investments through a variety of approaches, such in governance roles or through shareholder activism. These investors will be seeking tools through which to decide how to add value, and innovative data sources will provide new touch points for engagement with companies and teams.

These six decision variables all represent “intermediate objectives” for investors and their portfolios. That is, while the ultimate goal for investors is to create high risk-adjusted net returns, the decisions investors take to reach that goal are ultimately framed in terms of these six variables. Put differently, an investor's ultimate performance can largely be deconstructed into contributions by these six variables. By extension, these variables provide a convenient (and insightful) bridge between the six key properties that contribute to the quality of an ESG dataset (reliability, granularity, freshness, comprehensiveness, actionability, and scarcity) and the eventual performance that an investor can deliver when it makes decisions based on such data. Thus, by connecting the key properties of ESG datasets with the decision variables behind investors' performance, we derive a user-centric approach to establishing the value and quality of an ESG dataset. From a practical standpoint, this derivation can be captured through a simple matrix, as we next show.

4.3 Investment Decision-to-Data Matrix

As mentioned, the weights that a given investor will – or, more normatively, should – place on the various properties that contribute to ESG data quality (i.e., reliability, granularity, freshness, comprehensiveness, actionability, and scarcity) are partly a function of the priority an investor assigns to the decision variables listed above. Additionally, these weights will steer not only what ESG datasets an investor pursues (and their quality), but also its performance overall. To this end, it is essential to realize that each of the six properties that contribute to ESG data quality has a distinct level of relevance to the six key investment decision variables (i.e., risk, performance, cost, construction, commitment, and influence): each property does not matter equally to each variable. Without doubt, the extent to which a given property matters for a given decision variable depends on the investor in question and the input available in their production of investment returns. Still, there is enough consistency across investors to provide some relative indication of how important each property is to each variable–at least from the standpoint of a "typical" investor (not that such an entity actually exists!). We illustrate these correlations in the "investment data-to-decision matrix" in Figure 1. For every row in the matrix, a column that contains text signifies that the associated property of ESG data is likely to be of primary importance.

[insert Figure 1 here]

Risk and outperformance (row [a] and [b] in Figure 1) are two main drivers that provide immediately realizable investment returns by generating beta and alpha respectively. Beta via effective risk management refers to investments that generate competitive investment returns by managing traditional risks (or manage market volatility relative to idiosyncratic factors). Risk management is most suitably performed with a "wide" (i.e., global) and "frequent" data perspectives. First, understanding the magnitudes of values more comprehensively than its peer group can help an investor to contextualize and make the most of every unit of risk. A more comprehensive dataset can provide more substantial fodder for analysis and can yield more nuanced insights. In many cases, responsibly handling investment risk involves detecting and navigating such subtleties. Second, investors need to access ESG data at the level of frequency that they make investment decisions. For instance, equity investors rebalance their portfolios every month or even more often in daily basis. For investment practice, therefore, outdated data inhibits proper measurement of risk. The continuing evolution of ESG hazards makes freshness of an ESG dataset crucial for planning for and managing ESG-related risks.

Outperformance, or alpha, refers to investments generating excess returns relative to the returns of a market index or benchmark, which are considered to represent the market's movement. For this type of investment, it is critical to access "scarce" and "granular" data. First, delivering superior performance generally relies on building and leveraging competitive advantages that others cannot access. Therefore, having scarce and unique ESG data that is possessed by few (or no) others can therefore confer useful advantages that lead to better performance. Second, outperformance typically comes from concentrating risk and capital, rather than spreading it (e.g., via portfolio diversification). To responsibly concentrate a portfolio into specific assets, however, an investor should have access to detailed, fine-grained data.

Some investors have concerns over whether ESG or alternative data and its integration is worth the cost (see row [c] in Figure 1). Based on our experience, these forms of innovative data can offer incredible insights as to whether the alpha being paid for is worth the cost being paid. In this category, effective cost control means understanding all of the details of a transaction, investment or fund, which implies that the granularity is critical. Additionally, the comprehensive accumulation of portfolio analytics offers greater insights into the competitiveness of the cost of the investment strategy. More data on fees offers more opportunity for best pricing and negotiation. Lastly, the freshness of the data offers additional utility for investors, as costs can and should change over time, especially as expected returns for certain products erode over time. In this regard, granularity, freshness and comprehensiveness of the innovative data should be secured for the cost-conscious investors.

Today, a growing number of asset owners and managers cite the pursuit of long-term performance as their primary objectives for ESG integration (Eccles et al., 2017). When investors endeavour to enter into long-term positions in an asset, innovative data sources can offer investors useful context for making stronger commitments to long-term strategies (see row [d] in Figure 1). Indeed, the ESG data can offer new understanding of the underlying assets as well as the products being used to access. In this commitment lens, the data has to be above all reliable. In order to make long-term–and sometimes irreversible–commitments investors must have confidence that their data can be counted upon. Next, the data should be granular in nature, offering the investor detailed appreciation of the risks being assessed. And the data should be actionable, lest the investor may not actually make a commitment. In short, investors can more successfully and confidently "commit" to assets for which their understanding is deepest, and ESG and alternative data can truly help in this regard.

Many investors seek to influence the behaviour – and thus performance – of portfolio companies and assets via governance rights or shareholder activities. In order to empower investors to make the best use of these attempts to influence companies, ESG data can be particularly useful (see row [e] in Figure 1). In order to have influence over underlying portfolio assets, the investors must make a strong case for action on the part of others. This implies that the data used should be reliable, granular, fresh, comprehensive and actionable. The only factor that does not really much matter in this case is the scarcity of the data. In fact, the more widespread the data, the more likely an investor will be able to influence the behaviour of a company. The only factor that does not really much matter in this case is the scarcity of the data. In fact, the more widespread the data, the more likely an investor will be able to influence the behaviour of a company.

As noted earlier, investors are all endowed with different resources through which to make investments. They generally have different governance structures, cultures, and technologies, and they thus utilize different processes, people, and information to make investments. The way in which these factors of production come together is termed in this paper as “construction.” This refers to the actual process of recruiting different inputs to build portfolios. In order to do this effectively, an investor must assess in which category of ESG data they have an advantage and then use that advantage to guide and influence the construction of the portfolio. As this implies, construction does not require any single data characteristic. Rather, construction utilizes the data characteristics in order to decide on how the portfolio will be built; leveraging comparative advantages in the data in order to seek investment returns. If a fund has zero comparative advantages, then the construction will be passive and simple. If the fund has rich advantages, then it can pursue more active and bespoke strategies. The character of the data will profoundly change the construction of the portfolio.

5 Conclusion

The explosive growth of ESG data and data analytics has created choice overload. Today’s ESG data can no longer be defined by discrete dimensions, sources, or types. More specifically, traditional approaches to evaluate ESG data quality are often limited to its structure; fixated only on sources (e.g., strategic processes, operational processes, etc.); oriented exclusively toward one specific investment purpose (e.g., alpha generation, impact generation); and defined as taxonomy rather than grades of fitness. With technological advancement, however, alternative ESG data is becoming continuous and going beyond its previous boundaries. However, current practice is not optimizing ESG data quality and leveraging advanced data technologies available today.

Alternatively, we propose a “user-oriented” approach to evaluate the data. In this framework, we characterize ESG data in terms of its width and depth. Further, it is the users who decide the width and depth of ESG data and evaluate the data quality. Thus, we identify six dimensions of ESG data quality, which have been extended due to the advancement in data analytics (i.e., reliability, granularity, freshness, comprehensiveness, actionability, and scarcity), and six dominant variables that are used by investors in their decision-making (i.e., risk, performance, cost, construction, commitment, and influence). We then create the "investment decision-to-data matrix" and discuss that each of the six properties of ESG data quality has a distinct level of relevance to the six key investment decision variables.

While we in this paper focus on a few critical aspects of ESG data quality in delivering different investment objectives, we acknowledge that it is also important to understand the interconnectedness of all six data properties and that biased toward a certain character of ESG data can reduce the value of ESG integration. For instance, if an investor seeking to generate alpha collects and communicates with fresh but not scarce ESG data for its investment decisions, the value of ESG integration compare to the cost would drop. Speed-based alpha generation, which refers to the investment generates such excessive returns relying on the speed of the algorithmic trading but not on value-added, can be one example of sub-optimal use of data.

The unique contribution of this study is that it demonstrates how to understand and enhance ESG data quality by leveraging advanced data technologies available today. Today, most investors seek one generic ESG metric, which however brings an unavoidable trade-off between its validity and reliability. Alternatively, we suggest that investors should specify their investment and risk preferences and be able to source the optimal ESG data for their own objective functions. Therefore, the investment decision-to-data matrix presented in this study can provide the first conceptual framework that enables a broad range of investors effectively use new tools of data collection and analytics.

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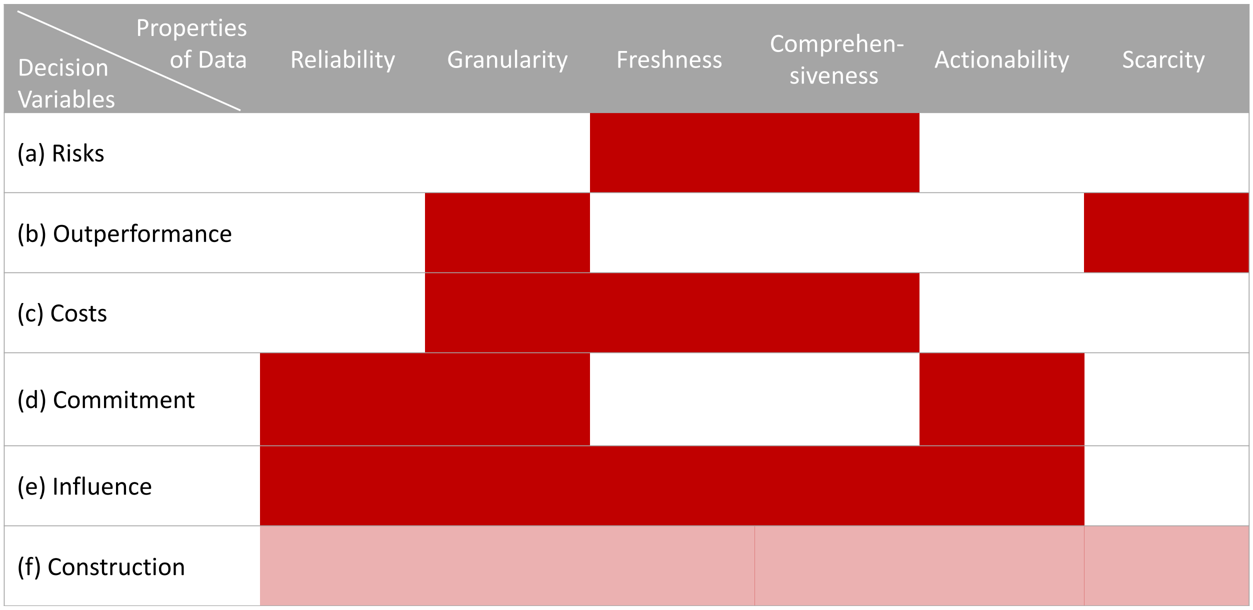
Figure 1. Investment Decision-to-Data Matrix



A cell colored solid red represents that the character of the data is particularly critical in delivering the corresponding decision variable. A cell colored light red represents that the character of the data will drive the corresponding decision variable.