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Lean Six Sigma's Impact on Firm Innovation Performance

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ABSTRACT

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Following Toyota's dramatic rise to prominence within the automotive industry in the late 1980's, firms around the globe have widely sought to adopt Lean Six Sigma (LSS) as a means of reducing costs, improving quality, and gaining an overall competitive advantage. While the operational benefits of LSS are largely undisputed, there are criticisms of the movement with regards to its effect on firm innovation capability. Prior academic studies investigating the relationship between LSS and innovation are largely conceptual in nature, rely heavily on qualitative data, and display a high degree of variability in results. The objective of this work was to empirically confirm whether LSS adoption had a positive, negative, or neutral impact on firm innovation performance.

Financial data was collected for 151 publicly traded firms over the period from 1985 to 2018. The year of company-wide adoption of LSS was identified for each sample firm. Firms were paired with industry rivals using Coarsened Exact Matching (CEM), and statistical regressions were performed to show correlations between LSS implementation (as measured by inventory turns) and innovation performance (as measured by Total Factor Productivity, Research Quotient, and Tobin's Quotient). Regression results indicated that LSS implementation had a positive correlation with firm process innovation performance and the overall market perception of firm innovation and value, and a negative-to-neutral correlation with firm product innovation performance. Additional regressions performed at the industry-sector level revealed that the LSS-innovation relationship varies greatly by industry environment and is subject to unique industry effects and management implementation decisions.

Keywords: lean manufacturing, six sigma, lean six sigma, LSS, innovation, product innovation, process innovation, Tobin's quotient, TQ, total factor productivity, TFP, research quotient, RQ, Austin Michael Strong

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1 INTRODUCTION

1.1 Lean Six Sigma (LSS) and Innovation: An Uncertain Relationship

Lean Six Sigma, typically abbreviated as "LSS" or simply referred to as "Lean", is a management philosophy that combines elements of traditional Lean Manufacturing and Six Sigma (George, 2002) and has become widely adopted by firms as a means of improving product quality, bottom-line costs, and customer lead times in order to create a competitive advantage in the marketplace. LSS as a managerial concept pursues the continuous elimination of waste or *muda* in all business processes through *kaizen*, a mindset and operational strategy that seeks to achieve small, incremental, and continuous improvements. More narrowly, Six Sigma seeks to improve the quality of process outputs by identifying and removing the causes of defects and minimizing variability in operational processes. While the Lean and Six Sigma efforts are sometimes managed as separate activities within a firm, they are often employed together as a synergistic strategy (George, 2002), thus for the purposes of this study they will be considered together as one approach.

There are typically three main objectives in Lean Six Sigma philosophy: (1) improving the flow of the production system; (2) applying only value-adding time and steps into the organization; (3) reducing all waste and variability (Hopp, 2011). The prevalence and adoption of LSS over the past 30 years has become so widespread it has been commonly termed as the "Lean Revolution" (Womack, Jones, Roos, 1990).

As a result of its systematic elimination of operational waste, LSS is often credited with a series of operational and organizational benefits: improved quality and lower defect rates, reduced inventory levels, enhancement of overall manufacturing flexibility, safer work environments, improved employee morale, reduced need for production space, and increased ability to both identify and elimination sources of organizational waste (Liker, 2004; Cavallini, 2008; Chen & Taylor, 2009). Recent studies have also confirmed the existence of tangible financial competitive advantages among firms that have implemented LSS principles, particularly in terms of returns on assets (Jones, 2013).

Despite the many financial and operational benefits that result from successful implementation of LSS systems, there are criticisms of the movement in regard to its impact on firm innovation performance. One of the chief complaints among critics is that LSS imposes an overly strict set of criteria governing activities that add value to the business and thus discourages innovative "blue sky" thinking that can more easily occur in less structured environments. "Blue sky" work is critical to the creation of new products that are vital to a company's long-term vitality and potential for growth (Hindo, 2007; Johnstone, 2011). Subscribers to this view tend to perceive LSS management philosophy as a culprit in the dilution and suppression of organizational creativity and innovation (Tushman, 2006).

By contrast, proponents of LSS management point to historical evidences that would seem to indicate that its structured process improvement framework enables companies to create an organizational climate where innovation is expected (Bryne, 2007) and that the reduction of organizational waste actually frees up resources to be utilized in furthering creative initiatives (Antony, 2014; Zhen 2017). Other researchers hold a more neutral view, claiming that LSS and innovation are not inherently opposed and can co-exist perfectly in a disciplined and balanced organization (Hoerl, 2010; Rae, 2007).

Prior research involving the impact of LSS on firm innovation is noticeably scarce and their relationships are largely unproven (Shaeffer & Moeller, 2012). The few prior studies into the LSS/innovation relationship are primarily conceptual in nature (Chen & Taylor, 2009) or rely heavily on “self-reported perceptions” typically obtained via qualitative data surveys to company executives, lean practitioners, and employees (Kim, Kumar, & Kumar, 2012; Zhen, 2017; Terziovski, 2014). This research will break new ground by taking a quantitative approach that will utilize publicly available data to create a series of empirical LSS and innovation metrics that will then be compared using statistical regression correlation. Therefore, the current work will provide concrete evidence of the role that LSS plays in regard to innovation within a firm and help to answer the question: is a company’s ability to innovate a positive, negative, or neutral function of its LSS implementation? The answers may play a crucial role in management decisions seeking to implement LSS methodologies, where concerns about the subsequent impact on innovation may exist.

1.2 Problem Statement

This thesis research is centered upon investigating the question: “Does successful implementation and adoption of LSS enhance or impede firm innovation performance?”. Evidence in the literature points to cases where implementation of LSS has improved both product and process innovation, but an equal number of cases where product innovation in particular has suffered after implementation of LSS. The work proposed in this thesis will take a quantitative approach to studying this problem, as a contrast to most prior efforts which provided qualitative evidence via surveys and case studies.

Specifically, this research will seek to analyze the impact that successful LSS implementation (as measured by inventory turns and firm LSS adoption dates) has upon both product innovation performance (as measured by Research Quotient or RQ) and process innovation performance (as measured by Total Factor Productivity or TFP) in addition to the total impact on the market valuation of innovation (as measured by Tobin's Quotient or TQ).

1.2.1 Hypotheses

Prior theoretical research on innovation suggests that a focus on process innovation, as seen when LSS is implemented, tends to have immediate and predictable benefits. For example, improved streamlining of a supply chain purchasing process will show immediate promise against efficiency measures like speed to market or overall cost of delivery. Systematic LSS elimination of excess inventory or non-value-added steps will free up operational capacity and financial capital for alternative investment (Johnstone, 2011). These measurable efficiency and operational improvements are highly valued by market investors and subsequently lead to a rise in the market's overall valuation of the firm (Cockburn & Griliches, 1988). The relative short time horizon and tangible nature of process innovation benefits, in combination with a subsequent rise in market valuation, make a strong case for both immediate and future investment of management resources (Tushman, 2006).

By contrast, product innovations, especially those of a disruptive or radical nature, have much more uncertain outcomes and require longer time horizons to realize (Lewis, 2000). It is hypothesized that the combination of increased risk and difficulty in measuring the tangible long-term benefits of product innovation makes it more difficult to create a compelling case for investment to management whose short-term incentives may be more suitably met by the immediate benefits offered by process innovations, ultimately leading management to favor process innovation investment over product innovation investment (Christensen, 2013; Parast, 2011). This "Innovator's Dilemma" may be particularly true within companies who are highly committed to LSS philosophy, where the "slack time" needed for successful product innovation (Penrose, 1959) can potentially be viewed as non-value adding *muda* and is subsequently eliminated from the organization (Chen & Taylor, 2009).

Given these factors, it is hypothesized that a company that adopts LSS methodology, practices, and culture will experience immediate and tangible short-term efficiency benefits that will be reflected in a subsequent rise in the market valuation of the firm. These benefits will likely incentivize management to further invest in future process innovations and may divert management resources from investment into product innovations whose value is realized much further into the future and whose outcomes are more uncertain.

Thus, summarizing the prior discussion, the hypotheses that will be tested during the course of this thesis research can be stated as follows:

- **Hypothesis 1:** Lean Six Sigma, as measured by firm inventory turns (Equation 3-1), will have a positive impact on firm process innovation, as measured by Total Factor Productivity (Equation 3-2).
- **Hypothesis 2:** Lean Six Sigma, as measured by firm inventory turns (Equation 3-1), will have a negative impact on firm product innovation, as measured by Research Quotient (Equation 3-3).
- **Hypothesis 3:** Lean Six Sigma, as measured by firm inventory turns (Equation 3-1), will have a positive impact on firm market valuation, as measured by Tobin's Quotient (Equation 3-4).

1.2.2 Delimitations and Assumptions

This research will primarily be concerned with analyzing the impact that the adoption of LSS has upon firm innovation performance. As such, this research will not provide an extensive description of LSS methodology, strategy, or practices. Similarly, this paper will not provide an in-depth description of innovation practices, taxonomies, or strategies.

While the statistical approach used in this research is appropriate for analyzing general correlations, data required to estimate the true extent of an individual firm's proper implementation of LSS or efficient utilization of innovation capabilities would require access to internal metrics that are generally unavailable to the public. Thus, this research will also not investigate whether selected firms have properly implemented LSS or the extent to which such firms have successfully leveraged their innovation capabilities.

2 LITERATURE REVIEW

2.1 Introduction

Lean Six Sigma (LSS) and innovation are two major driving forces of modern business strategy and success. However, an increasing number of researchers and critics have wondered if these two factors are inherently incompatible, noting that some aspects of LSS enterprise management may suppress and dilute organizational creativity and innovation performance, thus harming a corporation's long-term viability.

It is therefore necessary to perform a thorough literature review on the topics of LSS history and common terminology, LSS metrics, innovation types, innovation metrics, and prior research examining the relationship between LSS and innovation performance within firms.

2.2 Lean Six Sigma: A Historical Overview

Lean Six Sigma, often referred to as simply "Lean" or "LSS", is a systematic methodology used for the elimination of waste within a business process or system. Lean management philosophy originated from the Toyota Group's "*Toyota Production System*" (TPS), which was developed throughout the latter half of the 20th century and which strategy was largely credited with transforming Toyota from a small automatic loom manufacturer into one of the world's largest automakers (Khadem, 2006).

Toyota's gradual, but increasingly public rise to the top of the automotive industry's pecking order was closely linked with its adoption of Lean principles, and there soon followed a mass proliferation of continuous improvement management strategies and company specific production systems, also known colloquially as XPS's, over a wide array of business types and entities in what has been termed the "Lean Revolution" (Womack, Jones, & Roos, 1990).

Chrysler's introduction of the Chrysler Operating system in 1994 represented one of the earliest adoptions of Lean methodology outside of Toyota and was quickly followed by the bulk of the world's leading auto makers implementing their own versions of Toyota's TPS. The Lean Revolution soon spread far beyond the bounds of the automotive industry; the US agricultural machinery manufacturer Deere and Company launched their John Deere Production System in 2002. Electrolux, the Swedish producer of household appliances, implemented the Electrolux Manufacturing System in 2005. Siemens, the German electronics and electrical engineering conglomerate, introduced the Siemens Production System in 2008. The same year, the largest food and nutrition company in the world, the Swiss based Nestle' Group, introduced the Nestle' Continuous Excellence program (Schoenberger, 2007; Netland, 2013). Before long, Lean practices had even spread to non-manufacturing industries such as Verizon, which introduced its Verizon Lean Six Sigma program in 2012, and Cardinal Health which implemented its LSS program, Operational Excellence, in 2001.

Though the principles of the "*Toyota Production System*" had been evolving organically within the Toyota company for decades, the term "Lean" was first coined by John Krafcik as part of a master's thesis at the MIT Sloan School of Management in the late 1990's (Krafcik, 1998). Krafcik's initial research was both expanded and popularized by the internationally best-selling book "*The Machine that Changed the World"* which summarized the research results of a 5 year study into the performance of the automotive industry by the MIT based International Motor Vehicle Program (IMVP), under the direction of James Womack, Daniel Jones, and Daniel Roos (Womack, Jones, & Roos, 1990).

Centered on comparing Japanese automakers with American and European competitors, the study ultimately found Japanese manufacturers to be more affected by a ratio of 2:1. This performance difference was attributed to the impact that the implementation of LSS had upon the Japanese automotive manufacturing sector, specifically improved productivity, fast lead times, increased quality, and a more responsive supply chain. Subsequent studies have confirmed the IMVP results, further expanding Lean's reputation as a strong competitive advantage strategy (Boston Consulting Group, 1993). More recent studies have confirmed the financial benefit of LSS manufacturing, while also establishing that these financial advantages may be sustainable (Cavallini, 2008; Jones, 2013).

By the early 2000's, Lean philosophy had become blended in both culture and practice with the Six Sigma methodology that was pioneered by Motorola in the late 1980's. The term *Six Sigma* originated from terminology associated with statistical modeling of manufacturing processes, a six-sigma process being one in which 99.99966% of all outputs are expected to be defect-free (George, 2002). The joint-term "Lean Six Sigma" was first created with the release of a book entitled "*Leaning into Six Sigma: The Path to integration of Lean Enterprise and Six Sigma"* in 2001 by Barbara Wheat, Chuck Mills, and Mike Carnell. Lean management's focus on waste elimination was a natural marriage with Six Sigma's structured processes designed to reduce variability and defects, and the terminology and practices of Lean Six Sigma have since become commonplace.

2.3 Lean Six Sigma Methodology

Synergistically, Lean exposes sources of process variation and Six Sigma aims to reduce that variation by enabling a virtuous cycle of iterative improvements towards the goal of continuous flow (Wheat, Mills, & Carnell, 2001). The overall goal of LSS philosophy is to design and manufacture products or services of high quality and low cost in an efficient manner through eliminating all "*muda*", the Japanese term for waste, while simultaneously increasing process flow and reducing process variation. Essentially, Lean is centered on making obvious what adds value by reducing everything else within the process, as exemplified by the practice of lowering inventory levels to make systemic production problems more obvious (Ahrens, 2006).

In the seminal book "*Lean Thinking*", Womack and Jones prescribe five core philosophical steps for the proper and effective implementation of an LSS production system: 1) precisely specify value by specific product, 2) identify the value stream for each product, 3) make value flow without interruptions, 4) let the customer pull value from the producer, and 5) pursue perfection (Womack & Jones, 1996).

These general guidelines work in conjunction with the common components and tools of any LSS system including work cell with cross-trained operators, quick setup and changeovers, single piece flow that is determined by customer demand, total productive maintenance (TPM), andon cords, quality circles, built in quality ("*jidok*a"), 5S visual management, balanced production ("*heijunka*"), and target costing (Liker, 2004; Schoenberger, 2007). These basic LSS building blocks are summarized in what is commonly known as the "TPS House" model (Figure 2-1) developed by Toyota as a tool for communicating LSS principles in a concise manner.

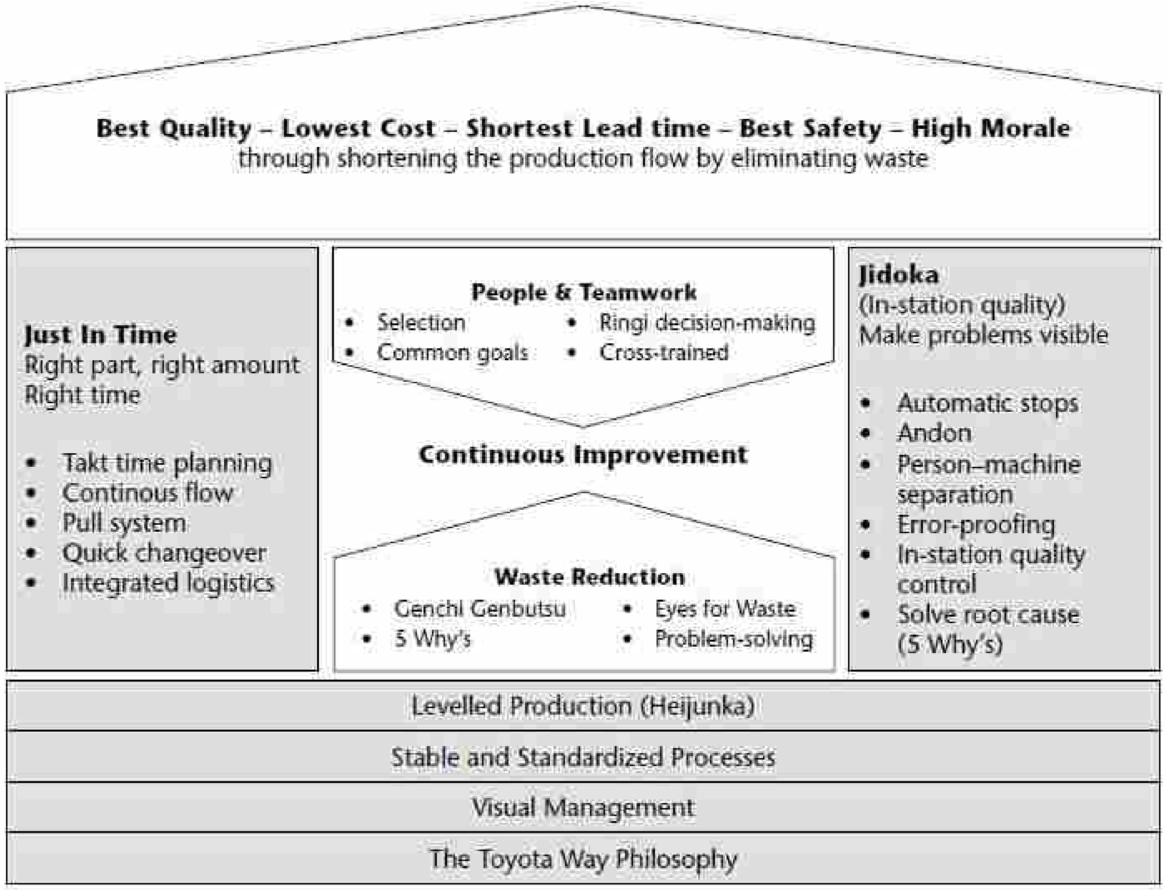

Figure 2-1: TPS House

Among LSS principles, standardization is considered a foundational component of successful production. Standardization in work tasks is viewed as a stabilizing agent that allows workers to identify innovative solutions that can be translated into continuous incremental improvements to the production system (Kim, Kumar, & Kumar, 2012). Likewise, LSS promotes standardization among product components in order to reduce variability and to ensure that final designs are compatible with existing processes so that the firm's resources can be leveraged as much as possible (Mehri, 2006).

As another means of reducing both variability and waste, LSS often employs the DMAIC process, an acronym that stands for: define, measure, analyze, improve, control. A closely related tool is the Design for Six Sigma, or DFSS, process which purports to systemize a new product's development process so that the product can be made to LSS quality from the start (Hindo, 2007).

LSS strategy works from the perspective of the client who consumes a product or service; "value" in a Lean system is defined as any action or process that a customer would be willing to pay for, while "waste" constitutes "everything that increases cost without adding any value in the eyes of the customer" (Dahlgaard, 2006). These wastes are typically categorized into 7 distinct categories, colloquially known as the "7 deadly wastes" (Figure 2-2), though LSS also takes into account waste created through overburden ("*muri*") and waste created through unevenness "*mura*").

Finally, LSS practitioners are quick to emphasize that a simple adoption of LSS techniques will ultimately lead to failure if the "*Toyota Culture*" doesn't become engrained in the organization as whole from a cultural standpoint (Liker, 2004). LSS advocates insist that the full extent of benefits derived from LSS implementation will be never be realized if LSS tools aren't fully supported by a company cultural transformation that is led by the firm's highest-ranking executives (Womack & Jones, 1996).

Failures to properly implement a "TPS style" culture are considered one of the leading causes of misapplied LSS deployments, a reality often ignored or misunderstood by non-Japanese firms seeking to mimic Toyota's unprecedented success (Liker 2004). LSS practitioners frequently insist that internal LSS champions become as familiar with the human element of the LSS system, as they are with the mechanical tools.

Waste	*Definition*	*Examples*
Overproduction	Generating more info & products than needed	-Reports no one reads -Unnecessary meetings -Batch production
Transportation	Movement of info & products that does not add value	-Retrieving/Storing files and paperwork -Moving parts to staging areas before assembly
Motion	Movement of people that does not add value	-Looking for tools -Gathering info -Looking for tools, equipment
Waiting	Idle time when material/people/info is not ready	-Waiting for paint to dry -Waiting for tool to be returned -Waiting for inspection
Over-Processing	Efforts that create no value for the consumers viewpoint	-Creating reports -Removing packaging from parts -Prepping tools
Inventory	More materials/info on hand than needed at the time	-Emails waiting to be read -Just-In-Case inventory -Unused records in database
Defects	Work that contains errors, rework, mistakes, missing parts	-Missing info/parts -Out of specs -Late parts due to rejection tags

Figure 2-2: The 7 Deadly Wastes

2.4 Measurement of a Lean Six Sigma System

Most firms employing LSS utilize a series of internal company metrics to determine the overall effectiveness of the organization. Commonly utilized "measures of success" include the following: order lead time, Dock-to-Dock (DTD) time, First-Time-Through (FTT) percentage, Overall Equipment Effectiveness (OEE), Build-to-Schedule (BTS) ratio, days on hand inventory levels, manufacturing cycle time, 5S diagnostic rating, setup time, machine downtime, scrap rates, rework rates, average lot sizes, flow distances, number of employee suggestions implemented, number of employees capable of cross-functional performance, and administrative transaction time (Khadem, 2006; Wan, 2008; Duque & Cadavid 2007).

Without detailed knowledge of an individual firm's operation and financial data, it is difficult to state with certainty the extent to which a company has successfully adopted Lean Six Sigma. Though the metrics listed above, such as product lead time and inventory levels as compared to industry competitors, have traditionally been used as rough indicators of firm leanness, the data needed to calculate such metrics is both complex and often not publicly available.

In lieu of this dilemma, it has been suggested that inventory turns (Equation 2-1), a metric easily calculated from publicly available firm data, is a viable substitute for product lead time which is considered one of the core internal LSS measures (Jones, 2013). Production indicators, such as inventory turns, are assumed to drive financial results in manufacturing firms, and as such, financial reports may be considered reliable sources of operational metrics (Cavallini, 2008).

$$\text{Inventory Turns} = \frac{\text{Cost of Goods Sold (COGS)}}{\text{Total Average Inventory}} \tag{2-1}$$

Inventory turnover is a ratio showing how many times a company's inventory is sold and replaced over a period of time. Underneath LSS philosophy, inventory is considered waste, and thus inventory reduction is considered a chief aim of any Lean system. As inventory is reduced, the inventory turns ratio will subsequently increase. As such, a company with a greater number of inventory turns is generally considered "more lean" than a company with a smaller number of turns (Demeter, 2011). This measurement is found to correlate positively with long-term Lean trends (Schoenberger, 2007).

2.5 Innovation: An Overview

In general, organizational innovation refers to the creation or adoption of new ideas, knowledge, skills, technologies, and methods that can create value and improve firm competitiveness. Innovation is generally described as the commercialization of newly designed and implemented products or processes (Smeds, 1994). It has been noted that higher levels of innovation and creativity are more valued in the nascent stages of a firm's research and production efforts, whereas time and efficiency become increasingly important towards the end of the R&D process as the product or service moves closer to commercialization (Kratzer, 2008).

Firms are becoming increasingly aware of the importance of maintaining and furthering their own innovation capabilities in order to both maintain their current profit streams and market valuations (Hall, 1999) and to avoid being displaced by long-standing rivals or disrupted by aggressive new market entrants (Christensen, 2013). Among the multiple innovation classification systems and taxonomies, there are generally two broad categories as applied to firm innovation: product innovation and process innovation.

Product innovations refer to the creation of new products or services, as well as improvements on existing products or services (Kim, Kumar, & Kumar, 2012). By contrast, process innovations refer to the changes in the method of producing products or services, focusing on improvements to both the effectiveness and efficiencies of production or service processes (Bon & Mustafa, 2013). Process innovation is typically associated with the sequences and nature of the production process that improves the activity and the efficiency of production activities (Tushman, 2006).

Research by Kim, Kumar, and Kumar (2012) suggests that both product and process innovation can be further segmented into incremental and radical innovations based on the degree of the technological change or the extent of departure from previous concepts or practices as follows:

- Radical process innovation refers to innovation associated with the application of new or significantly improved elements into an organization's production or service operations with the purpose of accomplishing lower costs and/or higher product quality.
- Incremental process innovation is identified as innovation associated with the application of minor or incrementally improved elements into an organization's production or service operations with the purpose of achieving lower costs and/or higher product quality.
- Radical product innovation is defined as innovation associated with the introduction of products (or services) that incorporate substantially different technology from that now in use for existing products.
- Incremental product innovation refers to innovation related to the introduction of products (or services) that provide new features, improvements, or benefits to existing technology in the existing market.

It should be noted that while the classification distinctions between incremental and radical innovation are important from a literature review perspective and have been used by innovation scholars to create a taxonomy of innovation types (Figure 2-3), in practice it is extremely difficult to differentiate between the radical and incremental degrees of innovation without access to internal company data, and as such, this research will not delineate between incremental and radical innovation in its methods or results.

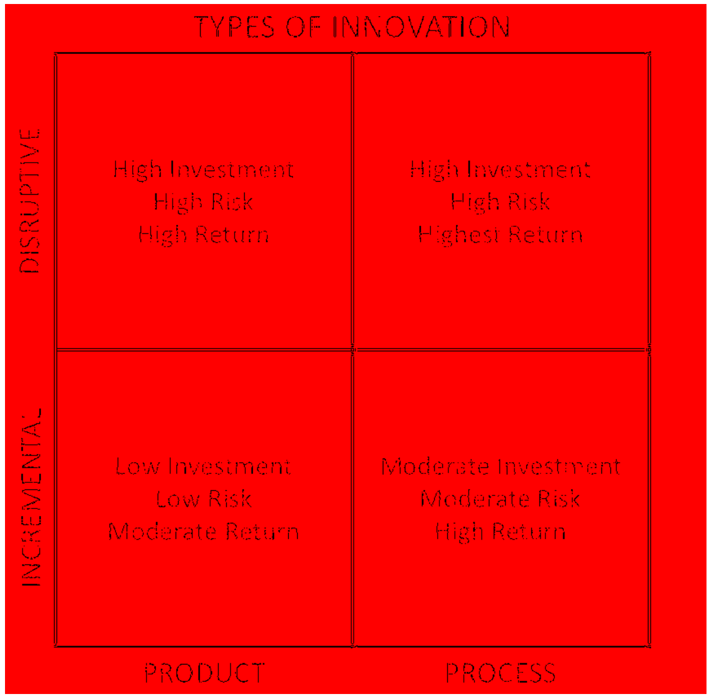

Figure 2-3: Innovation Taxonomy Matrix

2.6 Innovation Metrics

As the study of innovation has grown in both prominence and importance, researchers have sought to identify measures of innovation and creativity that are both objective and accurate. Early innovation indicators have included metrics such as amount of R&D spend, time to market of new products (TTM), percentage of revenue derived from new products, mean number of innovation adoptions (MNI) as compared to industry rivals, number of products currently in the R&D pipeline, mean time of innovation adoption (MTI) as compared to competitors, number of ideas generated, patent counts, and patent citations (Kirsner, 2015; Kim, Kumar, & Kumar, 2012; Moura, 2007).

However, the perfect innovation metric has proven elusive and an increasing number of firms are seeking to utilize innovation measures more concretely tied to operational and financial performance, as a method of tying innovation investment to outcomes. An extensive study of 198 innovation executives of leading North American firms concluded:

> "Innovation executives who had been in the role for two or more years almost universally said that they have moved away from more generic activity measures — like how many people had participated in a company crowdsourcing initiative — and toward more specific impact measures that matter to the CEO or COO" such as P&L impact, effectiveness of R&D spend, etc." (Kirsner, 2015)

While these measures each provide a unique aspect of the overall value of innovation, one of the primary limitations associated with such measures is their heavy dependence on internal firm data that is generally unavailable to outside academic investigation and study.

Among the first generation of innovation metrics, perhaps the most commonly utilized in the realm of academia is the use of patent statistics. To an extent, patents do measure the output of innovation activities (Antonelli, 2009), and are typically awarded to novel, non-obvious designs that represent advancements over existing technology. As such, patents have the advantage of being a quantitative indicator of research output, as opposed to metrics such as R&D expenditures, which reflect inputs to research (Englander, 1988). For these reasons, some researchers have argued that patent data are among the most reliable and valid measures of innovation activity (Griliches, Pakes, & Bronwyn, 1987; Tushman, 2006; Podolny & Stuart, 1995).

More recent research has begun to question the validity of patent measures and suggests that there are many limitations to the various patent statistics as currently utilized in innovation research. One of the primary drawbacks is related to the fact that not all innovations are patented, and thus the number of patents over time may actually understate actual growth in innovation. The reasons for this phenomenon are varied. First, some innovations simply don't meet the patentability criteria and are thus excluded from any innovation database (Antonelli, 2009). Furthermore, firms often strategically decide not to patent their most valuable innovations especially in cases of innovations with a high level of natural appropriability (Abrams, Akcigit, & Popadak, 2013) or choose not to do so because the cost of obtaining and reinforcing patents have risen at much higher rates relative to alternative protection mechanisms (Lanjouw, 2004). Prior studies have found that fewer than 50% of publicly traded firms who conduct R&D actually file patents for their innovations, thus severely limiting sample size and decreasing the statistical testing power based on these measures for publicly traded companies (Cooper, Yang, & Knott, 2015).

Beyond the practical problem of limited sample size, it is also difficult to measure the strategic or innovative value of individual patents. While some patented innovations have enormous economic impact, many others become "dead-end branches". Highlighting this problem was a study by Scherer and Harhoff which concluded that only 10% of U.S patents account for 81-85% of the economic value of all U.S patents (Scherer & Harhoff, 2000). To cope with this problem, researchers have begun to weight patents by the number of citations they receive or use the total citations (rather than total patents) received by the firm. While the use of patent citations has been found to be a better predictor of firm value than patent counts (Hall, Jaffe, & Trajtenberg, 2001) this correction is still problematic as patent citation studies reveal a high degree of variance: only a few patents out of hundreds, if not thousands, actually contain significant value-driving content (Antonelli, 2009; Abrams, Akcigit, & Popadak, 2013). Thus, while citations may help mitigate the non-uniformity problem of patent value, they don't solve it.

Another practical problem with patent data is its tendency to be subject to "truncation bias" (Hall, Jaffe, & Trajtenberg, 2001). This bias is best explained by the reality that patent citations can take years to materialize, meaning that an older patent can receive more citations than a newer patent, even if the older citation has only marginal value in comparison (Scherer & Harhoff, 2000).

In summary:

> "Research and development statistics provide a partial account of the amount of resources used in the generation of new technological knowledge, patents measure to some an extent the output of such activities, but neither one provides a reliable account of the actual capability of firms to exploit the technological knowledge that has been generated." (Antonelli, 2009)

Given the concerns with traditional R&D and patent-based measures of innovation and the desire of innovation executives to more closely tie innovation metrics with operational and financial outcomes, recent academic literature has introduced alternative firm-level measures of innovation: Total Factor Productivity (TFP), Research Quotient (RQ), and Tobin's Quotient (TQ). While none of these indicators in isolation represent a "perfect innovation metric", each measures a different aspect of innovation, and when taken together, allow a more accurate understanding of the nuanced impact that LSS will have upon firm innovation activities.

2.6.1 **Total Factor Productivity (TFP)**

Total Factor Productivity (Equation 2-2) is a measure of the overall effectiveness with which capital and labor are used in a production process. It provides a broader gauge of firm-level performance than some of the more conventional productivity efficiency measures, such as labor productivity or firm profitability. One way to interpret TFP is the efficiency with which an organization translates production inputs into economic returns. (Imrohoroglu & Tuzel, 2014).

Though TFP was originally devised for calculation on the national scale, several recent papers (Beveren, 2008; Imrohoroglu & Tuzel, 2014) have provided detailed methodology for its accurate calculation at the firm level as follows:

$$\text{Total Factor Productivity} = Y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + w_{it} + n_{it} \tag{2-2}$$

In the equation above, Y_{it} is the log value added for firm I in period *t,* k_{it} represents the log values of capital, l_{it} represents the log values of labor, w_{it} is productivity, and n_{it} is an error term not known by the firm or the researcher.

As TFP is a measure of the efficiency of all inputs into a production process, increases in TFP usually result from technological innovations or improvements (Syverson, 2011). As such, TFP is commonly used in academic literature as a process innovation indicator because it can account for the effect of invention on overall firm productivity (Lanjouw, 2004; Englander, 1988; Hall, 1999; Hulten, 2000).

Because TFP is the remainder in the firm production function after taking into account the contributions of measurable inputs, there is a concern that TFP doesn't isolate the contributions of R&D, and thus should be used primarily as a process innovation metric rather than as a product innovation metric (Cooper, Yang, & Knott, 2015).

TFP's use as an organizational process innovation metric is also favored by several studies which have proven the feasibility of an accurate assessment of TFP at the firm level and provided detailed methods for its computation from publicly available financial data (Olley, 1996; Beveren, 2008; Imrohoroglu & Tuzel, 2014). A recent study into TFP's use as an innovation indicator concluded:

> "The failure of the traditional indicators of innovative output suggests that that we use total factor productivity (TFP) measures to grasp the actual extent to which firms are able to generate and exploit technological knowledge. TFP provides a reliable measure of the extent to which firms are able to increase their output beyond the expected levels based upon the increase of inputs. While R&D and patent statistics only measure the firm's capability of generating technological knowledge, TFP is able to apprise for the capability to generate and exploit technological, organizational, and financial innovations." (Antonelli, 2009)

One of the weaknesses of utilizing TFP as a measure of process innovation is that there are occasionally long and uncertain lags between spending on innovation and the impact those investments have on the "bottom line". These lags mean that one may have to wait for long periods of time to see the effects in productivity or financial return, making the exercise of limited value for planning purposes (Hall, 1999).

However, TFP has been found to positively correlate with product innovation/R&D metrics such as RQ (Knott & Vieregger, 2015) and with firm market value as measured by market to book ratios such as Tobin's Q (Imrohoroglu & Tuzel, 2014; Antonelli, 2009).

2.6.2 Research Quotient (RQ)

A recent innovation in the analysis and measurement of a firm's product innovation/R&D has been the development of the concept of Research Quotient (Equation 2-3) which was originally published in 2008 by Dr. Anne Marie Knott of Washington University in St. Louis and is now formally adopted by the Wharton Research Data Services (WRDS) database. A company's Research Quotient (RQ) is the firm specific output elasticity of R&D. More specifically, RQ represents the percentage increase in the firm's revenue from a 1% increase in its R&D investment and is considered a measure of product innovation (Halperin, 2016).

The way to interpret RQ is a firm's ability to generate revenue from its R&D investment. Thus, a firm can have a high RQ by generating a large number of innovations and being reasonably effective in exploiting them, or by generating a smaller number of innovations and being extremely effective in exploiting them (Knott, 2008).

$$Research\ Quotient = Y = A_i K_{i,t}^{\alpha} L_{i,t}^{\beta} R_{i,t-1}^{\gamma} S_{i,t-1}^{\delta} D_{i,t}^{\phi} e_{i,t} \qquad (2\text{-}3)$$

In the equation above, Y is output, A_i represents a firm fixed effect, $K_{i,t}$ is capital, $L_{i,t}$ is labor, $R_{i,t-1}$ is lagged R&D, $S_{i,t-1}$ is lagged spillovers, and $D_{i,t}$ is advertising. RQ values are automatically pre-calculated and provided via the Wharton Research Data Services (WRDS) database.

RQ is considered to hold several key advantages over traditional product innovation indicators such as patent measures. Firstly, RQ is considered universal, in that it is estimated entirely from standard publicly available financial data, and can thus be derived for any firm engaged in R&D. Secondly, RQ is uniform, in that it is a unit-less ratio whose interpretation is easily applicable across firms regardless of industry or size (Cooper, Knott, & Yang, 2015). RQ has been found to be negatively correlated with patent counts and patent intensity, but positively correlated with other innovation metrics such as R&D expenditure, Total Factor Productivity, Holt's Innovation Premium, and firm market value (Knott & Vieregger, 2015). Additionally, RQ is negatively correlated with cooperative/outsourced R&D but is positively correlated with internal R&D (Knott, 2012).

2.6.3 Tobin's Quotient (TQ)

Popularized by Nobel laureate James Tobin in 1978, Tobin's Q, also abbreviated as "TQ" or simply "Q", is the ratio of the market value of a firm relative to the replacement cost of its tangible assets (equation 2-4). Tobin hypothesized that the combined market value of each company in the stock market should equal its combined asset value. In other words, the market value of a U.S company should equal what it would cost to build an identical firm today. If the market value is equal to the replacement value, the TQ ratio is equal to 1. A TQ value > 1 suggests that the market value of a company is greater than the replacement cost of its assets and implies that the firm may be overvalued. This would suggest that the market value reflects some unmeasured or unrecorded assets of the company (Tobin, 1977).

$$Tobin's\ Quotient = \frac{Total\ Market\ Value\ of\ the\ Firm}{Total\ Tangible\ Asset\ Value\ of\ the\ Firm} \tag{2-4}$$

A wide array of research has related Tobin's Q with the intangible capital that enables firms to both generate and introduce technological (product innovations) and organizational (process innovations) innovations and the subsequent firm profitability that stems from their exploitation (Cockburn & Griliches, 1988; Hall, Jaffe, & Trajtenberg, 2001; Megna, 1993). One of the early studies into this relationship concluded:

> "Market level measures of firm value such as Tobin's Q can provide an understanding of the stock market's valuation of a firm's innovative activity. These measures can estimate the relative valuation of firm's tangible and intangible assets, focusing on knowledge capital in the form of accumulated R&D efforts and patent rights, and ignoring other intangibles such as goodwill, advertising, and sector-specific human capital. The market's valuation of a given amount of innovative activity will vary according to how successfully a firm can appropriate the returns from R&D investments." (Cockburn & Griliches, 1988)

Other studies have positively linked firm market value measures, such as TQ, with R&D investment and operational improvements (Hall, 1999; Villalonga, 2004; Joseshki, 2013) and have positively correlated TQ with both TFP and RQ (Antonelli, 2009; Cooper, Knott, & Yang, 2015). Thus, Tobin's Q may be considered as an indicator of the "market response to innovation" or a general "net effect" measure of both process innovation and product innovation within an individual firm. As such, TQ reflects the premium that investors are willing to pay based on what they perceive as the strong innovation capability of a firm (Rubera, 2013).

TQ has gained favor as a general innovation metric, and as it is readily calculated from publicly available financial data, it avoids the lag problems associated with TFP, as well as the timing of cost and revenue inputs required by RQ, and is capable of forward looking evaluation (Hall, 1999).

The main conclusion of the works relating market value and innovation is that market indicators enable observers to identify innovative capabilities as a form of intangible capital, but that each individual innovation metric gathers different elements of the overall picture of "organizational creativity", and as such, empirical analysis should include as many innovation measures as possible when analyzing a firm's innovation performance (Antonelli, 2009).

2.7 Lean Six Sigma (LSS) and Innovation: A Controversial Combination

As noted in the introduction of this paper, the relationship between LSS and innovation performance is a hotly debated topic among management and academic circles. An investigation of the current literature reveals three general schools of thought with regards to the LSS/innovation interaction: positive impact, negative impact, and neutral impact. A summary review of each of these views is detailed in the sections below.

2.7.1 Positive Impact of LSS on Innovation Performance

LSS proponents have long maintained that knowledge creation from LSS practices has a positive effect on organizational innovation (Bryne, 2007), and point to case examples where firm-wide LSS implementation has led to dramatic improvements into both process innovation and product innovation. As an example, Parast (2011) credits Caterpillar Inc's LSS program as directly leading to numerous product innovations, such as its successful low-emission diesel engine, and to redesigned processes, including a streamlined supply chain (Parast, 2011). Other examples are found in the pharmaceutical industry where researchers point to an increasing body of evidence suggesting that LSS programs are improving drug-research R&D cycle times by up to 50%, with companies like Eli Lilly and Covance claiming more than $1 billion and $30 million, respectively, in cumulative benefits from LSS adoption (Johnstone, 2011). A recent study of 249 Chinese firms indicated that increased management focus on LSS practices positively correlated with improvements in product, process, and administrative innovation, and that there were no significant differences in the relationship between LSS practices and organization innovation in terms of firm size (He, Deng, Zhang, Zu, & Antony 2017).

Azis and Osada (2010) suggest that the DMAIC (Define-Measure-Analyze-Improve-Control) methodology often employed by LSS practitioners creates incremental innovation by promoting improvement based on the existing conditions, while the DFSS (Design for Six Sigma) approach allows for radical innovation by designing new products, services, or business processes according to customer needs and expectations (Azis & Osada, 2010). This systematic focus on the "voice of the customer" and use of quantitative metrics also helps firms identify emerging market trends, particularly as they pertain to product needs (Hoerl, 2007).

LSS teams typically benchmark different processes to find out the best practices, which can be used as learning examples and support innovative activities, especially as such benchmarks are tied to core business performance metrics. This may create a virtuous cycle in which businesses become more efficient in identifying and adopting best practices and methods in bringing new products from conception to commercial success (Kim, Kumar, & Kumar, 2012).

Reinersten and Schaffer (2005) note that low-cost, rapid cycles of learning achieved through *kaizen* improvements and philosophy can directly reduce organizational and individual risk aversion because the cost and consequences of a negative outcome are reduced (Reinersten & Shaffer, 2005). Empirical results of a survey of 201 LSS practitioners revealed that LSS's structured methods are very robust in stimulating an individual's exploration (tendency to experiment, take risks, innovation, play, and search) and exploitation (tendency to increase efficiency by leveraging existing firm resources), and tend to enhance displays of creative project management (Hwang, Lee, & Seo, 2017).

Bryne (2007), analyzed the innovation performance of several companies that had embraced LSS and found that the most successful companies were those that had deliberately extended LSS principles into their innovation agenda and had used it to enable breakthrough innovations and an overall cultural transformation to one that supported continual innovation (Bryne, 2007). In addition, the particular role structures of LSS have been found to promote team work and shared learning and interaction between cross-functional work areas, which leads to a more creative environment and innovation minded culture (Gutierrez, 2017). As an example, Barhnhart describes that during a three-day LSS workshop with drug discovery teams, social bonds and team unity were fostered, while cross-functional frictions were reduced as employees better understood the LSS principle that "the process, not the person, was the root of production issues and that the process can be controlled" (Barnhart, 2008).

The so called "productivity dilemma" has been studied extensively with regard to Toyota, which is a firm that has been able to balance operational efficiency with product innovation. One description of Toyota's approach is that of "deliberate perturbation and exploratory interpretation", where the apparent conflict between exploration and exploitation can be minimized (Brunner et al, 2010). One example is the case of Toyota reducing inventory buffers in order to surface problems in its production system or supply chain. By focusing on the problems, the resulting process innovations can make the production system more robust, while the total inventory in the supply chain can be reduced (Fujimoto, 1999; Fullerton & McWatters, 2001). Toyota has also been described as a firm that "actively embraces and cultivates contradictions", where it "deliberately forces contradictory viewpoints within the organization and challenges employees to find solutions by transcending differences rather than by resorting to compromises" (Adler et al, 2009).

One of the attributes that allows Toyota to excel in both process innovation and product innovation is continuous learning. Examples of this include the value stream mapping exercise, where the current situation is rigorously established, then the ideal situation is envisioned (where the difference can be significant); or the notion that all members of the organization are able, and expected, to use their intellect to make improvements through kaizen, an incremental improvement process than can also stimulate significant innovative leaps (Adler et al, 2009).

2.7.2 Negative Impact of LSS on Innovation Performance

Despite its well-proven operational benefits, LSS management is not without its critics. Some management thinkers, executives, and academic researchers have become concerned that the focus that LSS practices place upon mechanisms (such as product and process standardization) aimed at increasing productivity and controlling costs may actually have an overall negative impact on the firm's creative capabilities, particularly product innovation performance (Lindeke, Wyrick, & Chen 2009). As an example, critics point to the dramatic fall of 3M from industry innovation rankings in the mid 2000s, following the firm wide adoption of LSS during the tenure of CEO James McNerney (Hindo, 2007).

One of the most notable attempts to capture this negative impact was a study conducted by Tushman and Benner (2006) in an analysis of the paint and photography industries. Patents granted to U.S paint and photography companies were analyzed over a 20-year period, before and after firm adoption of LSS. Their work showed that after LSS implementation, patents issued primarily on prior work made up a dramatically larger share of the total, while those not based on prior work dwindled, suggesting that LSS will lead to more incremental innovation at the expense of more exploratory blue-sky work. (Benner & Tushman, 2002). Further case studies evaluating the impact of LSS practices on an organization's competitiveness also found that the more successfully LSS principles are applied in an organization, the more focused the organization tends to be on incremental production changes as compared to radical innovation initiatives (Mehri, 2011; Tushman, 2006).

Since the process of investigating potential early stage innovations requires greater lengths of experimentation and high levels of risk, exploratory activities tended to be eliminated from the management's priority list at an early stage. Thus, it was discovered that going "too lean" could be harmful to product design systems (Lewis, 2000). Other studies have noted that standardization in LSS design is often interpreted as being directly anti-innovative, because of the implication that the standard way is the "right way". In such a scenario, creative improvements can be stifled, suggesting that LSS has an overall negative effect on company's radical innovation capability (Chen & Taylor, 2009; Johnstone, 2011). Furthermore, it has been found that it may be difficult to prevent an LSS focus on process innovation from spreading to "centers of innovation", within a firm, progressively reducing the "organization's dynamic capabilities" (Cole & Matsumiya, 2007).

Other researchers theorize that the LSS culture to reduce slack, risks, and variability is expected to have a negative impact on a company's culture to foster innovations, particularly the willingness to devote resources to projects with significant levels of uncertainty and variability (Lindeke, Wyrick, & Chen 2009; Johnstone, 2011). LSS philosophy traditionally asserts that "value" can only be defined by the end users and asserts that customer needs and wants should be followed closely in product design and manufacturing (Liker, 2004), with deviations to this definition being considered *muda*. However, this assumption may hinder radical disruptive innovations that create technology "push" opportunities because exclusively following the customer's definition of value overlooks the reality that customers can be wrong, or at least short-sighted with regards to future trends and product needs (Parast, 2011; Christensen, 2013).

It is also noticeable that many organizations that employ LSS tend to be larger in scale and more complex in R&D management structures due to the complicated nature of the company's services or products. This may be inadvertently harmful to innovation as larger sized teams are generally found to be less creative, because they face a greater challenge than smaller teams in achieving timely and sufficient distribution of information (Kratzer, 2008). In cases where LSS organizations used improved efficiencies to eliminate employee headcount, it has been noted that the resulting workload creates an increase in stress in the remaining workers that has a tendency to negatively impact individual creativity (Oldham & Cummings, 1996). The multi-functional and multi-responsibility requirements on LSS workers also leads to a decreased expertise in workers' specialized areas. Since expertise is another key contributing factor to creativity, decreased innovation is expected as a result (Amabile, 1998).

2.7.3 Neutral Impact of LSS on Innovation Performance

A third body of research suggests that LSS's impact on firm innovation performance, while nuanced and complex, is not inherently positive nor negative, but rather is dependent on the specific management decisions made during LSS implementation. This view is best encapsulated by Johnstone's (2011) conclusion of a study on the relationship between LSS and innovation within the pharmaceutical industry:

> "Deploying lean thinking does not, as a direct consequence, enhance or drive innovation, nor is it contraindicated. Instead, we believe that the fate of innovation under a continuous improvement drive (or vice versa) depends on the choices that are made and the climate that is created during the deployment journey." (Johnstone, 2011)

Other researchers state that organizational balance between LSS and innovation initiatives is needed, as focusing solely on innovation to the exclusion of LSS, or vice versa, is likely to have severe negative financial implications for the firm (Hoerl, 2007). This balance is difficult to achieve since innovations, particularly product innovations, that serve different customer sets or rely on new and unknown technologies are highly uncertain and difficult to measure and/or predict. Such exploratory activities are increasingly unattractive when compared with the short-term measurable benefits garnered from process improvements such as LSS (Tushman, 2006). The relative certainty of process innovation can crowd out exploratory learning and product innovation by triggering a reduction in investments in experimentation if not carefully guarded against by management who must maintain a longer view of the overall value to the company in order to avoid ultimate failure (Christensen, 2013; Tushman, 2006). Thus, LSS (and other process innovations) are not considered inherently anti-innovative by nature, but instead, may provide an overpowering temptation for management resources from executives whose performance is most tightly linked to short term measures.

Other studies have noted that while LSS tends to have a positive impact on process innovation and incremental innovation, it has a neutral (as opposed to a negative) impact on both product and radical innovation. An in-depth study of 10 UK firms found that LSS adoption had a strong positive correlation with process innovation indicators, but no statistically significant relationship with either radical or product innovation measures (Figure 2-4; Antony, 2016).

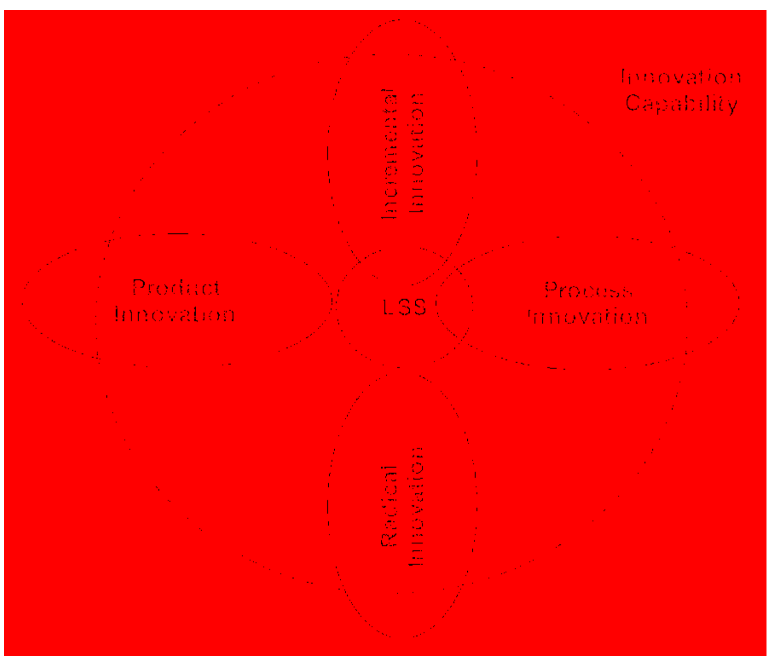

Figure 2-4: LSS Impact on Innovation Capability

Another study of 220 Australian organizations found that LSS does not have a statistically significant relationship with product innovation measures such as time-to-market (TTM) of new products, but that LSS's tendency to drive out variance increasing activities had a negative impact on metrics like creative slack time per employee. . The overall conclusion was that LSS adoption is likely to stifle product innovation performance while simultaneously improving process innovation performance (Terziovski, 2014).

3 METHODOLOGY

3.1 Introduction

This chapter provides an outline of the methods and tools used to gather and analyze the data pertinent to this research. Background information, definitions, and justifications for the use indicators used as metrics of company Lean Six Sigma (LSS) performance and innovation performance will also be provided.

Although prior academic researchers have investigated the potential impact LSS may have on firm innovation performance (including both product and process innovation dimensions) conceptually and qualitatively, none have attempted to investigate this effect via quantitative analysis. In order to analyze the impact that LSS has on firm innovation, the following method was used for this research:

Financial and operational data for 151 companies, mostly selected from the manufacturing sector, over the period from 1985 to 2017 were collected. Focal firms were selected based upon both documented evidence of official enterprise-wide LSS adoption and successful LSS performance, as indicated by receipt of LSS certifications, awards, or repeated citation in academic literature. Rivals for each focal firm were selected via careful analysis of peer comparison data in business intelligence databases. Statistical regressions performed on this data set were used to show correlations between firm LSS metrics (including inventory turns and company LSS adoption dates) and firm innovation metrics (including Total Factor Productivity

(TFP), Research Quotient (RQ), R&D investment, and Tobin's Quotient (TQ)). Regressions were performed using the Coarsened Exact Matching (CEM) method (detailed in Section 3.7).

3.2 Qualifiers

This research is solely focused on publicly traded firms based both in the United States and internationally. Additionally, the majority of the selected sample firms are classified as manufacturing firms. The reasons for this selection are as follows:

- The United States government requires publicly traded companies to provide specific financial and operational data to the public. This information is provided via annual 10-k reports and is readily available at the Security Exchange Commission (SEC) website (www.sec.gov) or via specialized databases, such as the Wharton Research Data Services (WRDS). Financial and operational information for a large number of publicly traded international companies is likewise readily available via the WRDS database.
- This research uses inventory turns (equation 3-1) as an indicator of the leanness of a firm. Inventory data is more easily quantified in manufacturing companies than in service companies, due to the discrete nature of manufacturing products. The United States Department of Labor defines a manufacturing entity as one who is "engaged in the chemical or mechanical transformation of raw materials or processed substances into new products." (US Government Code Section: 14835-14843).

3.3 Data Sources and Tools

Data required for this research was obtained from annual corporate 10k reports using the Wharton Data Research Services (WRDS) database. WRDS is a comprehensive data research platform and business intelligence tool for academic, government, non-profit institutions, and corporate firms. WRDS was developed in 1993 to support faculty research at the Wharton School of the University of Pennsylvania. WRDS has since evolved to become the leading business intelligence tool for a global research community of 30,000+ users at over 375 institutions in 33 countries (www.wharton.wrds.com).

Statistical regressions and data cleaning performed as part of this research were carried out using the statistical computing software "R". R is widely used among statisticians and data miners for its ability to provide comprehensive data analysis. R provides a wide variety of statistical modelling (linear and nonlinear), classical statistical tests, time-series analysis, classification, clustering, etc. The software is supported by the R Founding for Statistical Computing (www.r-project.org).

In order to ensure data homogeneity between firms, all financial data were provided in U.S. dollars (USD). In cases where international firms recorded financial data in local currencies, data was translated into USD via historical currency exchange rate tables provided by the Bank of England (www.bankofengland.co.uk).

Datasets were exported to Microsoft Excel in .csv format to check more thoroughly for errors, data consistencies, and to perform preliminary regressions for statistical validity. However, it should be noted that final regressions and sub setting was achieved via R.

3.4 Selection of Sample Firms

In total, 151 publicly traded firms were utilized in this study. Of this set, 78 were identified as the initial focal firm set, with the remaining 73 firms being identified as focal firm rivals. A full list of the firms utilized in this study is included in Appendix A. Each firm is primarily identified via its “gvKey”, the unique company identifier assigned in WRDS. Methodology for creating this sample set of companies is described in the next paragraph.

3.4.1 Identification of LSS Focal Firms

In order to more accurately analyze the impact that firm LSS adoption and performance had upon organizational innovation, this research sought to utilize “high-performing” LSS firms as the focal firm sample set, as opposed to firms that merely claimed to have adopted LSS, but in practice were not good representations of LSS implementation (Liker, 2004).

As a method of eliminating “LSS pretenders”, the initial sample set of focal LSS firms was taken from the list of Shingo Prize for Operational Excellence and Malcolm Baldridge National Quality Award recipients. These national awards were considered reasonable proxies for successful LSS implementation, as recipient firms must meet substantial operational performance standards and are subjected to a series of external audits analyzing company LSS metrics and data. Details regarding both LSS awards are included below:

- The Malcom Baldridge National Quality Award recognizes U.S. organizations in the business, health care, education, and nonprofit sectors for performance excellence. The Baldridge Award is the only formal recognition of the performance excellence of both public and private U.S. organizations given by the President of the United States. It is administered by the Baldridge Performance Excellence Program, which is managed by the National Institute of Standards and Technology (NIST), an agency of the U.S. Department of Commerce. Up to 18 awards may be given annually across six eligibility categories – manufacturing, service, small business, education, health care, and non-profit. The program and award were named for Malcolm Baldridge, who served as the United States Secretary of Commerce during the Reagan administration from 1981 to 1987. The award is given at the organizational level and is not given for specific products or services (www.nist.gov/baldrige).

- The Shingo Prize for Operational Excellence is an annual award given to organizations worldwide by the Shingo Institute, part of the Jon M. Huntsman School of Business at Utah State University. Considered the "Nobel Prize of Lean Six Sigma", an organization must apply for the award by first submitting an achievement report that provides data about recent LSS business improvements and accomplishments. The firm is then subjected to an onsite audit performed by Shingo Institute examiners. Those meeting the criteria are awarded the Shingo Prize. Other awards include the Shingo Silver Medallion, and the Shingo Bronze Medallion (www.shingoprize.org).

As not all high performing LSS firms may have applied for either a Baldridge Award or Shingo Prize, other firms were included in the focal firm set if recognized repeatedly in academic literature focusing on LSS performance (i.e. Toyota, Audi AG, etc.). In total 78 focal firms were identified as high performing LSS focal firms. While the number of firms is considered acceptable for statistical sampling purposes, this research does not consider nor imply that the 78 firms selected are the highest performing LSS firms globally, or that firms not selected for the study have not adopted LSS.

3.4.2 Identification of LSS Focal Firm Rivals

In order to compare firms utilizing the Coarsened Exact Matching (CEM) approach detailed in Section 3.7 it was necessary to identify 2 rivals for each LSS focal firm who competed within the same industry and were relatively close in size as measured by revenue and market capitalization. As a method of mitigating database bias and ensuring accuracy, rivals were identified by triangulating the peer comparison results found in three separate business intelligence databases: Dow Jones Factiva, D&B Hoovers, and Morningstar. Rivals failing to meet inclusion in all three databases were not included in the sample set.

It should be noted that due to the relatively small size of industry competitive circles, some LSS focal firms were identified as primary rivals to other LSS focal firms. This classification resulted in the total number of unique firms doubling, rather than tripling, for a total of 73 additional rival firms.

3.5 LSS Performance Indicators (Independent Variables)

As stated previously in Section 3.1, this research utilized inventory turns (Equation 3-1) as a proxy measure for company LSS performance. Additionally, it was critical to identify the year in which the firm adopted LSS on an enterprise-wide level in order to analyze the time-based impact of LSS implementation on both innovation and LSS metrics.

3.5.1 Inventory Turns

The use of inventory turns as an acceptable core measure of LSS production systems is well established in academic research (Schoenberger, 2007; Cavallini, 2008; Jones, 2013). Inventory turnover is a ratio showing how many times a company's inventory is sold and replaced over a period of time, and measures how long a company takes to sell its on-hand inventory. As inventory is reduced it must be replaced more often if demand remains constant, so the inventory turns ratio will subsequently increase. Within the WRDS COMPUSTAT database, company inventory turns are calculated as follows (Equation 3-1):

$$Inventory\ Turns = \frac{Cost\ of\ Goods\ Sold\ (COGS)}{Total\ Annual\ Inventory\ (INVT)} \tag{3-1}$$

Because LSS philosophy considers inventory as waste, inventory reduction is considered a chief aim of any LSS system. As such, a company with a greater number of inventory turns is generally considered “more lean” than a company with a smaller number of turns (Demeter, 2011). Lower inventories cost less than higher inventories, but service level is also important. A lower level of inventory turns indicates greater flexibility in a manufacturing system, because small lot sizes require quick changeovers on equipment used for multiple products. This flexibility equates to shorter lead times for customers, which is considered a competitive advantage. Therefore, companies that implement LSS successfully enjoy both lower cost and shorter lead times.

3.5.2 LSS Adoption Date

Firm LSS adoption dates, were identified via manual investigation of both primary sources (company websites, official company press releases, company quarterly reports) and secondary sources (published academic studies or business literature on LSS adoption and performance). Only sources that explicitly recognized official LSS adoption as a company strategy at the firm-wide level were regarded as valid. LSS adoptions that pertained only to individual business units or locations (e.g. individual plants or factories) were not considered valid dates for firm-wide adoption of LSS and were excluded from the study.

Out of the 151 sample firms, only 18 were found to have no credible source of an official LSS adoption date. This large number of adoption reporting firms was unsurprising considering the tendency of business rivals to mimic industry best practices in addition to the desire of executives to publicize efficiency improvements to analysts, employees, and stockholder audiences. A list of firm LSS adoption dates can be found in Appendix A.

3.6 Innovation Performance Indicators (Dependent Variables)

As stated in Section 3.1, this research utilizes Total Factor Productivity (TFP) as a measure of firm process innovation, Research Quotient (RQ) as a measure of firm product innovation, and Tobin's Q (TQ) as a measure of the "market response to innovation" or a general "net effect" measure of both process innovation and product innovation within an individual firm.

3.6.1 Total Factor Productivity (Firm Level)

As discussed in Section 2.6.1 (Equation 2-2), TFP is a measure of the overall effectiveness with which capital and labor are used in a production process and is widely used in academic research as measure of process innovation (Syverson, 2011; Lanjouw, 2004; Hall, 1999; Hulten, 2000; Antonelli, 2009). It should be noted that since LSS is considered a process innovation enabler, it is expected to contribute positively to a firm's TFP.

The main data source for all TFP calculations performed was WRDS COMPUSTAT. Observations of financial firms (SIC classifications between 6000 and 6999) and regulated firms (SIC classification between 4900 and 4999) were deleted to remove year and industry effects. Inputs into the production function utilized the following WRDS variables: sales (SALE), number of employees (EMP), gross property, plant, and equipment (PPEGT), depreciation (OIBDP, DP), accumulated depreciation (DPACT), and capital expenditures (CAPX).

Firm level data were supplemented with price indexes for Gross Domestic Product (GDP) as a deflator for investment and capital. These index values were collected from the Bureau of Economic Analysis (GDP deflator index = NIPA Table 1.1.9, line 1; Price index for non-residential private fixed investment = NIPA Table 5.3.4, line 2). National average wage index data were obtained from the Social Security Administration website (www.ssa.gov).

Several studies have provided detailed methods for the computation of TFP from publicly available data (Olley, 1996; Beveren, 2008) with Tuzel in particular (Imrohoroglu & Tuzel, 2014) detailing a methodology (Equation 3-2) for computing TFP at the firm level as follows:

$$Firm\ Level\ TFP = P_{it} = exp(y_{it} - \hat{\beta}_0 - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it}) \tag{3-2}$$

In the equation above P_{it} is productivity, y_{it} is the log value added for firm *i* in period *t*, k_{it} represents the log values of capital, l_{it} represents the log values of labor, and β_0, β_l, β_k represent production functional parameters.

Out of the 151 sample firms, TFP data were calculated for 99 firms, with a total of 2,484 observations. Observations that were missing needed inputs for TFP calculation were dropped from the sample set.

3.6.2 Research Quotient (Firm Level)

As discussed in Section 2.6.2 (Equation 2-3), RQ is the firm specific output elasticity of R&D and is a measure of a firm's ability to generate revenue from its R&D investment (Knott, 2012). Within the WRDS COMPUSTAT database, RQ is calculated at the firm level as follows:

$$Firm\ Level\ RQ = lnY_{it} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i})lnK_{it} + (\beta_2 + \beta_{2i})lnL_{it} + (\beta_3 + \beta_{3i})lnR_{i,t-1} + (\beta_4 + \beta_{4i})lnS_{i,t-1} + (\beta_5 + \beta_{5i})lnD_{it} + \varepsilon_{it} \tag{3-3}$$

In the equation above, Y is output (revenues), β_0, $\beta_{\_i}$ represent the direct effect and the firm specific error for each exponent, $K_{i,t}$ is capital (net property, plant, and equipment), $L_{i,t}$ is labor (full-time equivalent employees), $R_{i,t-1}$ is lagged R&D, $S_{i,t-1}$ is lagged spillovers, $D_{i,t}$ is advertising.

More specifically, RQ represents the percentage increase in the firm's revenue from a 1% increase in its R&D investment and is considered a measure of product innovation (Halperin, 2016). Thus, a firm can have a high RQ by generating a large number of innovations and being reasonably effective in exploiting them, or by generating a smaller number of innovations and being extremely effective in exploiting them (Knott, 2008).

Within the WRDS database, RQ is automatically calculated for any firm reporting the required R&D expenditures and inputs and RQ values are readily available via the WRDS database query (see "*WRDS RQ database user's manual*" for further details). Out of the 151 sample firms, RQ data was obtained for 103 firms, with a total of 2,196 observations.

3.6.3 Tobin's Quotient (Firm Level)

As discussed in Section 2.6.3 (Equation 2-4), TQ is the ratio of the market value of a firm relative to the replacement cost of its tangible assets (Tobin, 1977). Instead of using the traditional calculation of TQ, which is costly in terms of its data requirements and computational effort, a simplified variation of TQ (Equation 3-4), known in academic literature as "approximate TQ" (Chung & Pruitt, 1994) was used for this research.

$$Approximate\ TQ = \frac{(MVE+PS+DEBT)}{TA} \tag{3-4}$$

In the equation above MVE is firm market value, PS is liquidating value of the firm's outstanding preferred stock, DEBT is the value of the firm's short-term liabilities net of its short-term assets, plus the book value of the firm's long-term debt, and TA represents the book value of the total assets of the firm.

In academic research, TQ is commonly related to the intangible capital that enables firms to generate both product and process innovations, and the subsequent profitability that stems from their exploitation (Cockburn & Griliches, 1988; Hall, Jaffe, & Trajtenberg, 2001; Megna, 1993). As such, TQ is widely used as a general measure of the overall market valuation of firm innovation as it measures the "net effect" of both process and product innovation capabilities within a firm (Rubera, 2013; Antonelli, 2009). All inputs needed to calculate TQ were obtained via WRDS COMPUSTAT. Out of the 151 sample firms, TQ data was obtained for 140 firms, with a total of 3,353 observations.

3.6.4 R&D Investment

In addition to the innovation metrics described in Sections 3.6.1, 3.6.2, and 3.6.3, this research also measured the impact that LSS implementation (as measured by inventory turns and LSS adoption date) had upon firm investment into R&D activities. While R&D investment is an input rather than an output of innovation performance, it was determined necessary to test whether or not adoption of LSS would impact firm resource allocation per the hypothesis stated in Section 1.2.1. Within the WRDS database, firm R&D investment is calculated as follows:

$$R\&D\ Investment = \frac{R\&D\ Expenses\ (XRD)}{Net\ Sales\ (SALE)} \tag{3-5}$$

Equation 3-5 expresses the percentage of company revenue that is subsequently applied to firm R&D activities. Out of the 151 sample firms, R&D investment data was obtained for 119 firms, with a total of 3,180 observations.

3.7 Coarsened Exact Matching (CEM)

Matching is a nonparametric method of preprocessing data to control for some or all of the potentially confounding influence of pretreatment control variables by reducing imbalance between the treated and control groups. Coarsened Exact Matching (CEM) is a Monotonic Imbalance Bounding (MIB) matching method – which means that the balance between the treated and control groups is chosen by users based on forecasts rather than discovered through the laborious process of checking after the fact and repeatedly re-estimating. Thus, adjusting the imbalance on one variable has no effect on the maximum imbalance of any other (Iacus, King, & Porro, 2008). CEM also strictly bounds user choice both the degree of model dependence and the average treatment effect estimation error, eliminates the need for a separate procedure to restrict data to common empirical support, meets the congruence principle, is robust to measurement error, works well with multiple imputation methods for missing data, can be completely automated, and is extremely fast to compute (even with large data sets). After preprocessing data with CEM, it is possible to use a simple difference in means, or any other model that would have been applied without matching (Iacus, King, & Porro, 2009).

As a check on the validity of the CEM pairing, the control (pre-LSS adoption) and treatment (post-LSS adoption) groups should have relatively similar, but distinct sample means in addition to relatively minor changes in the respective standard deviations. Results from CEM testing (Table X) on the sample set indicate that variance is within acceptable boundaries, and that the CEM approach is valid for this sample set of firms.

Table 3-1: Coarsened Exact Matching (CEM) Statistics

Sample	Mean	Median	Std. Deviation
Total Factor Productivity			
Before Lean	−0.129	−0.143	0.32
Adopted Lean	-0.152	-0.186	0.356
R&D / Sales Performance			
Before Lean	0.04	0.029	0.04
Adopted Lean	0.044	0.032	0.047
Research Quotient Performance			
Before Lean	0.147	0.142	0.055
Adopted Lean	0.128	0.126	0.05
Tobin's Q Performance			
Before Lean	17 849.4	4 163.8	42 399.47
Adopted Lean	32 858.5	11 507.2	53 697.47

Use of the CEM pairing for control and treatment groups was further validated via the creation of "Kernel Density Charts" (Figure 3-1, Figure 3-2, Figure 3-3, Figure 3-4) for each of the innovation metrics utilized in this study. Kernel Density Charts are useful for displaying the overall spread of the sampled data (similar to a smoothed histogram), as the data is represented by the area under the curve. Most data are expected to conform to fairly normal bell curve distribution, with a slight shifting of the mean between control and treatment groups. For CEM validation purposes, control and treatment groups should also have a significant amount of overlap as an indication of a "good match".

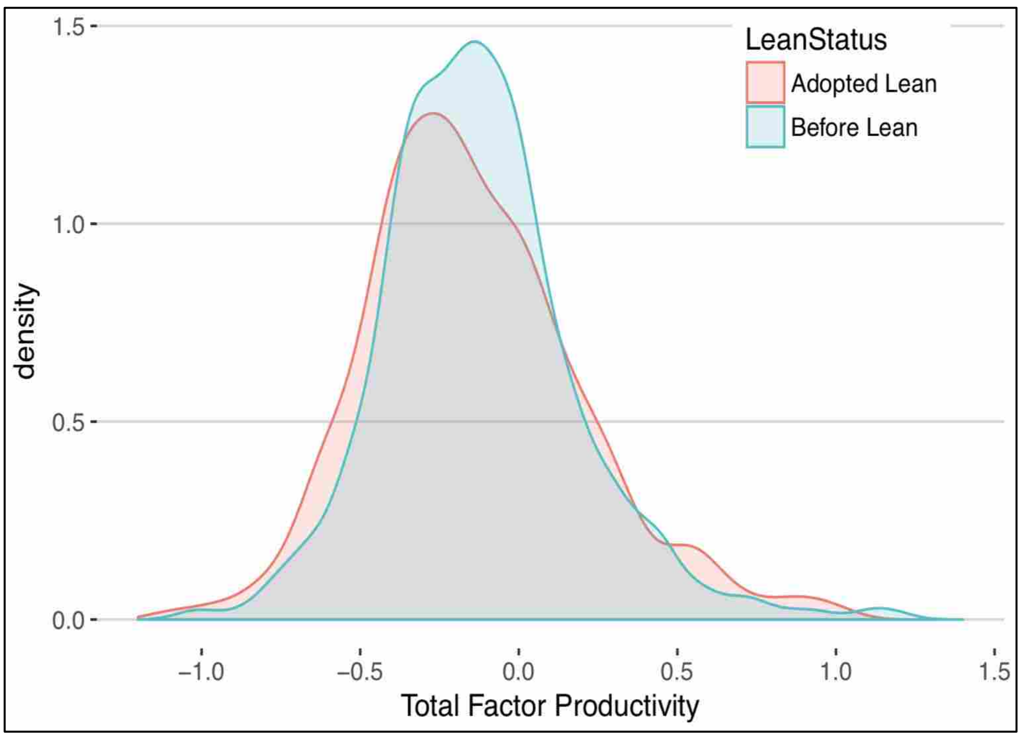

Figure 3-1: Total Factor Productivity CEM Kernel Density

Results from the TFP Kernel Density Chart (Figure 3-1) show a high degree of overlap, indicating strong CEM matching. The data conforms to an expected bell curve function, indicating that it is normally distributed. The data also indicates a slight negative shift in average (mean) firm TFP measures after adoption of LSS, which is in contradiction with Hypothesis 1

(Section 1.2.1) which expected process innovation measures to increase after firm implementation of LSS. While the negative shift in post-LSS TFP was unexpected, this initial result stems from the univariate nature of Kernel Density Charts; multiple regression analysis shows that the negative shift is attributable to other factors (i.e. firm effects, industry effects, and year effects) rather than the adoption of LSS.

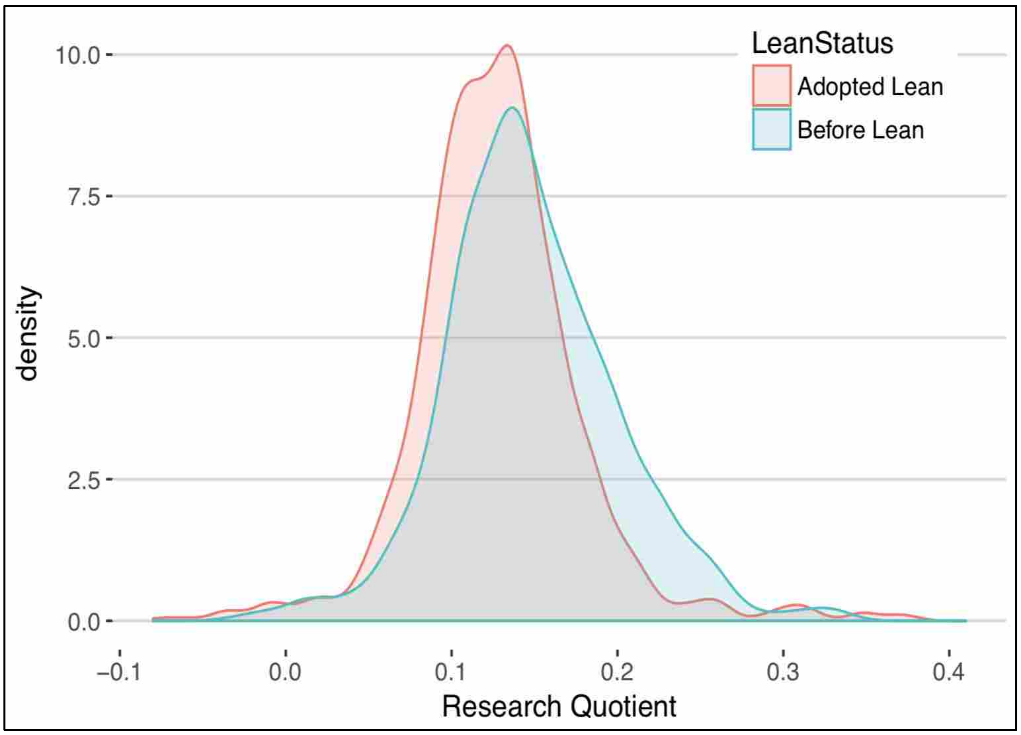

Figure 3-2: Research Quotient CEM Kernel Density

Results from the RQ Kernel Density Chart (Figure 3-2) show a high degree of overlap, indicating strong CEM matching. . The data also indicates a noticeable negative shift in average (mean) firm RQ measures after adoption of LSS, which supports Hypothesis 2 (Section 1.2.1) which expected some product innovation measures to decrease after firm implementation of LSS.

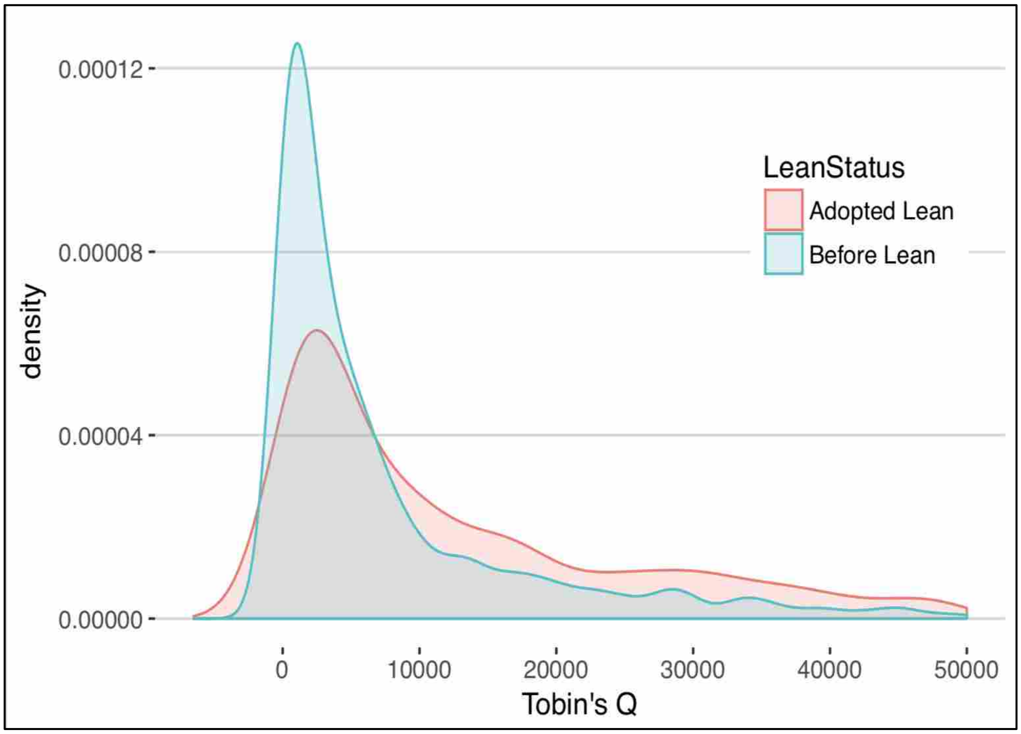

Figure 3-3: Tobin's Quotient CEM Kernel Density

Results from the TQ Kernel Density Chart (Figure 3-3) show a high degree of overlap, indicating strong CEM matching. The data conforms to an expected bell curve function, indicating that it is normally distributed. The data also indicates a noticeable positive shift in average (mean) firm TQ measures after adoption of LSS, which supports Hypothesis 3 (Section 1.2.1) which expected the market value of net firm innovation to increase after firm implementation of LSS.

It is noteworthy that average firm TQ measures were the most impacted by LSS treatment, as shown by the flattening of the data peak. This effect was confirmed via more granular analysis of the dataset (see Table 3.1).

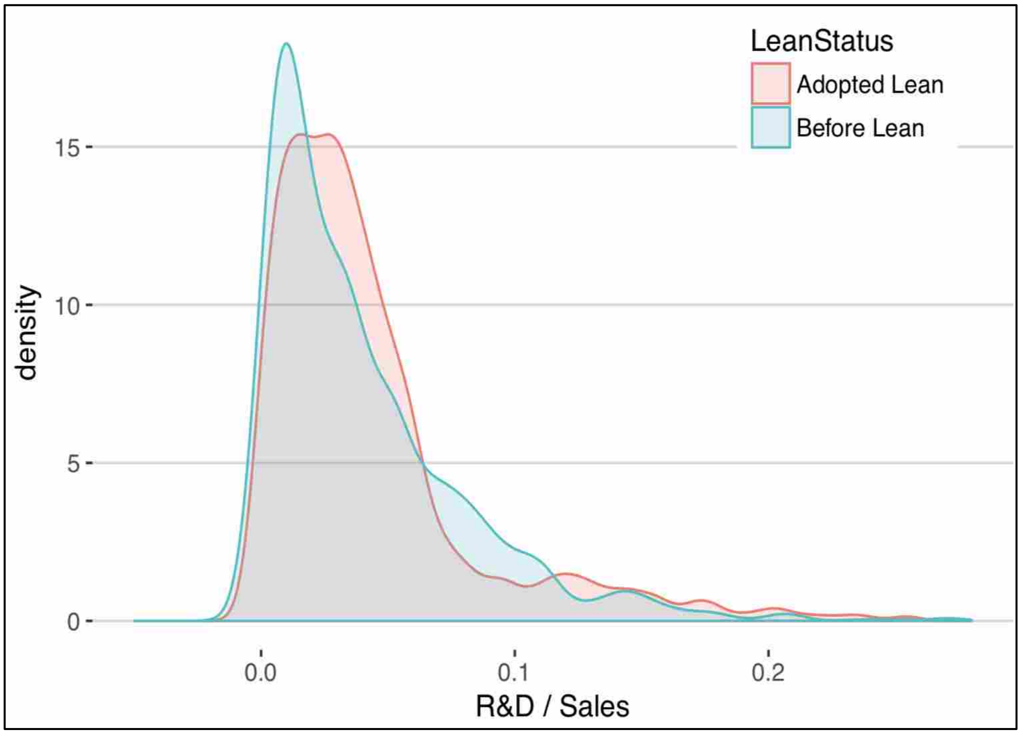

Figure 3-4: R&D Investment CEM Kernel Density

Results from the R&D/Sales Kernel Density Chart (Figure 3-4) show a high degree of overlap, indicating strong CEM matching. The data conforms to an expected bell curve function, indicating that it is normally distributed. The data also indicates a somewhat negative shift of the overall sample mean from control (pre LSS) to treatment (post LSS) groups per Table 3-1.

4 RESULTS

4.1 Introduction

This chapter provides an overview of the results of time series charts comparing Lean Six Sigma (LSS) adoption time against firm innovation performance metrics. This chapter will also discuss results of the statistical regressions comparing LSS implementation against firm innovation performance metrics. Firms used in regressions were paired using the Coarsened Exact Matching (CEM) methodology detailed in Section 3.7.

4.2 Impact of LSS Age on Inventory Turns

In order to validate the assumption that LSS adoption would increase the average number of inventory turns per firm (thus solidifying justification for the use of inventory turns as a proxy measure for successful LSS implementation), company inventory turn data was plotted against corresponding LSS adoption date (Figure 4-1) for all 151 sample firms. The X-axis ("LSS Age") of Figure 4-1 denotes the number of years prior to and following official firm-wide adoption/implementation of LSS, with "year 0" being the year of LSS adoption. The Y-axis represents the total number of inventory turns per firm.

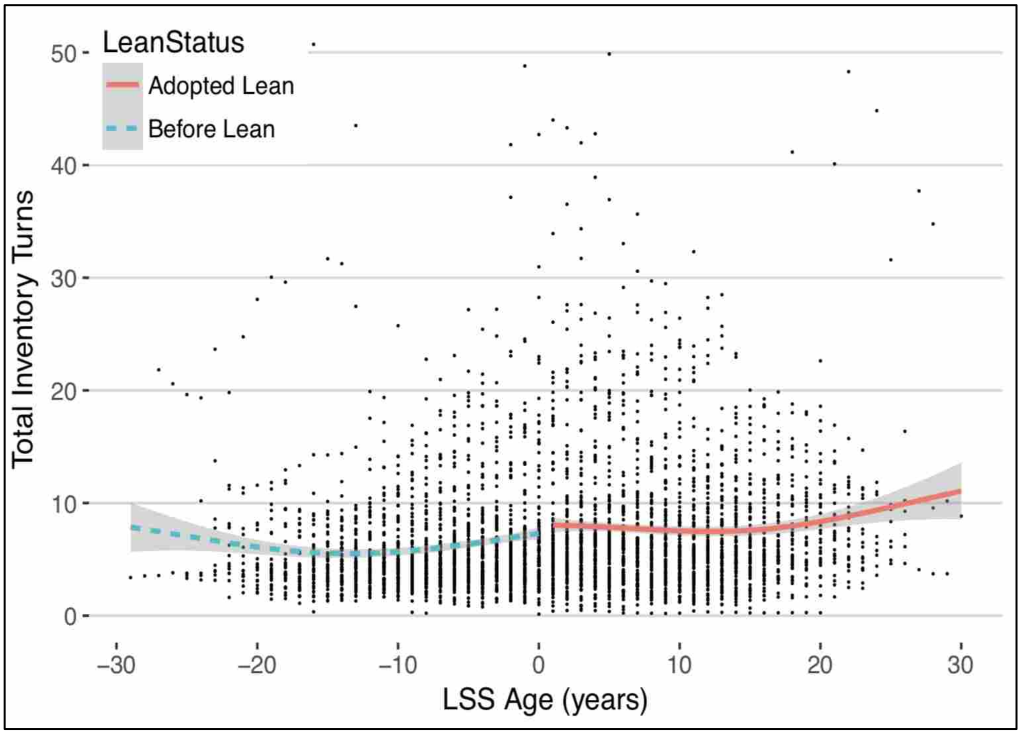

Figure 4-1: LSS Age vs. Inventory Turns

It should be noted that overall firm inventory turns increase after LSS adoption, with a discrete increase in inventory turns occurring in year 1 immediately following official firm adoption of LSS. This result indicates that, on average, firms reduce overall inventory levels (and subsequently increase inventory turns) in accordance with LSS philosophy that inventory is a form of waste or *muda*. This further validates the use of inventory turns as a reliable proxy measure for firm "leanness" (Schoenberger, 2007; Jones 2013).

It is also noteworthy that firm inventory turns continue to increase over time after LSS adoption, suggesting that firms with more LSS experience become more effective in reducing waste throughout the overall production system, and that LSS performance improves with time.

4.3 Impact of LSS Age on Firm Innovation Performance Metrics

It was deemed necessary to investigate the impact that the length of LSS adoption time (aka "LSS Age") would have upon firm innovation performance as measured by Total Factor Productivity (TFP), Research Quotient (RQ), Tobin's Quotient (TQ), and R&D Investment (R&D expenses / Sales).

For each of the following "LSS Age" charts, the X-axis ("LSS Age") denotes the number of years prior to and following official firm-wide adoption/implementation of LSS, with "year 0" being the year of LSS adoption. The Y-axis represents the level of the respective innovation metric (TFP, RQ, TQ, or R&D Investment). The results of this analysis are detailed below.

4.3.1 LSS Age vs. TFP

This research utilized TFP as a proxy measure for process innovation. As LSS itself is considered a process innovation, it was hypothesized (Section 1.2.1) that TFP levels would increase as the length of firm LSS implementation (as indicated by "LSS Age") increased given the tendency of LSS firms to develop expertise in extracting efficiencies from production systems as demonstrated in Figure 4-2.

This analysis included 99 firms reporting 2,484 observations of TFP against "LSS Age" (Figure 4-2). Results indicate an overall increase in TFP levels after firm adoption of LSS, with a discrete jump in TFP being observed in the year immediately following the official LSS rollout. It is also noteworthy that most firms had been experiencing an overall decrease in process innovation as measured by TFP prior to LSS adoption, and that this trend was reversed following LSS implementation. Additionally, firms who have practiced LSS for a longer period of time (as indicated by "LSS Age") generally have higher TFP levels, suggesting that LSS firms become more adept at implementing and exploiting process innovations over time. In total these results seem to lend support to Hypothesis 1 (Section 1.2.1), that LSS has a positive impact on firm process innovation.

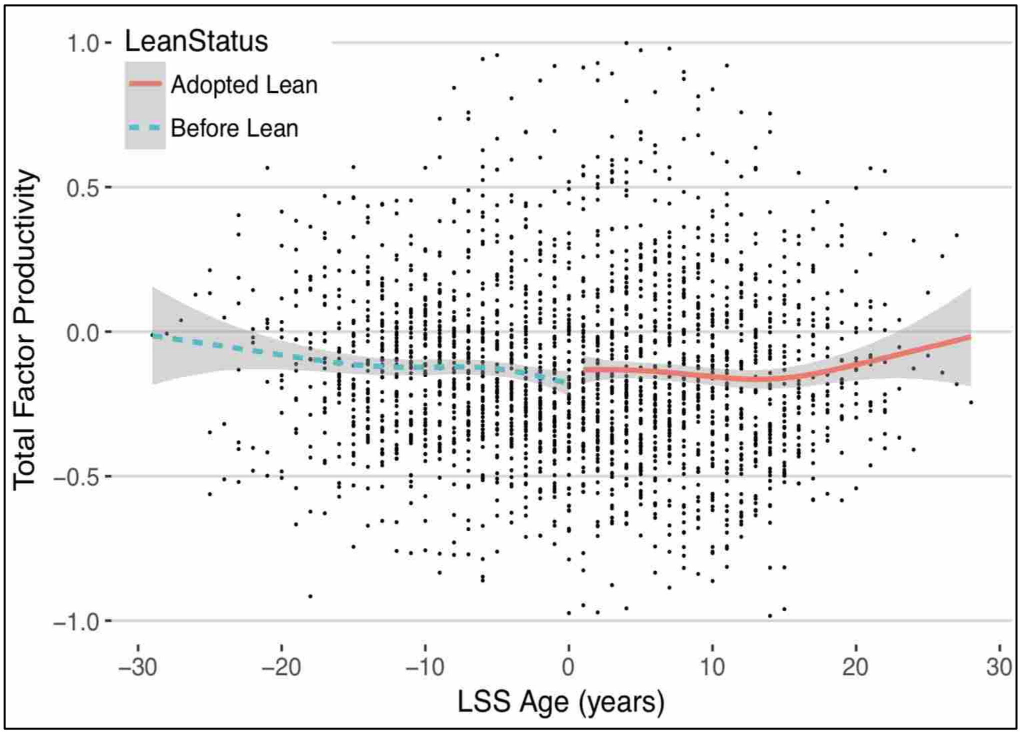

Figure 4-2: LSS Age vs. TFP

4.3.2 LSS Age vs. RQ

This research utilized RQ as a proxy measure for product innovation. It was hypothesized that RQ levels would decrease as the length of firm LSS implementation increased, given the tendency of LSS firms to eliminate "non-value-added activities" (i.e. employee slack time). This analysis included 103 firms reporting 2,196 observations of RQ against "LSS Age" (Figure 4-3). Results indicate an overall negative trend in firm RQ after official adoption of LSS, with a discrete fall in RQ being observed in the year immediately following LSS implementation. RQ levels continue to fall as time of LSS implementation increases, suggesting that product innovation may be starved of management resources and attention as LSS becomes entrenched in company strategy and culture.

It is notable that RQ levels tend to trend highly positive in the early stages of a company's life-cycle, suggesting that management focus is centered on perfecting product offerings to solidify the firm's marketplace offering. The drop in RQ later in the company lifecycle suggests that product innovation efforts may wane as a function of increased organizational complexity and need to develop greater overall efficiency. In total these results seem to lend support to Hypothesis 2 (Section 1.2.1), that LSS may have a negative impact on firm product innovation.

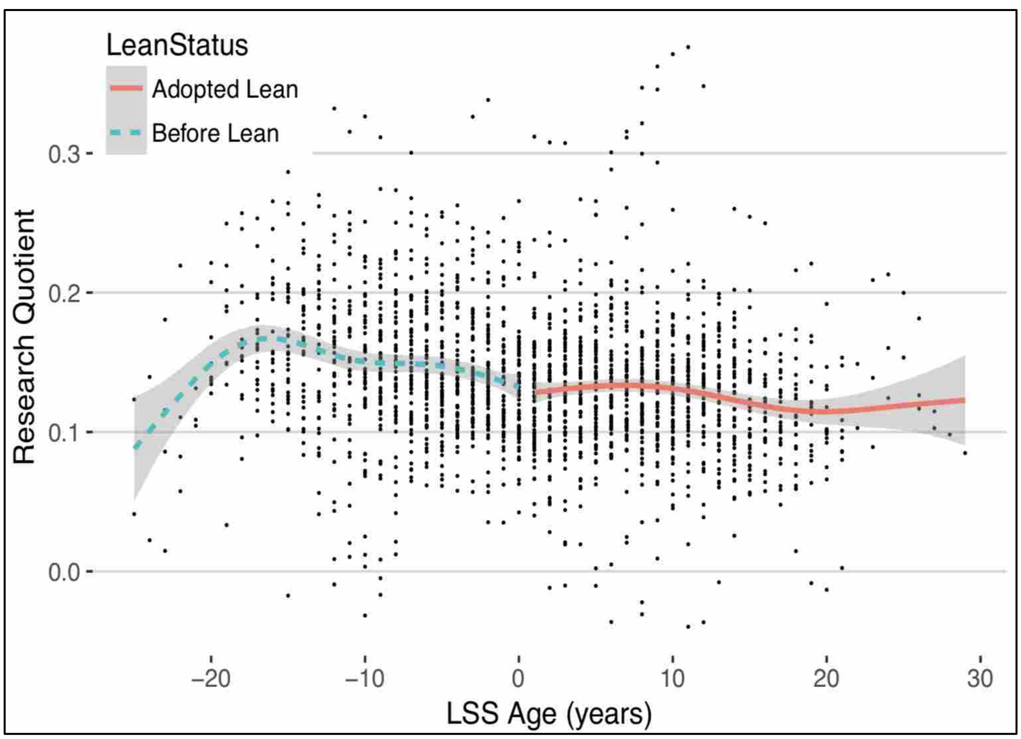

Figure 4-3: LSS Age vs. RQ

4.3.3 LSS Age vs. TQ

This research utilized TQ as a general measure of firm innovation. More specifically, TQ is a proxy measure for the market's valuation of firm innovation and is considered as the "net effect" of both product and process innovation within a firm, as these are difficult to differentiate at the market level (see Section 2.6.3. This analysis included 140 firms reporting 3,353 observations of TQ against "LSS Age" (Figure 4-4).

While results show an overall increase in TQ over time, there is a discrete jump in firm TQ after official LSS adoption. It is also noteworthy that overall TQ levels are significantly higher after LSS implementation, suggesting that the market values the LSS effect on financial performance of these firms, lending support to Hypothesis 3 (Section 1.2.1).

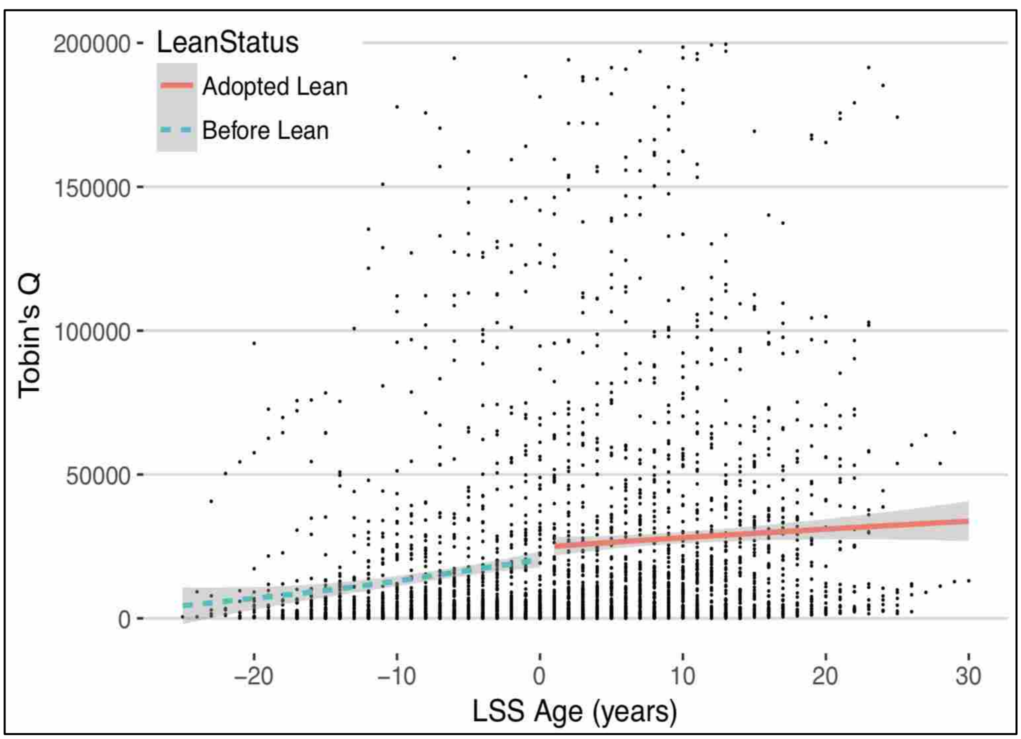

Figure 4-4: LSS Age vs. TQ

4.3.4 Impact of LSS Age on R&D Investment

In order to investigate the validity of the hypothesis (Section 1.2.1) that firm-wide adoption of LSS would divert management resources towards process innovation activities and programs (e.g. further development of LSS initiatives) and away from product innovation inputs, the length of LSS adoption/implementation was compared against R&D Investment (R&D Expense / Sales) per Figure 4-5. This analysis included 119 firms reporting 3,180 observations of R&D Investment against LSS Age. Results indicate that R&D investment levels remain fairly constant after LSS implementation, suggesting that financial inputs into the R&D process do not change after management focus increases on LSS. This finding does not support the hypothesis that LSS implementation inadvertently diverts management resources from the R&D sector.

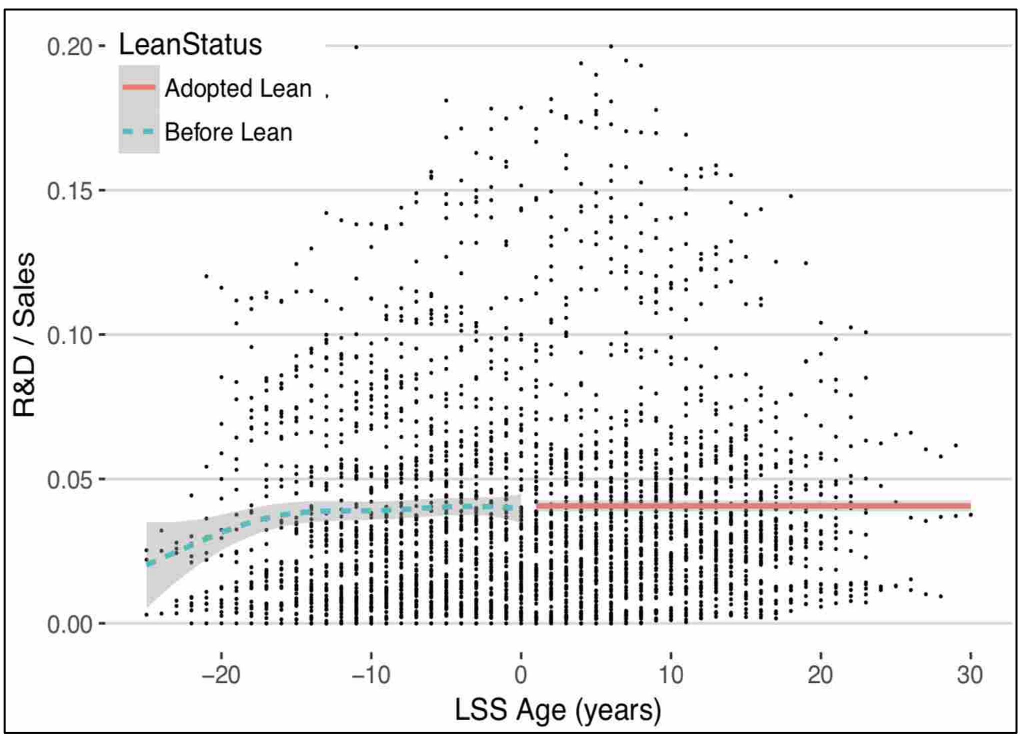

Figure 4-5: LSS Age vs. R&D Investment

4.4 Summary of High-Level Regression Analysis Results

As stated in Section 3.1 statistical regressions were performed comparing measures of LSS implementation (inventory turns, LSS adoption date) with firm innovation performance measures (TFP, RQ, TQ, R&D Investment). Utilizing the Coarsened Exact Matching (CEM) methodology detailed in Section 3.7, firms were paired against industry rivals of similar size (as measured by market cap and revenue). Additional controls were implemented to account for firm, industry, and year effects. Results of regression analysis of the sample set of firms as a whole are detailed in Table 4-1 below:

Table 4-1: Regression Results (Inventory Turns vs. Innovation Metrics)

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

The regression results indicate that overall firm innovation, as measured by TQ, dramatically increases with adoption of LSS, as measured by inventory turns. The correlation value of inventory turns and TQ is noticeably strong ($R^2 = 0.728$), which is considerable given the large number of firms (N = 140) and total number of TQ observations (N = 3,353). Similarly, product innovation, as measured by TFP, appears positively impacted by LSS adoption and has solid statistical correlation with inventory turns ($R^2 = 0.556$). Product innovation, as measured by RQ is slightly negatively impacted by LSS implementation and also holds a noticeable statistical correlation with turns ($R^2 = 0.515$). Surprisingly, this is in contrast to R&D investment which is somewhat positively impacted by LSS, but the statistical correlation in this instance ($R^2 = 0.238$) is weaker, making it difficult to draw any firm conclusions on this relationship.

These results indicate that LSS has a tendency to positively impact process innovation while slightly reducing product innovation effectiveness, with the overall net effect on firm innovation performance being strongly positive. It is noteworthy that the negative impact upon product innovation is minimal to neutral (Post LSS Intercept = -0.002), but as will be seen later for an industry level analysis, product innovation can indeed be suppressed by LSS implementation and therefore some ideas for mitigating this possible negative impact will be discussed (see Section 4.6).

4.5 Industry-Level Regression Results

In order to better understand factors driving the high-level regression results comprised of the entire sample set of firms (see Section 4.4), additional regressions were performed at the industry level for each of the innovation metrics utilized in this study (TFP, RQ, R&D

Investment, and TQ). Performing regressions at the industry-level provides insight into the unique impact that LSS implementation can have on firm innovation performance in industries that vary widely on factors such as product lifecycle, economic drivers, competitive landscape, regulation requirements, etc. Among the sample set of 151 firms, 41 unique industries were identified.

Only results at the 90% confidence level (p value < 0.10) were included for industry-level regressions for both the Pre-LSS (control) and Post-LSS (treatment) groups. LSS impact on innovation was considered "confirmed" if both the Pre-LSS and Post-LSS sample groups were found to have p-values < 0.10, as this enabled accurate analysis of the shift in the dependent variable intercept between control and treatment groups. LSS impact was considered "potential" if only the Post-LSS field was found to have a p value < 0.10, as the result prior to LSS treatment was not sufficiently free of variance to be considered statistically significant. LSS impact was considered "unknown" if only the Pre-LSS field was found to have a p value < 0.10, as the result after LSS treatment was not sufficiently free of variance to be considered statistically significant and therefore impossible to draw sound conclusions from. Lastly, it should be noted that in most instances the number of firms per industry, was relatively small (~5 firms/industry) and that future industry studies may benefit from increasing the number of observed firms to confirm the industry effects.

4.5.1 Industry-Level TFP Regression

As noted in Section 4.4, process innovation (as measured by TFP) generally increased across all firms as LSS implementation increased. At the industry level, 16 of 41 industries were found to have statistically significant results relating to TFP (see Table 4-2). Of these, 6 (3 confirmed, 3 potential) indicated a positive LSS impact on TFP, and 9 (3 confirmed, 6 potential) indicated a negative LSS impact on TFP. This suggests that the overall positive trend toward TFP found in the high-level regression results (Table 4-1), is primarily driven by a few select industries where the positive impact of LSS on process innovation is extremely pronounced.

Among the industries confirming a positive impact on process innovation, Business Equipment (R^2 = 0.816) and Medical Laboratories & Research (R^2 = 0.586) displayed a high degree of correlation. Among the industries confirming a negative impact on process innovation, Major Integrated Oil & Gas (R^2 = 0.893) and Wireless Communication (R^2 = 0.897) displayed high degrees of correlation.

Table 4-2: Industry-Level TFP Regression Results

Industry	Intercept	t-value	Post LSS	t-value	R^2	F	N (obsv.)	N (firms)	LSS Impact
Aerospace & Defense	(0.013)	(0.131)	(0.149)	(2.421)	0.177	0.739	178	6	▼
Auto Parts	(0.183)	(1.261)	(0.058)	(1.849)	0.212	1.472	263	11	▼
Business Equipment	0.213	1.763	0.209	3.172	0.816	7.032	88	3	★
Communication Equipment	(0.180)	(1.264)	(3.883)	(6.291)	0.389	1.890	139	5	▼
Diversified Electronics	(0.178)	(1.016)	0.172	4.654	0.455	2.531	171	6	▲
Drugs - Wholesale	(0.048)	(0.271)	(0.194)	(3.631)	0.699	3.320	91	3	▼
Electronic Equipment	(0.135)	(0.531)	0.466	2.590	0.253	0.665	98	3	▲
Farm & Construction Machinery	(0.255)	(2.090)	0.190	2.468	0.249	1.214	161	6	★
Industrial Equipment & Components	(0.227)	(2.617)	(0.021)	(0.445)	0.151	0.859	205	7	◆
Machine Tools & Accessories	(0.563)	(1.743)	(0.368)	(1.864)	0.294	0.378	71	3	★
Major Integrated Oil & Gas	0.486	4.685	(0.260)	(3.319)	0.893	7.370	66	2	★
Medical Laboratories & Research	(0.255)	(3.126)	0.079	2.264	0.586	1.375	65	2	★
Printed Circuit Boards	(0.227)	(0.728)	(0.309)	(2.569)	0.386	1.457	93	4	▼
Semiconductor - Integrated Circuits	(0.072)	(0.212)	(0.383)	(2.864)	0.814	3.013	60	2	▼
Steel & Iron	0.462	1.060	0.800	4.675	0.632	1.392	66	2	▲
Wireless Communication	0.204	2.554	(0.092)	(2.758)	0.897	8.727	71	3	★

Key

Confirmed Positive LSS Impact ★ Potential Positive LSS Impact ▲ Unknown LSS Impact ◆
Confirmed Negative LSS Impact ★ Potential Negative LSS Impact ▼

Note: All results with p-values < 0.10 are detailed above. Results with p-values >.10 are highlighted in red. Fields are considered "confirmed" if both Pre & Post LSS fields have p < 0.10. If only Post LSS has a p < 0.10, impact is considered "potential". If only Pre LSS has a p < 0.10, impact is considered "unknown".

4.5.2 Industry-Level R&D Investment Regression

As noted in Section 4.4, investment into R&D (as measured by R&D expenses / sales) either slightly rose or remained steady across most firms as LSS implementation increased. At the industry level, 12 of 41 industries were found to have statistically significant results relating to R&D investment (see Table 4-3). Of these, 3 (all potential) indicated a positive LSS impact on R&D investment, and 4 (3 confirmed, 1 potential) indicated a negative LSS impact on R&D investment, with the remaining 5 industries demonstrating an unknown LSS impact. Among these industries, R^2 values are generally high, with only 3 industries reporting R^2 values < 0.50.

Table 4-3: Industry-Level R&D Investment Regression Results

Industry	Intercept	t-value	Post LSS	t-value	R^2	F	N (obsv)	N (firms)	LSS Impact
Aerospace & Defense	[illegible]	[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	
[illegible]	[illegible]	[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	
[illegible]	[illegible]	[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]			[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	

Key

[illegible]

[illegible]

Among the industries confirming a negative impact on R&D investment, Electronic Equipment (R^2 = 0.803) and Farm & Construction Machinery (R^2 = 0.864) explained a very high degree of the variance. However, both of these cases indicated only a minor drop in R&D

investment levels, suggesting that the overall LSS impact on R&D resource allocation appears to somewhat neutral and that firms are likely to maintain, rather than dramatically reduce, historic levels of R&D expense.

4.5.3 Industry-Level RQ Regression

As noted in Section 4.4, product innovation (as measured by RQ) experienced a slight decline across most firms as LSS implementation increased. At the industry level, 23 of 41 industries were found to have statistically significant results relating to RQ levels (see Table 4-4). Of these, 7 (6 confirmed, 1 potential) indicated a positive LSS impact on RQ, and 6 (5 confirmed, 1 potential) indicated a negative LSS impact on RQ, with the remaining 10 industries demonstrating an unknown LSS impact. The high level of LSS/product innovation correlation among both positive and negative confirmations indicates that product innovation's relationship with LSS can vary dramatically by industry type.

Among the 6 industries confirming a positive impact on RQ (Communication Equipment, Diverse Electronics, Electronic Equipment, Information Technology Services, Medical Laboratories, and Printed Circuit Board), most were classified within the electronic and tech sectors, suggesting that LSS may enhance product innovation in industries characterized by quick R&D cycles and high product lifecycle churn. This is in contrast to the 5 industries confirming a negative impact on RQ (Aluminum, Farm & Construction Machinery, Industrial Equipment, Medical Equipment, Semi-Conductors), where the majority of these industries have relatively slower R&D cycles and longer product lifecycles. This implies that the relationship between LSS and product innovation may be related to the speed of R&D development within a particular firm or industry.

Table 4-4: Industry-Level RQ Regression Results

Industry	Intercept	t-value	Post LSS	t-value	R^2	F	N (obsv.	N (firms	LSS Impact
Aerospace & Defense	0.089	4.389	(0.013)	(0.766)	0.468	2.264	178	6	◆
Aluminium	0.206	3.714	(0.063)	(2.062)	0.543	1.453	101	5	★
Appliances	0.183	4.237	(0.034)	(1.489)	0.722	3.575	98	3	◆
Auto Manufacturers - Major	0.144	6.441	0.011	0.691	0.607	3.717	156	5	◆
Auto Parts	0.169	7.857	(0.023)	(1.532)	0.659	6.384	371	15	◆
Business Equipment	0.166	11.646	(0.002)	(0.125)	0.892	10.025	88	3	◆
Communication Equipment	0.153	5.070	0.038	1.692	0.618	2.351	139	5	★
Diversified Electronics	0.144	9.200	0.043	3.902	0.708	5.581	171	6	★
Diversified Machinery	0.200	11.785	0.033	1.648	0.751	8.954	224	7	◆
Drug Manufacturers	0.150	8.090	0.027	1.403	0.567	3.410	132	4	◆
Electronic Equipment	0.238	25.826	0.034	4.906	0.968	28.316	162	5	★
Farm & Construction Machinery	0.146	9.495	(0.032)	(3.146)	0.666	5.066	167	7	★
Industrial Equipment & Component	0.119	6.360	(0.039)	(3.136)	0.498	3.793	237	8	★
Information Technology Services	0.226	8.087	0.036	1.893	0.637	4.087	129	4	★
Machine Tools & Accessories	0.041	4.513	0.002	0.151	0.989	37.696	71	3	◆
Major Integrated Oil & Gas	(0.001)	(0.023)	0.066	2.634	0.740	4.634	98	3	▲
Medical Appliances & Equipment	0.135	8.774	(0.019)	(1.198)	0.807	3.772	66	2	◆
Medical Instruments & Supplies	0.158	13.155	(0.057)	(3.712)	0.992	8.183	93	3	★
Medical Laboratories & Research	0.106	7.704	0.027	3.035	0.838	5.015	98	3	★
Packaging & Containers	0.042	1.443	(0.046)	(3.223)	0.734	3.108	97	3	▼
Printed Circuit Boards	0.120	3.871	0.103	5.365	0.913	11.555	139	6	★
Semiconductor - Integrated Circuits	0.193	6.677	(0.116)	(6.949)	0.889	7.988	85	3	★
Trucks & Other Vehicles	0.156	4.637	0.029	1.084	0.461	0.759	66	2	◆

Key

Confirmed Positive LSS Impact ★ — Potential Positive LSS Impact ▲ — Unknown LSS Impact ◆

Confirmed Negative LSS Impact ★ — Potential Negative LSS Impact ▼

Note: All results with p-values < 0.10 are detailed above. Results with p-values >.10 are highlighted in red. Fields are considered "confirmed" if both Pre & Post LSS fields have p < 0.10. If only Post LSS has a p < 0.10, impact is considered "potential". If only Pre LSS has a p < 0.10, impact is considered "unknown".

4.5.4 Industry-Level TQ Regression

Per observations in Section 4.4, the overall market response to firm innovation (as measured by TQ) experienced a significant increase across the majority of firms as LSS implementation increased. At the industry level, 19 of 41 industries were found to have statistically significant results relating to TQ levels (see Table 4-5). Of these, 8 (2 confirmed, 6 potential) indicated a positive LSS impact on TQ, and 5 (1 confirmed, 4 potential) indicated a negative LSS impact on TQ, with the remaining 6 industries demonstrating an unknown LSS impact. It is noteworthy that among these industries, R^2 values are extremely high with an average industry R^2 of 0.808, and no industry displaying a R^2 value < 0.56. This not only indicates a high degree of correlation between inventory turns and TQ outcomes, but also suggests that the market generally responds very favorably to firm implementation of LSS.

Table 4-5: Industry-Level TQ Regression Results

Industry	Intercept	t-value	Post LSS	t-value	R^2	F	N (obs.)	N (firms)	LSS Impact
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

It should also be noted that in cases where LSS had a positive impact on TQ, the degree of positive impact was typically very large, as seen in the large swings from negative TQ values to positive TQ values. Negative swings were generally smaller by comparison, indicating that changes in firm value may be heavily influenced by operational benefits arising from LSS in addition to perceptions of innovation capability

4.5.5 Summary of Industry-Level Regression Results

An overview of the industry-level regression results for TFP, R&D investment, RQ, and TQ is provided in Table 4-6 below. Regressions performed at the industry-level revealed a high degree of nuance to the overall results discussed in Section 4.4, which helps to establish the fact that the LSS-innovation relationship is complicated and subject to a wide variety of industry and even firm specific factors. It should be noted that while the number of observations at the industry-level were significant, in many instances, the number of actual firms in each industry segment is relatively small; therefore, further studies would benefit from an increase in the number of sampled firms per industry, so as to avoid bias in the data.

Postulations about the nature of industry specific LSS impact on process, product, and overall firm innovation are provided below based on the results of regressions performed. These hypotheses are conceptual, given the limitations of firm number per industry and lack of internal firm data, but are provided as a preliminary explanation of industry regression results:

- *Auto Manufacturers:* Automobile assemblers (ex: Ford Motor, Daimler AG, etc.) displayed a potential decrease in TQ. Inventory turns (the primary measure of LSS performance in this study) may be less critical to this group because the business model for large automakers generally allows for relatively large finished goods inventory buffers. This means that increased turns may not have a large impact in the market's perception of firm value or innovation as compared to other internal LSS metrics not considered in this study.

- *Auto Parts*: Automobile parts suppliers (ex: Autoliv Inc, Meritor Inc, etc.) displayed a strong confirmed increase in TQ, with a potential decrease in TFP and potential increase in R&D investment. Survival in this industry depends on a strong combination of product quality and operational efficiency, especially as cost reduction is expected by downstream automakers every year. Additionally, many auto-makers become part of a wider LSS-enterprise led by the downstream automobile assembler, with Toyota's "Lean Enterprise" being a chief example. In this scenario, part suppliers are under pressure to provide high levels of product innovation (as evidenced by increased R&D investment) and reap higher market valuations stemming of decreased LSS driven lead time reductions.
- *Business Equipment*: This industry contains a wide variety of business-to-business product manufacturers (ex: Herman Miller Inc, Steelcase Inc) and is characterized by relatively high labor content. Given the tendency of LSS to reduce both labor and lead time, it is unsurprising that firms in this industry experience strong confirmed positive impacts to both TFP and TQ measures.
- *Chemicals*: Chemical firms, such as DowDuPont and BASF, have a significant degree of innovation value tied up in intellectual property (ex: chemical compound patents, processing patents, etc.) and therefore are not as dependent on efficiency. However, chemical products are also often classified as commodities, where efficiency gains can be important to margins. This dual-nature of a chemical firm's "patented commodity" product portfolio helps to explain why an increase in firm LSS adoption would result in a potential increase in TQ.

- *Electronic Equipment*: Electronic equipment manufacturers (ex: Honeywell, Sony Corp, Eastman Kodak Co, etc.) displayed a positive LSS impact across all innovation measures except R&D investment. These industries are characterized by relatively fast product churn and may benefit strongly from a reduction of R&D cycle times (a common LSS benefit).
- *Food – Major Diversified:* Food manufacturers and assemblers (ex: Kraft Heinz, Nestle, Unilever, etc.) have highly commoditized product portfolios. Consumers in the food industry tend to have high price sensitivity, and cost/efficiency advantages would be highly valued by the market, explaining the positive impact LSS has on TQ.
- *Major Integrated Oil & Gas*: This industry displays a negative LSS impact on both TFP and TQ, with a positive impact on RQ. Energy companies (ex: Chevron, Exxon Mobil, etc.) are very capital-intensive businesses where efficiency efforts and product innovations can be easily overshadowed by commodity prices, thus potentially explaining the negative trend in TQ measures.
- *Packaging & Containers:* This industry displays a negative impact upon both RQ and TQ. While packaging companies (ex: Rexam PLC, etc.) would typically benefit from LSS efficiencies in a commodity market, these firms tend to be pure-play companies with long term contracts. Consolidation in the packaging industry has improved pricing power significantly, and subsequently diminished the competitive advantage that LSS would provide in the eyes of investors.

Table 4-6: Industry-Level Regression Results Summary Table

4.6 Proposed LSS Implementation Strategies

Prior studies centering on the LSS-innovation relationship have proposed several strategies that may enable firms to preserve a high degree of fidelity to LSS principles in addition to maintaining a thriving and continuous product innovation practice (Chen & Taylor, 2009; Johnstone, 2011). These proposed strategies are outlined below:

- *Strategy #1 – Outsource Innovation:* One strategy is to simply outsource innovations to independent third-party R&D centers, especially in instances where there are high risks and development costs associated with the new product design, both of which tend to be viewed as "waste" within an LSS system (Mehri, 2006). This strategy can include using national labs for development projects or pushing development work to upstream suppliers. The outsourcing strategy is most effective for companies in an industry where technology progress speed is high, demand is increasing at a dramatic rate (resulting in new specialist organizations for innovative processes), and where suppliers have high-impact and swift levels of innovation (Quinn, 2000). However, too much outsourcing of innovation capabilities can be detrimental to the health of a company's long-term competitiveness since the firm may ultimately lose the ability to develop any internal product innovations given the path dependent nature of many technologies.

- *Strategy #2 – Establish an Independent Innovation Center*: As an alternative to traditional R&D centers that fall within a firm's traditional financial and operational systems, Lindeke, *et al* propose the concept of autonomous innovation centers (also known as "Temporal Think Tanks" or T3™) as an innovation tool for LSS organizations (Lindeke, Wyrick, Chen, 2009). To run a T3 center, employees from various departments are temporarily teamed up in an independent organization that focuses on generating product ideas that are later assessed, selected, and incorporated into the LSS production system. Upon returning to their original assignments, former T3 employees are expected to bring back the innovative culture and atmosphere to their home departments as a way of maintaining an "innovative environment" within an LSS focused firm. Because the T3 center is structurally independent from the "mother LSS firm", its cost structure is not required to achieve high profit margins from the existing market, which allows the T3 to focus on disruptive product innovations that will prove vital to the firm's long-term vitality (Christensen, 2013). The chief vulnerability of this strategy lies in the size of the LSS firm's workforce: since key employees and leaders will be taken from their home departments for a period of time to work in the T3, this strategy only works when a company is able to remove part of its staff without affecting core operations. If the number of employees is relatively low, or if the demand of production exceeds the supply of the workforce, this option may be harmful to the productivity of the organization.

- *Strategy #3 – Establish a Lean Innovation System*: Another approach that can reduce the potentially negative effects of LSS on production innovation is known as the "lean innovation system" (Schuh & Hieber, 2011). The lean innovation system is a mapping system that defines values for an innovation project based on external and internal customers and embeds LSS principles within the R&D process to generate product differentiation with reduced resources and waste. Underneath a lean innovation system, new ideas are purposefully identified as value-adding to potential products, an assumption not explicitly stated under traditional LSS philosophy.

While relatively few firms have systematically implemented lean innovation systems, this approach is considered most beneficial for organizations with strong R&D and LSS expertise, but do not have the resources available to implement an independent innovation center (Chen & Taylor, 2009).

- *Strategy #4 – Implement an Innovative Product Development Process*: A methodology called "Innovative Product Development Process" (IPDP) can also be adopted by LSS organizations as a means of increasing firm product innovation capability (Yamashina, Ito, & Kawada, 2002). IPDP integrates concepts from Quality Function Deployment (QFD) and the Theory of Inventive Problem Solving (TRIZ) in order to systematically build innovation into the product planning stage through the product design stage. When applying the IPDP technique, QFD is first used to determine the areas where innovation is most needed based on customer requirements. TRIZ is then implemented to define the solutions necessary to improve these areas. Though IPDP holds promise as a method of promoting efficient levels of innovation within an LSS system one of the primary risks of the IPDP methodology is that it is still in the conceptual stages and has not been systematically introduced into any existing firms (Chen & Taylor 2009). Similar to the "lean innovation system", this strategy is ideal for a company that has an expertise in R&D innovation but lacks the capacity or resources required for the establishment of an independent innovation center.

5 CONCLUSION

5.1 Summary of Findings

The primary purpose of this study was to investigate the validity of the claim that Lean Six Sigma (LSS) implementation has a negative impact on firm innovation capability. Statistical regressions performed on 151 firms comparing pre-LSS and post-LSS innovation metrics with the degree of LSS implementation (as measured by inventory turns) demonstrated that in general, LSS has a positive impact on both process and overall firm innovation, and a slightly negative-to-neutral impact on product innovation and firm tendency to invest in R&D activities.

However, additional regressions performed at the industry sector level revealed that the LSS impact on firm innovation is extremely nuanced and complex, and that the general finding described above does not hold true for every industry. Unique industry environments appear to have a strong impact on the LSS-innovation relationship and further studies are needed to investigate the influence of LSS adoption within individual industries.

In total, the results of this study clearly indicated that the blanket claim that LSS is inherently dangerous to firm innovation is false. Rather, the impact that LSS has on firm innovation appears to be driven primarily by industry factors, and even more importantly, individual management decisions during LSS implementation.

Recognizing that LSS implementation can sometimes harm product innovation effectiveness, prior research efforts (see Section 4.6) have proposed various strategies intended to help executives achieve the needed balance between LSS and innovation at the firm level. It is also necessary for managers to understand the true requirements and cultural change needed for successful LSS adoption, as misapplied LSS can be as harmful to firm innovation and operations.

5.2 Suggestions for Further Research into LSS-Innovation Relationships

Findings from this empirical approach suggest that after LSS implementation, firms tend to maintain current levels of R&D investment (contradicting claims that such funding would be slashed as "waste") but may simultaneously experience a slight decrease in management attention to product innovation activities as LSS culture places greater focus on current customers and current process improvements. Investigation at the firm level is needed to verify whether this resource re-allocation truly occurs after LSS adoption, or whether the decline in product innovation is driven by other factors.

Additional investigation of the LSS-innovation relationship at the industry level would also be beneficial given the relatively small number of firms-per-industry in this study. Future industry studies may particularly benefit from a literature review centered on the economic and competitive drivers unique to the industry in question, in order to better understand the effect that these factors may have on both LSS implementation and innovation performance.

As this study focused primarily on LSS and innovation metrics readily calculated from publicly available data, it is recommended that future studies utilize the internal LSS metrics (described in Section 2.7) and internal innovation metrics (described in Section 2.6) in combination with the publicly available metrics (described in Section 2.6.1 – 2.6.3) used in this research both to validate the usefulness of publicly available LSS data and innovation metrics and to verify the results of the statistical regressions performed.

Given the lack of a “perfect” innovation metric, it is also recommended that further regressions be performed comparing the impact that LSS implementation has on other publicly available innovation measures such as patent counts or patent citations. One insight from this research is that multiple innovation measures are required to accurately capture a company’s true innovation performance. Therefore, future studies should seek to include as many innovation measures as possible in order to better understand the complex relationship between LSS implementation and resulting firm innovation performance.

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APPENDICES

APPENDIX A. LEAN SIX SIGMA FIRMS

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
1072	AVX Corporation	N/A	Diversified Machinery	1972
1078	Abbott Labs	2001	Medical Appliances & Equipment	1888
1300	Honeywell	2004	Diversified Machinery	1906
2049	Barnes Group Inc.	2000	Industrial Equipment & Components	1857
2086	Baxter International	2001	Medical Instruments & Supplies	1931
2111	Becton Dickinson	2000	Medical Instruments & Supplies	1897
2136	Verizon	2012	Wireless Communication	1983
2285	Boeing	1996	Aerospace Defense Products & Services	1916
2338	Rexam Beverage	2004	Packaging & Containers	1923
2403	Bristol Myers Squibb	2005	Drug Manufacturers	1887
2751	Cardinal Health	2001	Drugs Wholesale	1971
2817	Caterpillar	2005	Farm & Construction Machinery	1925
2991	Chevron	2000	Major Integrated Oil & Gas	1879
3243	Citigroup	1997	Financial Services	1812
3532	Corning Inc.	1994	Diversified Electronics	1851

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
3580	Crane Co.	1997	Diversified Machinery	1855
3619	Crown Holdings	N/A	Packaging & Containers	1892
3650	Cummins	2000	Diversified Machinery	1919
3734	Dana Inc	1994	Auto Parts	1904
3735	Danaher	1988	Diversified Machinery	1969
3835	John Deere & Company	1994	Farm & Construction Machinery	1837
4060	DowDuPont	1998	Chemicals	1802
4091	Ducommun Inc	2004	Aerospace Defense Products & Services	1849
4194	Eastman Kodak Company	1998	Electronic Equipment	1888
4199	Eaton Corporation PLC	1999	Diversified Machinery	1911
4321	Emerson Electric	1999	Industrial Electrical Equipment	1890
4503	Exxon Mobil Corporation	2008	Major Integrated Oil & Gas	1870
4839	Ford Motor Company	1995	Auto Manufacturers - Major	1903
4925	Fujifilm Corporation	N/A	Optics	1934
5046	General Dynamics Corp	2008	Aerospace Defense Products & Services	1899
5047	General Electric	1995	Diversified Machinery	1892
5073	General Motors	1994	Auto Manufacturers - Major	1908
5234	Goodyear Tire & Rubber Company	2000	Rubber & Plastics	1898
5492	Harris Corp	1999	Communication Equipment	1895

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
5568	The Kraft Heinz Co.	2013	Food- Major Diversified	1923
5606	HP	1994	Diversified Computer Systems	1939
5690	HNI Company	1992	Business Equipment	1944
5860	ITT Inc	2000	Diversified Machinery	1920
6066	IBM	2005	Information Technology Services	1911
6266	Johnson & Johnson	2001	Drug Manufacturers	1886
6268	Johnson Controls	2000	Auto Parts	1885
6495	Komatsu Ltd	1993	Farm & Construction Machinery	1921
6774	Lockheed Martin	2000	Aerospace Defense Products & Services	1926
7171	McKesson Corp	1999	Drugs Wholesale	1833
7228	Medtronic	2003	Medical Appliances & Equipment	1949
7257	Merck & Co.	2006	Drug Manufacturers	1891
7291	MEI	2001	Diversified Electronics	1969
7401	Herman Miller	1995	Business Equipment	1905
7435	3M	2001	Diversified Machinery	1902
7585	Motorola	2005	Communication Equipment	1928
7647	Bank of America	2001	Financial Services	1904
7985	Northrop Grumman	2004	Aerospace Defense Products & Services	1939
7991	Terex	2002	Farm & Construction Machinery	1933
8020	Novo Nordisk	2003	Drug Manufacturers	1923
8030	Nucor	2000	Steel & Iron	1940
8215	Owens-Illinois, Inc.	2008	Packaging & Containers	1929

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
8247	PPG Industries	1994	Chemicals	1883
8253	Paccar	1997	Trucks & Other Vehicles	1905
8358	Parker Hannifin	2003	Industrial Equipment & Components	1917
8463	Pentair	2005	Industrial Equipment & Components	1966
8530	Pfizer	2003	Drug Manufacturers	1849
8972	Raytheon	1999	Aerospace Defense Products & Services	1922
9203	Rockwell Automation, Inc	2002	Diversified Machinery	1903
9771	A. O. Smith Corporation	N/A	Industrial Electrical Equipment	1904
9818	Sony	1996	Electronic Goods	1946
9899	AT&T	1989	Wireless Communication	1885
10195	Superior Industries International	N/A	Auto Parts	1957
10499	Texas Instruments Inc.	1994	Semiconductor - Integrated Circuits	1930
10519	Textron	2002	Aerospace Defense Products & Services	1923
10530	Thermo Fisher Scientific	2010	Medical Laboratories & Research	1902
10581	The Timken Company	2010	Machine Tools & Accessories	1899
10846	Unilever	1995	Personal Products	1930
10983	United Technologies Corp	1994	Aerospace Defense Products & Services	1934
11217	Volvo	2007	Auto Manufacturers - Major	1927
11465	Whirlpool	1997	Appliances	1911
11636	Xerox	2002	Information Technology Services	1906

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
11721	Oshkosh Corporation	2004	Trucks & Other Vehicles	1917
12053	Dell EMC	2002	Information Technology Services	1979
12383	Norsk Hydro	2007	Aluminum	1905
12384	Royal Dutch Shell	2007	Major Integrated Oil & Gas	1890
12945	Plexus Corp	N/A	Printed Circuit Boards	1979
13570	Middleby Corp	1998	Diversified Machinery	1888
14620	Electrolux	2005	Appliances	1919
15172	Chrysler	1995	Auto Manufacturers - Major	1925
15509	HSBC	2005	Financial Services	1865
16477	Lear Corporation	1994	Auto Parts	1917
16603	Nestle	2008	Food- Major Diversified	1866
17436	BASF SE	2000	Chemicals	1865
17828	Daimler AG	2000	Auto Manufacturers - Major	1926
17874	T-Mobile	2003	Wireless Communication	1990
18931	Isuzu Motors Ltd.	1970	Auto Manufacturers - Major	1878
19113	Nissan	1994	Auto Manufacturers - Major	1933
19349	Siemens	2005	Electronic Equipment	1847
19565	Rio Tinto Ltd.	2004	Industrial Metals & Mine	1873
19661	Toyota	1986	Auto Manufacturers - Major	1973
22343	KLX Inc.	N/A	Aerospace Defense Products & Services	1987
23753	Dorman Products Inc	N/A	Auto Parts	1978

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
23978	United States Steel Corp	2013	Steel & Iron	1901
24293	Kaiser Aluminum	2000	Aluminum	1946
24800	QUALCOMM, Inc	2007	Communication Equipment	1985
25180	AGCO Corp	2013	Farm & Construction Machinery	1990
25279	Boston Scientific	2001	Medical Appliances & Equipment	1979
27638	Alcoa Corp	2003	Aluminum	1888
28139	Sanmina Corp	N/A	Diversified Electronics	1980
28192	Arconic	N/A	Industrial Metals	2016
28195	Jabil	2010	Printed Circuit Boards	1966
28742	BorgWarner Inc	2002	Auto Parts	1880
29722	DSP Group Inc.	N/A	Semiconductor - Integrated Circuits	1987
29930	Motorcar Parts of America	N/A	Auto Parts	1968
30170	Flex	2008	Printed Circuit Boards	1969
30247	Merix	1994	Printed Circuit Boards	1994
30260	Simpson Manufacturing Co	2009	Small Tools & Accessories	1956
31142	STMicroelectronics	N/A	Semiconductor - Integrated Circuits	1957
31673	AmerisourceBergen Corp	2016	Drugs Wholesale	2001
62856	Asahi Glass Company	N/A	Glass Ceramics	1907
63477	BAE Systems	1997	Aerospace Defense Products & Services	1960
64690	Autoliv	1995	Auto Parts	1956
65248	ArcelorMittal USA LLC	2017	Steel & Iron	2006
65399	Meritor Inc.	2001	Auto Parts	1997

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
66290	Steelcase Inc	2002	Business Equipment	1912
100369	Bridgestone	2009	Rubber & Plastics	1931
100499	Rolls-Royce Holdings Plc	2003	Aerospace Defense Products & Services	1904
100609	Continental AG	2001	Auto Parts	1871
100716	Yaskawa Electric Corp	2003	Electronic Equipment	1915
100737	Volkswagen	1992	Auto Manufacturers - Major	1937
101120	Audi AG	1997	Auto Manufacturers - Major	1910
101202	Air Liquide SA	N/A	Chemicals	1902
101204	SANOFI	2001	Drug Manufacturers	1973
101276	Groupe PSA	2009	Auto Manufacturers - Major	1976
101277	Michelin	2006	Rubber & Plastics	1889
101310	Novartis AG	2004	Drug Manufacturers	1996
102476	Haldex	2003	Auto Parts	1887
102523	Valeo	1990	Auto Parts	1923
104607	Hyundai	1997	Auto Manufacturers - Major	1947
112158	Celestica	1999	Printed Circuit Boards	1994
117861	American Axle & Manufacturing Inc	2002	Auto Parts	1994
118122	Delphi Automotive PLC	1997	Auto Parts	1994
119316	Trex Inc.	2011	General Building Materials	1996
121718	Juniper Networks	N/A	Networking & Communication Devices	1996
136648	Visteon	1996	Auto Parts	2000
144066	Rockwell Collins	2006	Aerospace Defense Products & Services	1933
155394	LKQ Corp	2009	Auto Parts	1998

Company gvKey	Company Name	LSS Adoption Date	Company Industry	Founding Date
164494	Spirit AeroSystems Holdings	2007	Aerospace Defense Products & Services	2005
164557	RBC Bearings Inc	N/A	Machine Tools & Accessories	1919
175689	Armstrong World Industries	1990	General Building Materials	1860
177925	WABCO Holdings, Inc.	2005	Auto Parts	1869
210418	ABB Corporation	1998	Diversified Machinery	1988
220833	Airbus	1999	Aerospace Defense Products & Services	1970
293827	United Company Rusal AO	2003	Aluminum	2000
295786	CNH Industrial	N/A	Farm & Construction Machinery	1999
318659	Hella	1991	Auto Parts	1899

APPENDIX B. INDUSTRIES

Industry	# of Firms
Aerospace Defense Products & Services	14
Aluminum	4
Appliances	2
Auto Manufacturers - Major	12
Auto Parts	18
Business Equipment	3
Chemicals	4
Communication Equipment	3
Diversified Computer Systems	1
Diversified Electronics	3
Diversified Machinery	12
Drug Manufacturers	7
Drugs Wholesale	3
Electronic Equipment	3
Electronic Goods	1
Farm & Construction Machinery	6
Financial Services	3
Food- Major Diversified	2
General Building Materials	2
Glass Ceramics	1
Industrial Electrical Equipment	2
Industrial Equipment & Components	3
Industrial Metals	1
Industrial Metals & Mine	1
Information Technology Services	3
Machine Tools & Accessories	2
Major Integrated Oil & Gas	3
Medical Appliances & Equipment	3
Medical Instruments & Supplies	2

Industry	# of Firms
Medical Laboratories & Research	1
Networking & Communication Devices	1
Optics	1
Packaging & Containers	3
Personal Products	1
Printed Circuit Boards	5
Rubber & Plastics	3
Semiconductor - Integrated Circuits	3
Small Tools & Accessories	1
Steel & Iron	3
Trucks & Other Vehicles	2
Wireless Communication	3
Total	151