# Construction of a Firm-Level Innovation Index and Assessment of its Impact on Stock Market Performance

Thesis submitted for the award of the degree

of

**DOCTOR OF PHILOSOPHY (Ph.D.)**

by

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## DECLARATION

I certify that this thesis titled 'Construction of a Firm-Level Innovation Index and Assessment of its Impact on Stock Market Performance' is my original work. The research work has not been submitted by me to any other university or institute for award of any degree or diploma. Any material previously published or written by any other author included in the text has been duly acknowledged and referenced in this thesis.

Aman Preet Singh

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# CERTIFICATE

It is certified that Mr. Aman Preet Singh, Registration Number 901813001, has completed his PhD thesis titled ‘Construction of a Firm-Level Innovation Index and Assessment of its Impact on Stock Market Performance’ under my supervision. This PhD thesis is an authentic research study carried out by him and it is being submitted to LM Thapar School of Management, Thapar Institute of Engineering and Technology, Patiala, for the award of the degree of Doctor of Philosophy (PhD). To the best of my knowledge, this research work has not been submitted to any other university or institute for the award of any degree or diploma.

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# 1. Abstract

This study measures innovation outcomes within a firm by constructing a composite index. The composite index is constructed by relying on firm level data that is official and publicly available. The constructed composite index treats innovation as a holistic process that is comprised of three inter-related stages – inputs, throughputs, and outputs. It is recognized that innovation may occur across each of these stages inside a firm. To this end, a comprehensive theoretical framework is expounded after a thorough review of existing literature. The reliance of this index on reliable and publicly available sources of information makes it suitable for a wide range of internal as well as external stakeholders who typically do not have access to the inner workings of a firm including its innovation endeavors. Such stakeholders may include academic researchers, supply chain partners, research collaborators, management of competitive firms, and industry-wide policy makers. The construction of the index followed an established six step process comprising of the following steps – phenomenon definition, indicator selection, normalization, weighting of the normalized indicators, aggregation of the normalized indicators, and validation of the composite index. By theoretically viewing innovation as an encompassing conversion process but by relying on a manageable number of eight basic indicators for index construction, this study attempts to incorporate theoretical comprehensiveness and parsimony. The theoretical framework identified for this study is applicable across industrial contexts and for goods and/or service-oriented firms. A sample of S&P 500 firms was drawn, and innovation outcome data was collected for a ten-year period so that each firm in the sample was given a composite index score at the end of its fiscal year. Findings reveal that the theoretical framework is robust to choice of aggregation method and that the innovation index depicts a positive impact on abnormal stock returns as predicted by prior research on innovation's impact. The assessment of the impact of innovation index on abnormal stock returns was conducted as part of panel data regression over the ten-year period for which innovation outcome data was collected and by controlling for ubiquitous financial variables at firm level. This index contributes to the existing body of literature on firm level innovation measurement by measuring innovation outcomes as a holistic construct and by relying solely on public and official sources of information making it suitable for a range of stakeholders, internal and external.

## 2. Introduction

Man's mind is his basic means of survival. Man does not come into being armed with fangs, claws, extraordinary agility, or a keen sense of smell. Everything that man requires in order to survive first has to be discovered. Reason is that mental faculty of man that identifies and integrates the material provided by his senses into concepts (Rand, 1964). Reason is man's most fundamental tool of knowledge – it is only by an exercise of reason that men and women accurately and adequately perceive the world around them and act accordingly. Because man's ability to acquire knowledge of the universe is limitless – either through new discoveries or by learning of his past – man's ability to apply that knowledge to suit his purposes and to further his life is also limitless. If man is to further his lifespan and not perish, his only appropriate course of action is new discoveries of knowledge and the appropriate application of those discoveries to the development of newer and improved tools of production and products that fulfill his needs.

In modern industrial society, men and women have undertaken the task of mass-scale production by organizing their effort into commercial firms. These firms are dedicated to the production and sale of specialized goods and services. If man must continually improve his tools of production and the products thereof, a fundamental dictum for commercial firms ought to be that they must innovate to grow and prosper.

### 2.1. Importance of Innovation for Business

Innovation is ubiquitous in business with firms regularly including this term in their vision, mission, and objective statements (Kahn, 2018). Firms routinely hire chief innovation officers and recognize that innovation is a prerequisite for longevity (Kahn, 2018). Innovation has been linked to improved productivity and business growth (Alhstrom, 2010). A considerable body of literature has shown innovation activity to influence business survival (Cefis and Marsili, 2005; Esteve-Pérez et al., 2004; Ericson and Pakes, 1995).

Both technical and non-technical innovations have been deemed important to achieving superior firm performance that can include measures of sales, growth, profitability, and stock market performance (Ngo & O'Cass, 2013). Innovative firms are said to attract superior talent and fulfil customer requirements (Tredgold, 2018). An innovation strategy is deemed mandatory for firms in order to implement sound business decisions involving trade-offs and in choosing appropriate practices (Pisano, 2015).  Innovative firms exhibit higher profit margins, greater market share, and lesser sensitivity to cyclical downturns (Geroski, et al., 1993). Innovation has been found to significantly improve the sales performance of firms, their productivity in terms of sales per employee, and employment growth (Klomp & Van Leeuwen, 2001). Likewise, innovative service firms have been shown to outperform non-innovative firms in terms of growth rate of sales and employees, and labour productivity (Cainelli, et. al, 2004). Firms that implement effective innovation programs have depicted, on average, a 32% improvement in return on assets (ROA) and a 34% improvement in return on sales (ROS) (Zhang, et. al, 2014). Sorescu and Spanjol (2008) found breakthrough innovations to positively impact the equity value of firms.

Thus, the importance of innovation for business survival, longevity, and overall success is well-recognized and well-established.

### 2.2. Innovation Measurement

Once it is accepted that innovation is crucial for commercial enterprises, the accurate measurement of innovation at firm level becomes critical. Because innovation is a multifaceted phenomenon (Wolfe, 1994), the measurement of innovation accurately is a complex task (Frenkel et al., 2000). Further, because innovation is recognized to be both a process and an outcome (Kahn, 2018), the identification of what it is about innovation that is being measured adds to the complexity of this measurement. Ideally, a construct that recognizes both the process and outcome aspect of innovation is desirable. Another dimension to the problem of measuring innovation at firm level stems from the fact that not all stakeholders have equal access to innovation activity inside a firm. Internal stakeholders such as firm management would be privy to more information than external stakeholders such as investors or academic researchers. Thus, measurement approaches and techniques need to contextually cater to different audiences.

Typically, when the construct to be measured is multidimensional and it is desirable to assign a single score to such a construct, this multidimensional construct is transformed into a composite index. A composite index, also known as a composite indicator, is a statistical tool that combines multiple variables into a single measure. This is done to provide a more comprehensive and holistic view of a complex concept or phenomenon (such as innovation) that cannot be adequately captured by a single variable (Nardo et al., 2005).

### 2.3. Purpose of the Study

Recognizing the critical importance of innovation measurement, this study aims to construct a composite index of innovation outcomes at firm level with the following desired characteristics.

i. The composite index should recognize and consider both the process nature of innovation and measure innovation outcomes at each stage of the innovation process.
ii. The index should be an adequate and accurate measurement of innovation outcomes at firm level per existing understanding of what innovation is.
iii. The index should be suitable for both internal and external stakeholders. In practice, this implies that the index should be able to be constructed from publicly available data that is accessible to all stakeholders of the firm.

There are several compelling reasons to prioritize innovative outcomes over other facets of innovation when it comes to constructing an index of innovation that is suitable for both external and internal stakeholders. First, innovation outcomes, in contrast to innovation effectiveness or quality, can provide a more tangible and immediate measure of a firm's innovation endeavours. This measure gives a direct insight into the firm's current innovation landscape, quantifying the tangible outputs of innovative efforts, such as the number of new products, patents, or processes developed within a given period. Robust innovation outcomes signal a firm's dedication to innovative pursuits and its capacity to consistently churn out new and enhanced goods or services. Elements of innovation outcomes, like patent counts or new product introductions, can be more readily quantified and monitored over time compared to metrics of innovation quality or effectiveness. Furthermore, many firms transparently disclose their innovation milestones in annual reports, press announcements, and patent submissions. This transparency facilitates the development of an index based on such data for external stakeholders. A composite index centred around innovation outcomes might also exhibit predictive capabilities, a hypothesis this study intends to explore. Thus, considering the varied interests of external and internal stakeholders, crafting an index focused on innovation outcomes emerges as a logical first step.

### 2.4. Research Gaps

Composite innovation indices at firm level do exist. These indices are, typically, geared towards the requirements of internal stakeholders who are privy to the innovation activities of their firms. Consequently, such indices rely almost exclusively on survey data making them unsuitable for external stakeholders, some of whom may neither have the inclination nor the opportunity to collect such forms of innovation observations that are only internally obtainable. Thus, this study aims to construct an index of innovation that relies exclusively on firm level data, which is reliable, official, and publicly accessible without special access. This is a significant research gap in the literature on innovation indices that this study seeks to fill.

Second, a significant number of existing indices of innovation at firm level are constructed for a specific industry such as the global airlines industry (Yu et al., 2022), the Italian plastic materials sector (Ponta et al., 2021), the Spanish media industry (García-Avilés et al., 2016), and Canadian manufacturing firms (Tang & Le, 2007). This study seeks to add to the limited body of literature on innovation indices by constructing an index of innovation across the ten GICS industrial sectors that all firms in the United States are classified into.

Third, to the best of the author's knowledge, only one index of innovation outcomes at firm level was able to be identified in existing literature that was applicable across industrial sectors. Feeny & Rogers (2003) construct an index of innovation outcomes for publicly listed corporations in Australia. This study seeks to add to this scant literature by constructing an index of innovation outcomes for publicly listed corporations in the United States.

Finally, during the course of a review of innovation indices at firm level, it was discovered that no index was constructed that viewed innovation as a holistic construct with input, throughput, and output measures. It was, further, discovered that existing indices also did not consider the process nature of innovation and measured innovation outcomes at each relevant stage of this process. Thus, this study seeks to fill this research gap by constructing an index of innovation outcomes at firm level that views innovation as a holistic process with input, throughput, and output measures.

### 2.5. Research Objectives

In light of the identified gaps in the literature on firm-level innovation measurement, this thesis delineates three primary research objectives.

Objective 1: Identification of a Theoretical Framework for Innovation

This objective entails the identification of a comprehensive theoretical framework that encapsulates the process of innovation within firms. This framework should holistically cover all aspects of innovation, from the initial inputs through the developmental throughputs to the final outputs. The aim is to establish a theoretical base that accurately mirrors the complex and systemic nature of innovation at firm level. This framework will underpin the development of the innovation index.

Objective 2: Construction of a Composite Innovation Index

The second objective focuses on the construction of a composite index of innovation outcomes at the firm level. This index will be developed in alignment with the identified theoretical framework and is intended to be applicable and beneficial for a broad range of stakeholders, both internal and external to the firm. The construction process will involve the careful selection and integration of relevant indicators that are representative of innovation processes including output measures of innovation. The index will utilize publicly available, official, and reliable data sources to enhance its accessibility and relevance for a diverse set of stakeholders.

Objective 3: Evaluation of the Index's Impact on Stock Market Performance

The third objective is to empirically assess the impact of the innovation index on the stock market performance of firms. This evaluation seeks to externally validate the index and to substantiate the index's utility in reflecting market valuation and investor confidence associated with a firm's innovation activities. By examining the relationship between index scores and stock market metrics, the study aims to illuminate the practical significance of innovation measurement in guiding investment decisions and informing strategic business management.

Collectively, these objectives aim to enrich both the theoretical discourse and empirical application of innovation measurement at firm level.

### 2.6. Research Contributions

This study makes several significant contributions to the field of innovation measurement and analysis. These contributions are delineated as follows.

<u>Advancement of a Comprehensive Theoretical Framework</u>

This research advances a comprehensive theoretical framework for understanding innovation as an integrated process encompassing inputs, throughputs, and outputs with appropriate operationalization. This approach enriches the conceptualization of innovation within firms, bridging a gap in the literature where innovation has traditionally been viewed in isolated segments.

<u>Creation of a Composite Innovation Outcome Index</u>

A pivotal contribution of this research is the creation of a composite innovation index applicable to a broad spectrum of stakeholders. This index, grounded in publicly available firm-level data, transcends the limitations of industry-specific or survey-based indices. It provides a universally applicable, practical tool for evaluating firm-level innovation outputs, thereby responding to a noted deficiency in current research on innovation index construction.

<u>Impact of Innovation Index upon Stock Market Performance</u>

Significantly, this study correlates the developed innovation index with stock market performance, offering empirical evidence of the economic ramifications of firm-level innovation. This aspect of the research not only validates the practical utility of the innovation index but also establishes a connection between theoretical innovation models and observable financial outcomes.

Cross-Industrial Sector Applicability

By focusing on the development of an innovation index applicable across various industrial sectors, this research broadens the applicability and relevance of innovation measurement. This cross-sectoral approach fills a critical gap in existing literature, which often limits innovation indices to specific industries.

Emphasizing Innovation as Both Process and Outcome

This study also contributes to the field by emphasizing innovation as both a process and an outcome. This dual perspective offers a more nuanced view of innovation activities within firms, aligning the innovation index with the multifaceted nature of innovation processes.

In conclusion, this study contributes to the field of innovation measurement at the firm level. It addresses previously identified research gaps, introduces an accessible innovation measurement tool, and establishes a link between innovation activities and financial performance. These contributions provide insights and practical tools for academics, business practitioners, and policy makers engaged in the innovation domain.

## 2.7. Organization of this Study

The remainder of this thesis is organized as follows.

A review of literature identifies issues pertaining to measurement of innovation at firm level and reviews existing models of innovation to identify an appropriate theoretical framework for this study. Existing indices of innovation at firm level are reviewed to identify the gaps in index construction literature that this study fills. Further, existing literature that investigates the impact of facets of innovation on firm market value is reviewed to understand the impact that the innovation index ought to have on stock returns.

In the research methodology section, the five-step method of index construction is discussed. A description of the sample and data collection procedures are outlined. Instances of observations pertaining to organizational, marketing, product, and process innovations from the sample are depicted. The use of panel data regression methodology to assess the impact of the innovation index on stock market returns is discussed.

In the findings section, index scores for the sample of firms and their rankings are presented. A three-step validation of the composite index is undertaken, and results are shown. A recommendation on the choice of normalization and aggregation methods for index construction is made.

Implications of the study, applications of the innovation index for a broad range of stakeholders, and limitations of the index are presented in the discussion section. This study concludes with some directions for future research.

## 3. Review of Literature

In this section, we review existing literature pertaining to the following aspects. First, a review of issues surrounding measurement of innovation at firm level is presented. Second, to identify an appropriate theoretical framework for innovation outcomes, a review of existing models of innovation is undertaken and based on the gaps in literature, an appropriate theoretical framework is identified. Third, in order to operationalize the identified theoretical framework, an appropriate design template is identified in existing literature which is then applied to the framework. Fourth, a review of existing indices of innovation at firm level is conducted to explain how this study fills a significant research gap and how it contributes to the existing body of literature on innovation indices. Finally, because one way this study validates the composite index is by assessing its impact on abnormal stock returns, we review existing literature on the impact of innovation outcomes on stock market returns.

### 3.1. Measuring Innovation at Firm Level

Innovation is a complex and multidimensional construct that has been the subject of scrutiny from scholars with diverse backgrounds and philosophic positions (Wolfe, 1994). The measurement of innovation within firms is an equally significant and complex issue (Frenkel et al., 2000) challenging academic researchers and firm managers alike (Adams et al., 2006; Dewangan & Godse, 2014). Innovation measurement is inherently complex because the innovation process, by its very nature, cuts across departments and encompasses the whole firm (Björk et al., 2023). Yet, the accurate measurement of innovation is crucial if firms want to implement their innovation endeavours successfully. Björk et al. (2023) identify three reasons in prior research as to why measuring innovation is at the center of making innovation happen. First, when firms can measure innovation accurately, they are able to articulate their innovation strategy effectively to employees and initiate appropriate discussions about how to implement strategy. Second, firms have limited resources which makes it critical to be able to measure innovation to pinpoint problems and rectify them as they occur. Third, when innovation activities are measured, new learning insights are gleaned, and fresh commercial opportunities identified. In addition, prior research has also recognized that innovation is principally measured at firm level to enhance managerial decision making, to undertake suitable audits, and to assure of sound governance (Birchall et al., 2004; Birchall & Tovstiga, 2005).

Studies proposing aspects of innovation measures are frequent – however, their treatment of this subject has historically been fragmented (Adams et al., 2006). Typically, this has resulted in firms measuring innovation in terms of either its inputs or outputs whilst ignoring process or throughput measures (Cordero, 1990). Milbergs and Vonortas (2004) echo a similar sentiment when they assert that current innovation indicators are largely an artifact of the industrial era reflecting goods rather than intellectual endeavours and processes more appropriate for a knowledge-based economy. Thus, early on, in academic literature a need has been recognized for a generalized and holistic framework of measurement for innovation processes that would enable firm management to evaluate and correct these when required (Cebon & Newton, 1999).

On the input side of innovation, there has been a greater focus on measuring financial aspects and less emphasis on knowledge inputs and organizational aspects. (Adams et al., 2006). At the output or commercialization stage, Adams et al. (2006) recognize the predominance of product launch measures but a lack of measures that focus on other aspects such as marketing capabilities and organizational initiatives including customer reach and market planning. Overall, in their synthesis of literature, Adams et al. (2006) conclude that in the practice of organizational management, innovation measurement appears to be infrequent and ad-hoc with its reliance on outdated, underspecified models of innovation measurement. Some possible reasons they cite for this situation include academic research inconsistency, complexity of measures, and inadequate synthesis into a meaningful construct. They recognize that while product innovation has received importance as a measured construct in innovation studies, process and organizational innovations have not been adequately measured. They also contend a lack of innovation measures pertaining to service-oriented firms. In similar vein, Birchall et al. (2011) contend that there is a lack of reliable frameworks representing the innovation process. Moreover, even when an appropriate normative framework of innovation has been identified in prior research, studies that address the implementation of innovation measurement are scarce (Björk et al., 2023).

Birchall et al. (2004) suggest that sets of metrics for innovation be parsimonious and that they be simple, clear, and accessible to all stakeholders including external. Björk et al. (2023) also caution firms against an excessive number of metrics that strains both limited resources and attentions spans. Their optimal recommended number is five to seven basic indicators pertaining to the innovation process. In line with previously identified measurement inadequacies, Björk et al. (2023) also stress upon a holistic measure of the innovation process and not one that focuses only on input or output metrics alone.

Dewangan & Godse (2014) envisage that a uniform innovation performance measurement framework would lead to adoption of pertinent industry standards and competitive benchmarking among firms. To adopt such a uniform and effective innovation performance measurement framework, they recommend that innovation be measured across its lifecycle, i.e., it be process oriented, that such a framework cater to the goals of both internal and external stakeholders, and that it be easy to adopt and use.

Thus, before an appropriate theoretical framework can be identified for this study and operationalised suitably, prior research points to certain desirable characteristics that such a framework ought to possess. First, innovation is a multidimensional construct that spans the entirety of the firm cutting across departments and traditional intra-firm boundaries. The implication being that any theoretical framework of innovation must recognize its multidimensional nature and all-encompassing firm scope. Second, the theoretical framework must not only be applicable to an industrial era, manufacturing firm but also be equally applicable to service-oriented firms that are part of the knowledge economy. Third, the framework must not focus solely on either inputs or outputs alone but on the entire innovation process including input, throughput, and output measures. The input stage of the innovation conversion process must incorporate knowledge and organizational metrics. Likewise, the output stage must not just focus on product introductions but also on marketing and organization aspects pertaining to this stage. Fourth, the operationalization of the framework ought to be parsimonious with an ideal number of five to seven basic indicators and that the framework and its operationalization be accessible to all stakeholders – internal and external. Finally, the framework must be easy to adopt and use.

Recognizing some of these desirable characteristics, the Oslo Manual – Guidelines for Collecting and Interpreting Innovation Data (OECD/Eurostat, 2005), Third Edition updates its innovation measurement framework to recognize the existence and persistence of innovation processes in service-oriented firms and by adding two additional types of innovation – marketing and organizational. Thus, the Oslo manual evolved from technological product or process innovation to explicate a more complete framework.

### 3.2. A Review of Innovation Models and Identification of a Theoretical Framework

A model represents an aspect of reality that is required to be studied, controlled, changed, or managed (Pidd, 1997). Bagno et al. (2017) identify four categories of innovation management models in academic literature:

i. NPD (New Product Development) Linear Models
ii. Funnel Models
iii. Models focused on Organizational Strategy and Intra-Organizational Interactions
iv. Capability-centered Models

NPD Linear Models

These models are centred around new product development and are strongly oriented in their view on innovation as a process. Some of the earliest NPD linear models of innovation were stage models that viewed innovation as a linear, sequential activity (Forrest, 1991). In its most rudimentary form, the innovation process was seen as a two-stage process with the first stage involving idea generation and invention and the subsequent stage concerned with the commercialization of the prototype (Landau, 1982). Based on function, Saren (1984) then identified five kinds of models – departmental stage, activity stage, decision stage, conversion process models, and response models.

Departmental-Stage Models: These models view the innovation process as a sequence of stages, each associated with a specific department within the firm. The stages typically include idea generation, research, development, production, and marketing. However, these models are simplistic and treat innovation as a linear process that moves from one department to another, failing to capture the complex, iterative, and interactive nature of innovation

(Robertson, 1974). Moreover, these models contribute nothing in terms of a description or understanding of the innovation process itself.

Activity-Stage Models: These models offer a more accurate and generalizable description of the innovation process compared to department-stage models by breaking down the process into a series of activities that occur in a sequence. They provide more information about the tasks conducted during each stage of the innovation process and the form of the potential new product as it moves between stages. Utterback (1974) proposed a model with three stages: idea generation, problem solving or idea development, and implementation. Each stage involves specific activities. While this approach clearly outlined a sequential process it did not account for what decisions were made and when. King (1973) proposed a model with three broad activity steps: planning, development, and evaluation. This model also highlights the factors that influence specific activities and the existence of 'feedback loops' within stages. More complex models combine the activity-stage approach with a department-stage approach. These models associate various activity-stages with the departments or teams within the firm that conduct these functions. Examples of such models are provided by Granstrand and Fernlund (1978) and Twiss (1980). However, activity-stage models continue to imply a straightforward progression from stage to stage and do not indicate the alternative paths available at points in the process. Several alternatives are possible, and decisions need to be made at these points.

Decision-Stage Models: Innovation can also be seen as a series of decisions, each presenting multiple choices, according to decision-stage models. This perspective acknowledges the intricacy of managing innovation due to the multitude of options available and the often-insufficient information to base decisions on (Robertson & Fox, 1977). In this viewpoint, the innovation process is perceived as a sequence of decision points, each associated with a specific activity or department. For instance, decisions related to marketing, R&D, production, and finance are grouped accordingly. However, the sequence of these decisions is not explicitly indicated in this approach (Rubenstein & Ettlie, 1979). One of the models that adopt this approach is the Risk Management Modules by Cooper and More (1979). They view innovation as an evolutionary sequence of modules, each consisting of four activities: information gathering, evaluation of information, decision-making, and identification of remaining uncertainties. Two types of decisions are involved in each module: whether to continue or stop the project, and if continued, what further information is required. Another model by Cox and Styles (1979) breaks down the innovation process into seven activity phases. They emphasize that the end of a phase represents a clear decision point, and the division of activities into phases is a function of the criteria used. Thus, decision-stage models provide a practical basis for examining the innovation process by allowing the use of analytical techniques such as decision theory, probability analysis, and computer simulation. They also facilitate the examination of the innovation process in terms of inputs and outputs between phases (Cox & Styles, 1979).

Conversion Process Models: These models view innovation as a system that transforms inputs into outputs, rather than a sequence of stages. This perspective sees innovation as a more fluid and less orderly process, acknowledging the role of chance and creativity that may not be captured in stage-based models. In this approach, inputs such as raw materials, scientific knowledge, and workforce are transformed into outputs, which are new products (Twiss, 1980). The order of these inputs is not specified, and they can come from various activities, information, and departments within the firm. This approach allows for multiple inputs and does not specify their order, thus avoiding the sequential approach of other models. It represents the firm as a user of distinct types of inputs, but the order of their use is not specified (Twiss, 1980) (Figure 1). Schon (1967) presents a distinct perspective on the conversion process model, arguing that innovation is the conversion of uncertainty into risk. He suggests that as the innovation process progresses, the requirements change continuously in response to unexpected findings. Schon's model is more abstract than Twiss's but similarly adopts a 'conversion process' approach.

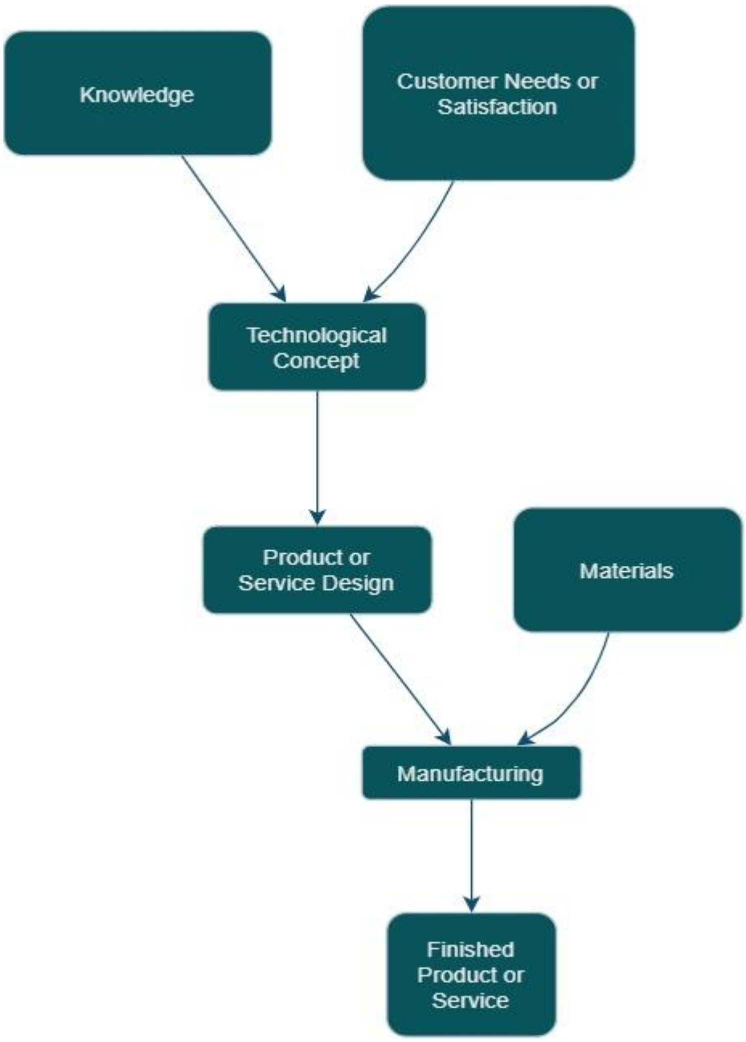


**Figure 1: Innovation Conversion Model**

Response Models: This model's approach to understanding innovation is based on the concept of change and how individuals and organizations react to it. This perspective is rooted in behavioral psychology and can be represented as a four-stage process: Perception, Search, Evaluation, and Response. In this context, an individual or organization first perceives the change, then seeks information about its implications, evaluates these implications, and finally reacts to the change (Becker & Whisler, 1967). In the context of organizational behavior, Becker and Whisler (1967) proposed a similar four-stage process for innovative behavior in firms. The stages are:

i. Stimulus: This is the initial stage where individuals within a firm are stimulated to conceive a new idea.
ii. Conception: At this stage, the idea for an innovation is conceived.
iii. Proposal: The inventor or product champion proposes a project for development.
iv. Adoption: The final stage involves the adoption or rejection of the innovation.

This model views innovation as a firm's response to an internal or external stimulus. The process involves the stages that determine the firm's response to change. However, it's important to note that this model primarily focuses on the early stages of the innovation process and doesn't delve into the development and testing work that occurs between the Proposal and Adoption stages.

Funnel Models

These models also view innovation as a process but present this process as a funnel emphasizing the selectivity of innovation ideas. While selectivity was always implicit in NPD linear models, funnel models are explicit and graphical in their description (Bagno et al., 2017). After the diffusion of open innovation ideas, Docherty (2006) sought to modify the classic funnel with inputs and outputs pertaining to open innovation (Figure 2).

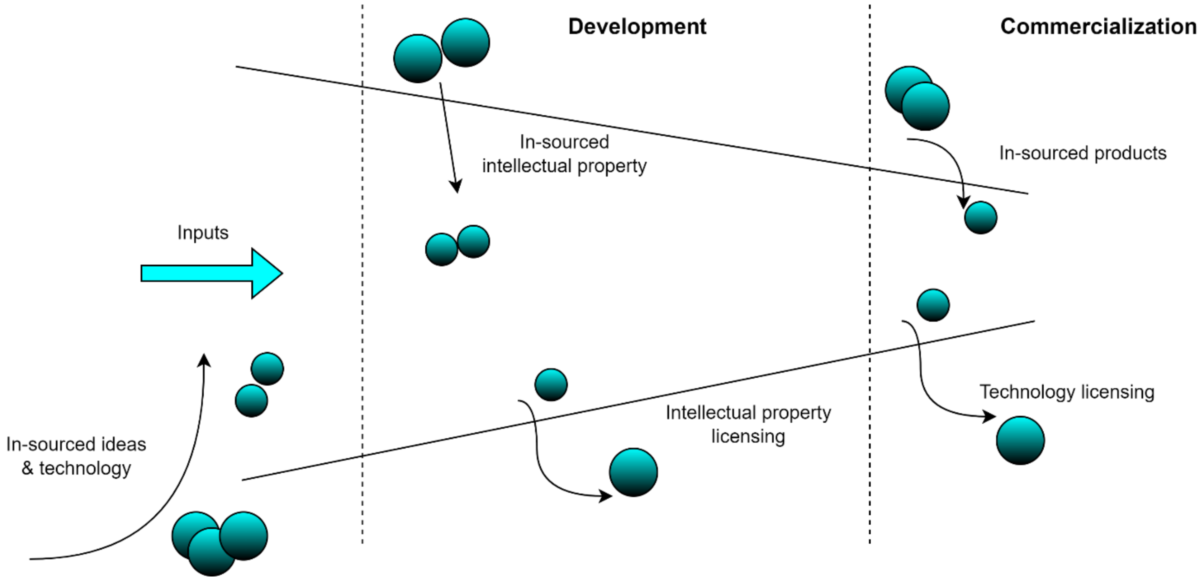


**Figure 2: Docherty's Open Innovation Funnel**

Source: Docherty (2006).

In funnel models, the essential nature of the models – a process view of innovation – as in the NPD models remains intact. However, funnel models expand upon this process by underscoring the scarcity of resources within a firm, by highlighting the progression of a few select ideas that reach the commercialization stage, and by incorporating newer notions of open innovation (Bagno et al., 2017).

<u>Models focused on Organizational Strategy and Intra-Organizational Interactions</u>

These models stress upon the function of strategy, organizational structure, and allocation of resources in aiding innovation as a process. Innovation is seen as transformative for the organization further enhancing its ability for future innovations (Bagno et al, 2017). For instance, Levy (1998) in an innovation model for hi-tech firms maps the innovation process to the specific department that is expected to carry out that function and depicts the flow of information (formal and informal) between each department. Jonash and Sommerlatte (1999) conceptualize innovation as comprising of pathways with each pathway being associated with its unique characteristics. They identify five innovation pathways that collectively depict innovation inside the firm. These pathways are the innovation process pathway comprising of ideation, development, and commercialization; the innovation organization pathway comprising of leadership, alliances, and collaboration; the innovation resources pathway comprising of human, financial, and intellectual characteristics; the innovation strategy pathway comprising of platforms, partners, and projects; and finally, the innovation learning pathway that lends the model a circular, virtuous cycle. We note that this model goes beyond the traditional innovation process comprising of ideation, development, and commercialization by identifying other pathways as equally essential to intra-firm innovation. Thus, while this model sees innovation as a process it identifies additional characteristics and traits such as leadership, partnerships, resources, and strategic elements that aid in making innovation happen.

Capability-Centered Models

These models also attempt to describe innovation beyond the offering of new products and focus, instead, on the overall organization for innovation in the firm (Bagno et al., 2017). They tend to differentiate radical from incremental innovation (i.e., the degree of innovation) by postulating distinct approaches (Bagno et al., 2017). Hansen and Birkinshaw's (2007) "innovation value chain" views innovation as a linked chain that commences with idea generation and proceeds to innovation diffusion via a conversion link (Figure 3).

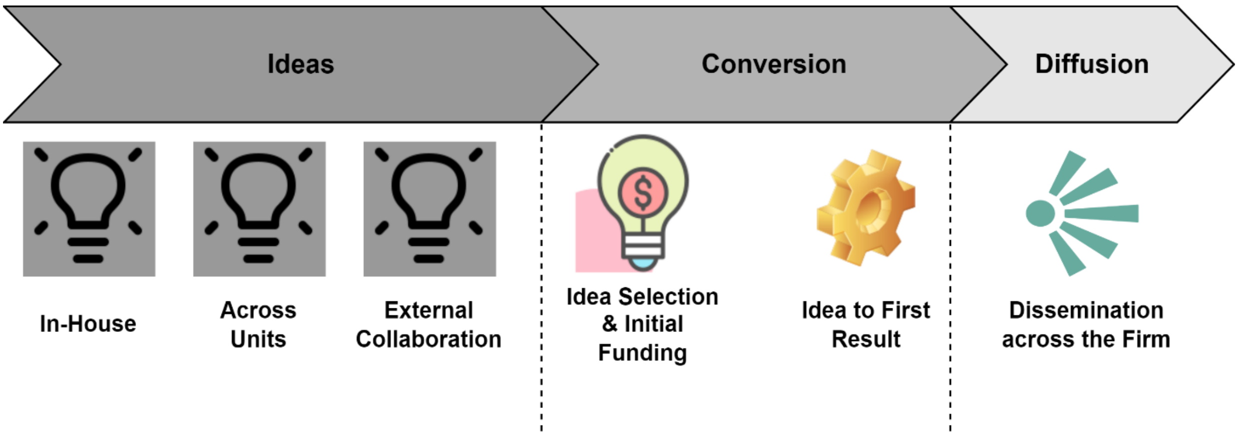


**Figure 3: Innovation Value Chain**

Source: Hansen and Birkinshaw (2007)

Meant to be a framework for evaluating innovation capability inside an organization, the innovation value chain recommends that managers address the weakest link first. Goffin and Mitchell (2010) present a model with the typical new product development (NPD) process, but they let innovation strategy lead the entire process and include human resource and organizational elements in support of the NPD process. In line with the overall idea of organisational ambidexterity, Bessant et al. (2005) considered separate innovation processes for incremental and radical innovations. Their model also included innovation strategy and other organizational characteristics in the background while including organizational learning as a compulsory final state at the end. O'Connor et al. (2008) proposed a model for radical innovation called the DNA model which divided the radical innovation process into three stages – conceptualization, experimentation, and commercialization. At the conceptualization stage, radical innovation opportunities are ideated with the aid of basic research, internal search for existing capabilities, and a hunt for external opportunities that may materialize to licensing, purchase, or investment. This then is termed the discovery phase. During the experimentation stage, the impetus is upon shielding the discovery from day-to-day exigencies to further evolve the opportunity into a credible business proposition. This incubation phase may involve learning more about the potential markets or taking the necessary steps to create a market. Finally, in the commercialization stage, the innovation takes the form of an implementable business opportunity that is accelerated towards a self-sustaining, profitable business.

A few common characteristics are observed in our review of models at this point. First, innovation is conceived as a process that explicitly (as in the NPD models) or implicitly (as in funnel or capability models) ends or nears the end with the implementation of the innovation in a commercial context. Some models (Jonash & Sommerlatte, 1999; Kamm, 1987) do view innovation as a virtuous cycle with the end outcome as a form of organizational learning or feedback loop to be applied to subsequent innovations. However, the implicit premise here is also that the innovation process ends when the new product is deployed in a commercial context and when a subsequent cycle of fresh ideation to the next new product commences. Second, this review suggests that the innovation process germinated with an idea for what the end product would accomplish. Thus, an explicit future state for an imagined product is envisaged. This idea could originate in an examination of end user (market) needs or it could originate in a novel application of an emerging technology (Twiss, 1980). Ideas can be generated in-house, across business units, or in external collaborations (Hansen & Birkinshaw, 2007; Docherty, 2006). They can also be generated as a firm's response to changes in its internal and / or external environment (Becker and Whisler, 1967).

Morad et al. (2021), in a synthesis of 100 innovation definitions examined from multiple disciplines, present a multidisciplinary, conceptual model of innovation in terms of five meta-components that they define as,

"Innovation is defining a need or a problem, generating new or changed ideas, and developing an outcome in accordance with new or changed ideas, implementing a new or improved outcome for the addressee, and adopting a new or improved outcome with added value."

In this definition, also, we observe the emphasis on new ideas that are the genesis of the innovation. These five meta-components are explained next (Morad et al., 2021).

1. "Defining a need or a problem."
   This is the first step in the innovation process that identifies the goal of innovation based on end user needs or problems. At this step, the opportunity for innovation is identified. This opportunity may present itself internally within the firm or externally within the market.
2. "Generating new or changed ideas."
   At this stage, ideas that accomplish the goal of innovation are identified and the concept is realized. The realization may take the form of a patentable invention, a prototype, a new discovery, or a new solution.
3. "Developing an outcome in accordance with new or changed ideas."
   This refers to the implementation of a new or changed idea for the end user. The implementation may take the form of a new product (good or service) that has been manufactured and is introduced into the market. It may take the form of a new process within the firm that is deployed, or it may also take the form of an organizational innovation that is appropriately deployed depending on context.
4. "Implementing a new or improved outcome for the addressee."
   At this stage, the focus is on how the end user (addressee) makes use of the innovation. This stage is concerned with the application or utilization of the innovation by the end user. In other words, we are concerned with the impact or influence of the

innovation on people for whom the innovation was meant or those that have adopted it. This impact may be gauged by the economic worth of the innovation.

5. "Adopting a new or improved outcome with added value."

   This refers to the degree of acceptance by the end user of the innovation and the ability or efficacy of the innovation to improve upon an existing situation.

Identification of a Theoretical Framework

A conceptual model or theoretical framework provides a systematic structure that can identify and organize the variables that might influence a complex concept or phenomenon of interest. A theoretical framework offers a lens through which the complex relationships between these variables can be understood and interpreted. In the context of constructing a composite index, a theoretical framework helps to ensure that the index is not merely a collection of related variables, but a meaningful representation of the underlying construct. It guides the selection of appropriate variables, the development of a robust measurement model, and the interpretation of the index scores (OECD/European Union/EC-JRC, 2008). It can facilitate the communication of the composite index to various stakeholders and explain what the index represents, why it is important, and how it should be interpreted. This can enhance the transparency and acceptability of the index and promote its use in decision-making.

Our review of models suggested, explicitly or implicitly, that innovation is a process from idea generation to end product commercialization. This makes intuitive sense. If the essence of innovation is 'newness' (Johannessen et al., 2001) and innovation results in an improvement over the existing order, then it stands to reason that innovation germinates with the conception of an original idea – an idealized future state – which when implemented results in the improvement. In the context of commercial firms, the only way they can fulfill their commercial mandate to generate a profit (Friedman, 2007) is by offering products that meet end user needs and which the consumer consents to purchase. Intermediate forms of innovation – process, marketing, and organizational – function to support the final sale of products to the end user. These intermediate forms of innovation assist the firm in improving efficiencies, in increasing sales and market share, and in improving the organization of people at work all with the end goal of a continued sale of products (goods and/or services).

Therefore, our first expectation is that the theoretical framework ought to view innovation as a process which commences with the conception of an idea and leads to the point a product has been introduced in the market.

Next, our review of innovation measurement suggested that an appropriate theoretical framework must view innovation as a process which should incorporate input, throughput, and output measures. The Morad et al. (2021) synthesis also explicitly recognizes the existence of an input stage (“generating new or changed ideas”) and the existence of throughput and output stages (“developing an outcome in accordance with new or changed ideas”). In our review of innovation models, Twiss’s (1980) conversion process model explicitly identifies a throughput stage which ‘converts’ or ‘transforms’ inputs into outputs as do other NPD linear models including departmental-stage and activity-stage models. Docherty’s open innovation funnel (Docherty, 2006) and Jonash & Sommerlatte’s (1999) innovation pathway model also recognize the input, throughput, and output stages inherent in innovation processes as did Goffin and Mitchell’s (2010) capability-centered model.

Further, when we reviewed the literature on innovation measurement, it was observed that innovation is multidimensional that spans the entirety of the firm cutting across intra-firm, departmental boundaries. It was recognized that any framework for innovation measurement should incorporate organizational and knowledge variables at the input stage and that technological product and process innovation measurements ought to be supplemented by organizational and marketing innovation measurements (OECD/Eurostat, 2005). The emphasis on organizational innovation was also witnessed in Docherty’s open innovation funnel (Docherty, 2006) with its emphasis on open innovation inputs and outputs, in Jonash and Sommerlatte’s (1999) innovation pathway model with its introduction of the innovation organization and innovation resource pathways, and in capability-centered models such as Goffin and Mitchell’s (2010) model which introduced organizational elements in support of the NPD process. Therefore, our additional expectation is that the theoretical framework incorporates additional forms of innovations such as organizational and marketing in addition to the typical technological product and process innovations.

At this juncture, it is pertinent to introduce definitions for product, process, organizational, and process innovations that are desirable for inclusion in our framework. We turn our attention to the Organization for Economic Cooperation and Development (OECD) which is an international organization comprising of 38 member nations across the globe and focused upon developing evidence-based international standards. The OECD has published four editions of guidelines for collecting, reporting, and using data on innovation. Popularly known as the Oslo manual, the first edition was introduced in 1992 and the most recent version was published in 2018. We refer to the third edition of the Oslo manual published in 2005 for identifying appropriate definitions (OECD/Eurostat, 2005).

1. Product (Goods or Services) Innovation: This type of innovation pertains to the development of a novel product or a substantial enhancement of an existing product's characteristics or intended uses. This includes significant improvements in technical specifications, components and materials, software, user-friendliness, or other functional characteristics. Product innovations can be tangible goods or intangible services and can be derived from new technological developments or the innovative application of existing technology. The objective of such innovations is to better cater to customer needs, penetrate new markets, or gain a competitive advantage.
2. Process Innovation: This form of innovation refers to the implementation of a new or significantly improved production or delivery method which can include significant changes in techniques, equipment, and/or software. The goal of process innovation is to increase efficiency in the production or delivery process, thereby reducing costs or enhancing quality. Like product innovations, process innovations can be driven by new technological advancements or innovative applications of existing technology.
3. Marketing Innovation: This type of innovation involves the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion, or pricing. The objective of marketing innovation is to better meet customer needs, open new markets, or reposition an enterprise's product in the market, or otherwise affect the product's market potential. The source of innovation can be new technological developments or innovative applications of existing technology.
4. Organizational Innovation: This type of innovation involves the implementation of a new organizational method in the firm's business practices, workplace organization, or external relations. The aim of organizational innovation is to improve performance, boost employee satisfaction, access new assets, or reduce supply costs. new

technological advancements or innovative applications of existing technology. Like the other types of innovation, organizational innovation can be driven by new technological advancements or innovative applications of existing technology.

From the definition of product innovation, we note that it includes both goods and services. This makes this definition applicable to manufacturing and service firms.

Before presenting an appropriate theoretical framework for this study, we reiterate the desirable characteristics of such a framework. First, the framework should recognize innovation as a process with input, throughput, and output stages leading to an implementation of a product innovation. Second, at the input stage, it is desirable to measure knowledge and organizational characteristics while at the output stage it is desirable to measure organizational and marketing characteristics in addition to product innovations. Third, our framework should be applicable to firms in the manufacturing sector and service-oriented firms of the knowledge economy. Finally, the framework should be able to be operationalized with an optimal number of basic indicators.

Figure 4 is a representation of the theoretical framework for this study. From this figure, we note that the innovation process is divided into three stages – input, throughput, and output. At the input stage, existing knowledge and customer requirements are ideated into a technological concept which is translated into the design of a product or service. At this stage, the framework recognizes the presence of knowledge characteristics by acknowledging that a firm may choose to patent its inventive output. It also recognizes the presence of organizational characteristics by acknowledging that a firm may choose to implement organizational innovations at the input stage. The framework germinates the innovation process with an idea of a technological concept which is an idealized future state of an envisaged product or service. At the throughput stage, the product or service design (prototype) is manufactured with an appropriate input of material resources. At this stage, it is recognized that the firm may choose to innovate in processes and organizational innovations. These organizational innovations are specific to the throughput stage. This stage is appropriately the conversion or developmental stage encountered in prior literature where the idea is given tangible form.

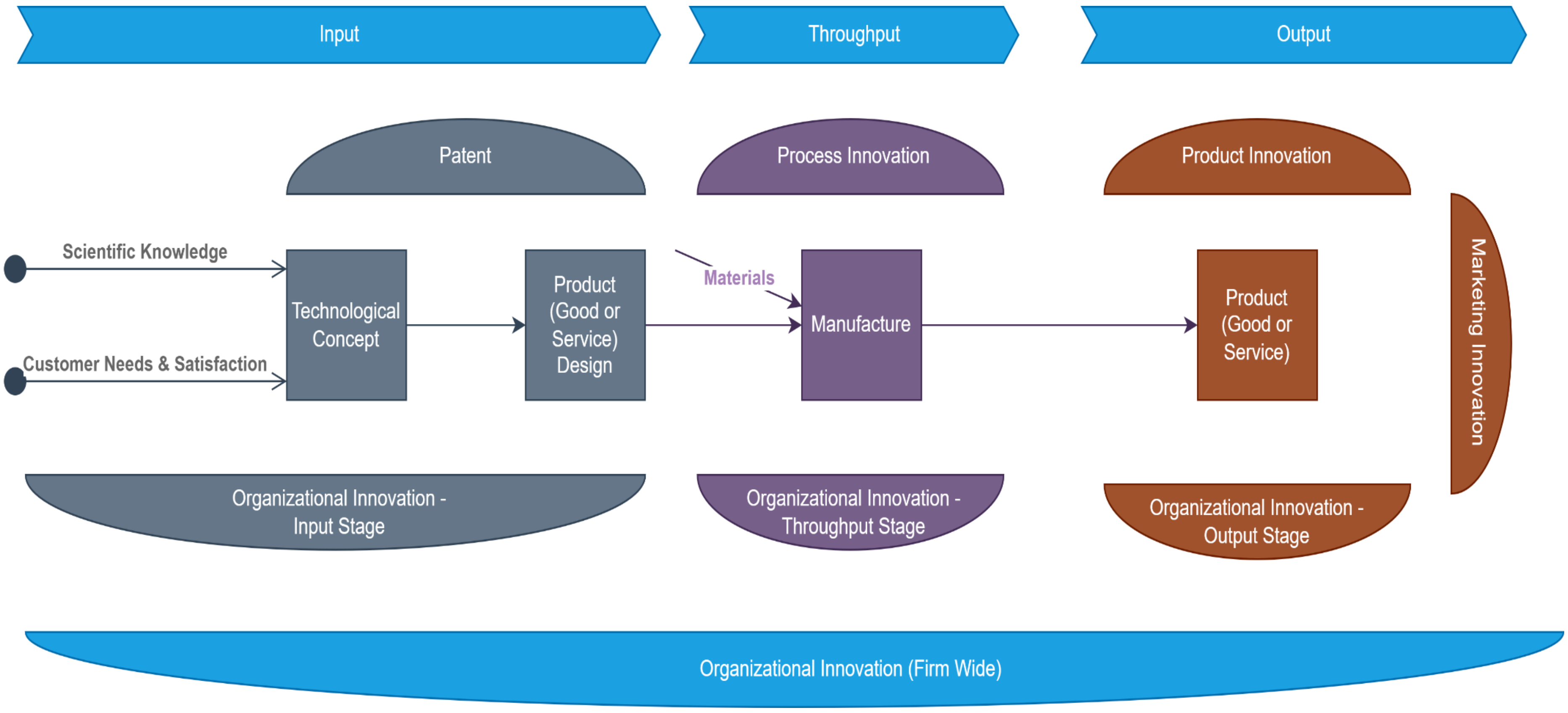


**Figure 4 – Theoretical Framework**

At the output stage, the product innovation is implemented (commercialized or taken to the market) and at this stage it is recognized that the firm may choose to engage in marketing and organizational innovations in addition to product innovations. Organizational innovations at the output stage are specific to this stage. To incorporate newer developments such as open innovations (Docherty, 2006) and business model innovations (Spieth et al., 2014) which may be classified as organizational innovations that can be firm wide, this framework also recognizes the presence of such innovations.

A clarification upon the scope of organizational innovations in this framework is in order. In the output stage of Figure 4, organizational innovations would involve those methods in the firm's business practices, workplace organization, or external relations that pertain to the sale, marketing, and distribution of finished goods or services. Organizational innovations at the throughput stage would involve those methods in the firm's business practices, workplace organization, or external relations that pertain to production and logistics in the manufacturing process. At the input stage, the firm accepts knowledge inputs and an awareness of customer needs which it then seeks to transform into finished, marketable outputs. In the process, the firm will develop a technological concept and would seek to translate this concept into a working prototype for goods or a service design. Therefore, organizational innovations at the input stage would involve those methods in the firm's business practices, workplace organization, or external relations that pertain to the development of a technological concept and its translation into a goods or services design.

Operationalization of the Theoretical Framework

We are now ready to organize our theoretical framework and its components in a "hierarchical design" as elucidated in Maggino (2017b, p. 90). The purpose of organising the theoretical framework in this manner is to be able to identify relevant variables, dimensions, and basic indicators. Data would be collected for the basic indicators.

The components of this hierarchical design are as follows:

a. The conceptual model or the theoretical framework which defines the phenomenon to be studied, identifies its domains and overall aspects. This is what we have discussed earlier and illustrated in Figure 4.

b. The variables which identify the aspects that define the phenomenon. Each variable represents or labels a specific aspect or facet of the phenomenon under study. In our theoretical framework, there are four variables representing four overarching facets that identify innovation as a conversion process. These are inputs, throughputs, outputs, and organizational innovation (firm wide). These variables, collectively, allow us to consistently specify the theoretical framework.
c. Dimensions represent factors of each variable. Collectively factors define the variable. In our framework, inputs are represented by two dimensions – patents and organizational innovations at the input stage. Throughput is represented by two dimensions – process innovations and organizational innovations at the throughput stage. Outputs are represented by three dimensions – organizational innovations at the output stage, product (goods or services) innovations, and marketing innovations.
d. Finally, basic indicators actually measure each dimension. All our dimensions are represented by single indicators which are a count of the number of times that that dimension has occurred. At the input stage, with the appropriate combination of materials and manufacturing techniques, a prototype or service design is introduced which is later mass produced into marketable goods or services. Thus, the input stage of Figure 4 encompasses the outputs of invention that can potentially be mass produced. Such inventive output is either not disclosed publicly or is declared with intellectual property protection. One form of such protection is patents which are seen as legally recognized instruments of protecting firm inventive output (OECD, 2009). According to the OECD Patent Statistics Manual (OECD, 2009: 12), "patent indicators convey information on the output and processes of inventive activities." One type of patent indicator, patent applications, is a straightforward indicator of the inventive output of the firm and is simply the number of patents applied for by the firm. Therefore, this indicator has been utilized as a relevant basic indicator at the input stage of the innovation process. Recognizing that patenting is more commonly witnessed in firms that principally produce goods rather than services, a second indicator, organizational innovation at the input stage, has also been incorporated which should more appropriately reflect the innovation outcomes that service oriented firms undertake at the input stage.

Figure 5 is a hierarchical design representation of all variables, dimensions, and basic indicators that represent out theoretical framework. We note that, in total, we have eight basic indicators for which data would be collected. This is an optimal number of indicators that appropriately balances our twin objectives of comprehensiveness and parsimony (Birchall et al., 2004; Björk et al., 2023).

When selecting basic indicators, it must be ensured that such indicators also meet a threshold of quality. Maggino (2017b) identifies four dimensions of quality pertaining to indicators – methodological soundness, integrity, serviceability, and accessibility. Methodological soundness refers to the accuracy and validity of indicators, and their precision and reliability in measuring the underlying concept with a low degree of distortion. Integrity refers to transparency in data collection and dissemination in an ethically correct manner. Serviceability refers to the appropriateness of indicators in meeting users' needs, their being practicable, updatable, and thrifty, their being well-timed and punctual, periodic, and regular, and their possessing discriminant ability in recording differences between units. Accessibility refers to indicators being discoverable, accessible, useable, capable of being analysed, and interpretable. We discuss in greater detail each of these dimensions of indicator quality as it pertains to the eight basic indicators that constitute the theoretical framework of this study.

i. Methodological soundness – It is contended that each of our basic indicators are accurate and valid in representing their relevant dimension because the dimensions that they represent are well-defined and delineated and because these indicators exactly measure the dimension being defined (precision). Further, our indicators are reliable because they are unique in the sense that no closely related substitutes are available to permit subjective choice and because they are collected from highly reliable official publications. For instance, the patent dimension is accurately and validly captured by one basic indicator of patent activity – patents applied for which measures the patent activity dimension exactly. This indicator is reliable because it uniquely identifies inventive activity and because the data for it is obtained from official patent and trademark office records.

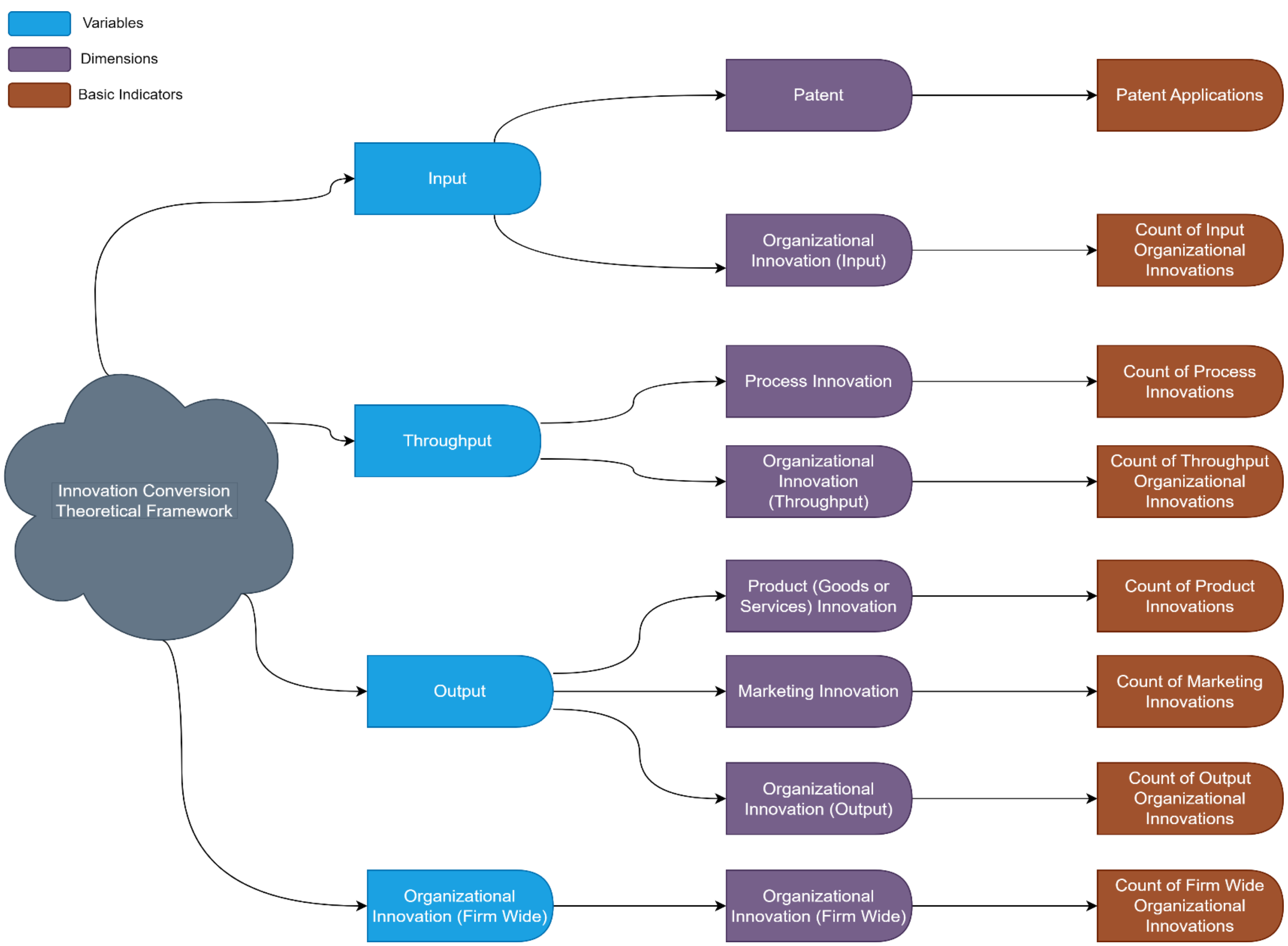


**Figure 5: Hierarchical Design Representation**

Similarly, the marketing innovation dimension is accurately and validly represented by a count of the marketing innovations that a firm demonstrates in a given period and each marketing innovation instance is identified per the precise OECD definition. The count of marketing innovations exactly measures this dimension and data for marketing innovations is collected from official, highly reliable sources.

ii. Integrity – Because data for each of our indicators is collected from official and publicly available firm records and because our indicators follow precise OECD definitions, it is contended that the data collection process is transparent. Further, complete records of each item or observation are available for every indicator except patent indicators for which aggregate counts in each fiscal year were obtained. The reliance on official records and internationally recognized and scientifically validated definitions implies that the data collection process is conducted ethically. There were no human or animal subjects involved during data collection.

iii. Serviceability – Each indicator has been selected in a manner so as to be readily available in official and publicly available sources which are, typically, the only reliable sources available for external stakeholders. This suggests that indicators have been chosen from the standpoint of meeting end user needs. Each of the collected indicators is updated at least every fiscal year. Annual and corporate governance reports are updated annually. Detailed quarterly reports are also available. Press releases are available almost immediately on company websites or press-release aggregation portals. Patent information from the patent and trademark office is also updated almost immediately. This suggests that the chosen indicators are both practical and easily updated over time. Because each of our eight indicators is a count of a specific dimensional outcome, it is contended that each indicator possesses good discriminant ability in recording differences between units (firms).

iv. Accessibility – Each of our indicators is easily discoverable because, should a firm exhibit innovation outcomes in any of the specified dimensions, firm management is keen to record such information in public information sources. Our indicators are accessible because data for each has been collected from official and publicly available sources for which no data access cost was incurred. Because each of our indicators are in count form, they lend themselves to being capable of being utilized appropriately for index construction and subsequent analysis. Given the detailed definitions of what each indicator measures, it's clear that they can be interpreted accurately by users.

Hitherto, we have identified a theoretical framework suitable for this study and operationalized it in terms of variables, dimensions, and basic indicators and justified the quality of these eight indicators.

Next, we review existing indices of innovation at firm level to highlight how our index of innovation outcomes fills gaps in existing literature.

### 3.3. A Review of Indices of Innovation at Firm Level

Eight indices of innovation were identified in academic literature that attempt to measure one or the other facet of innovation at firm level. Studies were identified from 2003 to 2022 and are listed in Table 1 which also explains how these studies are different from the index constructed in this study. A brief on these studies follows.

Yu et al. (2022) aimed to construct an innovation capital index for the global airline industry using a method called hierarchical data envelopment analysis (H-DEA). The goal of this index was to measure the effectiveness of innovation within airlines, with a particular focus on those ranked in the World's Top 100 Airlines in 2018. We note that this study focuses on the airlines industry alone and measures effectiveness of innovation and not innovation outcomes.

Ponta et al. (2021) present a way to gauge innovation performance through the lens of patent activity. The Innovation Patent Index (IPI) is the tool introduced in their study, which quantifies innovation by examining the number and quality of patents. The quantity is measured by the number of patents, while the quality is assessed on the number of citations a patent receives, the geographic scope of the patent, and the number of claims made in the patent. These dimensions are combined to form a composite index that provides a more comprehensive measure of innovation performance.

**Table 1 – Existing Firm Level Innovation Indices**

| Publication Year | Index Title | Industrial Sector | Facet(s) of Innovation Measured | Author(s) | How this index is different from current study |
|---|---|---|---|---|---|
| 2022 | Innovation Capital Index | Global Airlines Industry | Innovation effectiveness | Yu, Abdul Rashid, & See | Focus on airlines; measures innovation effectiveness, not outcomes |
| 2021 | Innovation Patent Index | Italian Plastic Materials Sector | Innovation quality through the lens of patent activity | Ponta, Puliga, & Manzini | Focus on plastic materials alone; Measures innovation quality, not outcomes; Does not look at innovation as a process of inputs, throughputs, & outputs |
| 2016 | Index of Media Innovation | Spanish Media Industry | Number and degree of media innovations | García-Avilés, Carvajal-Prieto, Lara-González, & Arias-Robles | Focus on media industry alone; Measures both qualitative & quantitative aspects of innovation |
| 2016 | Berkeley Innovation Index | None Specified | Innovation capability measured based on psychological profiles and perceptions of firm culture of innovation | Sidhu, Goubet, Webber, Fredh-Ojala, Johnsson, & Pries | Measures innovation potential not outcomes; Self-assessment tool suitable more for internal than external stakeholders |
| 2008 | Composite Innovation Index | German Firms across 23 Industries | Measures organizational innovation in terms of innovation posture, innovation propensity, & innovative performance | Carayannis & Provance | Measures organizational innovation as a multidimensional construct by measuring strategic orientation, activities that a firm undertakes to achieve innovation, and actual outcomes of innovation; Does not measure innovation outcomes exclusively |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | and does not treat innovation as a process in measuring outcomes |
| 2007 | Innovation Input Index and Innovation Output Index | Canadian Manufacturing Firms | Innovation Input and Innovation Output | Tang & Le | Focus only on manufacturing and not service oriented firms; Constructs an input and output innovation index but fails to adequately address the throughput component of innovation |
| 2004 | Index of Patent Quality | US Publicly Listed Corporations | Patent quality as identified by claims, forward citations, family size, and technological area | Lanjouw & Schankerman | Focus only on measuring quality of patents; As such, not a comprehensive measure of innovation outcomes |
| 2003 | Innovation Index | Australian Publicly Listed Corporations | Innovation activities as identified by R&D investment, patent, design and trademark applications | Feeny & Rogers | Focus on Australian public listed firms; Measures innovation activity such as R&D investment, etc. but is not a strict measure of innovation outcomes; Does not treat innovation as a process comprising of inputs, throughputs, & outputs. |

While this study measured innovation performance, it only considers the number and quality of patents to measure such performance. The reader will note that the number of patents applied for is a basic indicator in our theoretical framework at the input stage. As such, this study does not consider innovation as a process comprising of inputs, throughputs, and outputs. Further, this study, in its focus on patents alone also makes it unsuitable for service firms that patent less and are more focused on organizational innovations at the input stage. Also, this study strives to measure innovation performance which includes quality of patents as a dimension but not innovation outcomes.

García-Avilés et al. (2016) aimed to measure and analyse the number and degree of innovations in media outlets, which is seen as a crucial asset for survival in the media industry. Media innovation is viewed from a perspective encompassing goods, services, value chain processes, and the organization of the agents of media innovations. The context of the study is the Spanish media sector, and the index is based on four key factors that influence the measurement parameters: the concept of innovation, the area in which it takes place, the degree of innovation, and the technological basis. The dimensions included to construct the composite index are product, production and distribution processes, organization, and marketing. We note that this study focuses on the media industry alone in the context of Spain and considers both quantitative and qualitative measures of innovation.

At the organizational level, the Berkeley Innovation Index (BII) (Sidhu et al. 2016) provides a way for organizations to assess their innovation capability across five dimensions. By doing so, organizations can identify their strengths and weaknesses in innovation, and get guidance on how to improve. These five key dimensions of innovation are: mindset, need finding, ideation, teaming, and implementation. These dimensions are believed to be crucial components of the innovation process and the BII uses a combination of self-assessment and objective measures to assess these dimensions. The BII, then, measures the collective innovative capability of an organization by aggregating the individual innovation scores of the members of the organization. This provides a measure of the overall innovative potential of the organization. Consequently, the BII does not measure innovation outcomes, only innovation potential. Moreover, this is a self-assessment tool more appropriate for internal stakeholders than external.

Carayannis and Provance (2008) present a Composite Innovation Index that measures organizational innovation not just as a singular concept, but as a multi-dimensional construct. The context of their study is set within the broader discourse of innovation and regional development, with a focus on how firms' innovative capabilities can be accurately measured and compared. The authors argue that existing measures of innovation often fail to capture the full spectrum of a firm's innovative activities, and thus propose a more comprehensive approach. The authors identify three key dimensions that are included to construct the composite index: innovative posture, innovative propensity, and innovative performance. Innovative posture refers to a firm's strategic orientation towards innovation, including its willingness to take risks and pursue novel ideas. Innovative propensity refers to a firm's actual actions and behaviours in pursuing innovation, such as its investment in R&D and collaboration with other firms. Finally, innovative performance refers to the outcomes of a firm's innovative activities, such as the number of new goods or services introduced to the market.

Tang and Le (2007) examine innovation within firms and its impact on firm productivity. The authors argue that traditional measures of innovation, such as R&D expenditure or patent counts, are insufficient to capture the full spectrum of innovative activities within a firm. They suggest that a more comprehensive measure of innovation is needed to better understand its relationship with productivity. Consequently, they develop an input index of innovation and an output index of innovation. Their input index is comprised of three indicators pertaining to R&D, technology acquisition, and industrial technology. Their output index consists of three indicators pertaining to product and process innovations, and patent applications.

Lanjouw and Schankerman (2004) delve into the intricate relationship between patent quality and research productivity. The authors propose an index to measure innovation, focusing on the quality of patents rather than their quantity. They argue that the traditional approach of counting patents fails to capture the true essence of innovation, as it overlooks the varying quality of patents and suggest that a more nuanced approach, which considers the quality of patents, would provide a more accurate measure of innovation. Their theoretical model includes several dimensions to capture distinct aspects of patent quality. These include the number of claims made in a patent, which reflects the breadth of the patent; the number of forward citations, which indicates the impact of the patent on future innovations; and the number of countries in which the patent is filed, which suggests the commercial value of the patent.

Feeny and Rogers (2003) explore the relationship between innovation and firm performance by developing an index that measures the innovation activity of Australian firms. Their index considers multiple indicators of innovation such as the firm's investment in research and development (R&D), the number of patent applications, design applications, and trademark applications. By combining these indicators, the authors create a composite index that provides a holistic measure of a firm's innovation activity.

These eight indices measure effectiveness of innovation, quality of innovation including patent quality, volume of innovative activity and innovation capability. Thus, multiple facets of innovation have been measured in prior studies. Four of the eight indices focus on specific industrial sectors namely manufacturing, airlines, media, and plastic materials. Of the two indices that measure innovation activity, García-Avilés et al. (2016) focus on innovation activity in the Spanish media industry and Feeny & Rogers (2003) focus on Australian publicly listed corporations. Feeny & Rogers consider only four basic indicators of innovation activity for the construction of their innovation index. These include R&D expenditures, patent applications, trademark applications, and design applications.

Based on this review of research studies, we may conclude that a requirement of an index of innovation outcomes exists which has been constructed for a representative sample of all industrial sectors, one which considers innovation to be a conversion process per definition and is constructed to overcome the lack of access to firm-level innovation activity for all stakeholders.

### 3.4. Review of Innovation Outcome’s Impact on Stock Market Returns

We undertake this review as a first step towards external validation of our innovation index. Since the innovation index is based on a theoretical framework, it is important to validate this index by assessing its impact on an external measure. In this section, we discuss how prior research indicates innovation outcomes have a positive impact on stock market returns. Later, based on our discussion in this section and after completing index construction, we will elucidate and test a hypothesis pertaining to the impact of the innovation outcome index on abnormal stock returns. Reviewed studies in this section are classified according to basic indicators that are part of our theoretical framework. Outcome of each of these reviewed studies is summarized in Table 2.

Patent Applications or Patents Granted[1]

Shou et al. (2023), in a study on Chinese logistic companies assessed the impact of green patent applications upon Tobin's q[2]. They found an inverted U-shaped relationship between these variables, the implication being that an intermediate level of green patenting activity is most beneficial for market value.  Chen et al. (2019) sought to understand the relationship between patent count and market value and found a positive relationship. This study was conducted upon the American semiconductor industry for the period 1999 to 2012. Chen and Shih (2011) found a positive relationship between patent counts to sales and Tobin's q that followed an inverted U-shape meaning that after a certain point increase in patent counts can lead to decrease in Tobin's q. This suggests that while the number of patents can enhance firm performance, there may be diminishing returns to patenting activity. This study was conducted upon the American pharmaceutical industry for the period 1996 to 2007. Patel and Ward (2011) found that when a firm receives a patent grant, it positively impacts daily abnormal stock returns. This study also was also conducted upon the American pharmaceutical industry. Ayari et al. (2012), delve into the relationship between the count of renewable energy patents and stock returns in the renewable energy sector. Their findings suggest a positive correlation with a higher count of renewable energy patents tending to exhibit better returns. Hall et al. (2005) conducted a study on US firms between 1965 and 1996 and found that the ratio of patent counts to R&D stock significantly and positively impacted Tobin's q.  Bosworth & Rogers (2001), in a study on large Australian firms, found that the ratio of patents obtained to tangible assets had a significant and positive impact upon the firm's market value.

[1] While patents granted are not part of the basic indicators, given the close connection between patent applications and patents granted, a review of both kinds of studies is included.

[2] Tobin's Q is a financial metric used to compare a company's market value to its asset replacement value. Mathematically, it is defined as the ratio of the market value of the firm to the replacement cost of a firm's assets.

**Table 2 - Studies that Have Assessed the Impact of Innovation on Firm Value**

| Publication Year | Authors | Study Context | Facet of Innovation | Dependent Variable | Impact |
|---|---|---|---|---|---|
| **Patents** | | | | | |
| 2023 | Shou, Wu, Shao, Hu, & Lai | Chinese logistic companies | Green patent applications | Tobin's q | Positive - intermediate levels of patenting activity is most beneficial for market value |
| 2019 | Chen, Lin, Wu, Hung, Ting, & Hsieh | American semiconductor industry | Patent count | Firm market value | Positive |
| 2012 | Ayari, Blazsek, & Mendi | Renewable energy sector | Patent count | Stock return | Positive |
| 2011 | Chen & Shih | American pharmaceutical industry | Patent count divided by sales | Tobin's q | Positive but suggests diminishing returns to patenting activity |
| 2011 | Patel & Ward | American pharmaceutical industry | Patent grant | Abnormal stock return | Positive |
| 2005 | Hall, Jaffe, & Trajtenberg | US firms | Patent count divided by R&D stock | Tobin's q | Positive |
| 2001 | Bosworth & Rogers | Large Australian firms | Patent count divided by tangible assets | Market value | Positive |

| | | | | | |
|---|---|---|---|---|---|
| **Process Innovation** | | | | | |
| 2019 | Szutowski | Service firms in the European Union | Process innovation | Abnormal stock return | Positive |
| 2015 | Nicolau & Santa-María | Spanish Biotechnology sector | Process innovation | Abnormal stock return | Positive |
| 2013 | Nicolau & Santa-María | Spanish hotel firms | Process innovation | Market value | Positive |
| **Product Innovation** | | | | | |
| 2019 | Szutowski | Service firms in the European Union | Product (service) innovation | Abnormal stock return | Positive |
| 2015 | Nicolau & Santa-María (2015) | Spanish Biotechnology sector | Product innovation | Abnormal stock return | Positive |
| 2014 | Schöler, Skiera, & Tellis | Financial firms in the United States, Germany, United Kingdom, Switzerland, & France | Financial innovation | Abnormal stock return | Positive |
| 2013 | Ba, Lisic, Liu, & Stallaert | Global automobile companies | Green vehicle innovation | Abnormal stock return | Positive |
| 2013 | Nicolau & Santa-María | Spanish hotel industry | Product innovation | Market value | Positive |
| 2009 | Sood & Tellis | US firms across five industries - external lighting, display monitors, computer memory, | Product innovation | Abnormal stock return | Positive |

| | | | | | |
|---|---|---|---|---|---|
| | | data transfer technologies, & desktop printers | | | |
| 2009 | Srinivasan, Pauwels, Silva-Risso, & Hanssens | US automakers - Chrysler, Ford, General Motors, Honda, Nissan, & Toyota | Product innovation (new-to-firm & new-to-market) | Stock return | Positive |
| 1995 | Kelm, Narayanan, & Pinches | US firm | Product innovation | Excess stock return | Positive |
| **Marketing Innovation** | | | | | |
| 2013 | Nicolau & Santa-María | Spanish hotel industry | Marketing innovation | Market value | Positive |
| **Organizational Innovation** | | | | | |
| 2018 | Miglietta, Battisti, & Garcia-Perez | Six US listed firms that had paid dividends at a growing rate for over 60 years | Open innovation | Stock return | Positive |
| 2013 | Nicolau & Santa-María | Spanish hotel industry | Organizational innovation | Market value | Positive |
| 2012 | Nicolau & Santa-María | Largest airline in Spain | Business model innovation | Market value | Positive |
| **Innovation Award** | | | | | |
| 2023 | Singh & Garg | Fortune 500 firms | Innovation award (product & process, | Abnormal stock return | Positive |

| | | | | | |
|---|---|---|---|---|---|
| | | | organizational, marketing) | | |
| 2014 | Zhang, Yu, & Xia | US public firms | Product innovation award (goods and/or services) | Tobin’s q | Positive |
| 2013 | Nicolau & Santa-María | Spanish firms | Innovation award | Market value | Positive |

Process Innovations

Szutowski (2019) conducted a study on service firms in EU member states. He found that announcements of implementation of process innovations led to a positive impact on abnormal stock returns both in the short and long term. Nicolau & Santa-María (2015) found a positive impact of process innovation announcements upon abnormal returns in the Spanish biotechnology sector. In a study on the Spanish hotel industry, Nicolau & Santa-María (2013b) found a positive impact of process innovation announcements on the market value of two hotel firms.

Product Innovations (Goods or Services)

Szutowski (2019) conducted a study on service firms in EU member states. He found that announcements of service innovations led to a positive impact on abnormal stock returns both in the short and long term. Nicolau & Santa-María (2015) found a positive impact of product innovation announcements upon abnormal returns in the Spanish biotechnology sector. In a study on financial innovations conducted in the context of publicly traded financial firms in five nations - the United States, Germany, United Kingdom, Switzerland, and France – Schöler et al. (2014) found that financial innovations had a positive impact on cumulative abnormal stock returns. In a study on global automobile companies, Ba et al. (2013) found that green vehicle innovations had a positive impact on abnormal returns in an event study over a 14-year time span. In a study on the Spanish hotel industry, Nicolau & Santa-María (2013) found a positive impact of product innovation announcements on the market value of two hotel firms. Sood & Tellis (2009) in an event study on US firms across five industries - external lighting, display monitors, computer memory, data transfer technologies, and desktop printers – found new product launches to have a positive impact on abnormal returns. Srinivasan et al. (2009) assessed the impact of product innovations on stock returns and found them to impact positively. They conducted this study on six US automakers - Chrysler, Ford, General Motors, Honda, Nissan, and Toyota – representing 86% of the US car market from 1996 to 2002. A positive effect was found for both new-to-the-company and pioneering (new to the market) product innovations. Kelm et al. (1995) studied the impact of product introductions upon excess returns upon a sample of US firms. They found product introductions positively impact excess returns.

Marketing Innovations

In a study on the Spanish hotel industry, Nicolau & Santa-María (2013b) found a positive impact of marketing innovation announcements on the market value of two hotel firms.

Organizational Innovations

In a study on the Spanish hotel industry, Nicolau & Santa-María (2013b) found a positive impact of organizational innovation announcements on the market value of two hotel firms. In assessing the worth of business model innovations upon the market value of the largest airline in Spain, Nicolau & Santa-María (2012) found such innovations to have a positive impact on its market value. Miglietta et al. (2018) present circumstantial evidence pertaining to the impact of open innovation on the stock market return of firms. They identified six US listed firms that had paid dividends at a growing rate for over 60 years and had managed to surpass market yield. It was then determined if these firms had adopted an open innovation practice by analyzing multiple, credible published sources. All six firms had adopted an open innovation practice. Whilst the authors admit that their findings cannot be ascertained utilizing robust quantitative methodologies, they strongly contend that adoption of open innovation practices are contributors to these firms' extraordinary stock returns.

Innovation Awards

Three studies that have assessed the impact of innovation awards upon stock market performance are discussed. We include these studies because innovation awards can serve as an important proxy for innovative outcomes depicting excellence. Singh & Garg (2023) assessed the impact of innovation awards on abnormal stock returns. They classified innovation awards according to product and process, marketing, and organizational innovation. They found that innovation awards, overall, had a positive impact upon abnormal stock returns. They also found that product and process, marketing, and organizational innovation awards separately depicted a positive impact upon abnormal stock returns. Zhang et al. (2014) classified innovation awards pertaining to goods and/or service innovation and found them to positively impact Tobin's q both in an event study and as part of panel data regressions. Nicolau and Santa-María (2013a) also found a positive impact of innovation awards on the market value of a firm in an event study conducted upon Spanish firms.

Thus, evidence from prior research overwhelmingly indicates that multiple facets of innovation outcomes have a positive impact on stock returns.

# 4. Research Methodology

After having established our theoretical framework and having operationalized this framework in terms of eight basic indicators, we discuss the five-step innovation index construction methodology. Later in this section, a description of the S&P 500 sample and data collection procedures would also be highlighted. This section concludes with an outline of panel data regression methodology that was applied to assess the impact of the innovation index on abnormal stock returns.

## 4.1. Innovation Index Construction Methodology

Having introduced the theoretical framework and its operationalization in terms of variables, dimensions, and basic indicators, we are at the stage of outlining the fundamental steps of innovation index construction that were followed. These six steps are as follows (OECD/European Union/EC-JRC, 2008; Mazziotta & Pareto, 2017):

i. Phenomenon definition
ii. Indicator selection
iii. Normalization
iv. Weighting of the normalized indicators
v. Aggregation of the weighted indicators
vi. Validation of the composite index.

<u>Phenomenon Definition</u>

At this step, we defined the concept under study which in our case is innovation outcomes. We have identified a suitable theoretical framework as part of this step and have identified the relevant variables and dimensions that constitute this theoretical framework (refer figure 4). From the perspective of composite index construction, it is also imperative to identify the nature of the measurement model that our theoretical framework is. The identification of the appropriate measurement model at this step has ramifications in subsequent steps. In particular, the choice of measurement model determines the selection of indicators and aggregation techniques available to us (Mazziotta & Pareto, 2017).

Fundamentally, there are two kinds of measurement models – reflective and formative. In a reflective theoretical framework, the latent construct to be measured causes the indicators that measure it. Such frameworks are common in psychological studies where the latent construct is composed of indicators that all change when the latent construct changes. For instance, a Perceived Ease of Use model (Davis et al. 1989) that assesses "the degree to which a person believes that using a particular system would be free of effort" measured by six indicators is an instance of a reflective framework. Here, the indicators – "easy to learn, controllable, clear & understandable, flexible, easy to become skilful and easy to use" are reflections of a person's perception regarding ease of use which is the latent construct that is being measured. An increase or decrease in overall ease of use is expected to impact all indicators in varying degrees. In reflective models, the indicators that constitute the conceptual framework are expected to demonstrate high correlation (as in this instance) because they are all representing or measuring the same latent construct. Even if one of these indicators is dropped, the conceptual understanding of the construct is not altered. In formative models, the reverse is true. The composite construct that is being measured is *caused* by the indicators that constitute the theoretical framework. In such models the indicators are formative, i.e., they form or are a cause of the composite construct. Such models are common in socio-economic studies. Our theoretical framework for this study is a formative model because the variables, dimensions, and basic indicators result in the innovation outcome exhibited by the firm. In a formative model, each indicator represents a selective facet of the phenomenon under consideration. Collectively, they result in the phenomenon itself. Thus, the variables of input, throughput, output, and organizational innovation (firm wide) collectively result in the innovation outcome of the firm. Indicators in formative models, unlike those in reflective models, may or may not be correlated and typically do not exhibit high correlation. In reflective models, indicators are interchangeable since they all measure the same construct and are really reflections of the underlying latent variable. In formative models, indicators are not interchangeable since they measure selective facets of the phenomenon under consideration and collectively lead to the phenomenon. Removing any indicator in a formative model would change the very definition of the phenomenon (Maggino, 2017b). Figures 6 and 7 are a depiction of reflective and formative models.

Indicator Selection

We have selected eight basic indicators that represent eight dimensions and four variables of our theoretical framework as depicted in figure 5. We have discussed how each of our basic indicators meets the four dimensions of indicator quality namely methodological soundness, integrity, serviceability, and accessibility. As was stated earlier, the theoretical framework of this study being a formative model, only mild correlations between the basic indicators were observed. Similarly, mild correlations were observed between each of the four variables which are also composite indices that collectively form the innovation outcome index.

Normalization

At this step, our interest is in transforming each of our basic indicators to a common unit and similar range. Indicators often have different units of measurement and vary widely in their lowest to maximum values. If we do not normalize indicators, then aggregating those into a composite index would lend more implicit weight to indicators with higher ranges leading to an index that is not representative of the phenomenon under consideration. Also, an increase in some indicators may contribute positively to the composite index while a decrease in certain indicators might also contribute positively to the composite index. Thus, indicators may differ in their polarity in addition to their units of measurement or ranges. To address all these issues, we discuss certain normalization techniques and indicate which technique was deemed most suitable for our purposes (Mazziotta & Pareto, 2017). Five normalization methods were identified namely no normalization, ranking, standardization (Z-scores), re-scaling (Min-Max), distance from a reference (Indicization).

i. No normalization – In this method, the original data is aggregated without any transformation. This technique is suitable only when all indicators have the same unit of measurement and similar ranges. While our eight basic indicators are counts of varying aspects of innovation outcomes, the ranges of these indicators are markedly different from one another. This necessitates the use of a suitable normalization technique.

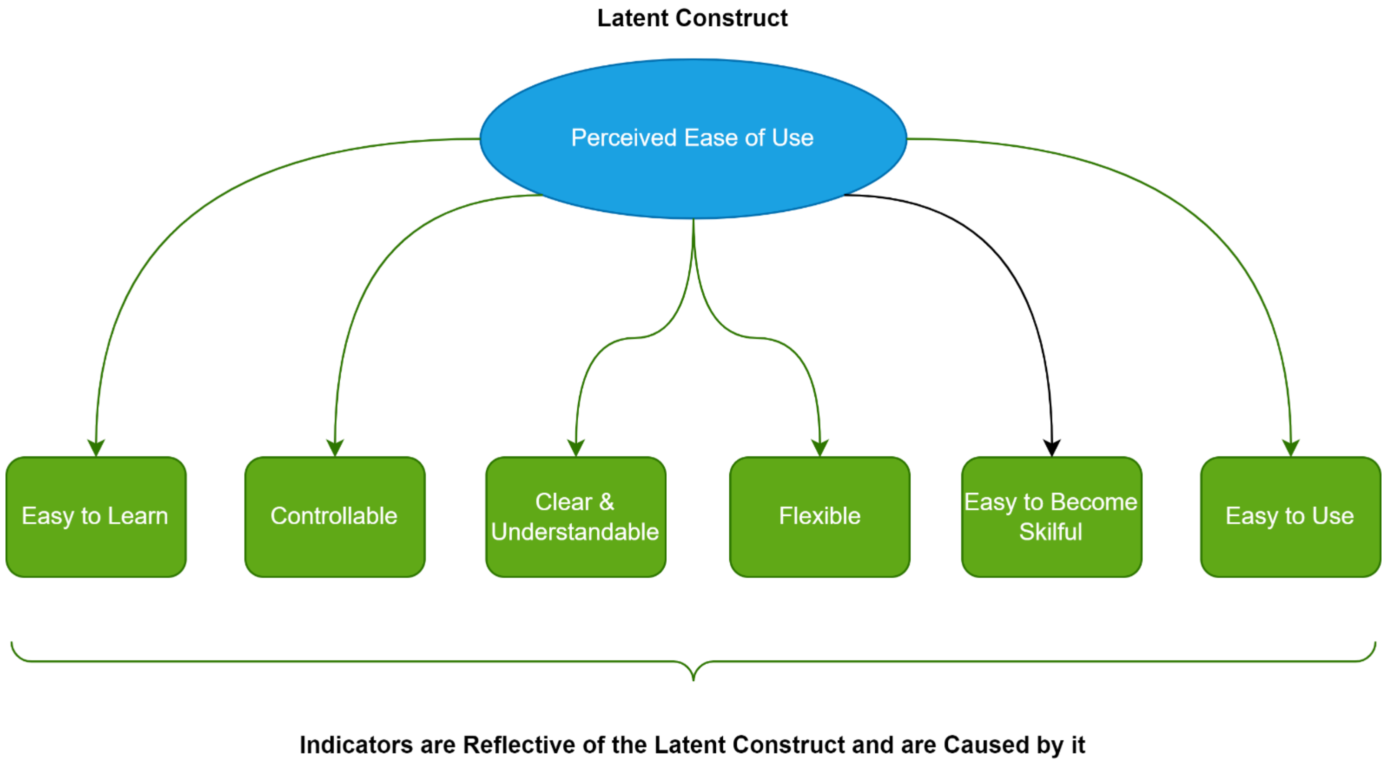


**Figure 6 – Reflective Model**

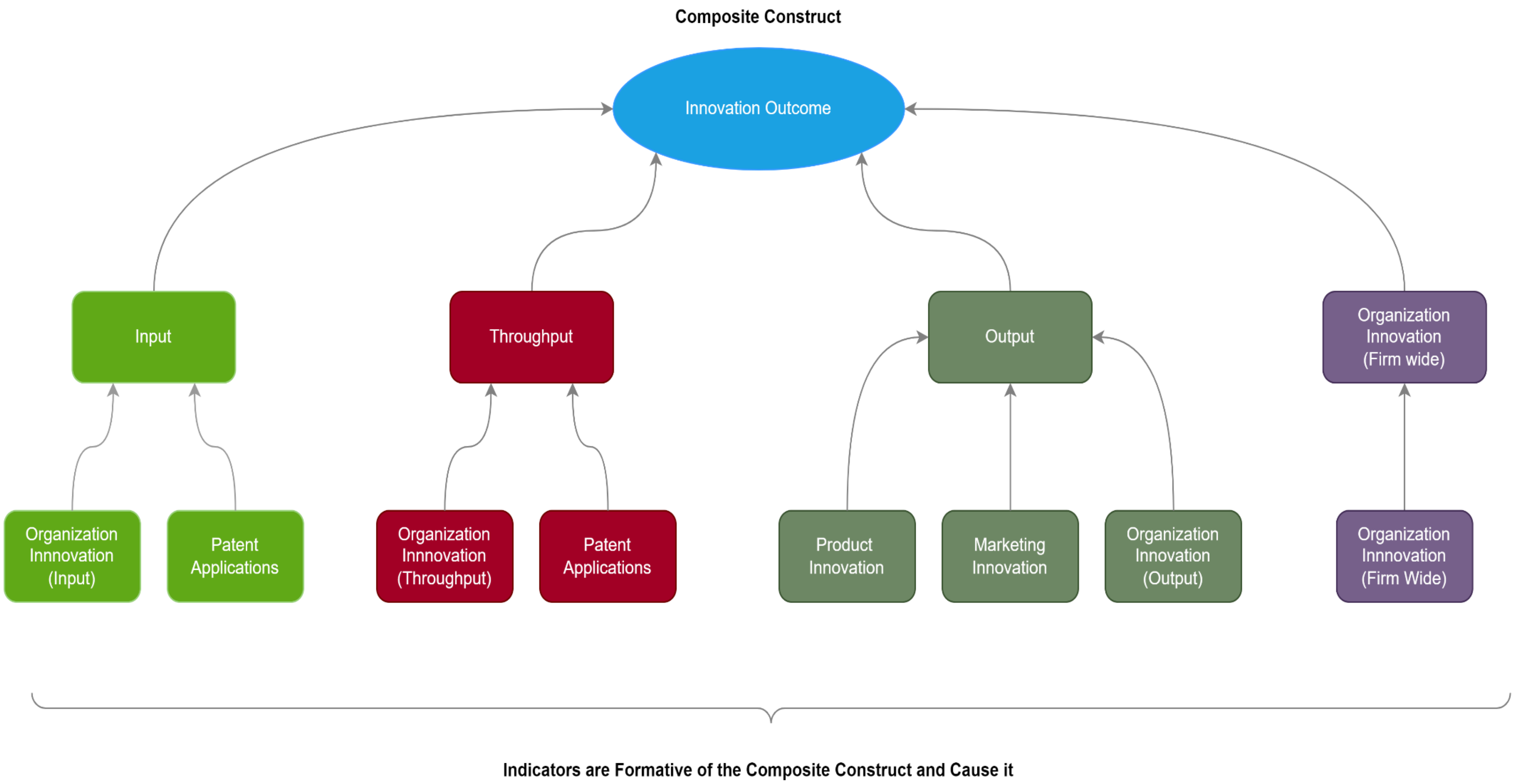


**Figure 7 – Formative Model**

ii. Ranking – Here, units are ranked according to the ranking of their indicator values. Thus, firm A in the year 2010 with the highest number of patent applications (irrespective of this absolute number) would receive a rank of 1 for patent applications while firm B with the lowest number of patent applications would receive the lowest rank possible given the sample size. There are certain disadvantages to this method for which it was not selected as a normalization technique. First, each of our indicator values are counts which are on the ratio scale. Transforming ratio scale values to ordinal (ranked) values introduces a loss of information which is undesirable from an analytical and predictive purpose. Second, formative models require aggregation using a mathematical function for which ordinal data is not suited (Mazziotta & Pareto, 2017).

iii. Standardization (Z-scores) – This is a process of converting all indicator values to a common scale that has a mean of 0 and a standard deviation of 1. The formula for standardization is as follows.

$$y_{ij} = \frac{x_{ij} - M(x_j)}{S(x_j)}$$

where $M(x_j)$ is the mean of indicator j and $S(x_j)$ is its standard deviation. The subscript i refers to the unit of analysis which is a firm in this study. The principal drawback of this technique making it unsuitable for our study is that any regression of abnormal stock returns on $y_{ij}$ would lead to effect sizes in terms of standard deviations which is not very intuitive. For instance, a one standard deviation increase in the innovation index score may lead to an increase of 0.5 standard deviations in abnormal stock returns. This is not easily comprehensible from an external stakeholder's perspective, and neither is it easy to visualize. Second, the technique produces negative values below the mean which also is not intuitive if one is observing the progression of index values over time.

iv. Rescaling (Min-Max) – This is a method of normalizing the range of all indicators between 0 and 1. To achieve this, maximum and minimum values of all indicators are identified. Then, the following formula is applied to each indicator.

$$y_{ij} = \frac{x_{ij} - \min_i(x_{ij})}{\max_i(x_{ij}) - \min_i(x_{ij})}$$

where i and j represent the unit of analysis (firm) and indicator respectively. There is a significant problem with this approach making it unsuitable for this study. The unsuitability emanates from the fact that $y_{ij}$ can take on zero values since all our basic indicators contain at least one zero value. A zero value implies that this technique cannot be used with the aggregation techniques suitable for formative models such as geometric and harmonic mean aggregation. Thus, we do not apply this technique for normalization.

v. Distance from a reference (Indicization) - Here, indicators are normalized by expressing them as a proportion of a reference value in percentage terms. This reference value is identified for each indicator either as an external benchmark or typically as the maximum value of each indicator. Thus, the maximum value of each indicator is normalized to take on a value of 100 and all other values of that indicator take on a proportion of this value of 100. The formula is shown below.

$$y_{ij} = \frac{x_{ij}}{x_{r_j}} 100$$

where $x_{r_j}$ in the denominator is the reference value for indicator j and $y_{ij}$ is the normalized value of indicator j with respect to unit i. In the absence of an external benchmark for each of our indicators, we have adopted the maximum value of each indicator as a reference. This is the normalization method that has been utilized for this study. We have three techniques available based on how the maximum value of each indicator is identified. In global standardization, the maximum value of each indicator was identified from the entire dataset, across firms and years. In yearly standardization, the maximum value of each indicator was identified year-wise considering all firms in that year. In firm-specific standardization, the maximum value of each indicator was identified firm-wise for all years that data is collected for that firm. We have adopted the global and yearly standardization techniques as part of this normalization method. This method of normalization is suitable for both bounded and unbounded indicators (Mazziotta & Pareto, 2017). Bounded indicators have values that are fixed within a range whereas unbounded indicators do not have a limit on the upper or maximum value. We note that our eight basic indicators are unbounded which means that they can take on any maximum value depending on the innovation outcome reported by the firm. Later, we will assess results of this method by conducting a sensitivity and robustness analysis. A significant advantage of this normalization method is that it does not confine the end user to use only the maximum values present in their sample. In this method, the user is free to use a suitable external benchmark should the opportunity arise.

<u>Weighting of the Normalized Indicators</u>

We select the importance to be given to each indicator in terms of weights assigned based on the theoretical framework of the study (Mazziotta & Pareto, 2017). The theoretical framework of this study, based on our review of literature and the OECD/Eurostat (2005) dimensions does not suggest that one aspect of innovation be given higher important over another. On the contrary, our theoretical framework stresses the unitary or unified nature of the innovation process which originates at the input stage and ends with a final output (good or service) via a throughput (or conversion) transformation. From the outset, it has been stressed in this study that firm-level innovation activity ought to be viewed and measured holistically considering all aspects of our framework. For these reasons, we do not define explicit weighting to any of our indicators. In practice, this implies that we apply equal weighting to each our basic indicators when developing the input, throughput, output, and organizational innovation (firm wide) variables. Then, when these four sub-indices are aggregated into the final innovation outcome score, we apply equal weights to each of these sub-indices. To illustrate how equal weighting was applied, the reader is referred to Figure 8. Our choice of no explicit weighting (equal weighting) is in line with the assertion of Booysen (2002) that in the absence of significant empirical evidence in prior literature or of solid theoretical grounding, equal weighting ought to be the norm and the burden of proof or justification should fall on differential weighting.

<u>Aggregation of the Weighted Indicators</u>

Once basic indicators have been normalized using an appropriate technique, the next step in composite index construction is to combine those indicator values in such a way as to obtain an aggregate final number which represents the volume of innovation outcomes in a firm. Earlier it was stated that the choice of aggregation technique is determined by the nature of the measurement model. As discussed, two kinds of measurement models exist – reflective and formative. Formative models are those wherein the basic indicators cause the composite construct and in reflective models, the latent construct causes the basic indicators. In other words, basic indicators 'form' the composite construct in formative models where as they 'reflect' the latent construct in reflective models. It was also explained previously that the theoretical framework for this study is a formative model. Since indicators in formative models explain differing facets of the same latent construct, we consider each indicator of a formative model to be indispensable to the theoretical framework. For instance, if we were to dispense away with the throughput aspect and its basic indicators from our theoretical framework, this would leave us with an incomplete definition of the innovation conversion process. The innovation conversion process is only a complete definition of innovation as a process when it is comprised of three stages – input -> throughput -> output. Thus, we may state that indicators in a formative model are non-substitutable.

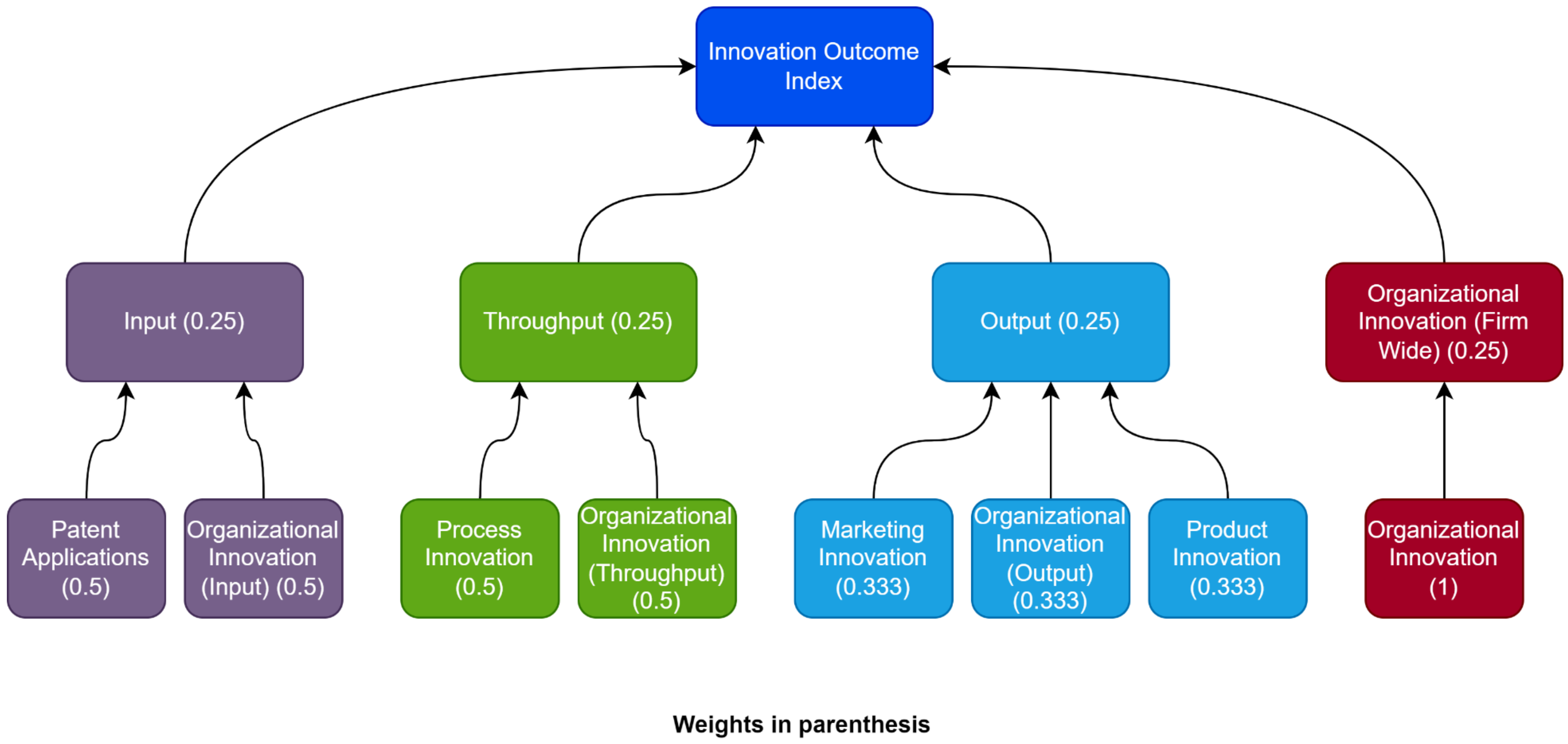


**Figure 8 – Equal Weighting**

Non-substitutability not only implies low correlation among indicators of a formative model but also that a high value in one indicator cannot offset a corresponding low value in another. In the context of our theoretical framework, this implies that a firm is not necessarily depicting high innovation activity if it only does a significant amount of patenting at the input stage but undertakes little process innovation at the throughput and product innovation at the output stages. In such a scenario, our aggregation technique must be such that the final innovation score is downward penalized for a low score at the throughput and output stages. Using different terminology, we restate the point that in formative models a deficit in one or more indicators may not be compensated for by a higher than usual score in another indicator. Thus, for formative models, we require a non-compensatory or partially compensatory approach to aggregation – one that penalizes any unbalance between the scores of constituent indicators (Mazziotta & Pareto, 2017). Our choice of aggregation function comes down to three techniques that utilize partial compensation to no compensation given the formative nature of our theoretical framework[3]. These techniques are applicable to composite indices that are positive – increasing values of the index correspond to an improvement in the phenomenon. For positive indices, a downward penalization must be applied wherein higher values in one or more indicator scores are penalized downwards to balance out the difference between constituent indicator scores.

i. In a non-compensatory approach with maximum downward penalization intensity, a minimum aggregation function is utilized that assigns the lowest possible value amongst all of the basic indicators as the final index score. Thus, any values higher than the lowest value have no effect upon the index score. Mathematically,

$$\text{Composite Index Score} = \min_{j}\left(y_{ij}\right)$$

This technique is not suitable for the purposes of this study because at least one observation over a multi-year period for all eight of our basic indicators

[3] See Table 7.3 on page 175 of Mazziotta & Pareto (2017) for a discussion on the aggregation functions available for formative and reflective measurement models.

corresponds to 0. This would mean that all firms across all years would receive the lowest possible composite index score of 0. This is meaningless as such a technique yields no discriminant ability at all to distinguish firms of varying innovation outcome levels. Further, this technique also does not offer any possibility of predictive power when regressing abnormal stock returns upon the composite index.

ii. In a partially compensatory approach with high downward penalization intensity, a harmonic mean aggregation function is utilized. Mathematically,

$$\text{Composite Index Score} = \left(\sum_{j=1}^{m} \frac{w_j}{y_{ij}}\right)^{-1}$$

where m denotes the number of indicators, $w_j$ denotes the weight of indicator j and $y_{ij}$ denotes the value of indicator j for unit i. This is one of the two techniques that have been utilized for aggregation in this study. It is pointed out that a harmonic mean aggregation would be impossible if any of the $y_{ij}$ in the denominator were to take on a zero value. Since all of our basic indicators do contain zero values, we have substituted each zero value with a miniscule non-zero value of the order of 1/100$^{th}$. This is a common technique in composite index construction and 1/100$^{th}$ of the smallest value of 1 that each of our basic indicator takes introduces a negligible distortion in our overall results.

iii. In a partially compensatory approach with low downward penalization intensity, a geometric mean aggregation function is utilized. Mathematically,

$$\text{Composite Index Score} = \prod_{j=1}^{m} y_{ij}^{w_j}$$

where m denotes the number of indicators, $w_j$ denotes the weight of indicator j and $y_{ij}$ denotes the value of indicator j for unit i. This is the second of two techniques that have been utilized for aggregation in this study. Here, it is recognized that while geometric mean aggregation is possible with zero values of the basic indicators, in the interest of comparability and robustness and sensitivity analysis later on when comparing with the findings of the harmonic mean aggregation, we have retained the miniscule value of 1/100 for zero values of the basic indicators when performing this aggregation.

Validation of the Composite Index

Validating the composite innovation index is a crucial step to ensure that it not only adheres to theoretical underpinnings but also has empirical relevance and robustness. This process was split into three distinct but interconnected steps:

i. Formative Framework Assessment:
   The foundation of this study is rooted in the formative nature of the theoretical framework. Thus, the initial step was to reinforce this assumption empirically. A detailed correlation matrix of the eight basic indicators and the four sub-indices was computed. As anticipated, findings presented mildly negative to low correlations, aligning with the formative structure of the framework. This step emphasizes the independent contribution of each component, confirming that no single element unduly dominated or was redundant.

ii. External Validation:
   Formative models, by their very nature, present a unique challenge when it comes to validation. Unlike reflective models, where the latent construct determines the manifest indicators, in formative models, the manifest indicators drive or form the composite construct. This inherent characteristic implies that the usual internal consistency checks, such as Cronbach's alpha, which are grounded in the assumption of high inter-correlations amongst indicators, may not be directly applicable or meaningful. Given this, external validation becomes paramount for several reasons (Maggino, 2017a):

   a. Completeness of the Construct: While a formative model is built upon the premise that the manifest indicators collectively form the latent construct, it does not inherently ensure the comprehensiveness of these indicators. There might always be a potential omitted variable bias. By correlating the composite index with an external criterion that it should theoretically predict, we can infer the comprehensiveness and relevance of our chosen indicators.

b. Causal Directionality: One of the common criticisms of formative models is the potential for reverse causality – could it be that the latent construct is influencing the indicators rather than the other way around? External validation, especially when grounded in a well-established theoretical framework, provides evidence for the assumed direction of causation.

c. Real-world Relevance: Formative models, while rooted in theory, gain true merit when they can explain or predict real-world phenomena. The choice of juxtaposing the innovation index with abnormal stock returns roots the model in empirical reality, ensuring that this construct has tangible implications beyond mere theoretical relevance.

The choice of abnormal stock returns as an external criterion resonates deeply with the core of this study. Innovation, by its very definition, implies novelty, uniqueness, and value creation. When firms engage in innovation, they are expected to generate value, not just in terms of products or processes, but also in terms of financial outcomes. The stock market, a barometer of a firm's future value, responds to this value creation. Thus, a positive and significant relationship between the innovation index and abnormal stock returns affirms the robustness and relevance of this index.

In essence, while our innovation index's formative nature necessitates a different validation approach than traditionally employed for reflective models, the external validation using abnormal stock returns serves as a linchpin, bridging the theoretical underpinnings of this construct with empirical reality. It not only affirms the directionality and completeness of our model but also underscores its relevance in explaining and predicting real-world financial outcomes.

iii. Sensitivity Analysis:

To ensure that the innovation index isn’t a mere artifact of specific methodological choices but is robust across varied techniques, a sensitivity analysis was undertaken.

The variability in innovation index scores, firm rankings, and their bearing on abnormal stock returns under different aggregation techniques has been examined. Such an analysis fortifies confidence in the index's stability and reliability. While intentions are outlined here, comprehensive findings, detailed methodologies, and implications stemming from this analysis will be elaborated upon in subsequent sections.

### 4.2. Sample Description and Data Collection

To develop an index of innovation outcomes, an appropriate sample of firms is required to be identified. Since this study does not focus on a specific industrial sector, say the pharmaceutical sector, the sample upon which the index is to be constructed should be a representative sample of all industrial sectors of the chosen economy.

For the purposes of this study, an appropriate sample was drawn from publicly listed firms on US stock exchanges. There are a few reasons as to why the stock market environment of the United States was chosen. NYSE and NASDAQ, the two major stock exchanges in the US, together, account for nearly $37 trillion USD of market capitalization (Szmigiera, 2020) making them the largest stock exchanges in the world. In a study that ranked 25 equity markets across the world (Siow & Aitken, 2003) upon market efficiency and integrity collectively, the New York Stock Exchange ranked only next to the Deutsch Borse. In the same study, the NYSE was rated the highest upon market efficiency alone. Lim (2007), in a ranking of stock market efficiency of thirteen countries, found the US stock market to be the most efficient. Tiwari et. al (2019), in an examination of ten countries for stock market efficiency, found the United States to be ranked fourth and fifth over the short and long term respectively. Since a critical aspect of index construction for this study is external validation of the index upon abnormal stock returns, an efficient stock market implies that stock prices faithfully reflect information including any innovation activity. An efficient stock market implies reduced noise that can make it easier to detect a genuine effect of the innovation index upon stock returns. For those using the innovation index, knowing that the sample firms are sourced from an efficient stock exchange instils greater confidence in the validity of the index. This is especially true for external stakeholders such as investors, business managers of supplier and partner firms, and academic researchers who value data from reliable sources. Moreover, an efficient stock market environment incentivizes firms to be forthcoming about their innovation activities publicly in the knowledge that any innovation milestones and success would be taken note by stock market participants and other stakeholders. Efficient stock markets foster informed and sophisticated investors – those that demand detailed information as a precondition for investing.

A stratified random sample with proportional allocation (Lohr, 2019) was drawn from the population of S&P 500 firms. The S&P 500 index includes the leading 500 US companies that represent approximately 80% of the total stock market capitalization. Firm population was finalized according to these criteria –

a. A firm should have been on the S&P 500 list of firms as of 31st Dec 2009. We deliberately choose the date of inclusion into the S&P 500 list prior to the date of actual data collection. This is done to avoid selection bias.
b. A firm should have had an unbroken share price history from 1st January 2008 till 31st December 2021. These dates were chosen so as to shield the period of analysis (2010 to 2019) from undue extraneous influence.
c. A firm should not have filed for bankruptcy protection from 1st January 2008 till 31st December 2021. This condition was imposed to shield the period of analysis from an extreme event that disrupts the ordinary working of the firm.
d. A firm should not have split into two distinct publicly traded firms from 1st January 2010 to 31st December 2020. This condition was imposed to avoid the ambiguity associated with selecting the firm that more closely resembles the parent entity.

After applying these criteria, 356 firms constituted the population set.

Firms listed on US stock exchanges can be divided into ten industrial sectors according to the Global Industry Classification Standard (GICS). Each firm on the population set was categorized into an appropriate GICS sector. Once firms were classified, the next step was to finalize the number of firms that were to be selected for each sector of the sample. Our sample of firms must be in the same approximate proportion as the number of firms in each industrial sector at the population level. In Table 2, the distribution of the population across GICS sectors is depicted. Table 2 also shows the number of firms that were sampled for each sector. With the exception of communication services which is over-represented by one firm in the sample since the total number of firms in the population set for communication services is only three, the remaining nine sectors are represented by numbers that are in approximate proportion to their actual number in the population set. Thus, out of a population of 356 firms, thirty-four firms were drawn. In a stratified random sample with proportional allocation, the population is divided into strata in the same proportion as the presence of strata in the population. The strata, in our case, are the ten GICS sectors. Firms are then randomly chosen within each stratum and the chosen firm is removed from the sample for subsequent drawing.

**Table 2 – Distribution of the population of firms across GICS sectors**

| GICS Sector | Population of Firms | Percentage of Firms | Sample of Firms |
|---|---|---|---|
| Communication Services | 3 | 0.8 | 2 |
| Consumer Discretionary | 59 | 16.6 | 6 |
| Consumer Staples | 26 | 7.3 | 2 |
| Energy | 22 | 6.2 | 2 |
| Financials | 68 | 19.1 | 6 |
| Health Care | 33 | 9.3 | 4 |
| Industrials | 52 | 14.6 | 4 |
| Information Technology | 47 | 13.2 | 4 |
| Materials | 21 | 5.9 | 2 |
| Utilities | 25 | 7.02 | 2 |

We note that these thirty-four sampled firms represent approximately 10% of the population.

The sampling strategy adopted has a few advantages. Because we are developing an index of innovation outcomes that is meant to be applicable to any commercial firm irrespective of the industrial sector it is classified into, it is only sensible for us to construct the index on a sample of firms that are representative of all sectors. Further, when we assess the impact of this innovation index on stock returns in panel data regressions as part of external validation, we can confidently assert that our findings are generalizable to the population.

Given the intricacies of data collection and analysis, especially with the vast scope of firms within the S&P 500, a pragmatic approach to sampling was imperative. While it was essential to maintain the rigorousness and representativeness of our sample, practical considerations also played a significant role in determining the sampling rate. After a thorough assessment, a proportional figure of 10% was chosen for the following reasons.

Statistical Robustness: In statistical terms, a 10% sampling rate from such a significant population as the S&P 500 is quite substantial. It provides a balance between ensuring a sizeable representation from each sector while still being manageable in terms of data collection and analysis.

Resource and Time Efficiency: The sheer number of firms within the S&P 500 implies a colossal amount of data to process and analyse. A 10% sampling rate ensures that the study remains comprehensive without becoming unwieldy or overextending the available resources.

Broad Representation: While aiming for a higher sampling rate might provide a more granular view, the 10% sample still offers a broad and representative cross-section of the firms, making the findings generalizable and applicable across sectors.

Data Collection

The sources of data for this study include annual reports, corporate responsibility and ESG reports, official web pages, and official press releases. Press releases were either identified on the official website of the firm or on two press release aggregator websites – PRNewsWire.com and BusinessWire.com. Patent application information was collected from PatentsView.org which is an intellectual property data dissemination and visualization platform supported by the U.S. Patent & Trademark Office (USPTO).

Data was collected for a 10-year period from 2010 to 2019.

Given the objective of this index, data sources are deemed appropriate and relevant to this index construction on the principle of "fitness for purpose." In academic literature, there have been criticisms levelled at the construction of composite innovation indices based on publicly available data when the primary purpose of such studies is to produce firm-level innovation rankings where there could be presence of significant self-selection bias in what information is being reported in firm publications (OECD / Eurostat, 2018). For instance, firms have every incentive to include only successful innovation activities and not those that did not result in an actual innovation. Further, firms may not like to report low-quality or minor innovations owing to publishing space constraints but only those that are highly visible and impactful. As such, even though this study relies on public information, these criticisms are not applicable to this study for the following reasons.

The primary purpose of this study is not to produce innovation rankings of firms from year to year. Our purpose here is, simply, to provide the firm stakeholder a tool to quantify the level of innovation outcomes depicted by a firm over a selected period. Do we claim that the firm is necessarily reporting all innovation outcomes that took place from selected data sources? Certainly not. But we are stating that the tool provided in this study does provide for a way to measure the innovation outcomes achieved by a firm *as reported by its management.* This should be no different than if we were to step inside the firm and asked firm management to respond to a survey on its innovative activities. Moreover, notwithstanding constraints of publication space which are increasingly not a concern in the digital era of today, firms have every incentive to report each implemented innovation which is what this study intends to measure. Our focus in this study is not on failed or unsuccessful attempts at innovation but on those innovations that, by definition, are implemented. Neither is our concern in this study on the quality or another facet of innovation that is difficult to glean. It is conceivable that firms may not like to report innovations that are of low quality or may not like to categorize their innovations upon a quality gradient, thus making it difficult and highly unreliable to grade an innovation upon its quality based only on official records. This possibility is recognized in this study and, hence, we do not attempt to measure the quality of innovation, only the volume of innovation outcomes.

Also, for the purposes of this study, the identified data sources are reliable and of high quality because they pertain only to publicly listed firms that are subject to intense scrutiny and cross-verification making outright falsification of claims extremely unlikely. In this regard, the data collection sources of this study are superior to a survey-based method whose source could be anonymized firm personnel reporting on innovation inside their firm.

Table 3 lists the thirty-four firms of the S&P 500 sample along with their GICS sector. For the eight basic indicators that constitute our theoretical framework, 40097 observations were recorded for the years 2010 to 2019. The bulk of these observations were for patent applications totaling 37369. Product, marketing, process, and organizational (at various levels) innovations collectively constituted the remaining 2728 observations.

**Table 3 – Sample of Firms Classified According to GICS Sector**

| GICS Sector | Firm | Stock Ticker |
|---|---|---|
| Communication Services | American Tower | AMT |
| Communication Services | AT&T | T |
| Consumer Discretionary | McDonalds | MCD |
| Consumer Discretionary | Lennar | LEN |
| Consumer Discretionary | Expedia | EXPE |
| Consumer Discretionary | Nike | NKE |
| Consumer Discretionary | Harley Davidson | HOG |
| Consumer Discretionary | Genuine Parts | GPC |
| Consumer Staples | JM Smucker | SJM |
| Consumer Staples | Hershey Foods | HSY |
| Energy | ConocoPhillips | COP |
| Energy | Hess Corp | HES |
| Financials | HCP REIT | HCP |
| Financials | American International Group | AIG |
| Financials | Comerica | CMA |
| Financials | First Horizon National Corp | FHN |
| Financials | Huntington Bancshares | HBAN |
| Financials | Avalon Bay Communities | AVB |
| Health Care | Amgen | AMGN |

| | | |
|---|---|---|
| Health Care | Davita | DVA |
| Health Care | Biogen | BIIB |
| Health Care | Laboratory Corporation of America | LH |
| Industrials | Northrop Grumman | NTH |
| Industrials | Southwest Airlines | LUV |
| Industrials | Republic Services | RSG |
| Industrials | Paccar | PCAR |
| Information Technology | Micron Technology | MU |
| Information Technology | Amphenol | APH |
| Information Technology | KLA Corp | KLAC |
| Information Technology | Xerox | XRX |
| Materials | Ball Corp | BLL |
| Materials | Weyerhaeuser | WY |
| Utilities | Duke Energy | DUK |
| Utilities | Consolidated Edison | ED |

Patent application data was identified in total per firm per fiscal year. For example, AT&T applied for 647 patents in the year 2010. This information was directly obtained from the website PatentsView.org. For all other basic indicators, each observation was recorded in an excel file along with the fiscal year, firm name, source of the observation and the appropriate type. For instance, in 2017, AT&T introduced a new IoT (internet of things) analytics solution. This observation was appropriately classified as a product innovation, per definition, obtained from an AT&T press release page on its official website and recorded accordingly. Each innovation observed was classified into an appropriate basic indicator only after a deliberative process. This deliberation included justifying how and why the observed innovation fit into an appropriate basic indicator category per the definition of that basic indicator. Actual instances of product, marketing and organizational innovations at the output stage are presented with a description of why the selected innovation was classified as such (Table 4).

**Table 4 - Product, Marketing, & Organizational Innovations at the Output Stage**

| Firm | Year | Innovation | Description |
|---|---|---|---|
| Product Innovations | | | |
| Northrop Grumman | 2010 | Northrop Grumman Delivers Critical Global Hawk Sensor to the U.S. Air Force | This is an example of a product innovation that pertains to the introduction of a new type of sensor for the Global Hawk aircraft |
| Nike | 2018 | Nike Vision Introduces Cutting-Edge Hyperforce Sunglasses Designed for Baseball & Training | A product innovation that introduces a new kind of sunglasses with cutting edge lens technology |
| Weyerhaeuser | 2010 | Weyerhaeuser Introduces Pro Series™ Lumber | A lumber board manufactured with proprietary technology that is also treated with a mold inhibitor |
| Southwest Airlines | 2010 | Southwest Airlines Introduces Mobile Site for Corporate Travelers | A service innovation that introduces a mobile version of Southwest's SWABiz.com corporate travel tool |
| Marketing Innovations | | | |
| Nike | 2018 | Nike Vision announces the release of the Fall 2017 SB Eyewear Collection. The collection is comprised of three new skate-inspired sunglass styles | A marketing innovation that involves significant changes in product design and opening a new market comprising action sports athletes |
| Southwest Airlines | 2018 | Southwest Airlines implemented a variable pricing model for EarlyBird Check-In based on the length of the flight and the historical popularity of | A marketing innovation that implements a new method involving significant changes in product pricing |

| | | | |
|---|---|---|---|
| | | EarlyBird Check-In on the route. | |
| McDonald’s | 2011 | McDonald’s “Mein Burger” campaign gave guests and fans in Germany the chance to create a burger online, thus enabling them to have a direct impact on the very heart of the McDonald’s brand – our products. | A marketing innovation that implements a new method involving significant changes in product promotion |
| Amgen | 2011 | World-Class Professional Golfer Phil Mickelson Launches 'On Course with Phil' for People with Certain Inflammatory Joint and Skin Conditions | A marketing innovation that implements a new method involving significant changes in product promotion |
| Organizational Innovations | | | |
| AT&T | 2016 | AT&T and HBO Reach Historic Multi-platform Programming Agreement | This is an instance of the implementation of a new organizational method involving external relations for AT&T at the output stage |
| Xerox | 2017 | Xerox Establishes Special Recognition for Managed Print Services-Savvy Channel Partners | In introducing a new accreditation program for channel partners, Xerox exhibits a new organizational method involving external relations at the output stage |
| Harley Davidson | 2011 | Retail2020 [being implemented in 2011], is a multi-year plan that keeps the Harley-Davidson dealer central to the experience. We’re re-engineering our retail capabilities—including every part of the customer experience—so every visit and interaction is premium, relevant and personal, every time | Retail2020 is implementation of new organizational methods in Harley’s business practices, workplace organization, and external relations at the output stage |
| Southwest Airlines | 2012 | We released an all-new Customer Experience Survey and Dashboard to help us understand our Customers’ travel experience with Southwest. We email a survey to 16,000 Customers the day following their flight and ask them to rate their satisfaction at each point of the travel experience, including Checkin, TSA Security, Gate Area, Inflight, Connection, and Arrival. The survey also asks the likelihood to recommend Southwest to friends, family, or colleagues. This is also known as the Net Promoter Score (NPS). | Southwest implements a new organizational tool that that is an improved method in external relations at the output stage |

Table 5 presents process and organizational innovations at the throughput stage with a description of why that innovation outcome was classified as such. Table 6 presents organizational innovations at the input stage and Table 7 presents organizational innovations that encompass the entirety of the theoretical framework, i.e. they cut across input, throughput, and output stages.

What is not an innovation?

It is also imperative, at this juncture, to discuss what changes were not considered innovations (OECD/Eurostat, 2005).

1. Discontinuing a process, organizational, or marketing method even if it results in an improvement in the firm's performance is not an innovation. Similarly, discontinuing to market or produce a product is not an innovation.
2. Routine, minor, and standardized updates to existing equipment or software are not considered process innovations. Similarly, replacement of existing equipment with new identical models are also not process innovations.
3. Changes in factor prices that result in a decrease in the price of goods or services sold or a decrease in unit costs are not considered innovations.
4. Custom orders that may be single and complex in their own right are not considered product innovations unless they are markedly different in attributes from products that the firm has previously made.
5. Seasonal or cyclical changes to goods or services in appearance or design are not considered either marketing or product innovations. For instance, routine changes in design to a clothing line of jackets for the coming season would not be considered a marketing or product innovation unless the jackets incorporate new features that enhance functionality or incorporate a fundamental change in product design that is part of a new marketing perspective.
6. For firms that handle goods and materials as well as those in the retailing, wholesaling, and distribution of goods, the introduction of a new good in their inventory is not a product innovation. However, if the firm introduces a new line or category of goods then it would be considered a product (service) innovation.

**Table 5 - Process and Organizational Innovations at the Throughput Stage**

| Firm | Year | Innovation | Description |
|---|---|---|---|
| Process Innovations | | | |
| Northrop Grumman | 2010 | Northrop Grumman Delivers Critical Global Hawk Sensor to the U.S. Air Force | This is an example of a product innovation that pertains to the introduction of a new type of sensor for the Global Hawk aircraft |
| Nike | 2018 | Nike Vision Introduces Cutting-Edge Hyperforce Sunglasses Designed for Baseball & Training | A product innovation that introduces a new kind of sunglasses with cutting edge lens technology |
| Weyerhaeuser | 2010 | Weyerhaeuser Introduces Pro Series™ Lumber | A lumber board manufactured with proprietary technology that is also treated with a mold inhibitor |
| Southwest Airlines | 2010 | Southwest Airlines Introduces Mobile Site for Corporate Travelers | A service innovation that introduces a mobile version of Southwest's SWABiz.com corporate travel tool |
| Organizational Innovations | | | |
| Northrop Grumman | 2016 | We established a Supply Chain Risk Management governance and operating model using 20 characteristics to collectively monitor and manage risks | An implementation of a new organizational method in the firm's business practices at the throughput stage |

| | | | |
|---|---|---|---|
| JM Smucker | 2014 | We began working with the Neumann Foundation in Indonesia. Here, we are collaborating on a direct outreach project to smallholder coffee producers in the mountain regions of southern Sumatra. Indonesia is a significant producer of coffee but is challenged by extremely low yields that often result in difficult economic, social, and environmental conditions. | An implementation of a new organizational method in the firm's business practices and external relations at the sourcing or throughput stage |
| Micron Technology | 2018 | Micron implemented a training program that focused on responsibilities and expectations for our suppliers, and more than 1,100 supplier representatives were trained. | An implementation of a new organizational method in the firm's business practices and external relations at the throughput stage |
| AIG | 2010 | As part of AIG's enhanced enterprise risk management framework, Chartis hired a Chief Risk Officer, created Senior ERM teams in Chartis U.S. and each of its Chartis International regions, enhanced its risk procedures and implemented an improved ERM framework. | An implementation of a new organizational method in the firm's business practices and workplace organization at the throughput stage |

**Table 6 - Organizational Innovations at the Input Stage**

| Firm | Year | Innovation | Description |
|---|---|---|---|
| Amgen | 2010 | Amgen began a Green Chemistry program in selected research areas. With this heightened environmental awareness, Amgen scientists have been finding ways to use safer chemicals, less energy, and more efficient practices | An implementation of a new organizational method in the firm's business practices and workplace organization at the input level |
| AT&T | 2010 | AT&T developed a collaborative program that includes “fast-pitch” sessions — a kind of tech innovation speed-dating — to evaluate ideas | An implementation of a new organizational method in the firm's business practices and external relations at the input level |
| Expedia | 2016 | Expedia Debuts New Expedia Labs Showcase for Developers | An implementation of an organizational innovation in the firm's business practices and external relations at the input level that showcases experimental and technological concepts built within Expedia or through collaborations |
| Harley-Davidson | 2018 | Harley-Davidson Creates New Advanced Technology R&D Facility in Silicon Valley | An implementation of an organizational innovation in the firm's workplace organization and business practices at the input level |

### Table 7 - Organizational Innovations that Span Entirety of the Theoretical Framework

| Firm | Year | Innovation | Description |
| --- | --- | --- | --- |
| ConocoPhillips | 2016 | We updated our human rights training module which reviews the company's position on respecting human rights, the importance to our business and our approach to managing human rights issues. It includes education on issues related to indigenous peoples, cultural awareness, labor standards risk, and risks associated with security and human rights. | An implementation of a new organizational method in the firm's business practices and external relations at all stages of the innovation conversion process |
| Duke Energy | 2016 | We updated and expanded our stakeholder engagement tools and deployed them companywide. We also created an External Relations Council comprised of company leaders to improve coordination and alignment of stakeholder interactions at the national, state, and local levels. | An implementation of a new organizational method in the firm's business practices and external relations company wide encompassing all stages of the innovation conversion process |
| McDonald's | 2012 | The Company implemented a new organizational structure for CSR & Sustainability to improve alignment, decision-making and integration with core business strategies and initiatives. Advised by McDonald's Global Sustainability Council, our new organization includes various groups working on key elements of our CSR & Sustainability strategy | An implementation of an organizational innovation in the firm's workplace organization applicable company wide |
| Weyerhaeuser | 2016 | The company's chief operating decision maker changed the information regularly reviewed for making decisions to allocate resources and assess performance. As a result, the company will report its financial performance based on three business segments: Timberlands; Real Estate, Energy and Natural Resources (Real Estate & ENR); Wood Products. | An implementation of an organizational innovation in the firm's business practices applicable company wide |

Distinguishing Innovation Types

There can appear borderline observations that may appear to fit into more than one category of innovation. In such cases, this study has either deliberated in sufficient depth as to ascertain the category that an observation was under, or multiple aspects of the observation were categorized into separate categories when warranted. In all cases, the definitions of each type and guidelines for distinguishing between innovation types as provided in the Oslo Manual (OECD/Eurostat, 2005) were followed. These guidelines are discussed further.

Product and Process Innovations: Ambiguities between product and process innovations typically arise in the case of services (as opposed to physical goods) when the consumption, distribution, and production of services appear to occur simultaneously as, for instance, a restaurant offering a meal that has been freshly prepared. In such cases, if the improvements or new additions pertain to characteristics of the service offered to customers, then it is a product innovation. However, if the changes pertain to techniques, equipment, or human skills needed to implement or perform the service, it is a process innovation. It is possible that in a service innovation, characteristics of both product and process innovation are present. In such cases, categorization is done in both.

Product (Goods) and Marketing Innovations: Innovations pertaining to the product's intended functionality or use are product innovations. However, innovations pertaining to the product's appearance or design or packaging that do not alter the functional or usage features of the product are marketing innovations. For instance, changes in apparel intended to improve functionality such as breathability, wrinkle-free usage, or waterproof characteristics pertain to product innovations. However, changes in design such as new shapes for a niche segment of customers, or characteristics that make the apparel look more exclusive is a marketing innovation.

Product (Service) and Marketing Innovations: The distinction between service innovation and marketing innovation depends upon whether the innovation pertains to a service or a marketing method. This is generally straightforward to ascertain by identifying the service offering of the firm. For instance, a firm that primarily sells electronic goods would be engaged in marketing innovation if it starts to sell its goods online after creating a website by opening up a new sales channel (eCommerce). However, a firm that offers eCommerce services such as Amazon would be making a product (service) innovation if it significantly revamps its website for additional end user functionality.

Process and Marketing Innovations: Both forms of innovations can involve improvements in the movement of information and goods, but their end purposes differ. Process innovations aim at decreasing costs or improving product quality by utilizing production or delivery methods. Marketing innovation aim to increase sales or market share through changes in product positioning or promotion or packaging.

Process and Organisational Innovations: While the purpose of both process and organisational innovations can be to improve efficiencies, process innovations involve production and supply methods whereas organisational innovations involve "business practices, external relations, and workplace organization" (OECD/Eurostat, 2005: 55). In simpler terms, process innovations deal with new software, equipment, methods, and procedures whereas organisational innovations deal with people and their organisation at work. Innovations can contain features of both and in that case the relevant parts were included in each category.

Marketing and Organisational Innovations: Organisational innovations may involve the sales function such as a better integration between sales and public relations or between sales and other management structures. However, as long as the sales function itself does not depict a marketing innovation, per definition, it would only constitute an organisational innovation. Again, innovations may incorporate elements of both marketing and organizational innovations and in such instances each aspect of the innovation was classified in the appropriate category.

## 4.3. Panel Data Regression Methodology

Once the innovation index was created, it was subject to panel data regressions along with other control variables. Specifically, abnormal stock returns were regressed on the innovation index to assess the effect size and direction of the index.

Data that comprises of cross-sectional units (firms) repeatedly measured over a period is termed longitudinal or panel data (Frees, 2004). Because panel data consists of both cross-sectional and time series elements, there are certain advantages that such data forms possess over pure cross-sectional or time series forms (Frees, 2004). Panel data analysis permits us to model and control for heterogeneity amongst firms without necessarily losing the observations of those firms (Baltagi, 2008). In contrast to cross-sectional models, panel data models can control for unobserved, time invariant, firm-specific effects leading to greater accuracy in variability estimates as well as inferences (Frees 2004: 22). Because each firm in our sample has the same number of time observations (ten years), we classify our data as a balanced panel as opposed to an unbalanced panel (Frees, 2004). Further, our data set is classified a short panel with fewer time observations (T=10) and more cross-sectional units (N=34) as opposed to a long panel (Colin & Trivedi, 2009: 230) and because the same set of cross-sectional units (firms) has been measured repeatedly, our data is classified a fixed panel as opposed to a rotating panel (Greene, 2008: 184).

Panel data regressions were employed using the generalized least squares method (GLS) and mixed effect models were fitted as appropriate. The mixed effect models were random in the cross-sectional dimension and fixed in the period dimension. The random effects in the cross-sectional dimension assume that firm-specific effects are uncorrelated with the explanatory variables meaning that any effect (like industry, location) is treated as a random variable that is uncorrelated with the other variables in the model and controlled for in the error term. This allows the model to generalize the findings to a larger population of firms. The fixed effects in the period dimension would control for any time-specific effects that are common to all firms, such as changes in market trends, regulatory changes, technological advancements.

A panel data regression can provide insights into longer term trends, controls for unobserved heterogeneity, thereby, reducing bias, confounding effects, and making it easier to make causal inferences. Panel data also provides more data variation, more degrees of freedom, and more efficiency than cross-sectional or time series data. The mixed effect model may be represented as –

$$\textbf{Abnormal-Stock-Return}_{it} = \beta_0 + \gamma_t + \beta_1\textbf{InnovationIndex}_{it} + \beta_2\textbf{ControlVariables}_{it} + \beta_3\textbf{ControlVariables}_{it-1} + \alpha_i + \mu_{it} \qquad \textbf{(1)}$$

In (1), $\alpha_i$ is the random effect in the cross-sectional dimension which is part of the error term and $\delta_t$ is the fixed effect, which is part of the intercept. A mixed effects model, to be valid, must satisfy certain assumptions (Wooldridge, 2018: 491).

These assumptions (Wooldridge, 2018: 491) are stated as follows.

1. Our first assumption is simply the assumption of the presence of $\boldsymbol{\alpha_i}$ as in (1) with the general model of the form (1). This is not an unreasonable assumption to make in the context of assessing the impact of the innovation index upon abnormal stock returns. The presence of $\alpha_i$ assumed to be uncorrelated with the explanatory variables implies only the presence of factors that change from firm to firm, remain constant over time, but may impact abnormal stock returns. These could include firm specific characteristics such as the quality of its corporate governance, company culture, brand strength and reputation, after-sales service or quality, etc.

2. We assume a random cross-section of selected firms. We have drawn a stratified random sample of 34 firms from a population of 356 firms, thereby, meeting this assumption.

3. We assume that the explanatory variables do not take on all zero values for every firm in our sample. That is, there should be some non-zero values present for a few firms, if not all. We also assume that perfect collinearity does not exist for explanatory variables in our analyses. To assess for collinearity in our variables, a correlational matrix was computed and is presented in Appendix 1. The innovation index variable is the one computed using the harmonic mean aggregation with Indicization normalization (global standardization). We note from Appendix 1 the presence of mild to negative collinearity amongst the variables.

4. In (1), we assume that the idiosyncratic error, $\mu_{it}$, is uncorrelated with the explanatory variables for all firms and in each period. We refer to this assumption as the "strictly exogenous" condition applied to all explanatory variables. Further, for a mixed effects model that is random in the cross-section (firm), we assume $\alpha_i$ is part of the idiosyncratic error and uncorrelated with the explanatory variables. In Appendix 2, we establish that the innovation index variable is uncorrelated with the idiosyncratic error, $\mu_{it}$ using the instrumental variable approach.

5. We assume homoskedasticity (equal variances) for idiosyncratic errors $\mu_{it}$.

6. We assume serial uncorrelation (across time) between the idiosyncratic errors for each cross-section (firm i).

The five factor, Fama-French model was selected for the control variables (Fama & French, 2015). The selected factors are firm size, operating profitability, book-to-market equity, and investment. These factors were deemed appropriate as control variables because this model is an empirically well-established asset pricing model with representation of both objective and subjective risk, and we expect an independent impact of these variables on abnormal stock returns at firm level. Our dependent variable is abnormal share price returns which is computed as the difference of stock returns and market return at the end of the fiscal year. To determine market return, it was also required to obtain an overall, US stock market return for each firm fiscal year. Market return is the return that an investor would obtain if they were to hold the entire range of stocks available in the market as a portfolio (Brealey, Myers, and Allen, 2020). The Russell 3000® Index was selected as an appropriate proxy for the market portfolio because it is a broad market-based index that consists of 3000 of the biggest US publicly traded companies representing 97% of the US stock market. Table 8 lists the control, explanatory, and dependent variables.

Control variables were introduced at both time 't' and 't-1' to capture both contemporaneous and lagged effects on the dependent variable. Such incorporation is pivotal in controlling for the multifaceted temporal influences characteristic of control variables in panel data. The issue of multicollinearity between some lagged control variables was addressed by employing first differencing. To mitigate potential heteroskedasticity in the model, the natural logarithm transformation was applied to all control variables. Robust standard errors were computed and clustered by unit to further address heteroskedasticity and autocorrelation in the model.

**Table 8 – Panel Data Regression Variables**

| Variable | Type | Description |
|---|---|---|
| Abnormal Stock Return | Dependent | Calculated as the difference between the stock return and the market return |
| Size | Control | Calculated as the product of share price and number of shares outstanding |
| Book to Market Equity (B/M) | Control | Calculated as the ratio of the Book Value of Equity to the Market Value of Equity |
| Operating Profitability | Control | Calculated as the ratio of Annual Revenues minus (Cost of Sales, Interest expense, and selling, general, and administrative expenses) to Book Value of Equity |
| Investment | Control | Calculated as the change in total assets from the preceding year |
| Innovation Index | Explanatory | The composite innovation outcome score obtained by a firm |

Such transformations can assist in stabilizing variances across entities, ensuring more consistent and reliable coefficient estimates. First differences of 'Book to Market Equity' and natural log of 'Size' were computed to address multicollinearity with their lags. The model's suitability was also ascertained using information criteria such as the Akaike Criterion and others. Further validation was obtained through the Pesaran CD test and the Hausman test, ensuring that the selected model was both cross-sectionally independent and appropriate to use for random effects in the cross-sectional (firm) dimension.

## 5. Results

### 5.1. Index Scores

Index scores are presented for the method utilizing Indicization normalization and Harmonic mean aggregation. Two sets of results are presented. The first set of results is based on a global standardization method wherein the Indicization normalization is applied to the entire sample across firms and years treating it as a unified data set. The second set of results is based on a yearly standardization method wherein the Indicization normalization is applied to the sample of firms each year. Global standardization is applicable when a firm's innovation outcome is required to be compared to other firms over the entire period. This could be especially useful for investors looking to understand a firm's innovation performance in the broader context of its historical performance and that of its competitors. It might be particularly useful for long-term investment strategies. Yearly standardization, on the other hand, contextualizes a firm's innovation outcomes within a given year, providing insights into annual fluctuations, trends, or sudden changes in innovation activity. It may be more useful for business managers who want to assess how their firm performed relative to competitors in a specific year. For short-term traders or investors, this might provide more actionable insights.

Year wise index scores are presented for the thirty-four firms in our sample. Table 9 presents scores utilizing global standardization and Table 10 presents them utilizing yearly standardization. Rankings for the top 5 firms each year are given in parentheses besides the index score.

From Table 9, we draw some immediate conclusions. Three firms have been in the top 5 for the greatest number of years – eight years for Nike and six years each for Northrop Grumman and AT&T. While Nike is in the 'Consumer discretionary' industrial sector, Northrop Grumman is in the 'Industrials' and AT&T is in the 'Communication Services' sector. Nike's highest innovation index score across the years has been 3.994 in year 2017 while Northrop's highest score was 0.528 in the year 2010.

## Table 9 – Innovation Index Scores (Global Standardization)

| Firm | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|
| AIG | 0.166 | 0.091 | 0.004 | 0.097 | 0.167 | 0.154 | 0.258 | **0.628 (2)** | **0.499 (4)** | 0.168 |
| American Tower | 0.065 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Amgen | **0.980 (1)** | **0.661 (3)** | 0.119 | 0.105 | **0.194 (5)** | 0.111 | 0.266 | 0.158 | 0.186 | 0.105 |
| Amphenol | 0.104 | 0.103 | 0.182 | 0.119 | 0.176 | 0.104 | **0.368 (5)** | 0.176 | 0.370 | 0.374 |
| AT&T | 0.208 | **1.348 (2)** | 0.120 | 0.106 | **0.225 (3)** | **1.049 (1)** | **5.077 (1)** | 0.225 | **0.688 (2)** | **1.051 (1)** |
| Avalon Bay | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Ball Corp | **0.474 (5)** | 0.173 | **0.352 (3)** | **0.482 (2)** | 0.174 | 0.151 | 0.114 | 0.194 | 0.201 | 0.171 |
| Biogen | 0.110 | 0.104 | 0.078 | **0.447 (4)** | 0.188 | 0.176 | 0.362 | **0.369 (4)** | 0.104 | 0.152 |
| Comerica | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Conoco Philips | 0.169 | 0.102 | 0.168 | 0.102 | 0.130 | 0.168 | 0.193 | 0.191 | 0.185 | 0.167 |
| Consolidated Edison | 0.472 | 0.154 | **0.186 (5)** | 0.149 | **0.223 (4)** | 0.004 | 0.167 | 0.102 | 0.105 | 0.100 |
| DaVita | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Duke Energy | 0.004 | 0.004 | **0.280 (4)** | 0.004 | 0.099 | 0.097 | 0.129 | **0.303 (5)** | 0.104 | 0.091 |
| Expedia | 0.112 | 0.004 | 0.148 | 0.084 | 0.094 | 0.092 | 0.098 | 0.142 | 0.106 | 0.066 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| First Horizon | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Genuine Parts | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.144 | 0.004 | 0.004 |
| Harley Davidson | **0.522 (3)** | 0.259 | 0.112 | **0.249 (5)** | 0.168 | 0.105 | 0.215 | 0.226 | 0.257 | **0.629 (3)** |
| Healthpeak | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Hershey Foods | 0.189 | 0.111 | 0.074 | 0.127 | **0.601 (1)** | 0.168 | **0.752 (2)** | 0.154 | **0.582 (3)** | 0.364 |
| Hess Corporation | 0.167 | 0.004 | 0.004 | **0.469 (3)** | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Huntington | 0.004 | 0.092 | 0.126 | 0.004 | 0.004 | 0.004 | 0.066 | 0.252 | 0.111 | 0.193 |
| JM Smucker | 0.172 | 0.100 | 0.170 | 0.159 | 0.181 | 0.103 | 0.004 | 0.004 | **0.432 (5)** | 0.142 |
| KLA Corp | 0.105 | 0.105 | 0.105 | 0.106 | 0.106 | 0.106 | 0.106 | 0.107 | 0.173 | 0.105 |
| Lab Corp | 0.192 | 0.093 | 0.167 | 0.192 | **0.315 (2)** | **0.182 (5)** | 0.172 | 0.149 | 0.147 | 0.146 |
| Lennar | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| McDonalds | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Micron Technology | 0.178 | 0.120 | 0.106 | 0.106 | 0.106 | 0.154 | 0.106 | 0.154 | 0.115 | **0.719 (2)** |
| Nike | **0.519 (4)** | **1.353 (1)** | **4.552 (1)** | **0.732 (1)** | 0.178 | 0.170 | **0.535 (4)** | **3.994 (1)** | **1.354 (1)** | **0.525 (4)** |
| Northrop Grumman | **0.528 (2)** | **0.527 (4)** | **0.524 (2)** | 0.154 | 0.167 | **0.525 (2)** | 0.174 | **0.380 (3)** | 0.105 | **0.523 (5)** |
| Paccar | 0.221 | 0.175 | 0.104 | 0.178 | 0.130 | **0.220 (3)** | 0.218 | 0.223 | 0.120 | 0.176 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Republic Services | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 | 0.004 |
| Southwest Airlines | 0.365 | 0.138 | 0.004 | 0.248 | 0.098 | 0.004 | 0.004 | 0.004 | 0.104 | 0.256 |
| Weyerhaeuser | 0.104 | 0.101 | 0.113 | 0.079 | 0.100 | 0.094 | 0.128 | 0.004 | 0.004 | 0.004 |
| Xerox | 0.167 | **0.376 (5)** | 0.106 | 0.178 | 0.178 | **0.207 (4)** | **0.683 (3)** | 0.194 | 0.194 | 0.154 |

**Table 10 – Innovation Index Scores (Yearly Standardization)**

| Firm | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|---|---|---|---|
| AIG | 0.199 | 0.185 | 0.008 | 0.221 | 0.416 | 0.452 | **0.405 (5)** | **1.486 (2)** | **0.817 (4)** | 0.423 |
| American Tower | 0.082 | 0.008 | 0.008 | 0.008 | 0.008 | 0.007 | 0.007 | 0.008 | 0.005 | 0.004 |
| Amgen | **1.359 (1)** | **1.037 (4)** | 0.229 | 0.241 | 0.349 | 0.267 | **0.442 (4)** | 0.395 | 0.717 | 0.225 |
| Amphenol | 0.129 | 0.208 | **0.515 (5)** | 0.250 | 0.307 | 0.249 | 0.298 | 0.258 | 0.704 | 0.691 |
| AT&T | 0.219 | **2.994 (2)** | 0.230 | 0.242 | 0.337 | **1.675 (1)** | **9.836 (1)** | 0.323 | **1.175 (2)** | **1.383 (2)** |
| Avalon Bay | 0.008 | 0.008 | 0.008 | 0.009 | 0.008 | 0.007 | 0.007 | 0.008 | 0.006 | 0.004 |
| Ball Corp | 0.681 | 0.315 | **0.801 (3)** | **1.164 (3)** | 0.305 | 0.393 | 0.195 | 0.277 | 0.264 | 0.259 |
| Biogen | 0.133 | 0.210 | 0.171 | **1.416 (2)** | **0.569 (3)** | **0.508 (5)** | 0.296 | **0.712 (4)** | 0.203 | 0.442 |
| Comerica | 0.008 | 0.008 | 0.008 | 0.009 | 0.008 | 0.007 | 0.007 | 0.008 | 0.006 | 0.004 |
| Conoco Philips | 0.195 | 0.207 | 0.397 | 0.260 | 0.238 | 0.204 | 0.182 | 0.331 | 0.226 | 0.222 |
| Consolidated Edison | **0.795 (3)** | 0.286 | 0.449 | 0.291 | **0.518 (4)** | 0.007 | 0.281 | 0.191 | 0.126 | 0.186 |
| DaVita | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.007 | 0.007 | 0.008 | 0.006 | 0.004 |
| Duke Energy | 0.008 | 0.008 | **0.579 (4)** | 0.009 | 0.244 | 0.170 | 0.207 | **0.592 (5)** | 0.207 | 0.156 |
| Expedia | 0.141 | 0.008 | 0.240 | 0.192 | 0.196 | 0.220 | 0.212 | 0.229 | 0.194 | 0.101 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| First Horizon | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.007 | 0.007 | 0.008 | 0.005 | 0.004 |
| Genuine Parts | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.007 | 0.007 | 0.222 | 0.006 | 0.004 |
| Harley Davidson | **0.855 (2)** | 0.515 | 0.185 | 0.335 | 0.296 | 0.150 | 0.325 | 0.324 | 0.270 | **0.905 (5)** |
| Healthpeak | 0.008 | 0.008 | 0.008 | 0.009 | 0.008 | 0.007 | 0.007 | 0.008 | 0.005 | 0.004 |
| Hershey Foods | 0.231 | 0.206 | 0.160 | 0.350 | **1.227 (1)** | 0.479 | **1.443 (2)** | 0.234 | **0.962 (3)** | 0.442 |
| Hess Corporation | 0.210 | 0.009 | 0.008 | **1.132 (4)** | 0.008 | 0.007 | 0.007 | 0.008 | 0.006 | 0.004 |
| Huntington | 0.008 | 0.175 | 0.323 | 0.008 | 0.008 | 0.007 | 0.099 | 0.495 | 0.276 | 0.253 |
| JM Smucker | 0.198 | 0.202 | 0.266 | 0.272 | 0.306 | 0.243 | 0.008 | 0.008 | 0.691 | 0.172 |
| KLA Corp | 0.129 | 0.212 | 0.221 | 0.242 | 0.218 | 0.252 | 0.169 | 0.200 | **0.793 (5)** | 0.227 |
| Lab Corp | 0.329 | 0.189 | 0.282 | 0.435 | **0.752 (2)** | **0.551 (4)** | 0.194 | 0.367 | 0.484 | 0.363 |
| Lennar | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 | 0.007 | 0.007 | 0.008 | 0.006 | 0.004 |
| McDonalds | 0.008 | 0.009 | 0.008 | 0.009 | 0.008 | 0.008 | 0.008 | 0.008 | 0.006 | 0.004 |
| Micron Technology | 0.258 | 0.220 | 0.222 | 0.242 | 0.218 | 0.404 | 0.169 | 0.383 | 0.237 | **1.915 (1)** |
| Nike | **0.705 (5)** | **3.036 (1)** | **9.784 (1)** | **3.767 (1)** | 0.310 | 0.206 | 0.390 | **8.022 (1)** | **4.157 (1)** | **1.238 (4)** |
| Northrop Grumman | **0.733 (4)** | **2.037 (3)** | **1.266 (2)** | **0.526 (5)** | **0.506 (5)** | **0.901 (2)** | 0.291 | **0.738 (3)** | 0.206 | **1.260 (3)** |
| Paccar | 0.336 | 0.319 | 0.220 | 0.295 | 0.241 | 0.419 | 0.328 | 0.320 | 0.229 | 0.270 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Republic Services | 0.008 | 0.008 | 0.008 | 0.009 | 0.008 | 0.007 | 0.008 | 0.008 | 0.005 | 0.004 |
| Southwest Airlines | 0.654 | 0.239 | 0.008 | 0.472 | 0.175 | 0.007 | 0.007 | 0.008 | 0.191 | 0.373 |
| Weyerhaeuser | 0.129 | 0.205 | 0.239 | 0.166 | 0.246 | 0.162 | 0.206 | 0.008 | 0.005 | 0.004 |
| Xerox | 0.182 | **0.891 (5)** | 0.222 | 0.295 | 0.310 | **0.678 (3)** | **0.809 (3)** | 0.566 | 0.787 | 0.466 |

The firm with the highest ever innovation index score was AT&T with 5.077 in the year 2016. The lowest score that was obtained in this sample was 0.004 and more than one firm received it over the years. From Table 10, the firm that was in the first position for the greatest number of years was Nike followed by AT&T which is in the 'Communication services' sector.

A desirable condition for firms over a period is to exhibit a high mean innovation index score with a low variability indicating consistency in innovation outcomes. Based on the scores obtained in Table 9 (global standardization), a scatter plot with mean innovation index scores on the x axis and the variability (standard deviation) in scores on the y axis is depicted in Figure 9.

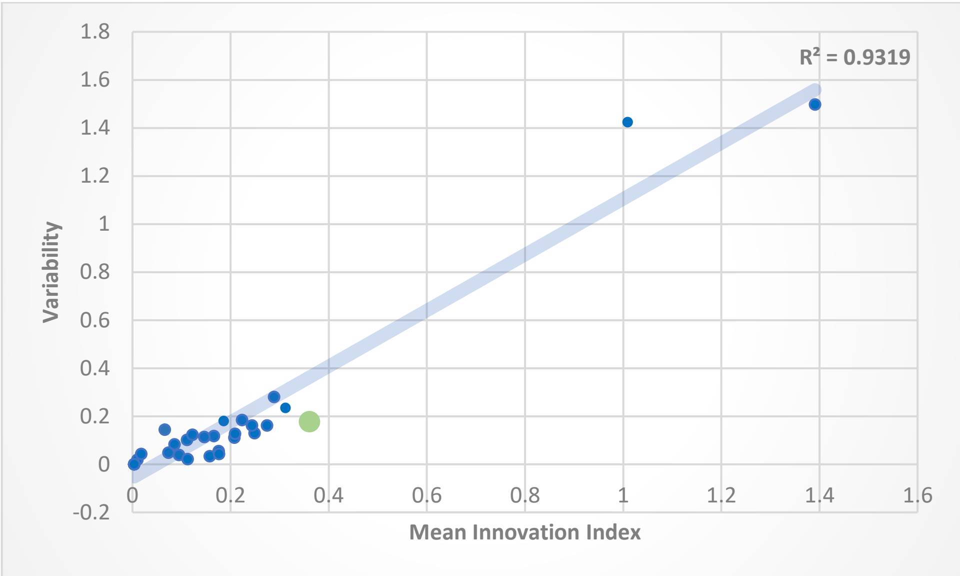


**Figure 9: Mean Index Scores & Variability (Global Standardization)**

A trendline fitted to the scatterplot in figure 9 reveals an $R^2$ value of 0.93. This suggests strong association and we may infer that as a firm increases its average innovation outcome level it also tends to increase the variability in its innovation outcomes. One firm marked in green bubble is highlighted in the scatterplot. This firm depicts medium levels of innovation outcomes at lower-than-average variability. The firm represented by the green bubble is Northrop Grumman. We noted earlier that Northrop Grumman was one of two firms along with Nike to have been in the top 5 position for six of ten years. We also note that the firm at the extreme right with the highest mean innovation score is Nike which also depicts lower than average variability slightly beneath the trendline. The firm with the second highest mean innovation score, AT&T, has a higher-than-average variability.

At this stage, we take a deeper look at the innovation outcome performance of AT&T and Nike, the firms with the highest mean innovation scores, based on global standardization. Figures 10 and 11 depict the innovation index scores for AT&T and Nike respectively.

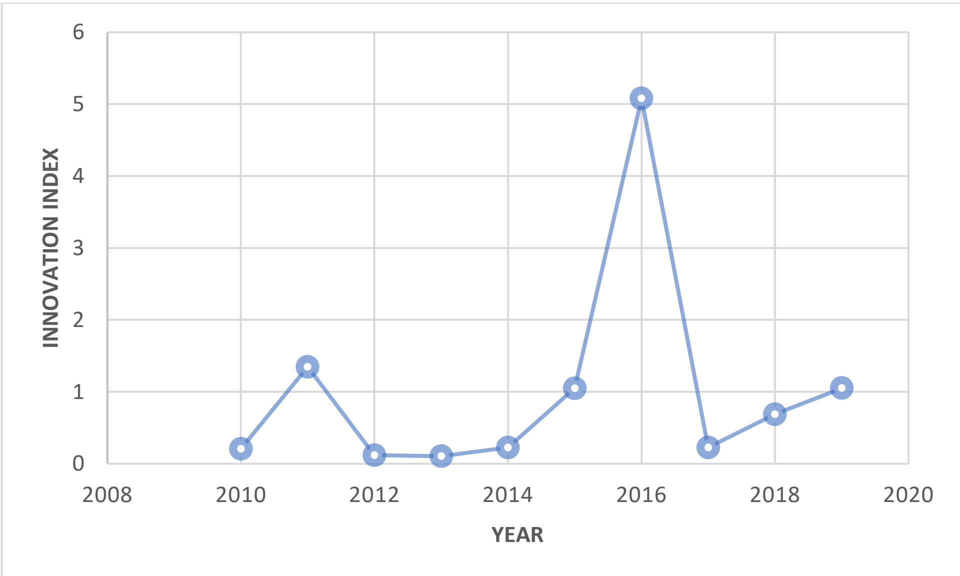


**Figure 10: Innovation Outcomes Over Time – AT&T**

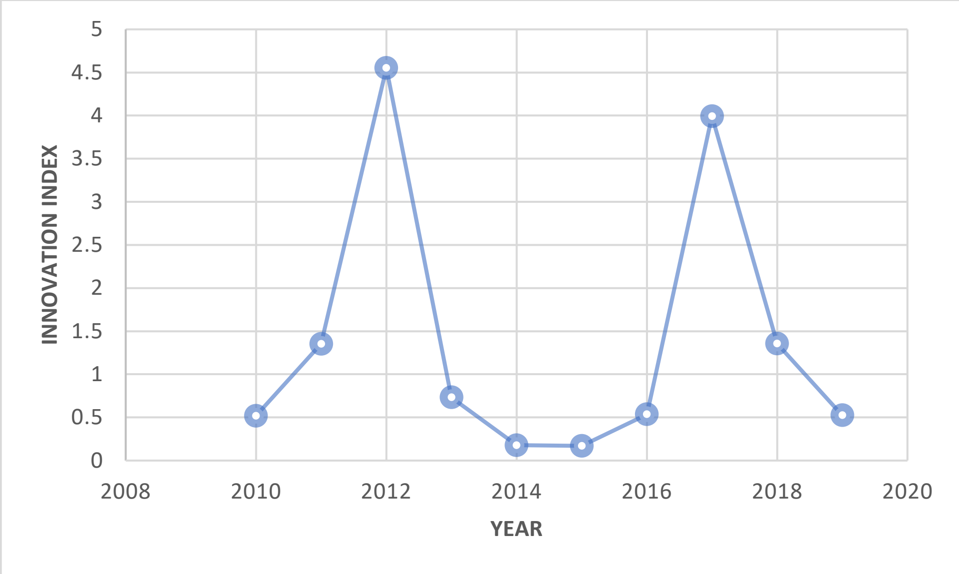


**Figure 11: Innovation Outcomes Over Time – Nike**

In figures 12, 13, 14, & 15, the four dimensions of the innovation index are juxtaposed for AT&T and Nike enabling a direct year on year comparison dimension-wise. The reader would recall that the four dimensions of the innovation index are input innovation, throughput innovation, output innovation, and organizational innovation (firm wide) (refer Figure 5). From Figure 12, it is readily apparent that both AT&T and Nike display tremendous variation in their input innovation outcomes. However, the maximum activity levels of AT&T are somewhat higher than those of Nike. Upon only a visual inspection, we also note that their input innovation outcomes are roughly countercyclical.

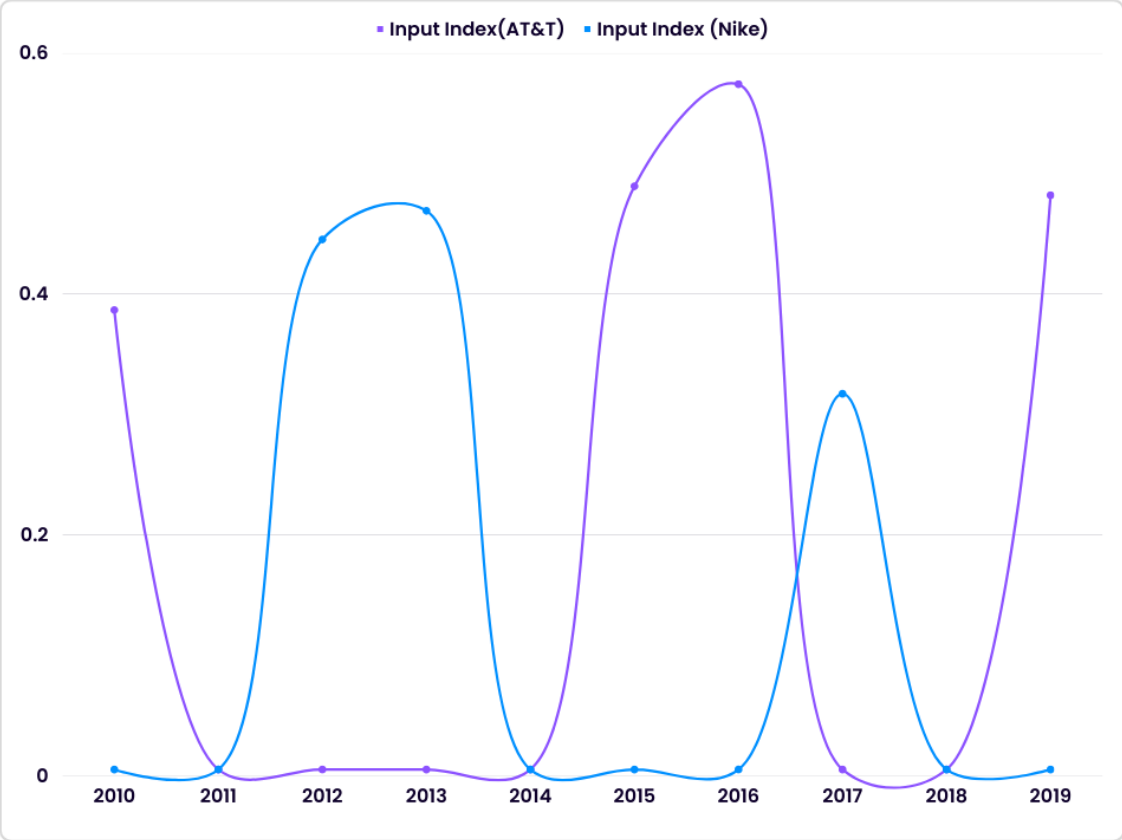


**Figure 12 – Input Innovation Index Over Time**

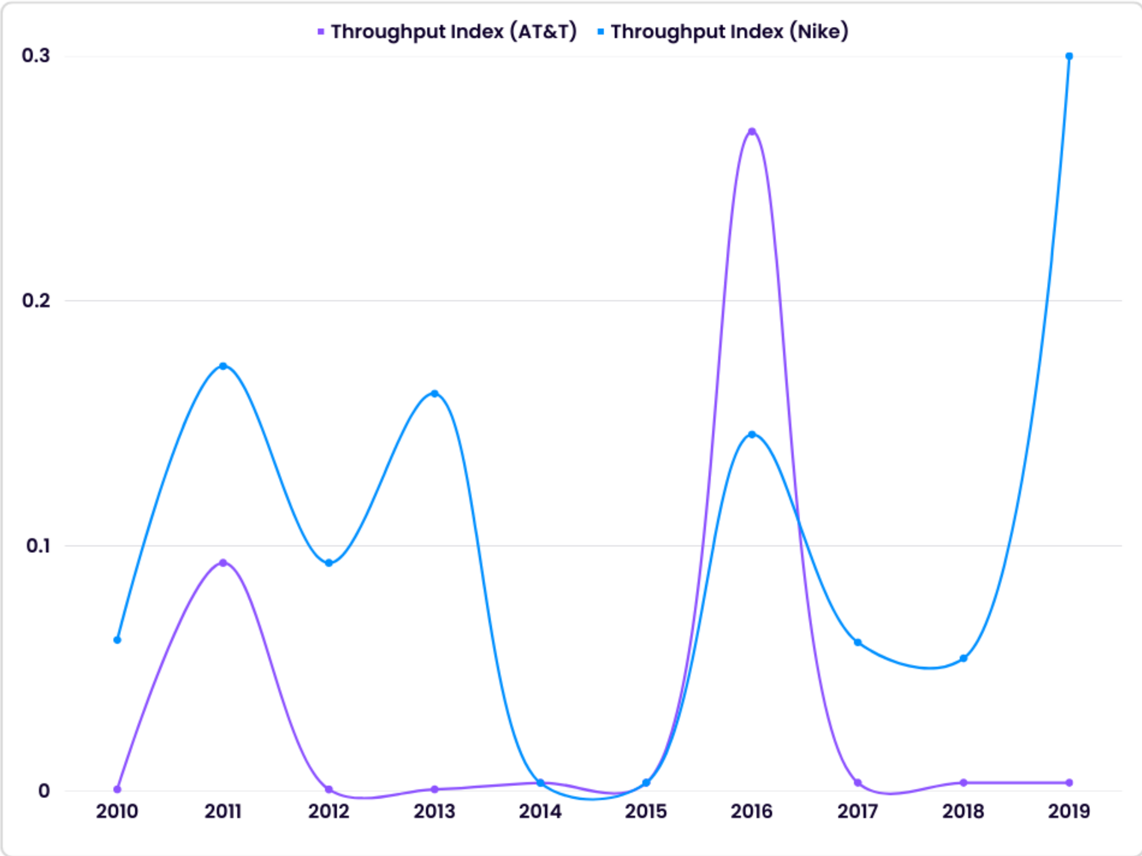


**Figure 13 – Throughput Innovation Index Over Time**

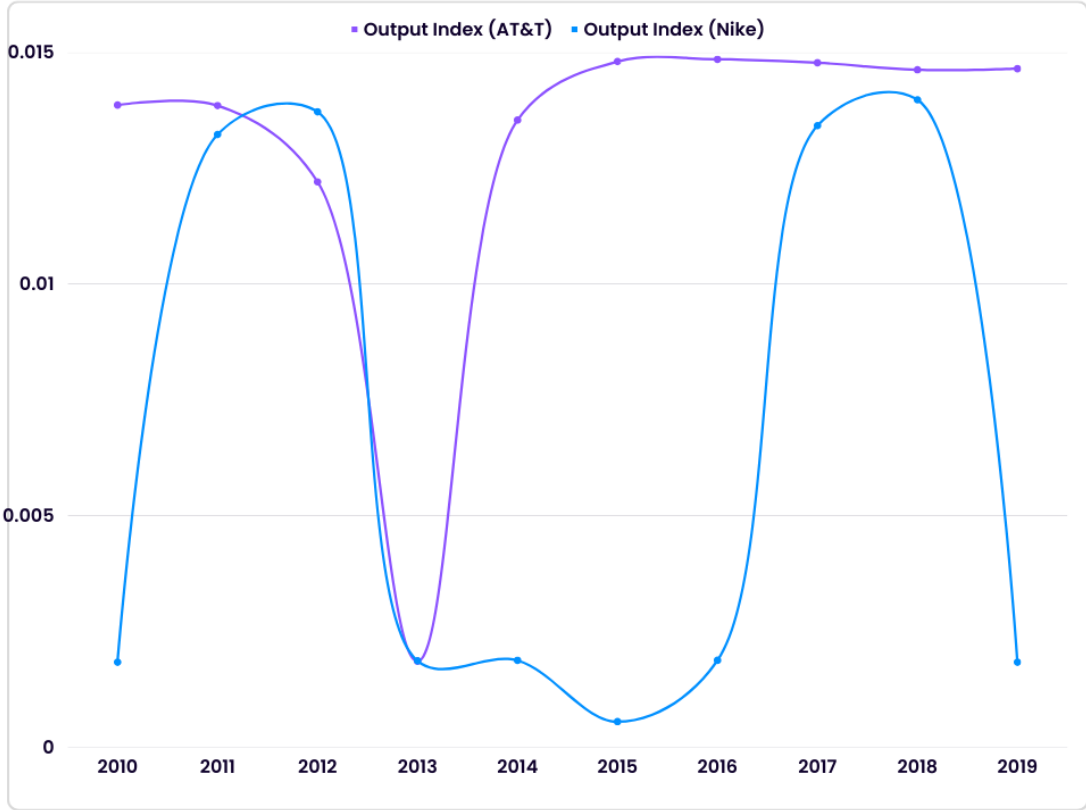


**Figure 14 – Output Innovation Index Over Time**

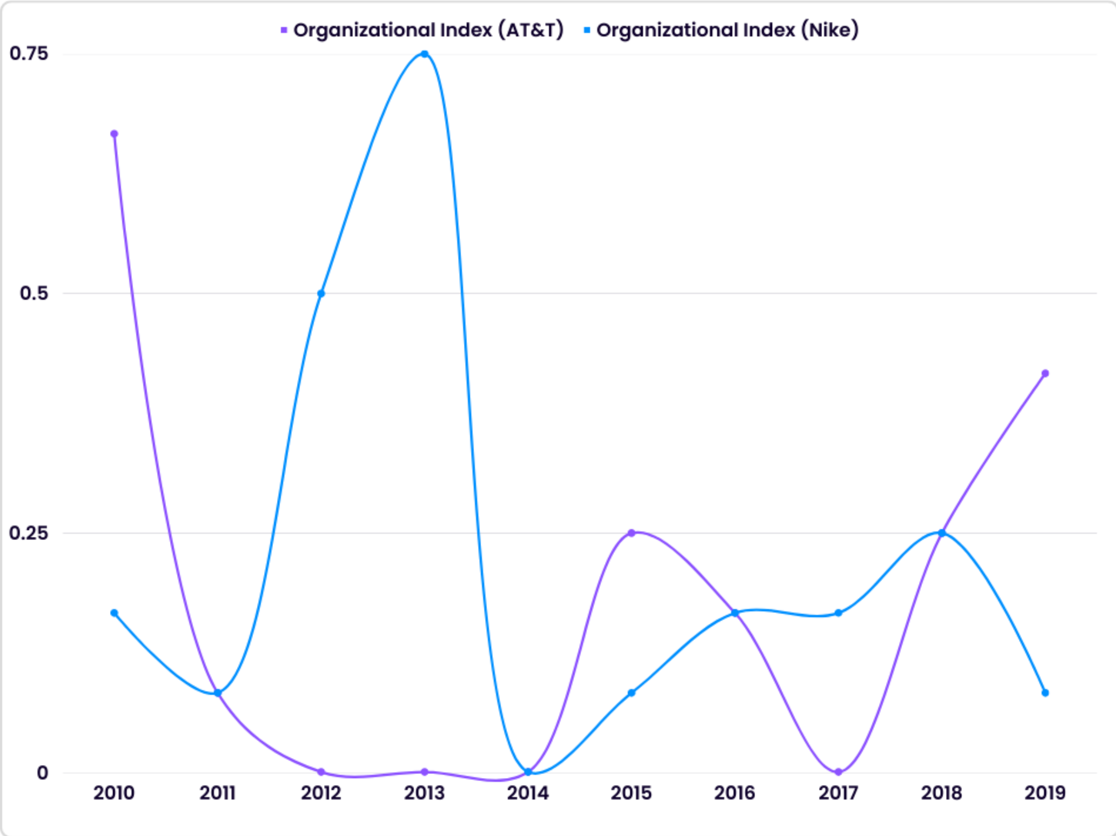


**Figure 15 – Organizational Innovation Index (Across) Over Time**

Figure 14 shows that the output innovation levels of AT&T are consistent in later years while Nike's output innovation levels are cyclical or phased throughout. From Figure 15, we note that while Nike's organizational innovation levels were much higher in the past, they have fallen roughly to the level of AT&Ts recently.

### 5.2. Validation

As discussed previously, this aspect of the study is divided into three steps.

i. Formative Framework Assessment
ii. External Validation
iii. Sensitivity Analysis

Formative Framework Assessment

A core tenet of formative frameworks is that the indicators are the cause of the composite variable that the framework is constructed to measure. Consequently, each element of the framework is irreplaceable as it uniquely identifies a facet of the phenomenon. This implies that in a formative framework, we should, typically, observe little to no correlation among the basic indicators if they really are measuring differing facets. To check if this is true of our formative framework, a correlation matrix was computed for the eight basic indicators of the framework. This matrix is shown in Table 11. From Table 11, it is observed that all correlations are below 0.40 and a few are negative. We infer that the correlations are of sufficiently low magnitude for us to conclude that each of the eight basic indicators is measuring a unique facet of the innovation outcomes. The highest correlation of 0.39 is between organizational innovations (firm wide) and organizational innovations at the throughput stage. We note that this correlation is sufficiently lower for us to accept that the two indicators do measure differing facets but that some correlation is to be expected. This is because organizational innovations that are firm wide, also include innovations at the throughput stage in tandem with organizational innovations in the other stages. For instance, business model innovations are organizational innovations at the firm level encompassing all stages including the throughput stage. It is conceivable that organizational innovations at the firm level may influence organizational innovations in the other stages and vice versa contributing to some correlation.

Likewise, when we compute correlations between the higher level four dimensions of the composite index, we observe low to negligible correlations. Table 12 depicts the correlation matrix for the four dimensions calculated using the Min-Max normalization method and aggregated using the Harmonic mean at global standardization.

**Table 11 – Correlation Matrix of the Basic Indicators**

| Correlation Matrix | Patent | Organization (Input) | Process | Organization (Throughput) | Product | Marketing | Organization (Output) | Organization (Firm Wide) |
|---|---|---|---|---|---|---|---|---|
| **Patent** | 1.00 | | | | | | | |
| **Organization (Input)** | 0.25 | 1.00 | | | | | | |
| **Process** | -0.02 | 0.05 | 1.00 | | | | | |
| **Organization (Throughput)** | 0.14 | 0.18 | 0.19 | 1.00 | | | | |
| **Product** | 0.29 | 0.14 | 0.19 | 0.00 | 1.00 | | | |
| **Marketing** | 0.27 | 0.31 | 0.16 | 0.04 | 0.29 | 1.00 | | |
| **Organization (Output)** | -0.07 | 0.00 | -0.03 | 0.02 | 0.01 | 0.08 | 1.00 | |
| **Organization (Firm Wide)** | 0.02 | 0.30 | 0.13 | 0.39 | 0.01 | -0.01 | -0.06 | 1.00 |

**Table 12 – Correlation Matrix of the Four Dimensions (Global Standardization)**

| Correlation Matrix | Input Innovation Index | Throughput Innovation Index | Output Innovation Index | Org Innovation Index (Firm Wide) |
|---|---|---|---|---|
| **Input Innovation Index** | 1.00 | | | |
| **Throughput Innovation Index** | 0.17 | 1.00 | | |
| **Output Innovation Index** | 0.003 | 0.05 | 1.00 | |
| **Org Innovation Index (Firm Wide)** | 0.23 | 0.28 | -0.01 | 1.00 |

<u>External Validation</u>

Since in a formative framework, the basic indicators cause the latent construct and measure a unique facet of the phenomenon, correlations between each indicator are expected to be low. This implies that internal consistency measures such as the Cronbach's alpha are not of much use because the indicators are not interchangeable. However, external validation techniques can be employed. If the theoretical framework is accurate and its operationalization in terms of dimensions and basic indicators measures the latent construct as intended, then we expect this construct to behave in a manner as other available constructs that measure the same or facets of the same phenomenon. In our case, the composite construct is innovation outcomes at firm level. Previously, in the literature review section, we have demonstrated that innovation outcome in its varying facets usually has a positive impact on share price returns. Thus, we expect a composite index of innovation outcome (if it is an accurate representation) to also behave in a similar manner when assessing its impact upon abnormal stock returns utilizing appropriate techniques. This is a form of external validation wherein we are assessing the impact of our composite index against an external measure (abnormal stock returns) whose components' impact on abnormal stock returns is well-established in prior research.

Consequently, based on our theoretical development and literature review pertaining to the impact of innovation outcomes on stock market returns, we state a hypothesis which we shall attempt to validate.

**Hypothesis – The composite index of innovation outcomes positively impacts abnormal stock returns.**

In previous sections, not only has a detailed literature review assessing the impact of facets of innovation outcomes upon abnormal stock returns been presented, but we also discussed the panel data regressions technique that was employed to assess the impact on abnormal stock returns. Given that we have previously discussed our treatment of control variables in the regression, we now present the findings. Table 13 presents the results of the impact of innovation index upon abnormal stock returns when the index was calculated using Harmonic mean aggregation and basic indicators were normalized using Indicization technique with global standardization. In the sensitivity analysis section, we will discuss the impact of the index created using the Geometric mean aggregation technique also.

From our findings, we state that a 1 unit increase in the innovation index leads to a 1.5% increase in abnormal stock returns at the end of the current fiscal year at 0.05 significance level, thereby, lending support to the hypothesis. For context, from Table 9 we note that the lowest and highest innovation index scores in our data set are 0.004 and 5.077.

## Table 13 – Impact of Innovation Index on Abnormal Stock Returns (t)

Dependent Variable**: $Log_n$ (Abnormal Stock Returns) (t)**

Method: Mixed Effect Model (Fixed Effects in Time & Random Effects in Cross-section)

Cross-sections included: 34

Total panel (balanced) observations: 306

Time Series Length: 9

Standard errors clustered by unit

| **Variable** | **Coefficient** | **Std. Error** | **z** | **p-value** |
|---|---|---|---|---|
| C | 0.018 | 0.090 | 0.2049 | 0.837 |
| **Innovation-Index $_{(t)}$** | **0.015** | **0.006** | **2.217** | **0.027**** |
| $Log_n$ (Investment) $_{(t)}$ | -0.521 | 0.208 | -2.500 | 0.012** |
| $Log_n$ (Investment) $_{(t-1)}$ | -0.125 | 0.096 | -1.299 | 0.194 |
| $Log_n$ (Operating-Profitability) $_{(t)}$ | 0.017 | 0.032 | 0.529 | 0.596 |
| $Log_n$ (Operating-Profitability) $_{(t-1)}$ | -0.019 | 0.016 | -1.192 | 0.233 |
| $Log_n$ (Size) $_{(t)}$ - $Log_n$ (Size) $_{(t-1)}$ | 0.962 | 0.138 | 6.961 | 0.000*** |
| $Log_n$ (B-to-M) $_{(t)}$ - $Log_n$ (B-to-M) $_{(t-1)}$ | 1.15 | 0.691 | 1.664 | 0.096* |

* 0.1 significance level
** 0.05 significance level
*** 0.01 significance level

Joint test on named regressors -
Asymptotic test statistic: Chi-square (4) = 216.693
with p-value = 3.320e-43

Breusch-Pagan test -

Null hypothesis: Variance of the unit-specific error = 0

Asymptotic test statistic: Chi-square (1) = 0.524

with p-value = 0.469

Hausman test -

Null hypothesis: GLS estimates are consistent.

Asymptotic test statistic: Chi-square (4) = 9.436

with p-value = 0.222

Wooldridge test for autocorrelation in panel data -

Null hypothesis: No first-order autocorrelation (rho = -0.5)

Test statistic: F (1, 33) = 0.713

with p-value = P (F (1, 33) > 0.713) = 0.404

Pesaran CD test for cross-sectional dependence -

Null hypothesis: No cross-sectional dependence

Asymptotic test statistic: z = 0.103

with p-value = 0.918

Sensitivity Analysis

Sensitivity analysis is undertaken for two reasons. First, given the formative nature of the theoretical framework, it is recognized that only some techniques of composite index construction are applicable. In the interest of methodological rigor and research transparency, the use of all such techniques towards index construction are desirable. After presenting findings from each technique, we may proceed to state the ideal combination of techniques for index construction. Second, we are interested in depicting the robustness of the framework to changes in techniques by showing the differences in outcomes that such changes impact.

Two methods of aggregation were admissible for our theoretical framework. Both the Harmonic and the Geometric mean methods of aggregation apply a downward penalization that are desirable for formative frameworks. One method of normalization was applicable, namely, the Indicization normalization. Thus, if we were to apply global standardization upon panel data to normalize the basic indicators, we obtain two distinct ways of constructing the innovation index. It is recognized that a user could also apply the yearly standardization to panel data for another two ways of constructing the index. Both global and yearly standardization are valid methods to apply on panel data and, as discussed previously, are applicable based upon the specific needs of the end user. For the purposes of our study in this section, we shall consider the two distinct cases that arise after applying global standardization only. These are –

i. Harmonic mean aggregation with Indicization normalization.
ii. Geometric mean aggregation with Indicization normalization.

Comparisons are presented in three ways. First, average firm rankings (over 10 years) are depicted across the two cases for each firm. Second, the Wilcoxon Signed-Rank test was applied to the complete set of firm rankings for each year to determine if there's a statistically significant difference between the medians of the two sets of data. Finally, effect sizes and significance of the innovation index upon abnormal stock returns are compared.

Table 14 depicts the average firm rankings for the Harmonic mean and the Geometric mean aggregation methods. We note that for top performing firms such as Nike, AT&T, and Northrop Grumman the average ranks of each firm over a 10-year period are very close.

**Table 14 – Average Firm Rankings**

| Average Firm Ranking | Harmonic-Indicization | Geometric-Indicization |
|---|---|---|
| AIG | 13.8 | 12.5 |
| American Tower | 29.9 | 29.4 |
| Amgen | 10.3 | 14.4 |
| Amphenol | 11.3 | 15.8 |
| **AT&T** | **5.6** | **6.5** |
| Avalon Bay | 25.3 | 18 |
| Ball Corp | 8.7 | 13.2 |
| Biogen | 11.4 | 14.7 |
| Comerica | 26.7 | 20.4 |
| Conoco Philips | 12.7 | 9.3 |
| Consolidated Edison | 13.6 | 16.3 |
| Davita | 26.8 | 23.9 |
| Duke Energy | 18.1 | 14.9 |
| Expedia | 19.7 | 23.9 |
| First Horizon | 30.3 | 29.2 |
| Genuine Parts | 30.5 | 30.3 |
| Harley Davidson | 8.3 | 12.1 |
| Healthpeak | 30.5 | 26.7 |
| Hershey Foods | 9.4 | 11.7 |
| Hess Corporation | 22.7 | 11.2 |
| Huntington | 20.4 | 21.8 |
| JM Smucker | 14.1 | 18.7 |
| KLA Corp | 16.8 | 22.7 |
| Lab Corp of America | 11.1 | 14.3 |

| | | |
|---|---|---|
| Lennar | 30.1 | 30.3 |
| McDonalds | 24.3 | 14.2 |
| Micron Technology | 13.3 | 15.8 |
| **Nike** | **3.3** | **3.8** |
| **Northrop Grumman** | **7.3** | **5.4** |
| Paccar | 10.3 | 17 |
| Republic Services | 27.7 | 25 |
| Southwest Airlines | 18.3 | 18.4 |
| Weyerhaeuser | 22.8 | 25.1 |
| Xerox | 9.6 | 8.1 |

For a more robust analysis, the Wilcoxon Signed-Rank test was applied to the complete set of firm rankings on a yearly basis. This means that the test was applied to 340 firm-year observations obtained by the Harmonic-Indicization and Geometric-Indicization techniques. The Wilcoxon Signed-Rank test is a non-parametric test used to determine if there's a statistically significant difference between the medians of two paired sets of data. Results of this test are shown in Table 15. We fail to reject the null hypothesis of zero median difference implying that there are no statistically significant differences in firm ranks.

**Table 15 - Test for Difference Between Firm Rankings (Harmonic & Geometric)**

**Method: Wilcoxon Signed-Rank Test**

Null hypothesis: the median difference is zero

n = 298

W+ = 26715, W- = 30352

(zero differences: 42, non-zero ties: 17)

Expected value = 28533.5

Variance = 3.27585e+006

z = -1.00446

P (Z < -1.00446) = 0.157579

**Two-tailed p-value = 0.315158**

Collectively, Tables 14 and 15 reinforce our contention that the theoretical framework is robust to differences in choice of aggregation method. Later, we will have more to say about which aggregation method is preferable.

We now compare the impact of innovation index upon abnormal stock returns when the index is calculated using Harmonic and Geometric aggregation techniques. The normalization method (Indicization) with both aggregation techniques does not change. Table 16 compares the effect sizes and levels of significance for each technique. We note that a 1 unit increase in the harmonic aggregation index leads to a 1.55% increase in abnormal stock returns whereas it leads to a 0.41% increase for the geometric aggregation index. For context, the maximum and minimum index scores when using harmonic mean aggregation are 5.077 and 0.004. The maximum and minimum index scores when using geometric mean aggregation are 26.285 and 0.022. So, while the harmonic aggregation index shows a larger effect, the range of maximum and minimum scores is about five times less than the geometric aggregation index. Both methods exhibit significance at the 5% level, suggesting that while there are differences in magnitude, both have relevance in explaining stock return variations.

**Table 16 – Comparison of Effect Sizes and Significance Levels**

| Dependent Variable: **$Log_n$ (Abnormal Stock Returns) (t)**<br>Method: Mixed Effect Model (Fixed Effects in Time & Random Effects in Cross-section)<br>Cross-sections included: 34<br>Total panel (balanced) observations: 306<br>Time Series Length: 9<br>Robust (HAC) standard errors | | | | |
|---|---|---|---|---|
| **Variable** | **Coefficient** | **Std. Error** | **z** | **p-value** |
| Innovation-Index-Geometric $_{(t)}$ | 0.004 | 0.002 | 2.182 | 0.029** |
| Innovation-Index-Harmonic $_{(t)}$ | 0.015 | 0.007 | 2.217 | 0.027** |
| ** At 0.05 significance level | | | | |

Comparing the influence of the two aggregation methods on abnormal stock returns, when assessed in terms of their respective ranges, is also insightful. An increase spanning the full range of the Harmonic index (from its minimum to maximum values) is associated with an approximately 7.61% change in abnormal stock returns. Conversely, a similar full-range increase for the Geometric Index translates to a larger effect size of approximately 13.13%.

It was stated earlier that formative models are comprised of basic indicators that are non-substitutable or irreplaceable. This implies that each basic indicator measures a unique aspect or facet of the phenomenon under consideration. Consequently, an aggregation method suitable for formative models must not let a high or a low score in one or few basic indicators 'hijack' or influence the final index score disproportionately. Both Harmonic and Geometric mean aggregation apply downward penalization to prevent an outlier value from unnecessary influencing the innovation index score. In this regard, the Harmonic mean aggregation is stronger, in terms of penalty, than the Geometric mean aggregation.

To illustrate how such a difference in penalization intensity acts out we consider the case of six firms in our sample that range from a high number of patent applications to extremely low levels. The strength of penalization becomes evident when comparing the Harmonic and Geometric mean aggregation methods in these firms. Firms and their associated average scores are depicted in Table 17.

**Table 17 – Patent Applications and Average Innovation Index Scores**

| | Patent Applications | Harmonic Average Score | Geometric Average Score |
|---|---|---|---|
| **Nike** | 7191 | 1.39 | 7.14 |
| **AT&T** | 8949 | 1.01 | 6.83 |
| **Northrop** | 1004 | 0.36 | 3.37 |
| **Hershey Foods** | 47 | 0.31 | 2.3 |
| **Ball Corp** | 158 | 0.25 | 1.18 |
| **Xerox** | 5898 | 0.24 | 2.11 |
| **Micron** | 10292 | 0.186 | 1.64 |
| **Consolidated Edison** | 52 | 0.17 | 0.86 |

The scores calculated using the geometric mean are generally larger than those calculated using the harmonic mean for the same number of patent applications. This can be further observed by considering firms with significant differences in patent applications but closer average scores. For instance, AT&T has 8949 patent applications with a harmonic score of 1.01 and a geometric score of 6.83. Micron has 10292 patent applications (which is higher than AT&T) but has a harmonic score of only 0.186 (significantly lower than AT&T's harmonic score) and a geometric score of 1.64 (also lower than AT&T's geometric score). This suggests that for firms with higher patent applications, the Harmonic mean penalizes them more heavily than the geometric mean. The Harmonic mean score for Micron decreases significantly in comparison to AT&T despite having more patent applications, but the Geometric mean score doesn't decrease proportionally. Northrop and Hershey Foods provide another interesting comparison. Despite Northrop having a much higher number of patent applications (1004 vs. 47), their Harmonic scores are relatively close (0.36 vs. 0.31). However, their Geometric scores, while still close, show a more discernible difference (3.37 vs. 2.3).

An exceptionally high or low value among the set can make the Harmonic mean penalize drastically. On the other hand, the Geometric mean, while still penalizing for variance, does so in a milder manner. This is why Micron, despite its massive patent applications, found itself scoring relatively higher when using the Geometric mean compared to the Harmonic mean.

### 5.3. Innovation Index Construction Recommendation

Based on preceding discussions, we can make recommendations for the construction of the innovation index.

First, it is recommended that the Indicization method of normalization be employed. This choice of normalization technique has several advantages. It is suitable for both bounded and unbounded indicators. It can overcome the problem of zero values in the basic indicators by adding a miniscule amount thus making it suitable for both the Harmonic and Geometric aggregation methods. More importantly, the Indicization method leaves open the possibility of an external benchmark that can be used when the context of the end user so permits.

Next, it is recommended that the maximum penalization intensity (that is also meaningful) be accorded when constructing the index. This is offered to us when we utilized the Harmonic mean aggregation. Our theoretical framework is a formative model wherein we have demonstrated that each of our basic indicators is measuring a unique aspect or facet of the phenomenon under consideration. That we have applied equal weighting at every level of index construction is further testament to the equal importance that our theoretical framework places on each component of the innovation process. Therefore, while both the Geometric and Harmonic mean aggregations do not cause a significant difference in rankings, we have observed the higher penalization intensity that the Harmonic mean aggregation accords. Moreover, the Harmonic mean aggregation also introduces noticeably less of an effect on abnormal stock returns. This effect is more representative of the actual underlying innovation outcomes than the effect of the Geometric mean aggregation that tends to let higher values in the basic indicator influence index scores.

## 6. Discussion

The endeavour to measure innovation within firms, as explored in this study, stands at the intersection of numerous conceptual models and theoretical frameworks identified in the literature. Each model offered a unique perspective on understanding and capturing the essence of innovation. Our study's approach, in constructing a composite innovation index, synthesizes these diverse perspectives, aligning with the multifaceted nature of innovation as a process that integrates inputs, throughputs, and outputs, and encompasses various forms of innovation including organizational and marketing innovations, alongside the traditional technological product and process innovations.

Consistent with the findings of our literature review, the chosen theoretical framework for this study recognizes innovation as a dynamic and continuous process that begins with the conception of an idea and culminates in the commercialization of a product or service. This perspective aligns with the conversion process models, such as that proposed by Twiss (1980), which view innovation as a transformation of inputs into outputs. The selection of this process-oriented approach ensures that the innovation index captures the entire innovation lifecycle within a firm, from ideation through development to realization.

Acknowledging the multidimensional nature of innovation, the framework adopted in this study extends beyond the traditional focus on technological products and processes. It incorporates organizational and marketing innovations, reflecting the broader scope of innovation activities within modern firms. This holistic approach resonates with the guidelines of the Oslo Manual (OECD/Eurostat, 2005), and models like Docherty's open innovation funnel and Jonash & Sommerlatte's innovation pathways, which emphasize the importance of diverse innovation types in capturing the full spectrum of a firm's innovative capacity.

Further, in line with the recommendation for a comprehensive measurement framework, the study's theoretical framework appropriately includes organizational and knowledge inputs at the innovation process's initial stages. It aligns with the findings of Morad et al. (2021) and models like Goffin and Mitchell's (2010) capability-centered model, which underscore the importance of integrating organizational elements into the innovation process.

Moreover, the theoretical framework's suitability for both internal and external stakeholders is another critical aspect of this study. By focusing on publicly available data sources, the constructed innovation index becomes a practical tool for a broad spectrum of stakeholders, ranging from investors and policymakers to academic researchers. This practical applicability of the framework underscores its relevance in the current business environment, where transparency and accessibility of information are paramount.

In constructing the index, the entire innovation index construction process has been elaborated. We have identified and explained our sources of definitions. The exact methodological steps were outlined as were the actions taken to accomplish those. We have also established that this index of innovation outcomes positively impacts abnormal stock returns at the end of the current fiscal year of the firm.

We may now draw some overall implications of this study.

a. Quantitative Framework for Innovation: This study underscores the feasibility of operationalizing a traditionally qualitative and diverse construct such as innovation. By delineating it into measurable variables derived from the innovation conversion model, the research pioneers a structured, quantitative approach to evaluating innovation.
b. Holistic Approach: The incorporation of inputs, throughputs, outputs, and organizational innovations emphasizes a holistic approach. It implies that innovation within a firm is not a disjointed array of activities but a cohesive, unified process that necessitates comprehensive examination.
c. Operational Feasibility: By relying solely on public, official, and reliable sources of information, this study highlights the operational feasibility of constructing an innovation index. Such an approach lends credibility to the methodology, making it replicable and more widely accepted in the academic and corporate worlds.
d. Balance of Depth and Simplicity: The emphasis on parsimony in the choice of indicators demonstrates that a balance can be struck between depth (fidelity to the theoretical construct) and simplicity. This addresses the potential risk of information overload for stakeholders, ensuring broader acceptance and utility.

e. Structured Methodology: The rigorous methodological steps elucidated in the study offer a blueprint for future research endeavors. They establish a structured methodology that can be adapted or built upon in subsequent academic inquiries.

f. Economic Relevance: The positive correlation between the innovation index and abnormal stock returns underscores the economic relevance and real-world applicability of the measure. It suggests that the market recognizes and rewards demonstrable innovation outcomes, reinforcing the value of such an index for investors.

g. External Validation: The study's findings provide external validation for the study’s theoretical framework, suggesting that its theoretical underpinnings hold empirical merit when adapted to a contemporary business landscape.

h. Publicly Available Data: The emphasis on public data in constructing the index underscores the democratization of information in today's digital era. It implies that innovation, as a construct, is no longer the esoteric domain of insiders but can be ascertained, understood, and evaluated by all stakeholders.

i. Stakeholder Empowerment: By constructing an index based on publicly available data, the study empowers stakeholders, including investors, analysts, and policymakers, to make informed decisions without proprietary inside information. It democratizes the evaluation process and levels the playing field.

j. Precedent for Future Constructs: The methodology and outcomes of this study could set a precedent for other academic endeavors aiming to quantify traditionally qualitative business constructs. The balance of theoretical fidelity and parsimony, combined with empirical validation, offers a robust model for similar research initiatives.

### 6.1. Applications of the Innovation Index

The innovation index developed in this study offers a comprehensive tool to gauge the innovation outcome of firms, derived from publicly available data. To ensure the index is utilitarian across different stakeholders, applications are categorized across a range of entities:

i. Corporate Management: The index can serve as a tool for top management to benchmark their organization's innovation activity relative to industry competitors. With these insights, they can allocate resources more effectively towards areas lagging in innovation. Management can use the index to track the firm's innovation trajectory over time. This aids in assessing the efficiency of innovation-centric initiatives.

ii. Investors and Financial Analysts: The index assists investors in identifying firms with robust innovation activity, potentially signaling better future financial returns and growth prospects. Investors can also gauge the suitability of a firm's innovation activity, assisting in determining the potential long-term viability and competitive positioning of the firm.

iii. Government and Policy Makers: Governments can leverage the index to understand the innovation landscape of their economy. This understanding can guide the formation of policies promoting innovation. By applying the index across different sectors, policy makers can identify sectors that require more innovation-centric policies or regulations.

iv. Academics and Researchers: The index provides a robust measure for academics to undertake comparative studies on innovation outcomes across industries, regions, or time periods. Researchers can use the index to validate or develop theories regarding innovation outcomes, especially in the context of its relationship with financial performance. For instance, utilizing the innovation index, the mediating or moderating role of innovation outcome can be assessed as part of a theoretical framework. In the past, scholars have undertaken studies assessing such roles as, for example, the Han et al. (1998) study which assesses the mediating role of organizational innovation (technical and administrative) between a firm's market orientation and business performance.

v. Industry Associations: The index can be employed to derive industry-specific benchmarks for innovation, aiding member firms in self-assessment. Armed with the index's insights, associations can advocate for industry-specific policies from governments or international bodies.

vi. Human Resource Professionals: Firms with high innovation indices can be positioned as leaders focused on innovation, aiding in the attraction of top talent looking for innovative work environments. By correlating firm performance on the index with workforce competencies, HR professionals can identify areas of training to bolster innovation. Further, the index can be split into constituent dimensions and the impact of each individual dimension on organizational performance can be assessed. For instance, the impact of organizational innovation (firm wide) on performance can be assessed when required. Prior research indicates that introduction of sophisticated HR related practices does not always translate into superior organizational performance (Darwish et al., 2020). Thus, such assessment utilizing the innovation index can be crucial in assessing the effectiveness of specific facets of innovation.

vii. Consultants and Business Advisors: Business consultants can utilize the innovation index as a diagnostic tool to identify innovation-related challenges for their clients. The index components can guide consultants in devising actionable recommendations for enhancing their client's innovation activity.

viii. Customers and Clients: B2B clients can use the index as a criterion when selecting vendors, ensuring partnerships with highly innovation active firms. In sectors where innovation volume also drives good or service quality, the index can influence B2C purchase decisions by informing potential customers about the innovativeness of providers.

ix. Competitors: Firms can use the index to measure their innovation performance relative to direct competitors, identifying areas of competitive advantage or vulnerability. For firms looking at strategic mergers or acquisitions, the index provides an additional metric to assess the innovative potential of target firms.

x. NGOs and Development Agencies: NGOs focused on business development can use the index to prioritize firms or sectors that showcase high innovation potential but lack resources. The index can assist in evaluating the effectiveness of programs aimed at fostering innovation in target sectors or regions.

xi. Emerging Market Firms: Such firms have been shown to typically focus on process and incremental innovation – frugal innovation – with lesser emphasis on product and business model innovations (Krishnan & Prashantham, 2019). The index can assist such firms in evaluating their and their competitors' standing on frugal vs. product and business model innovations with a view to closing this gap. There is also an intensified interest in assessing the determinants of firm innovation within an emerging market context owing to a lack of such studies (Batra et al., 2015). Thus, the index of innovation outcomes can serve as a reliable and empirically validated dependent variable.

The innovation index, thus, offers multifaceted applications, making it an invaluable tool for a plethora of stakeholders in the business ecosystem.

### 6.2. Limitations

Although this study comprehensively constructs an index based on publicly available data to measure the outcomes of innovation, it inherently lacks the depth to assess the quality or other qualitative facets of the innovations in question. For instance, while one can identify the number of patents filed by a company, the transformative potential or originality of each patent cannot be readily assessed through external data alone. This implies that while the index provides a broad measure of a firm's commitment to innovation, stakeholders should exercise caution when inferring the actual quality or depth of such innovations. Using innovation outcomes as a starting point is indeed promising, but it remains a preliminary step in understanding the full breadth and depth of a firm's innovative prowess.

As the study is based solely on publicly available information, it essentially relies on what the firm's management chooses to communicate. While the information that is disclosed is generally reliable and accurate, owing to regulatory requirements and the inherent accountability of public disclosures, it may not encompass the entirety of the firm's innovation outcomes. This means the derived innovation index might only capture a part of the picture. There could be significant internal innovation outcomes that firms choose not to disclose due to competitive reasons or other strategic considerations. Therefore, the innovation index should be interpreted as a representation of disclosed innovation rather than an exhaustive account.

While the study aims to provide a holistic measure of innovation outcomes, spanning inputs, throughputs, outputs, and organizational facets, it inherently becomes a broad-brush assessment. This comprehensive approach, although valuable for a macro view, may gloss over the intricacies or nuances of any specific facet of innovation. For stakeholders or researchers interested in an in-depth understanding of, say, the 'inputs' facet or the 'organizational innovations' facet, this index may serve as a starting point but will require modifications. Tailored adaptations of the model, focusing on specific facets, would be necessary to glean detailed insights into areas of innovation.

In essence, although this study offers an approach to quantifying innovation and provides insights into the innovation outcomes of firms based on publicly available data, it also underscores the inherent limitations of such an approach. Future research endeavours could aim to address these limitations, perhaps by integrating both public and proprietary data or by developing more nuanced, facet-specific indices.

# 7. Conclusion

Embarking on the intricate task of quantifying innovation within firms, this thesis has navigated the complexities of transforming a multifaceted, dynamic concept into a measurable entity. The construction of a composite innovation index, grounded in publicly available firm data, represents a significant stride in bridging the gap between theoretical innovation frameworks and practical, actionable metrics.

The study illuminates the nuances of innovation as a comprehensive process, transcending the traditional confines of technological innovation to embrace organizational and marketing innovations. By adopting this expansive view, the research offers a more holistic understanding of innovation outcomes within firms, encapsulating the entirety of the innovation lifecycle. The innovation index thus emerges not merely as a metric but as a narrative tool, elucidating the innovation journeys of firms, particularly, when the index is applied in temporal contexts.

The utility of the index spans a broad spectrum of stakeholders, offering corporate management a mirror to reflect on their innovation strategies, providing investors with a lens to evaluate potential growth opportunities, and equipping policymakers with a compass to navigate the innovation landscape. For the academic community, this index serves as a fertile ground for empirical inquiry, opening new avenues for exploration in the realm of innovation measurement.

In essence, this thesis spotlights the evolving nature of innovation measurement, contributing a robust, yet accessible, framework to the existing literature. It underscores the potential for further refinement and adaptation, encouraging continuous dialogue and exploration in the quest to decode the intricacies of innovation within firms. As it concludes, this research paves the way for future scholarly endeavors to further unravel the tapestry of innovation at firm level.

## 7.1. Directions for Future Research

a. Integration of Proprietary Data: A study that combines public and proprietary internal data can provide a more comprehensive view of a firm's innovative activities.

b. Qualitative Aspects of Innovation: Delve deeper into the qualitative dimensions of innovation, understanding not just the volume but also the quality and impact of these innovations.

c. Geographical Variations: Explore how innovation indices differ across countries and regions, given varied regulatory environments and innovation ecosystems.

d. Sector-Specific Indices: Construct innovation indices tailored for specific sectors or industries, accounting for their unique innovation pathways.

e. Longitudinal Study: Assess how the innovation index of a firm evolves over time, providing insights into the dynamism of the firm's innovation culture.

f. Stakeholder Perception: Evaluate how external stakeholders, such as customers and investors, perceive the innovations of a firm versus the index's representation.

g. Impact of Regulatory Changes: Examine how shifts in regulatory frameworks can influence a firm's innovation activity and its representation in the index.

h. Economic Impact: Research the broader macroeconomic implications of high innovation scores amongst firms in a particular region or sector.

i. Case Studies: Conduct detailed case studies of firms that consistently rank high on the innovation index to glean best practices and strategies.

j. Integration with Other Business Metrics: Explore correlations and causal relationships between the innovation index and other key business metrics like employee satisfaction, customer loyalty, and operational efficiency.

k. Feedback Mechanisms: Study how firms respond to their rankings on the innovation index over time, and if it influences their strategic choices related to innovation.

Each of these avenues holds the promise to extend the foundational work done in this study, offering deeper, more nuanced insights into the complex landscape of firm-level innovation.

# 8. Appendices

## Appendix 1

**Table 1A - Correlation Matrix for Panel Data Regression Variables**

| | Innovation Index | Size | Operating Profitability | Book-to-Market Equity | Investment |
|---|---|---|---|---|---|
| **Innovation Index** | 1.00 | | | | |
| **Size** | 0.31 | 1.00 | | | |
| **Operating Profitability** | 0.06 | -0.13 | 1.00 | | |
| **Book-to-Market Equity** | -0.03 | -0.17 | -0.03 | 1.00 | |
| **Investment** | -0.06 | -0.03 | -0.05 | -0.12 | 1.00 |

## Appendix 2

### A Test of the Strict Exogenous Condition for Innovation Index Variable

The strict exogeneity assumption (Wooldridge, 2018: 492) may be written as –

$$\mathbf{E\ (u_{it}\ |\ Innovation\_Index_i\ ,\ a_i) = 0}$$

Where $\mathbf{u_{it}}$ is the idiosyncratic error and $\mathbf{a_i}$ is the unobserved, time invariant, and firm specific effect. The assumption states that the innovation index explanatory variable is uncorrelated with the idiosyncratic error across all time periods given the presence of unobserved firm specific $a_i$. There are four conditions under which the exogeneity assumption may fail –

a. Simultaneous equation bias.
b. Omitted variable bias.
c. The presence of a lagged dependent variable in a regression model.
d. Error in measuring the explanatory variables.

Conditions a, c, and d aren't of particular concern to us because we use lagged explanatory and control variables in our model (though this may still lead to simultaneous equation bias), we do not have the presence of a lagged dependent variable, and our research design is such that we do not witness measurement error (including missing values) in measuring our innovation index. To explain further, the innovation index variable is measured over the course of the fiscal year and abnormal stock returns at the end of the fiscal year are regressed upon it. For the control variables, we have also taken first differences when appropriate.

Our primary concern is the presence of omitted variable bias. When discussing the time invariant and firm-specific $\mathbf{a_i}$, we alluded to firm-specific yet time invariant factors that could influence our dependent variable. We mentioned instances of such factors such as a firm's culture, the quality of its corporate governance, etc. that do not change over time. Although random effects in the cross-section controls for these time-invariant factors, we turn our attention to testing for the presence of similar firm-specific factors that could change over time. For instance, it may be that the firm innovation ability and capacity may change dramatically on a fiscal year basis to be correlated with the innovation index. This might be particularly true of high-growth and dynamic firms. It may be that some firms have a higher propensity to engage in innovation activities which may also tend to fluctuate based on changing managerial perceptions and attitudes but would correlate with the innovation index score.

One method for determining whether the exogeneity condition holds for an explanatory variable is by using instrumental variables. In this approach, we search for a suitable substitute for the explanatory variable suspected to violate the exogeneity assumption. The substitute variable is called an instrumental variable. Subject to certain conditions, a suitable instrumental variable can replace the explanatory variable in our regression model. This modified model is then estimated using a two-stage least squares approach (2SLS) and the estimates on the instrumental variable are compared with the estimates of the suspected explanatory variable in the original model (Wooldridge, 2018: 515). The original model is estimated using pooled ordinary least squares (OLS) for panel data. If the estimates of the explanatory and instrumental variable differ significantly, the exogeneity assumption is said to be violated and the explanatory variable is said to be endogenous.

We have utilized this approach to test for the exogeneity assumption for the innovation index variable and found it to not be violative of this assumption.

<u>Selection of an Instrumental Variable</u>

Denoting an instrumental variable as z, we state two assumptions that must be met for z to be a valid substitute for an explanatory variable (Wooldridge, 2018: 497). These are –

i. $Cov(z_{it}, x_{it}) \neq 0$

ii. $Cov(z_{it}, u_{it}) = 0$

The first assumption is a statement that the instrumental variable must be correlated with the suspected explanatory variable and the second assumption is a statement that the instrumental variable must not be correlated with the idiosyncratic errors. We can check the first assumption by regressing the explanatory variable in question upon the instrumental variable. If the parameter of the instrumental variable is non-zero at an acceptably small significance level, then this assumption holds. For the second assumption, we rely on reasoning and introspection based on overall construction of the model under consideration.

In our search for an instrumental variable, we decided to test the suitability of revenues earned by a firm over a fiscal year on the premise that firms with greater sales have more cash flow to fund innovation activities on a per fiscal year basis. To test our first assumption of the suitability of revenues as an instrumental variable, we employ the pooled OLS regression technique. Findings are depicted in Table 2A.

From Table 2A, we note the presence of a highly significant coefficient on the $Log_n$ (Revenues) variable.

Consequently, we accept this finding as support for the assumption that Cov ($z_{it}$, $x_{it}$) ≠ 0.

We also do not have reason to suspect that firm revenues need necessarily be correlated with components of the idiosyncratic error. Even if we were to assume that firm innovation ability and innovation capacity – unmeasured variables – exist as part of idiosyncratic errors, we have no strong reason to suspect why they ought to be correlated with our instrumental variable - firm revenues. Unlike innovation outcomes, which we do expect to be correlated with firm innovation ability, capacity, and propensity, there need not be such a direct correspondence with firm revenues. It is entirely plausible that large firms which are recipients of substantial revenues may be low on current innovation ability or capacity depending upon their managerial propensity to innovate or to invest in innovation. A converse scenario is also entirely plausible. A young firm that is a recipient of modest to low revenues may, otherwise, be high on innovation – both in ability and investment. In another scenario, whilst the managerial propensity to engage in innovation is expected to be correlated with the innovation outcomes achieved, we have no reason to suspect that such propensity might also be correlated with the revenues that a firm earns over a fiscal year. Thus, we are inclined to accept that the instrumental variable – firm revenues – is not correlated with the idiosyncratic error. In other words, we accept that Cov ($z_{it}$, $u_{it}$) = 0.

Having established the suitability of firm revenues as an instrumental variable, we proceed with instrumental variables estimation utilizing two-stage least squares (2SLS) (Wooldridge, 2018: 521) to test whether the estimates on the innovation index variable differ significantly from the estimates on the instrumental variable, firm revenue.

**Table 2A – Test for Significance of Firm Revenue**

Dependent Variable: Innovation-Index

Method: Pooled OLS

Cross-sections included: 34

Total panel (balanced) observations: 340

Time Series Length: 10

Standard errors clustered by unit

| Variable | Coefficient | Std. Error | z | p-value |
|---|---|---|---|---|
| C | -3.669 | 1.368 | -2.681 | 0.008*** |
| $Log_n$ (Revenues) | 0.137 | 0.049 | 2.805 | 0.005*** |
| $Log_n$ (Size) | 0.028 | 0.026 | 1.058 | 0.289 |
| $Log_n$ (Operating-Profitability) | 0.131 | 0.043 | 3.011 | 0.003*** |
| $Log_n$ (Investment) | -0.005 | 0.126 | -0.045 | 0.963 |
| $Log_n$ (B -to- M) | -0.203 | 0.183 | -1.108 | 0.268 |
| | | | | |
| Durbin-Watson stat | 1.496 | Adjusted R-squared | | 0.098 |
| R-squared | 0.135 | P-value (F) | | 0.000*** |

***at 0.01 (significance) level

Wooldridge test for autocorrelation in panel data -

Null hypothesis: No first-order autocorrelation (rho = 0)

Test statistic: t (33) = 2.600

with p-value = P (|t| > 2.600) = 0.014

| |
|---|
| White's test for heteroskedasticity -<br>Null hypothesis: heteroskedasticity not present<br>Test statistic: LM = 32.819<br>with p-value = P (Chi-square (19) > 32.819) = 0.025 |

Findings are presented in Table 2B. Here, we note the result of the Hausman test which tests the null hypothesis that the difference between the parameter estimates for the innovation index variable and those from the instrumental variable are significant. We find that they are not, thereby, establishing the consistency of the OLS estimates from the innovation index variable. This satisfies the strict exogeneity assumption.

**Table 2B – Test for Strict Exogeneity of Innovation Index Variable**

Dependent Variable: $Log_n$ (Abnormal Returns)

Method: TSLS, using 340 observations

Instrumented: Innovation-Index

Instruments: C, $Log_n$ (Size), $Log_n$ (Revenue), $Log_n$ (Investment), $Log_n$ (Operating-Profitability), $Log_n$ (B-to-M)

Standard errors clustered by unit

| Variable | Coefficient | Std. Error | z | p-value |
|---|---|---|---|---|
| C | 0.260 | 0.333 | 0.780 | 0.436 |
| Innovation-Index | 0.114 | 0.086 | 1.317 | 0.189 |
| $Log_n$ (Size) | -0.015 | 0.012 | -1.208 | 0.228 |
| $Log_n$ (Operating-Profitability) | 0.0007 | 0.021 | 0.035 | 0.971 |
| $Log_n$ (Investment) | 0.288 | 0.136 | 2.109 | 0.036** |
| $Log_n$ (B-to-M) | -0.122 | 0.099 | -1.229 | 0.212 |

**at 0.05 (significance) level

Hausman test -

Null hypothesis: OLS estimates are consistent.

Asymptotic test statistic: Chi-square (1) = 0.769

with p-value = 0.380

Weak instrument test -

First-stage F-statistic (1, 334) = 14.756

A value < 10 may indicate weak instruments

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