Integrated Approach to Assess Supply Chains: A Comparison to the Process Control at the Firm Level

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List of Abbreviations

AMOS: A statistical software package for Structural Equation Modeling (SEM) using structural covariance analysis

CRM: Customer Resource Management

CRP: Continuous Replenishment Program

ERP: Enterprise Resource Planning

ES: Enterprise System

HDI: Human Development Index

IT: Information Technology

LISREL: Linear Structural Relations – a statistical software package for SEM using structural covariance analysis

MLR: Multiple Linear Regression

MRP: Material Resource Planning

NIPALS: Nonlinear Iterative Partial Least Squares

OMS: Outsourcing and Multi-Suppliers

PCA: Principal Component Analysis

PCR: Principal Component Regression

PLS: Partial Least Squares

SCLP: Strategic Collaboration and Lean Practices

SCM: Supply Chain Management

SEM: Structural Equation Modeling

SME: Small and Medium Size Enterprises

SPSS: Statistical Package for the Social Sciences commercial software

VMI: Vendor-Managed Inventory

WPI: Work in Process Inventory

List of Symbols

$\| \|$	Euclidian norm
$\boldsymbol{i}$	a dummy index for counting samples (objects)
$\boldsymbol{j}$	a dummy index for counting independent (x) variables
$\boldsymbol{k}$	a dummy index for counting dependent (y) variables
$\boldsymbol{h}$	a dummy index for counting components or factors
$\boldsymbol{n}$	the number of samples in the calibration (training) set
m	the number of independent (x) variables
$\boldsymbol{p}$	the number of dependent (y) variables
a	the number of factors used (< rank of *X)*
$\boldsymbol{r}$	the number of samples in a prediction (test) set
x	a column vector of features for the independent variables (size *m x* 1)
y	a column vector of features for the dependent variables (size *p x* 1)
X	a matrix of features for the independent variables (size *n x m)*
Y	a matrix of features for the dependent variables (size *n x p)*
b	a column vector of sensitivities for the MLR method (size *m x* 1)
B	a matrix of sensitivities for the MLR method (size *m x p)*
$\boldsymbol{t_h}$	a column vector of scores for the X block, factor *h* (size *n x* 1)
$\mathbf{p'_h}$	a row vector of loadings for the X block, factor *h* (size 1 *x m)*
$\mathbf{w'_h}$	a row vector of weights for the X block, factor *h* (size 1 *x m)*
T	the matrix of X scores (size *n x a*)
P′	the matrix of X loadings (size a *x m)*
$\boldsymbol{u_h}$	a column vector of scores for the Y block, factor *h* (size *n x* 1)
$\boldsymbol{q'_h}$	a row vector of loadings for the Y block, factor *h* (size 1 *x p)*
$\boldsymbol{U}$	the matrix of Y scores (size n *x a)*
$\boldsymbol{Q'}$	the matrix of Y loadings (size a *x p)*
$\boldsymbol{M_h}$	a rank 1 matrix, outer product of t_h and p'_h (size *n x m)*
$\boldsymbol{E_h}$	the residual of X after subtraction of *h* components (size *n x m)*
$\boldsymbol{F_h}$	the residual of Y after subtraction of *h* components (size *n x p)*
$\boldsymbol{b_h}$	the regression coefficient for one PLS component
$\boldsymbol{I_m}$	the identity matrix of size *m x m*
$\boldsymbol{I_n}$	the identity matrix of size *n x n*
$\boldsymbol{r^2}$	square of correlation coefficient to assess the quality of the *training* model
$\boldsymbol{R^2}$	square of correlation coefficient to assess the quality of the *training* model (also accounts the residual error)
$\boldsymbol{q^2}$	square of correlation coefficient to assess the quality of the *test* set
$\boldsymbol{Q^2}$	square of correlation coefficient to assess the quality of the *test* set (also accounts the residual error)

Abstract

This study considers whether or not optimizing process metrics and settings across a supply chain gives significantly different outcomes than consideration at a firm level. While, the importance of supply chain integration has been shown in areas such as inventory management, this study appears to be the first empirical test for optimizing process settings. A Partial Least Squares (PLS) procedure is used to determine the crucial components and indicators that make up each component in a supply chain system. PLS allows supply chain members to have a greater understanding of critical coordination components in a given supply chain. Results and implications give an indication of what performance is possible with supply chain optimization versus local optimization on simulated and manufacturing data. It was found that pursuing an *integrated* approach over a traditional *independent* approach provides an improvement of 2% to 49% in predictive power for the supply chain under study.

1. Introduction

1.1. Background and Research Objectives

This research investigates manufacture-related supply chain data to determine crucial components and indicators that make up each component in supply chain systems. A data-driven approach is utilized to determine latent constructs hidden in a given supply chain system and to determine whether knowledge of these constructs can lead to better supply chain outcomes.

Over the past three decades, there has been a change in the focus of operation strategies of companies. While management operations during 1980s were shaped by *vertical*[1] integration (Hayes and Wheelwright, 1984), there had been a marked shift towards *horizontal*[2] alignment of process operations (Groshal and Bartlett, 1995; Frohlich and Westbrook, 2001). However, during 2000s, companies aimed to integrate their internal manufacturing and service processes to external suppliers and customers in unique supply chains. This approach of managing supply chains is known as Supply Chain Management (SCM) in the literature. SCM is defined as the design and management of value-added processes of a product across multiple organizations to satisfy the needs of the end-customer. The main objective of SCM is to use of technology and teamwork to build efficient and effective processes that create value for the end customer by reducing the overall supply chain cost. Thus, supply chain integration with suppliers and customers is considered as a crucial operation strategy. Lambert and Cooper (2000) also note that firms no longer compete as individual entities, but rather as integral parts of supply chains.

[1] Vertical integration refers to companies in a supply chain that are united through a common owner. Usually each supply chain member produces a different product or service, and these products combine to satisfy a common need.
[2] Horizontal integration is contrasted with the vertical integration. The goal of the horizontal integration is to consolidate companies operating in the same industry and in the same stage of production to monopolize an industry.

Synchronizing the upstream flow of incoming materials with the downstream operations to respond uncertainties in demand without creating excess inventory is one of the major goals in managing supply chain of a given company (Wangphanich *et al.*, 2010). However, numerous factors, namely inaccurate forecasting, long lead times, late deliveries and price fluctuations induce uncertainty in coordinating supply chains. Consequently, while early research focused on identifying the causes of variability and difficulties in monitoring supply chains (Sterman, 1989), the later research has concentrated on quantifying and searching for remedies to streamline supply chain operations (Cachon and Fisher, 2000; Disney and Towill, 2003; Boute *et al.*, 2007; Wangphanich *et al.*, 2010). However, successful integration of supply chain members to improve overall performance still remains a challenging task. It is difficult to detect, monitor and assess interactions between different supply chain members of a given system (Lee *et al.*, 1997; Chen *et al.*, 2000; Dejonckheere *et al.*, 2003). Besides interactions among supply chain members, numerous exogenous latent components (i.e., environmental factors) may also have an effect on the dynamics of the system. Examining relationships between multiple supply chain members is intricate, thus the SCM discipline develops a *conceptual framework*[3] to examine inter-company interaction. Frameworks are used to not only capture these latent components accurately, but also provide a methodology to assess interactions thoroughly.

Partial Least Squares (PLS) is an analytical technique that is extensively applied in *Chemometrics*[4] (examples include: Wold *et al.*, 2001 and Thissen *et al.*, 2004) and is particularly useful in detecting *latent* components[5]. Unlike other structural equation models like s*tructural covariance analysis*, the PLS approach does not place stringent requirements on *sample size*, *data normality*, *measurement scales* or *residual distributions* (Claassen, 2008). Once critical latent variables or components are detected using PLS, supply chain members can gain a greater understanding of the critical coordination factors and may use

[3] The *conceptual framework* in SCM consists of three interrelated elements: the supply chain *business processes*, the supply chain *network structure*, and the supply chain *management components*. The *business processes* refers to the activities that produce a specific value-added output to the customer. The *network structure* includes supply chain member firms and the links between these members. The *management components* are variables that enable integration and management of business processes along a supply chain (Lambert and Cooper, 2000: 69).
[4]Chemometrics, a highly interfacial discipline, extracts information from chemical systems by data-driven means.
[5] The term *latent component* refers to the unobservable factors in the measurement model (Lattin *et al.*, 2003: 14)

these insights to improve overall supply chain integration. Thereby, allowing companies to use resources more effectively. **The objective of this research is to determine whether the integration of process measurement and control across a supply chain offers a substantial advantage over the current practice of limiting process control and optimization at the firm level**.

1.2. Plan of the Thesis

This thesis is presented to describe background, methodology, data analysis and results of this research study. The study is presented in six sections and extensive appendix of data analysis is also provided.

- *Section 1* – **Background and research objectives**: the section introduces the subject of the thesis and states the key research objective of the study.
- *Section 2* – **Literature review**: this section is comprised of two sub-sections. The first part focuses on the Supply Chain Management (SCM) literature. This includes an overview of the field, dynamics of supply chains, and identified challenges in the field. A discussion about observed issues in the field is also provided. The second section of the literature review examines the Partial Least Squares (PLS) method that is used to test the hypothesis of the study. A brief introduction to Structural Equation Modeling (SEM) is provided to discuss the foundations of the PLS method. Supply chain studies that implement *predictive* and *causal* modeling approached of PLS are discussed in detail.
- *Section 3* – **Research model**: this section introduces the research model of the study along with the hypothesis of the study. Research propositions and tactics are also provided.
- *Section 4* – **Methodology**: the first part of this section introduces the underlying mathematical algorithm of the *predictive* PLS and its mathematical relation to the Principal Component Analysis (PCA). The discussion also provides information on how statistics are obtained from the PLS model. The second part of this section introduces the data of the study and outlines the procedure to analyze individual data sets. The last part of the section introduces PLS software programs. Discussion about both *predictive* and *causal* modeling PLS software programs are provided.
- *Section 5* – **Results**: this section presents the results of the model

- *Section 6* – **Discussion**: this section discusses the overall results of the study and gives recommendations. Limitations and contributions of the study, and suggested further research are also included in the discussion.

2. Literature Review

This section is composed of two parts. The chapter presents an overview of the Supply Chain Management (SCM) through a review of the relevant literature, emphasizing three key points, namely (2.1.2) dynamics of supply chains, (2.1.3) challenges in Supply Chain Management, and (2.1.4) observed issues in the literature. The second section of the chapter examines the use of Partial Least Squares (PLS) for analysis of data. Both the use of PLS in the social sciences (2.2.2.1) and applied sciences (2.2.2.3) are considered in this section. Supply chain studies that implemented the social sciences approach of PLS (2.2.2.2) and applied sciences approach of PLS (2.2.2.4) are also discussed.

2.1. Supply Chain Management

2.1.1. Overview

Over the last two decades, the focus of operations strategy in manufacturing has been shifting from optimizing internal operations to linking internal processes with external suppliers and customers (Frohlich and Westbrook, 2001). In fact, most successful manufacturers suggest that the integration of *upstream* and *downstream* processes is crucial in today's competitive business environment[6]. This notion of integrating processes paved the way for the theory and practice of *Supply Chain Management* (SCM) that integrates "key business processes from end user through original suppliers that provides products, services, and information that add value for customers and other stakeholders" (Lambert and Cooper, 2000: 66).

Because of the interdisciplinary nature of SCM, the literature on supply chain systems is wide-ranging in terms of constructs and operational measures. In fact, studies show that the field is still in its development phase and requires improvements in measurement instruments and theoretical models (Chen and Paulraj, 2004). When the term SCM was originally

[6] Upstream of a given company under study refers to the suppliers of that company. Similarly, downstream refers to the customers of that company.

introduced by practitioners and academicians in the early 1980s, it was considered as an alternative word for *logistics*. However, over the years, it has been realized that SCM encompasses all net value-adding activities to synchronize supply with demand. In the era of network competition, companies now realize that they need to establish solid inter-company networks, rather than solely competing as autonomous entities (Lambert *et al.*, 1998). However, studies show that management of inter-company integration is a challenging task due to its broad scope (Gunasekaran *et al*., 2001).

2.1.2. Dynamics of Supply Chains

Many articles examine the impact of SCM practices on comparative advantage and organizational performance (Gunesekaran *et al.*, 2001; Otto and Kotzab, 2003; Li *et al.*, 2006; Claassen *et al.*, 2008). Scholars believe that performance measures are critical to test the viability of supply chain strategies, since there is a lack of clear distinction between metrics at strategic, tactical and operational levels (Gunesekaran *et al.*, 2001; Otto and Kotzab, 2003). Gunesekaran *et al.* (2001) provide a thorough study that examines performance measures based on the four links of an integrated supply chain (i.e., plan; source; make/assemble; and delivery/customer). This integrated study reveals that different approaches to SCM lead to different awareness of what should be measured to assess performance. Although, the measurement and performance of a supply chain may be dependent on the unique notions and problems, the integrator of the supply chain should carefully assess the value of different goals that are relevant for managing a supply chain successfully. Thus, examining a combination of different performance metrics of SCM will allow better assessments of supply chain operations of a given system. As stated in the objective, this thesis examines the integration of different process measurement and metrics across a supply chain.

Lohman *et al.* (2004), and Folan and Browne (2005) assert that implementing supply chain wide performance measures are difficult for a number of reasons. Operational reporting histories of players along the supply chain tend to vary in terms of style, content and frequency, which results in decentralization. Next, there is a deficient insight in cohesion between metrics of performance measures. In addition, although companies are immersed with large amounts of data from all different sources, they can still be uncertain about what to measure and focus to improve the performance of a given supply chain. Finally, the information technology infrastructure is still dispersed even though the medium of information exchange (i.e., the Internet) brings a degree of unity. Furthermore, studies show that supply chains still suffer from poor communication between reporters and users that hampers smooth inter-organizational flow (Lohman *et al.*, 2004). Chen and Paulraj (2004) emphasize the importance of collaboration and coordination in supply chains that are composed of independent relationships that are developed and fostered through strategic collaboration. Their study not only identifies and validates key constructs of supply chains, but also urges scholars to develop performance measure instruments rather than merely building theoretical models. In fact, these instruments will allow companies to understand the impact of environmental uncertainty (such as variations in supply, demand and technology), and the importance of reducing the number of suppliers and maintaining long-term relationships.

Claassen *et al.* (2008) implement a quantitative study on performance measurement systems in supply chains by focusing solely on performance outcomes of Vendor-Managed Inventories[7] (VMI). The study not only compares theory and practice about performance outcomes of VMI from the buyer's perspective, but also identifies factors that enable successful VMI implementation. The authors implement the Partial Least Squares (PLS) method to investigate relationships between VMI enablers (i.e., information systems; information sharing; information quality; and relationship quality), perceived VMI success, and VMI outcomes (i.e., cost reductions; supply chain control; and customer service). The study reveals an interesting finding that although most vendors take responsibility for ordering, inventory management and replenishment, only a very small portion of them actually take the full *pipeline inventory*[8] control, where significant cost reductions are achieved.

As opposed to aforementioned studies that focus on integration process control in terms of forecasting, inventory system management, and the information control, this thesis presents a

[7] Vendor-managed inventory (VMI) is a type of business model in which the supplier takes the full responsibility for maintaining an agreed inventory of a material at the buyer's store. In return, the buyer of the product shares certain information to the supplier of the product.
[8] Pipeline inventory refers to goods that are still in transit or in the process of distribution. These goods have left the factory, but not arrived to the end customer yet.

different type of integration process control by comparing *integrated* and *independent* supply chain approaches together. Underlining the importance of SCM to understand and evaluate collaboration and coordination within firms also reveals numerous challenges in measuring and monitoring supply chain performance. The following section presents a number of major challenges in SCM.

2.1.3. Challenges in Supply Chain Management

As mentioned earlier, integrating different players along the supply chain is a challenging task due not only to the extent and dynamic[9] nature of supply chains, but also the conflicting interests and performance measures of supply chain members along the chain. However, this is clearly worth doing. For example, the well-known oscillating demand magnification problem, *Bullwhip Effect*[10], in SCM drew particular attention in the literature and this issue is thoroughly discussed in a number of articles (Lee *et al.*, 1997; Chen *et al.*, 2000; Dejonckheere *et al.*, 2003). The *Bullwhip* effect is prevalent across supply chains that are optimized at a firm level. Since the intent of this research is to determine whether the integration of process measurement and control across a supply chain offers a substantial advantage over the current practice of optimization at the firm level, understanding the sources of the bullwhip effect is important.

Lee *et al.* (1997) develop quantitative models to analyze the four sources of the bullwhip effect, namely: (1) demand signal processing, (2) rationing game, (3) order batching, and (4) price variations. The authors find some thought-provoking results from their study. First, they quantitatively show that information sharing may not be the ultimate solution to eliminate the problem of demand magnification since differences in forecasting methods, which cannot be eradicated simply by information sharing, affect the degree of the bullwhip effect. The authors suggest that shortening the lead-time and pursuing direct marketing in

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[9] The dynamic nature of a supply chain refers to the time correlation of supply chain operations. Supply chains can be regarded as constantly changing dynamic systems in terms of supply, demand, objectives, and operational features.

[10] The *Bullwhip* effect is an observed phenomenon in forecast driven distribution channels. Along the supply chain (moving up from the end customer to raw materials supplier), each supply chain member experiences greater variation in demand and this experiences greater need for safety stock. During rising demand, downstream members (i.e., customers) increase their orders. In periods of falling demand, orders of customers fall to reduce inventory. Variations are amplified as one moves upstream (i.e. towards the raw material supplier) along the supply chain.

addition to implementing VMI and Continuous Replenishment Program[11] (CRP) alleviate the bullwhip problem. Chen *et al.* (2000) suggest similar strategies may overcome demand magnification. They suggest that if every stage along the supply chain implements the same forecasting technique and inventory policy, the issue may be resolved. Furthermore, they quantitatively show that centralizing all demand information significantly reduces the bullwhip effect. On the other hand, Dejonckheere *et al.* (2003) analyze the behavior of order-up-to policies in terms of order-rate fluctuations by measuring the variance amplification of orders from a control engineering perspective. The authors implement some elegant methods in control systems engineering (i.e., transfer functions, frequency response curves and spectral analysis, and fast Fourier transform) to analyze the dynamic behavior of the replenishment rule. Furthermore, by accurately quantifying the magnitude of the variance amplification, they show that exponential smoothing based on order-up-to policies reduces the impact of the bullwhip effect. However, we should note that order-up-to policies always create a bullwhip effect, since forecast errors are considered to be the incorrect focus for the optimization routine (Dejonckheere *et al.*, 2003).

Furthermore, some articles discuss the effects of the bullwhip problem by examining another well-known logistical system case (i.e. the *Beer Game*[12]) to illustrate the reengineering concepts and tools in a multi-stage production and distribution system (Ackere *et al.*, 1993; Sparling, 2002). Ackere *et al.* (1993) not only examine the implications of the base model (original beer game), but also discuss variations to the original model. Their study reveals that it is crucial to not only link the customer to the factory, but also allow all parties along the supply chain to gain access to the actual customer demand data. By implementing appropriate simulation techniques, the authors show that these approaches greatly increase the overall performance of the supply chains. As mentioned previously, this thesis compares the *integrated* approach based on coordination of supply chain members with the *independent* approach of process control at the firm level. If the *integrated* approach of linking all parties along the supply chain performs better than the *independent* approach, this

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[11] Continuous replenishment program (CRP) refers to a replenishment process between distribution channel partners based on actual and forecasted product demand. This is different than the traditional replenishment process, in which replenishment decisions are based on economic order quantities.
[12] The beer game is a simulation game to demonstrate a number of key principals of SCM. The purpose of the game is to meet customer demand for cases of beer across a multi stage supply chain with minimal expenditure on inventory and backorders. Sparling (2002) outlines the details of the game.

thesis will quantitatively illustrate the significance of coordination to reduce supply chain inefficiencies identified by these aforementioned studies.

In short, although SCM offers the opportunity to capture the synergy of intra and inter-company integration, streamlining supply chains remains as a challenging task (Lambert and Cooper, 2000). The following section discusses observed issues in the literature to explain why existing approaches still cannot perfectly coordinate supply chains.

2.1.4. Observed Issues in the Literature

Studies show that there are still gaps in the literature on how to manage supply chain activities effectively (Chopra and Sodhi, 2004; Tang, 2006; Christopher and Holweg, 2011; Datta and Christopher, 2011). Some scholars focus on developing simple optimization models or heuristics to analyze supply chains quantitatively, others strive for improving the constituents of supply chains (i.e., information and product flows, manufacturing strategies, and information technologies) individually in the hope of improving the whole system.

However, the SCM literature still lacks overarching *conceptual frameworks* (Lambert and Cooper, 2000). An overarching framework does not necessarily mean that a company should strive for optimizing all the links throughout its supply chain. This may indeed be counterproductive, since determining every crucial component and constraint of a dynamic supply chain is a challenging task. Alternatively, a firm should develop an approach to determine which supply chain members and activities are critical to the success of the company (Lambert *et al.*, 1998). Lambert and Cooper (2000) present three elements of SCM as a conceptual framework (i.e., network structure, business processes, and management components). Even though *network structures* are easier to analyze quantitatively, *management components* are much more difficult to investigate, since this dimension includes complex subtle aspects (i.e., culture and attitude, power and leadership structure), which are difficult to measure and control. Furthermore, in terms of *business processes*, companies, especially large enterprises, usually have numerous processes consisting of different activities and links between activities that may be conflicting. A company that belongs to multiple supply chains may find it very difficult to streamline its *business processes*, since the company may be forced to give greater emphasis on processes that are controlled by more dominant supply chain members. However, the root cause of problems in business process management may lie within subtle links. This thesis implements Partial Least Squares (PLS), an analytical technique that is particularly useful in detecting latent components, to identify these subtle links in a given supply chain.

Having reviewed the dynamics of supply chains and observed issues in the literature, one should determine whether process measurement integration and control across a supply chain offer a substantial advantage over the current practice of limiting process control and optimization at the firm level. The next section will examine the social and applied sciences applications of PLS that will be used to assess the distinction between *integrated* and *independent* supply chain approaches.

2.2. Partial Least Squares (PLS)

The use of Partial Least Squares (PLS) for analysis of data offers a better understanding of the relationships inherent in the data set than other statistical techniques. This section introduces the application of PLS by reviewing *Structural Equation Modeling* (SEM) to discuss the foundations of the PLS method. The distinction between social sciences (*causal* modeling) and applied sciences (*predictive* modeling) approaches of PLS is explained in this section. Both *causal* modeling and *predictive* modeling PLS studies are covered in the literature review. Studies that implement the *causal* modeling PLS approach on SCM are discussed in detail.

2.2.1. A Brief Discussion on Structural Equation Models

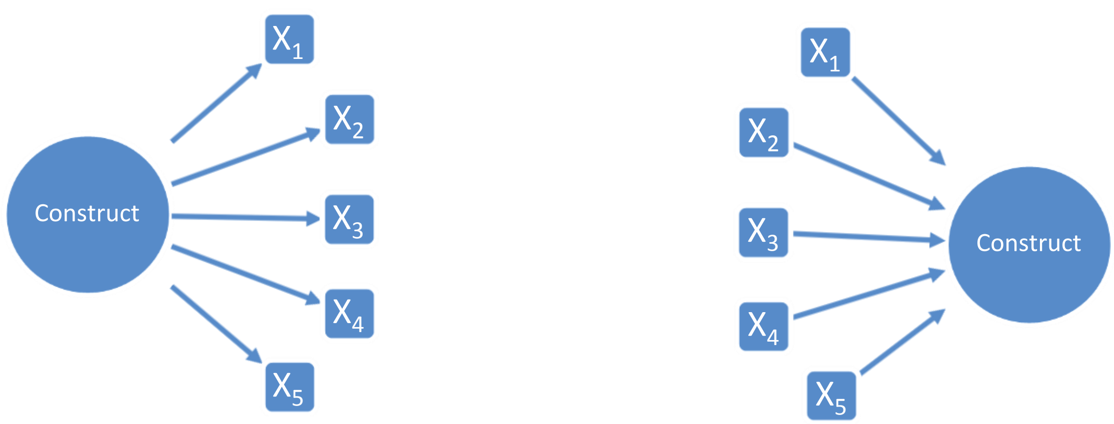
Structural Equation Modeling (SEM) is a technique that tests and estimates causal relationships by using a combination of qualitative causal assumptions and statistical data (Pearl, 2000). It is important to note that there are two major types of variables in SEM that one considers: *latent* and *manifest* variables. As its name suggests, *manifest* variables are defined and measured directly. An example of a *manifest* variable is *gender* or *marital status*. *Latent* variables are indirectly observed and inferred from *manifest* variables. For example, *quality of life* is a *latent* variable that can be measured in a number of ways, including:

1. Monetary indicators: GDP per capita and employment rate
2. Social indicators: Human Development Index (HDI), environment, physical and mental health, education, recreation and leisure time

Although there are no rules associated with the number of *manifest* variables to infer *latent* variables, multiple manifest variables are used per latent construct when there is either a chance of significant measurement error or the latent construct is complex (Linton, 2004).

The relationship between a *manifest* variable(s) and a *latent* variable can be either *reflective* or *formative*. In a *reflective* model (left-hand side of Figure 1), the latent variable is considered as the common cause of a manifest behavior. The causal action flows from the latent variable to the indicators (Edwards and Bagozzi, 2000). Therefore, any change in the latent variable results in a change in indicator behavior. On the contrary, manipulation of an indicator may not have an effect on the latent variable. In a *reflective* model, arrows point towards manifest variables and emanate from the latent construct. This is similar to Principal Component Analysis (PCA), where principal components represent latent constructs and the variables are manifest variables (Linton, 2004).

In a *formative* model, (right-hand side of Figure 1), there is a *causal relation* between the latent construct and manifest variables. In other words, the latent construct is defined by associated manifest variable(s). In formative models, it is crucial to use all relevant measures in the model (Linton, 2004).



Reflective **Formative**

Figure 1 - Causal Structures

2.2.2. Partial Least Squares (PLS) Overview

The PLS regression bears some relation to the principal components regression. Thus, comparing PLS with PCA provides valuable insight. PCA is a mathematical procedure that transforms correlated variables into a smaller number of uncorrelated variables, called *principal components*. The *first principal component* accounts for the greatest variability in the data, while each succeeding components accounts for a part of the remaining variability in the data (Chin *et al.*, 2003). The *principal component* can be regarded as a *latent construct*, meaning that a group of variables in the model is actually related to an *unidentified* variable that is measured indirectly by other variables. The objective of PCA is to remove the effects of principal components until most of the variation is explained (Linton, 2004). Furthermore, the explanatory power of the model can also be calculated while determining constituents of each principal component. Studies show that explanatory power of principal components declines rapidly (Linton, 2004).

PLS components are analogous to the PCA approach, but there are some important differences. One of the major differences between the two is that while PCA considers variation between a latent construct and variables, PLS considers variation between the dependent variable and manifest variables[13]. In terms of operational difference, selection criteria for the number of components also differ between two methodologies. Experience shows that selecting the first five components is usually sufficient, but if there are few numbers of variables, users are advised to use fewer PLS components (Linton, 2004).

The PLS method is particularly useful for analyzing complex models having a small sample size. Compared to the other commonly used structural equation models like s*tructural covariance analysis* (the technique used by programs such as LISREL and AMOS), PLS requires fewer constraints and assumptions. Similar to regression and analysis of variance, structural covariance analysis demands two critical assumptions, namely: *independence of causal variables* and *normality of all variables* (Chin *et al.*, 2003). Since these assumptions require data sets having large number of observations, this approach is not applicable to many data sets. In contrast, in PLS, the number of variables can even be greater than the number of observations (Wold, 1989; Tenenhaus *et al.*, 2005: 202). A rule of thumb for PLS

[13] PLS also considers latent variables, but latent variables in relation to the dependent variable (not just each other).

modeling suggests that the sample size should be equal to the larger of the following (Chin, 1998):

- Ten times the number of indicators of the scale with the largest number of formative indicators, or
- Ten times the largest number of structural paths directed at a particular construct in the inner path model.

Chin and Newsted (1999) illustrate a Monte Carlo simulation on PLS with small sample sizes and show that the PLS approach can even work well at sample sizes as low as twenty.

Besides the application of PLS to the *social sciences*, PLS has also developed in the *natural* (*applied*) *sciences*. Unlike the causal modeling technique of PLS in the social sciences, studies in the natural sciences are aimed at *predictive* modeling (Linton, 2004). Furthermore, different sets of tools and techniques are developed in the applied sciences to predict and solve non-linear problems that are uncommon in the social sciences. Further discussion on the non-linear aspect of the PLS method will not be provided, since this study implements purely linear PLS.

Having considered the background of PLS and its advantages over other SEM approaches, the following sections will examine two different versions of PLS, namely the *causal* and *predictive* modeling approaches. The literature review will also identify SCM studies that implement the PLS approach.

2.2.2.1. PLS in the Social Sciences – Causal PLS Modeling

Like other SEM techniques, PLS aims to minimize the amount of error in a given model by determining a set of coefficients that result in *least square minimization*[14] (Chin *et al.*, 2003). As with regression analysis, PLS minimizes the squared distance between the actual and predicted values (i.e., $\bar{X}$) of each observation by finding coefficients that minimize the *sum of least square error*[15] (Lattin *et al.*, 2003). PLS determines the best-fit model by following a recursive approach until it reaches the minimum possible error (Linton, 2004). Although,

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[14] The best fit minimizes the sum of squared residuals (the amount of error). A residual refers to the difference between an observed value and the fitted value provided by the model.

[15] Mathematically, sum of square error can be represented as $\sum(X - \bar{X})^2$

determining coefficients for models having a single manifest dependent variable and a set of causal manifest variables is straightforward, simultaneous solving may simply be impossible for most complex models like many supply chains that have multiple dependent variables. PLS overcomes this issue by pursuing a *divide-and-conquer* strategy, where the complex model is divided into smaller, manageable blocks that can be solved individually, assuming independence among dependent variables. At each iteration, the error term of the best solution of every block is summated in order to obtain the total error (Linton, 2004). This procedure is repeated until the least squares error can no longer be minimized further.

PLS is a powerful method, since it places minimal demands on *sample size*, *residual distributions*, and *measurement scales* (Chin *et al.*, 2003). The following list highlights reasons why the PLS approach is superior to other covariance-based methods:

1. *Assumptions*: Unlike any other data analytic methods, PLS is non-parametric, meaning that it does not have any assumptions on the nature of the distribution of data. PLS can handle data that do not satisfy the normality assumption. This flexibility is one of the major advantages of PLS over other methods. Furthermore, PLS does not assume independence between predictor variables. Independence assumption can be problematic particularly in other data analytic methods, where the modeler can wrongfully assume *independence* even if predictor variables are correlated with each other.
2. *Structural Equation Model*: As discussed previously, PLS models include both latent and manifest variables. PLS can utilize multiple dependent variables. This ability allows PLS to model real systems. In addition, PLS does not place stringent rules on the minimum sample size. For example, while covariance based structural equation models like LISREL requires a minimum sample size of 100 – 200 for any model (Chin *et al.*, 2003), the block modeling approach of PLS allows smaller data sets as low as thirty observations. The sample size requirement of other SEM techniques increases as the number of interaction term indicators due to the number of parameters being estimated. Because the minimum sample size is not determined by the number of relations and variables in the model, the sample size requirement is dictated by the largest (most complex) block under consideration (Chin *et al.*, 2003; Linton, 2004). Furthermore,

standard error estimation techniques (i.e., *bootstrapping* and *jackknifing*) can be used to test the statistical significance of the model even if the small sample size is small.

3. *Types of indicators*: PLS is compatible with both *reflective* and *formative* constructs. This strength is particularly useful to analyze complex systems that include both reflective and formative construct. This is in fact the case in numerous complex supply chains.

Even though, most articles covered in this study implemented PLS for *theory testing*, this method can also be used to suggest propositions where relationships do or do not exist (Chin *et al.*, 2003). In fact, Fornell and Bookstein (1982) underline that unlike alternative *covariance fitting* approaches (i.e., LISREL and AMOS), PLS avoids two critical problems, namely: *inadmissible solutions* and *factor indeterminacy*. If prior theory is strong, and the goal is to test and develop the theory further, full-information estimation methods, such as Maximum Likelihood, are more suitable. However, as a result of the *factor score estimation indeterminacy*, covariance-based methods do experience a loss of predictive accuracy (Chin *et al.*, 2003).

The PLS approach is also suitable for *application* and *prediction* as in PCA (Wold, 1982; Chin *et al.*, 2003). PLS overcomes the *factor indeterminacy* problem, since it provides exact component scores by estimating latent variables from the linear combinations of observed measures (Wold, 1982). Furthermore, since the PLS method uses an iterative algorithm by implementing a series of least squares analyses, this approach does not need to presume any distributional form (i.e., normality assumption) unlike other covariance-based methods. Chin *et al.* (2003) also note that this allows smaller sample size, where sample size should be greater than or equal to *ten times* the number of indicators for the scale having the largest number of formative indicators that scales for constructs designated with reflective indicators. Finally, studies show that the PLS method is powerful for explaining complex relationships (Fornell and Bookstein, 1982; Wold, 1982; Chin *et al.*, 2003).

Having considered the strengths of the PLS approach, the next section will review the literature and identify SCM studies that implemented PLS.

2.2.2.2. Supply Chain Management Studies implementing PLS (Social Sciences Context)

Even though, there has been a dearth of research on SCM studies implementing the *predictive modeling* PLS method (i.e., applied sciences version of PLS), a number of studies examine supply chains from the social sciences *causal modeling* perspective of PLS (Handfield and Nichols, 1999; Ravichandran and Rai, 2000; Sarkar *et al*., 2001; Kocabasoglu and Suresh, 2006; Koh *et al.*, 2007; Liang *et al.*, 2007; Vandaele and Gemmel, 2007; Braunscheidel and Suresh, 2009). The literature review reveals that the *Information Systems* discipline relies heavily on PLS for testing path models, more so than any other discipline (Wixom and Watson, 2001; Subramani, 2004; Hsieh *et al.*, 2006; Rosenzweig, 2009).

Kocabasoglu and Suresh (2006) examine the importance of *strategic sourcing*[16] – a key dimension of SCM – and discuss the challenges in adopting strategic sourcing by utilizing the PLS method. The study reveals that *status of purchasing*, *internal coordination*, *information sharing*, and *development of supplier* are the key latent components of strategic sourcing. Although the sample size is limited (140 U.S. manufacturing companies), the PLS method allows them to conduct an empirical analysis on relationships between different elements of strategic sourcing. As indicated previously, this thesis includes the discussions of coordination and the importance of information sharing by investigating the *integrated* supply chain approach.

A number of studies discuss the importance of the *integrated* supply chain approach by underlining the importance of supply chain coordination. Sarkar *et al.* (2001) investigate the effect of *alliance proactiveness*[17]– a crucial SCM dimension– on market-based firm performance. The authors test the effect of alliance proactiveness within a contingency framework by using data from 182 firms. PLS results reveal that alliance proactiveness allow superior market-based performance, especially for small firms and in unstable market environments. Proactiveness increases partnering options, thereby creating a performance advantage relative to alliance reactive firms. Rosenzweig (2009) explores the relationship

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[16] Strategic sourcing refers to a procurement process that continuously reevaluates and improves the purchasing activities of a company. For example, *outsourcing* (the transfer of staff and assets to a third part company that provides a service in return) is a type of sourcing strategy for services.

[17] Alliance proactiveness refers the extent to which an organization engages in identifying and responding to partnering opportunities (Sarkar *et al.*, 2001).

between *e-collaboration* and firm's *performance* by examining the influence of product complexity and market characteristics. The PLS analysis supports the notion that e-collaboration is related to better operational and business performance. The study also reveals that the relationship between operational performance and e-collaboration diminishes as the level of *environment munificence*[18] increases. In addition, compared to larger organizations, smaller organizations experience greater improvements in performance on account of their internet-enabled commerce. Hsieh *et al.* (2006) discuss how *information orientation*[19] influences information asymmetry and e-business adoption by implementing the PLS method to a data from 307 companies in China. The paper highlights that information orientation is critical to reduce information asymmetry, which is mediated by information sharing and information collection. This means that by motivating e-business adoption and alleviating information asymmetry, information orientation may improve decision making processes.

The study of Subramani (2004) also underlines that benefits from information technologies are distributed unevenly in favor of the supply chain network leader. Even though supplier participation is crucial for network leaders, relationships between suppliers and network leaders are usually asymmetric, in which network leaders play a central role in coordinating suppliers. For this reason, Subramani (2004) examines the supplier perspective in IT-mediated supplier-retailer relationships. The study implements the PLS method on a data from 131 suppliers to support the hypothesis that information technologies in supply chains lead to closed buyer-supplier relationships. The author notes that the PLS analysis is particularly useful to evaluate both the measurement model and structural model simultaneously. The study provides evidence that suppliers can benefit from SCM initiatives of network leaders.

Braunscheidel and Suresh (2009) explore constituents of s*upply chain agility*[20] – an emerging stream of research in SCM – by investigating the linkages among organizational practices

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[18] Environmental munificence is defined as "the amount of resources within an environmental context and extent to which that environment can support sustained growth" (Rosenzweig, 2009: 466).
[19] Information orientation is defined as the company's deeply rooted set of values and beliefs regarding information (Hsieh *et al.*, 2006: 828).
[20] Supply chain agility refers to an operational strategy that focuses on inducing velocity and flexibility in a given supply chain.

and cultural antecedents through the use of PLS. Even though, the authors note that investigating the agility of every process in an organization's extended supply chain is difficult, the study shows that *integral* and *external integration* with key suppliers and customers significantly affect the firm's supply chain agility. Similarly, results reveal that *market orientation* is crucial for both internal and external supply chain integration.

SCM practices include all activities undertaken in an organization to promote effective management of its supply chain. Koh *et al.* (2007) empirically tests a framework to identify relationships among SCM practices, *SCM-related organizational performance*, and *operational performance* by focusing solely on small and medium size enterprises (SMEs). SMEs significantly impact overall supply chain performance, since suppliers, distributors, producers and even customers in supply chains are typically SMEs. By implementing the PLS method on 203 manufacturing SMEs in the metal manufacturing sector, the authors identify two major factors in SCM practices, namely *outsourcing and multi-suppliers*[21] (OMS), and *strategic collaboration and lean practices*[22] (SCLP). Results show that both factors significantly influence operational performance positively.

The studies covered in this section emphasize that coordination and collaboration of supply chain members are crucial for efficient supply chains. This finding underlines the importance of the *integrated* supply chain approach covered in this thesis. Now that PLS – as it is used in the social sciences – has been reviewed and applications of PLS in SCM have been offered, the next section will examine PLS as it is used in the applied sciences.

2.2.2.3. PLS in the Applied Sciences – Predictive PLS Modeling

As mentioned previously, the PLS method has evolved separately in the natural sciences. However, there are some key differences between social science and applied science applications of PLS in terms of goal and methodology. Unlike the objective of causal modeling in social sciences, applied sciences implement PLS to create *predictive models* (Linton, 2004). Predictive models in applied sciences examine statistical significance of relationships to predict the value of dependent variables, unlike in social sciences.

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[21] OMS includes outsourcing, e-procurement, third party logistics, and sub-contracting.
[22] SCLP includes close partnership with suppliers and customers, just in time supply, supply chain benchmarking, strategic planning, and holding safety stock.

One can also identify differences between the mechanics of the PLS method and the interpretation of results in the applied and social sciences. In terms of modeling, the previous section underlined that the dependent variable in structural equation modeling of social sciences requires only a single *manifest* variable. Furthermore, since studies in social sciences strive to determine statistical significance of relationships, it is very common to have relationships between multiple variables. However since the major goal is to predict the value of the dependent variable in the applied sciences such as *Raman Spectroscopy*[23] (Berger *et al.*, 1997; Shafer-Peltier *et al.*, 2003; Thissen *et al.*, 2004; Braun *et al.*, 2010) and design of pharmaceuticals (Norinder *et al.*, 1997; Luco, 1999; Ho *et al.*, 2009; Li *et al.*, 2010), PLS in *predictive* modeling determines a set of loadings in order to best fit the predictor variable to the dependent variable. Therefore, PLS models in the applied sciences tend to include the entire set of possible independent manifest variables to have a better understanding about the dependent variable (Linton, 2004).

Linking best-fit latent constructs with the dependent variable in the applied sciences (*predictive*) is very different from the social sciences (*causal*) that highlight the links between manifest variables and latent constructs. The modeler can either use structural equation modeling or the best-fit approach, even though both techniques in fact support each other. For example, since the best-fit approach determines the explanatory power of variables, results obtained from a structural equation model can be compared to results from the best-fit. This approach actually reveals the degree of explanatory power loss as a result of the constraints required by the structural equation model (Linton, 2004).

There are two types of measure to assess the predictive accuracy of the model (Linton, 2004):

- Explanatory power of the *training model*[24]
- Predictive power on the *test data*[25]

[23] *Raman Spectroscopy* is a spectroscopic technique (the study between radiated energy and matter) used to study rotational, vibrational, and other low frequency modes in a system.
[24] Refers to observations used to determine loadings (Linton, 2004).
[25] Refers to the set of observations to test the predictive accuracy of the data (Linton, 2004).

The important point is to determine a methodology to partition the data set into *training* and *test data* sets. The two most common techniques, namely *Jackknifing* and *Bootstrapping*, will be discussed briefly now:

- *Bootstrapping*: this technique generates a number of data subsets of specified size to *train* the PLS model. The remaining data are used to assess the *predictive power* of the model (Linton, 2004). The effectiveness of this approach can be analyzed by calculating the average explanatory power of the PLS method.
- *Jackknifing*: PLS is applied to a subsample of all data, but one observation is removed to act as a test data set. This procedure is carried out recursively until every single observation is used as a test data set once. Similar to *bootstrapping*, the *average explanatory power* of the PLS can be used in order to examine the effectiveness of this method.

2.2.2.4. Supply Chain Management Studies implementing PLS (Applied Sciences Context)

Although, the literature is replete on applications of PLS in *Chemometrics* (Wold *et al.*, 2001; Thissen *et al.*, 2004) and social sciences application of PLS on SCM (Handfield and Nichols, 1999; Ravichandran and Rai, 2000; Sarkar *et al.*, 2001; Kocabasoglu and Suresh, 2006; Koh *et al.*, 2007; Liang *et al.*, 2007; Vandaele and Gemmel, 2007; Braunscheidel and Suresh, 2009), the *predictive* perspective of PLS is not applied on SCM studies. As it is discussed in the previous section, most studies in the SCM field implement surveys for theory building purposes, but none of them analyzes data retrieved from an *Enterprise System*[26] (ES). Tabulated quantitative data may be particularly useful to determine latent constructs in supply chains, since in predictive modeling attempt is given to include *all* the predictor variables that affect the dependent variable. In today's businesses, companies do collect and monitor a great amount of data from numerous sources, but usually they do not know necessary strategies on how to analyze these data effectively.

[26] Enterprise Systems refers to databases such as Enterprise Resource Systems (ERPs) and Customer Resource Management (CRM). ERP integrates internal and external management information across an entire organization by an integrated software application.

Having considered PLS as it is used in the social and applied sciences, the next section will now outline the research model of the study that investigates whether the integration of process measurement and control across a supply chain offers a substantial advantage over the current practice of optimization at the firm level.

3. Research Model

This section presents the research model of the study. Included in this discussion is a comparison between two different supply chain approaches, namely *integrated* and *independent*. The section presents the main hypothesis of the study along with relevant propositions and tactics.

3.1. Research Model

This study examines whether looking at manifest variables across an entire supply chain (*integrated* approach) provides benefit over the *independent* approach (the traditional approach) of considering improvements only within a firm in terms of process control and process equipment settings of the final product output.

The *independent* approach involves considering individual supply chain steps as optimizing their manufacturing process independent from each other. Figure 2 illustrates a typical *independent* supply chain approach, in which the impact of individual process steps on the overall *supply chain performance*[27] is analyzed with respect to the performance of the final end product. Consequently, individual steps are directly linked to the end-product performance as shown Figure 2. This poses a problem, since the *independent* approach overlooks the interactions between individual supply chain steps[28].

[27] In this study, the *supply chain performance* is based on the performance of the end product at the quality test. This performance metric is measured by a manifest variable, *Yield*. The *Yield* variable in the manufacturing data set (§4.2.1 on p. 39) is a binary variable that indicates whether the end product passes (i.e., *Yield* = 1) or fails (i.e., *Yield* = 0) the quality test. The *Yield* variable in the simulated data sets (§4.2.2 on p. 40) of the study is a continuous variable that measures the per cent of functional final product. The reason why the dependent variable *Yield* is chosen as a continuous variable in simulated data sets is provided in §4.2.2.

[28] Interactions between supply chain steps exist since the products flow from the first supply chain step to the final n^{th} step.

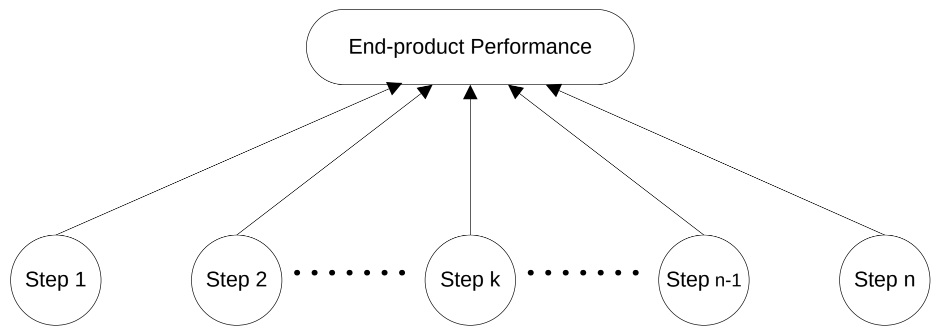

Figure 2 - Independent Supply Chain Approach Model

Alternatively, in the *integrated* approach as illustrated in Figure 3, individual supply chain steps are linked to a group of latent components to provide information about the overall supply chain performance. Depending on the nature of the supply chain, the number of retained latent components differs. Unlike the *independent* approach, the *integrated* approach captures the interactions between multiple process steps by having latent components that are defined by a number of individual process steps[29]. As illustrated in Figure 3, a supply chain step can be linked to one or more latent components depending on the interactions between supply chain steps. Since this approach also captures the interactions between supply chain steps, the *integrated* approach should provide better information about the supply chain performance than the *independent* supply chain perspective.

[29] One can argue that if the model has a single latent variable (i.e., all individual supply chain steps are grouped together by a single latent variable), there is a strong interaction between supply chain steps. The interaction strength is discussed in §4.3.1.2.

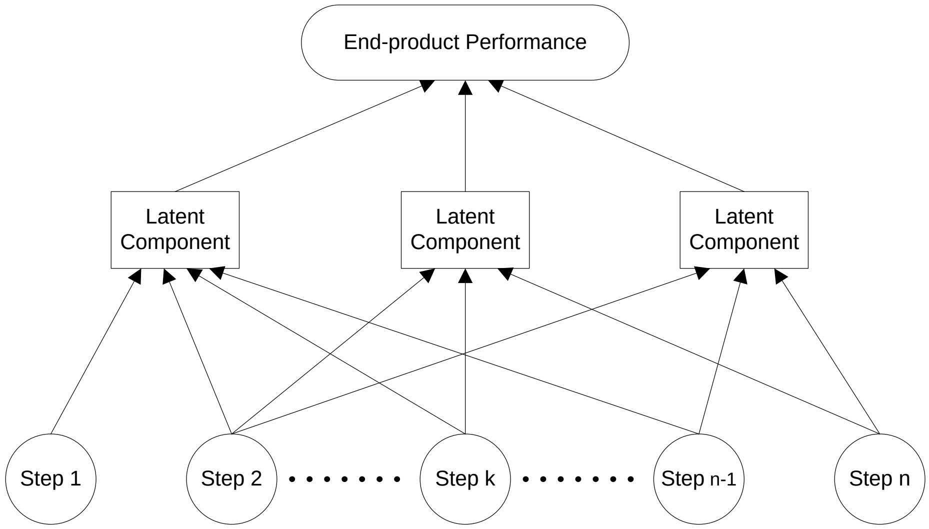

Figure 3 - Integrated Supply Chain Approach Model

This discussion leads to the following argument:

Hypothesis 1:

H_O: There is no difference between the *integrated* and *independent* approaches in explaining overall supply chain performance based on the process settings and measures of the final product output.

H_A: There is a difference between the *integrated* and *independent* approaches in explaining overall supply chain performance based on the process settings and measures of the final product output.

This hypothesis is analogous to the *systems argument* that integrated or whole approach is better than the sum of partial parts (Mantell, 1972). To determine whether the *integrated* approach is indeed different than the *independent* approach, a supply chain will be examined. Figure 4 illustrates the data analysis procedure of this study:

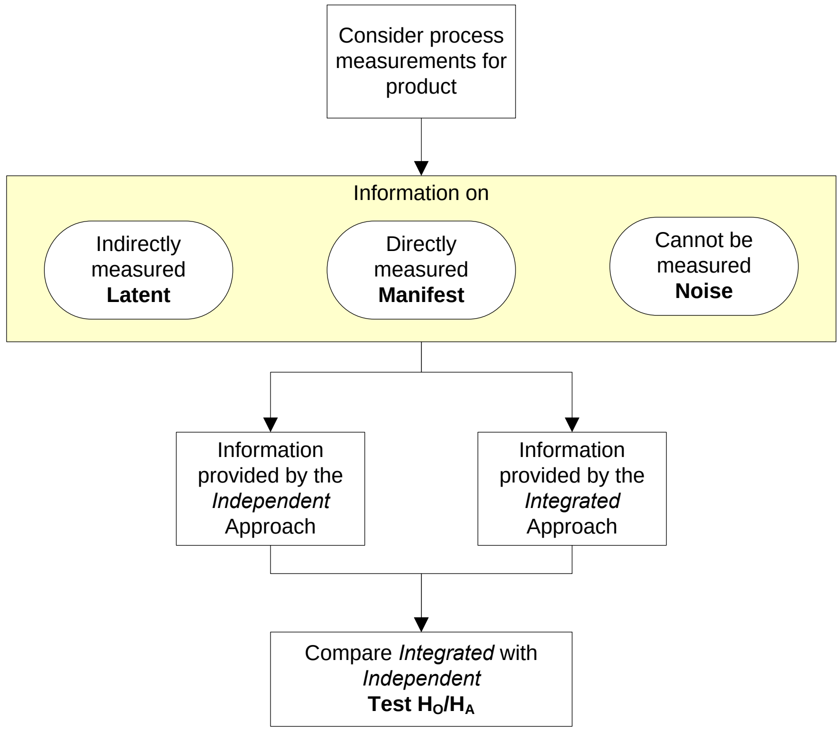

Figure 4 - Data Analysis Procedure

Figure 4 illustrates that this research will choose a product type and look at its process measurements of intermediary test results, excluding control and indirect results along the supply chain. The study will take all pieces of information together and provide insight on the following types of loadings[30]:

- Directly measured (Manifest)
- Indirectly measured (Latent)
- Cannot be measured (Noise)

Consider a single final product involving n process steps in a supply chain. The associated data and control of this process are shown in Figure 5.

[30] A *component loading* refers to the correlation coefficients between the variables and components (factors). Analogous to Pearson's r, the squared component loading corresponds to the percentage of variance in that indicator variable explained by the component. The sum of the squared component loadings for a component is divided by the number of variables to obtain a percentage of variance in all the variables accounted by each component. This approach is analogous to dividing the component's eigenvalue by the number of variables in the model.

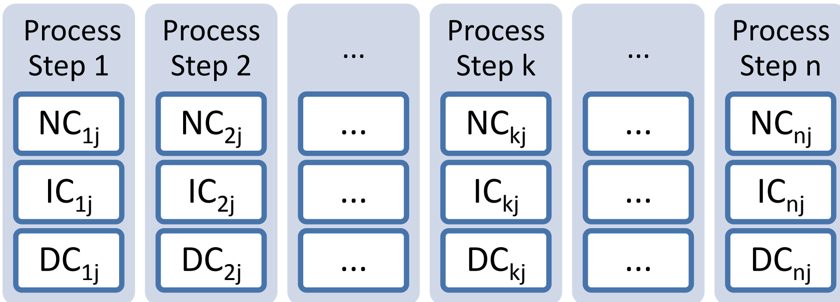

Figure 5 - Process Step Measurements

Consider the following definitions:

> A = process steps i = 1, … , k,…,n
>
> NC_{ij} = process measurable of step i that is not controlled ($i \in$ A)
>
> IC_{ij} = process measurable of step i that is controlled indirectly ($i \in$ A)
>
> DC_{ij} = process measurable of step i that is controlled directly ($i \in$ A)
>
> where;
>
> $j \geq 0$ ($j \in$ A) corresponds to the number of measures for any given process step and measure type

The research will then compare the information provided by the *independent approach*, which is based on local optimization, with the *integrated system* approach. Since each step may have a different number of three aforementioned loadings, understanding the right combination of these loadings that generate the most desired outcome is crucial. Alternatively, these process step measures can be treated as factors affecting the quality of the end product.

The PLS methodology will allow us to determine whether the factors are specific to a single process step (*independent*) or across multiple process steps (*integrated*).

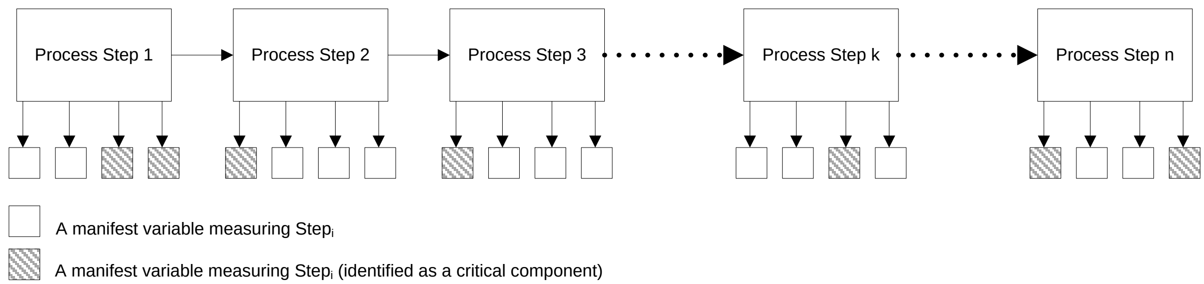

Figure 6 - Factors affecting the quality of a given end-product (an example)

Figure 6 illustrates a typical supply chain that has multiple step process (step 1 to n). Each process step is associated with multiple components (based on the three types of loadings) that affect the quality of its respective product, and ultimately the final end-product. The objective is to identify manifest variables that significantly affect the overall supply chain performance (shaded squares) by investigating the interactions between different process steps.

This research develops a generalizable technique for being able to assess the relationship between seemingly unrelated process steps that positively or negatively affect the quality of the end-product. Depending on the nature of the supply chain (i.e., integrated or segregated), the PLS approach will determine the following;

If the supply chain is:

- Closely integrated and process steps interact with each other extensively: local optimization will result in suboptimal solutions. Alternatively, pursuing global optimization will be an expensive approach due to the complexity of the problem. If this is the case, the proposed PLS can be used to measure the degree at which process steps interact with each other.
- Segregated and process steps have limited or no interaction with each other: local optimization (*independent approach*) is possible to streamline the system. This approach will allow the system integrator to eliminate process steps that have negative effects on the quality of the end-product. However, this is usually not the case in modern practices.

These arguments lead to following tactics:

Tactic A – ***Integrated****:* When process steps interact with each other extensively, the supply chain should be examined in an *integrated* manner to avoid suboptimal solutions.

Tactic B – ***Independent***: When process steps have limited or no interaction with each other, local optimization (*independent* approach) is possible to streamline a given supply chain.

Further explanation is offered to illustrate the distinction between *independent* and *integrated* approaches in supply chains. For example, if the process steps of a given supply chain are closely integrated, pursuing the local optimization approach may provide sub-optimal results as it is illustrated in Figure 7.

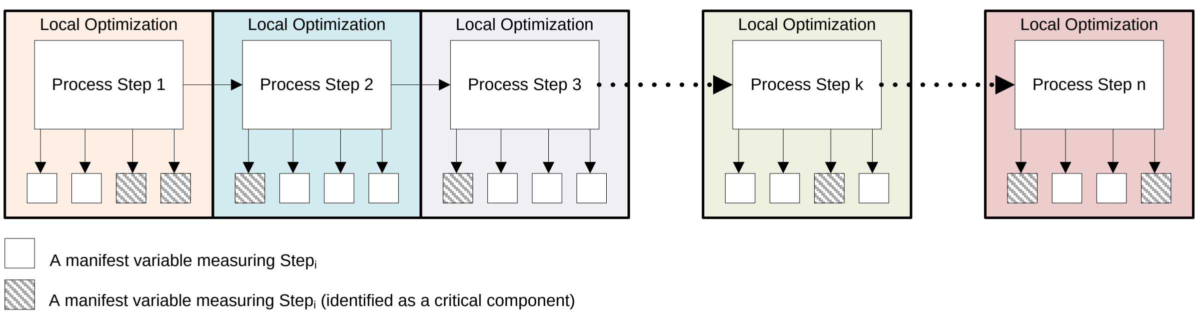

Figure 7 - Local Optimization Approach on an Integrated Supply Chain

If the local optimization approach is pursued at each process step, identified components (shaded square boxes) will be related to the quality of their respective product, but not to the end-product. Focusing on these components may not necessarily improve the overall supply chain performance (given that the supply chain is integrated), since identified component(s) of a given step may not interact with components from other process steps. Thus, pursuing an *integrated approach* is more appropriate for integrated supply chains (Figure 8). This argument leads to the opposition that:

Proposition 1*:* An *integrated* approach will allow supply chain members to have a greater understanding of the critical coordination components and use these insights to improve the overall supply chain performance.

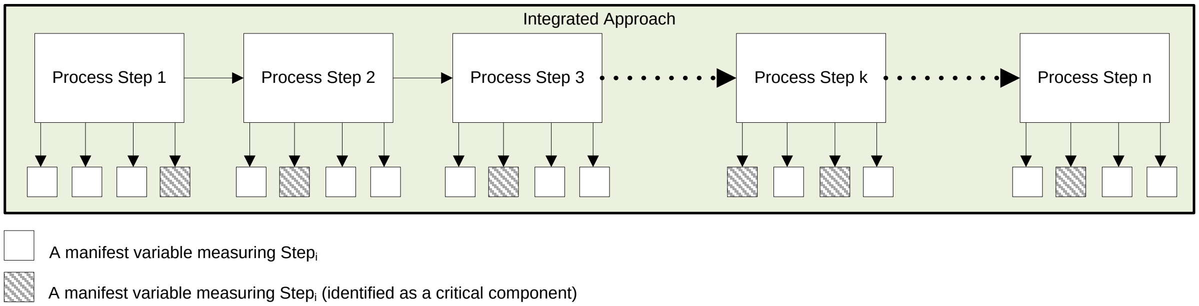

Figure 8 - Integrated Approach on a Typical Supply Chain

The *integrated approach* will not only determine the interaction among components of different process steps more accurately, but also allow streamlining the supply chain globally based on the performance of the end-product. *Integrated approach* does not necessarily mean that the system will be "optimized" globally rather than locally. Global optimization (such as using the Mixed Integer Linear Programming – MILP approach) can be virtually impossible, due to the extensive number of manifest and latent components and constraints. Alternatively, the proposed PLS approach can provide valuable information about process measurables associated with each process step. The degree at which process measurables interact with each other can be determined without relying on complex mathematical models.

This research uses real and simulated manufacturing data to improve processes of a given supply chain. Comparing the worst and the best-case scenario of both highly integrated and segregated supply chains will give an indication of what value is added through corresponding benefits of process control on the supply chain. Having discussed the research model of the study, the next chapter will outline the methodology of the study.

4. Methodology

This section presents the methodology of the study, following the description in the research model in Section 3. Included in this discussion are an overview of the (4.1) underlying mathematical model of PLS, (4.2) data of the study, and two (4.3) PLS software tools to implement necessary analyses.

4.1. Underlying Mathematical Model of PLS

This section summarizes the mathematical model of PLS based on the PLS regression. A mathematical discussion about the Principal Component Analysis (PCA) is also provided to explain the mathematical model of PLS, since PLS shares its roots with PCA. Consequently, before introducing the underlying mathematical model of predictive PLS, *Nonlinear Iterative Partial Least Squares* (NIPALS) method of *Principal Component Analysis* (PCA) will be explained. This section will use the nomenclature used in Wold and Kowalski (1984), and Geladi and Kowalski (1986). Relevant notation is provided in the *list of symbols* (p. viii).

4.1.1. Principal Component Analysis (PCA): NIPALS Method

Principal Component Analysis (PCA) can be regarded as a method to provide a matrix **X** of rank *r* as a sum of r matrices (i.e., M_h each having a rank of 1 (Geladi and Kowalski, 1986).

$$\boldsymbol{X} = M_1 + M_2 + M_3 + \cdots + M_r \quad (1)$$

M_h matrices can also be denoted by outer products of two vectors, a *score vector* t_h and a *loading vector* p_h':

$$\boldsymbol{X} = t_1 p_1' + t_2 p_2' + \cdots + t_a p_a' \quad (2)$$

This notation can also be represented as **X** = **TP′** (**T** has t *columns* and **P′** has p′ *rows*). The objective is to project columns and rows of **X** onto two separate single dimensions. *Nonlinear Iterative Partial Least Squares* (NIPALS) calculates each principal component in steps, rather than calculating all the principal components at once (Geladi and Kowalski, 1986). First, NIPALS calculates t_1 and p_1' from matrix **X**, then the outer product of $t_1 p_1'$ is subtracted from **X**. This provides the residual $\boldsymbol{E_1}$. After obtaining the residual, t_2 and p_2' can also be calculated by this iterative process.

$$\boldsymbol{E_1} = \boldsymbol{X} - \boldsymbol{t_1 p_1'}$$

$$\boldsymbol{E_2} = \boldsymbol{E_1} - \boldsymbol{t_2 p_2'} \tag{3}$$

$$\boldsymbol{E_h} = \boldsymbol{E_{h-1}} - \boldsymbol{t_h p_h'}$$

The recursive NIPALS algorithm works as follows (Geladi and Kowalski, 1986: 7):

1. Take a vector $\boldsymbol{x_j}$ from **X** and call it $\boldsymbol{t_h}$: $\boldsymbol{t_h} = \boldsymbol{x_j}$ (4)
2. Calculate $\boldsymbol{p_h'}$: $\boldsymbol{p_h'} = \boldsymbol{t_h' X / t_h' t_h}$ (5)
3. Normalize $\boldsymbol{p_h'}$ to length 1: $\boldsymbol{p'_{h\,new}} = \boldsymbol{p'_{h\,old}} / \|\boldsymbol{p'_{h\,old}}\|$ (6)
4. Calculate $\boldsymbol{t_h}$: $\boldsymbol{t_h} = \boldsymbol{X p_h / p_h' p_h}$ (7)
5. Compare $\boldsymbol{t_h}$ in step 2 with the one obtained in step 4. If they are the same, stop the iteration (i.e., iteration is converged). If they are different, return to step 2.

As shown in equation (3), after the first iteration (when the first component is calculated), matrix **X** in steps 2 and 4 should be replaced by $\boldsymbol{E_{h-1}}$ to calculate the h^{th} component.

Since, $\boldsymbol{t_h' t_h}$ in equation (5), $\|\boldsymbol{p_h'}\|$ in equation (6), and $\boldsymbol{p_h' p_h}$ in equation (7) are all scalar, they are usually denoted by a general constant **C**. Consequently, one can substitute equation (5) into equation (7) and obtain the following:

$$\boldsymbol{p_h'} = \boldsymbol{t_h' X}$$

$$\boldsymbol{t_h} = \boldsymbol{X p_h}$$

giving:

$$\boldsymbol{C p_h'} = (\boldsymbol{X p_h})' \boldsymbol{X}$$

$$\boldsymbol{C p_h'} = \boldsymbol{p_h' X' X}$$

$$(\boldsymbol{C I_m} - \boldsymbol{X' X}) \boldsymbol{p_h} = 0 \tag{8}$$

Geladi and Kowalski (1986) show that one can also substitute equation (7) into equation (5) to obtain:

$$(\boldsymbol{C}'\boldsymbol{I_n} - \boldsymbol{X}\boldsymbol{X}')\boldsymbol{t_h} = 0 \qquad (9)$$

Where; $\boldsymbol{I_n}$ and $\boldsymbol{I_m}$ are identity matrices of size $n \times n$ and $m \times m$, respectively. Geladi and Kowalski (1986: 8) note that equations (8) and (9) are actually eigenvalue equations for $\boldsymbol{X}'\boldsymbol{X}$ and $\boldsymbol{X}\boldsymbol{X}'$ as used in the classical calculation.

Studies show that a converged NIPALS algorithm gives the same solution as the eigenvalue equations (8) and (9) (Geladi and Kowalski, 1986; Rosipal, 2001). The outlined NIPALS algorithm is important to understand the underlying model of the predictive PLS approach. The next section will briefly explain the *Principal Component Regression* (PCR) before introducing the PLS regression.

4.1.2. Principal Component Regression (PCR)

The *principal component transformation* of the data matrix **X** that was introduced in the previous section can be explained by PCA (Geladi and Kowalski, 1986; Rosipal, 2001; Embrechts *et al.*, 2006):

$$\boldsymbol{T} = \boldsymbol{X}\boldsymbol{P} \qquad (10)$$

Equation (10) represents **X** as its score matrix **T**. By using this transformation, the multiple linear regression formula can be written as follows:

$$\boldsymbol{Y} = \boldsymbol{T}\boldsymbol{B} + \boldsymbol{E} \qquad (11)$$

$$\widehat{\boldsymbol{B}} = (\boldsymbol{T}'\boldsymbol{T})^{-1}\boldsymbol{T}'\boldsymbol{Y} \qquad (12)$$

One should note that the inverse of $\boldsymbol{T}'\boldsymbol{T}$ is not a problem, since scores have mutual orthogonality (Geladi and Kowalski, 1986: 9). Thus, the regression is well conditioned and can be used to overcome problems arising from exploratory variables that are close to being collinear. Also, the invertible matrix in the calculation of $\widehat{\boldsymbol{B}}$ eliminates the problem of multicollinearity. However, Geladi and Kowalski (1986) note that useful predictive information may result in discarded principal components, because of the two step method of PCR. A regression of the score matrix against one or more dependent variables is also possible. The ability to regress on multiple dependent variables is useful to assess complex systems such as supply chains, which may require assessing multiple performance metrics. However, this study considers one dependent variable (i.e., *Yield*) for simplicity.

This matrix notation (i.e., a data matrix being represented by a score matrix) can be used to describe partial least squares regression. The next section will describe the underlying model of PLS based on this matrix notation.

4.1.3. Partial Least Squares (PLS) Regression

As mentioned previously, the PLS approach is based on the NIPALS algorithm. A simple PLS model includes a regression between the scores of *independent* variables and *dependent* variable(s), denoted by **X** and **Y** matrices, respectively. Similar to PCR (§4.1.2), these score matrices represent data matrices.

The outer relation for the **X** block is (Geladi and Kowalski, 1986; Embrechts *et al.*, 2006):

$$\boldsymbol{X} = \boldsymbol{TP'} + \boldsymbol{E} = \sum \boldsymbol{t_h p'_h} + \boldsymbol{E} \qquad (13)$$

Similarly, the outer relation for the **Y** block is:

$$\boldsymbol{Y} = \boldsymbol{UQ'} + \boldsymbol{F^*} = \sum \boldsymbol{u_h q'_h} + \boldsymbol{F^*} \qquad (14)$$

The main objective is to describe **Y** by minimizing $\|\boldsymbol{F^*}\|$ and to provide a relation between **X** and **Y**. The inner relation (linking both **X** and **Y** blocks) can be achieved by **X** block score, **t**, against the **Y** block score **u**, for each component (Geladi and Kowalski, 1986).

$$\boldsymbol{\hat{u}_h} = \boldsymbol{b_h t_h} \qquad (15)$$

where,

$$\boldsymbol{b_h} = \boldsymbol{u'_h t_h / t'_h t_h}$$

The $\boldsymbol{b_h}$ can be considered as a regression coefficient, **b**, in the PCR model (Rosipal, 2001). However, the unrotated components does not provide the best model, since the relation between both blocks is weak as a result of calculating the principal components of both blocks separately (Geladi and Kowalski, 1986). Thus, the components are rotated to make them closer to the regression line and provide more information about each other.

4.1.3.1. Simplified PLS Model

Similar to the NIPALS algorithm, the PLS model can be written in an algorithmic form as follows (Geladi and Kowalski, 1986: 16):

<u>For each component</u>:

1. Take $\boldsymbol{u_{start}} = some\ \boldsymbol{y_j}$ (16)

<u>In the **X** block</u>:

2. $\boldsymbol{w'} = \boldsymbol{u'X}/\boldsymbol{u'u}$ (17)
3. $\boldsymbol{w'_{new}} = \boldsymbol{w'_{old}}/\|\boldsymbol{w'_{old}}\|$ (normalization) (18)
4. $\boldsymbol{t} = \boldsymbol{Xw}/\boldsymbol{w'w}$ (19)

<u>In the **Y** block</u>:

5. $\boldsymbol{q'} = \boldsymbol{t'Y}/\boldsymbol{t't}$ (20)
6. $\boldsymbol{q'_{new}} = \boldsymbol{q'_{old}}/\|\boldsymbol{q'_{old}}\|$ (normalization) (21)
7. $\boldsymbol{u} = \boldsymbol{Yq}/\boldsymbol{q'q}$ (22)

<u>Convergence check</u>:

8. Compare the **t** in step 4 with the one from the previous iteration. If they are equal, proceed to step 9, otherwise return to step 2

<u>Calculating the **X** loadings and rescaling the scores</u>:

9. $\boldsymbol{p'} = \boldsymbol{t'X}/\boldsymbol{t't}$ (23)
10. $\boldsymbol{p'_{new}} = \boldsymbol{p'_{old}}/\|\boldsymbol{p'_{old}}\|$ (normalization) (24)
11. $\boldsymbol{t_{new}} = \boldsymbol{t_{old}}/\|\boldsymbol{p'_{old}}\|$ (25)
12. $\boldsymbol{w'_{new}} = \boldsymbol{w'_{old}}/\|\boldsymbol{p'_{old}}\|$ (26)

p′, **q′**, and **w′** are saved for prediction, whereas **t** and **u** can be saved for classification and/or diagnostic purposes.

Finding the regression coefficient **b** for the inner relation:

13. $\boldsymbol{b} = \boldsymbol{u}'\boldsymbol{t}/\boldsymbol{t}'\boldsymbol{t}$ (27)

Calculating the residuals

Outer relation for the **X** block:

$$\boldsymbol{E_h} = \boldsymbol{E_{h-1}} - \boldsymbol{t_h}\boldsymbol{p}'_{\boldsymbol{h}};\ \boldsymbol{X} = \boldsymbol{E_0} \quad (28)$$

Mixed relation for the **Y** block:

$$\boldsymbol{F_h} = \boldsymbol{F_{h-1}} - \boldsymbol{b_h}\boldsymbol{t_h}\boldsymbol{q}'_{\boldsymbol{h}} \quad (29)$$

14. Return to Step 1 to implement the algorithm for the next component. But, after the first component, **X** in steps 2, 4 and 9; and **Y** in steps 5 and 7 are replaced by their corresponding residual matrices $\boldsymbol{E_h}$ and $\boldsymbol{F_h}$, respectively.

One should notice that instead of using $\boldsymbol{p'}$ in steps 2, 3, and 4, $\boldsymbol{w'}$ (i.e., weight) is used to have orthogonal $\boldsymbol{t}$ values. Similarly, $\boldsymbol{q'}$ denotes weight for block **Y**, to obtain orthogonal $\boldsymbol{u}$ values. Geladi and Kowalski (1986) note that equation (24) in step 10 allows us to calculate the new $\boldsymbol{t}$: $\boldsymbol{t} = \boldsymbol{XP}/\boldsymbol{p}'\boldsymbol{p}$, by the scalar multiplication with the norm of $\boldsymbol{p}'$ in equation (23), which ultimately gives equation (25). In order to eliminate error in the prediction, same rescaling is made to the weights to obtain equation (26). After this step, $\boldsymbol{t}$ is used for the inner relation like the case in equation (15) and residuals are calculated from equations (28) and (29). One should note that in the outer relation for the **Y** block (i.e., equation (29)), instead of using the column vector scores for factor **h** of the **Y** block (i.e., $\boldsymbol{u_h}$), we use an estimator (i.e., $\widehat{\boldsymbol{u}}_{\boldsymbol{h}} = \boldsymbol{b_h}\boldsymbol{t_h}$).

In short, there is an inner relation $\widehat{\boldsymbol{u}}_{\boldsymbol{h}} = \boldsymbol{b_h}\boldsymbol{t_h}$ (i.e., equation (15)) and there are outer relations $\boldsymbol{X} = \boldsymbol{TP}' + \boldsymbol{E}$ and $\boldsymbol{Y} = \boldsymbol{UQ}' + \boldsymbol{F}^*$ (i.e., equations 13 and 14, respectively). The outlined iterative PLS algorithm allows blocks **X** and **Y** to get each other's scores. This provides a better inner relation. However, to get orthogonal **X** scores like in the case of PCA, it is necessary to have weights. Having reviewed a simplified PLS model, the next section will briefly discuss the underlying mathematical model for prediction.

4.1.3.2. Prediction in PLS

Since predictive PLS is based on regression, the dependent block is *predicted* from the independent block. To build up the dependent block (i.e., **Y)**, the independent block (i.e., **X**) is decomposed (Geladi and Kowalski, 1986: 12). As mentioned in the simplified PLS algorithm in the previous section, $\mathbf{p'}$, $\mathbf{q'}$, and $\mathbf{w'}$ from the rescaling the scores part (i.e., equations (21), (24), and (26)) are saved for predicting every PLS factor. For the independent **X** block, **t** is estimated by multiplying **w** and **X** together:

$$\hat{\boldsymbol{t}}_{\boldsymbol{h}} = \boldsymbol{E}_{\boldsymbol{h-1}}\boldsymbol{w}_{\boldsymbol{h}} \tag{30}$$

$$\boldsymbol{E}_{\boldsymbol{h}} = \boldsymbol{E}_{\boldsymbol{h-1}} - \hat{\boldsymbol{t}}_{\boldsymbol{h}}\boldsymbol{p}'_{\boldsymbol{h}} \tag{31}$$

For the **Y** block:

$$\boldsymbol{Y} = \boldsymbol{F}_{\boldsymbol{h}} = \sum_{h=1} \boldsymbol{b}_{\boldsymbol{h}}\hat{\boldsymbol{t}}_{\boldsymbol{h}}\boldsymbol{q}'_{\boldsymbol{h}} \tag{32}$$

From the matrices of residuals $\boldsymbol{E}_{\boldsymbol{h}}$ and $\boldsymbol{F}_{\boldsymbol{h}}$ (i.e., equations (31) and (32), respectively) sum of squares can be calculated to find the regression. The next section will briefly explain how statistics can be obtained from these predictive PLS models.

4.1.3.3. Obtaining statistics from PLS

The sum of squares is calculated by the total sum of squares over a matrix, the sum of squares over columns, and the sum of squares over rows to construct variance-like estimators (Wold and Kowalski, 1984; Geladi and Kowalski, 1986). In order to assess how good a PLS model is, one can take the sum of squares of $\boldsymbol{F}_{\boldsymbol{h}}$ in equation (29). In contrast, the sum of squares of $\boldsymbol{E}_{\boldsymbol{h}}$ (i.e., equation (28)) indicates how much of the **X** block is not used in the model. Although we are more interested in the sum of squares of $\boldsymbol{F}_{\boldsymbol{h}}$, Geladi and Kowalski (1986) note that in some cases independent variables have large errors when a substantial part of the **X** block does not participate in the model. Thus, the sum of squares of $\boldsymbol{E}_{\boldsymbol{h}}$ may give valuable information about the cause of obtaining unexpected large errors.

The sum of squares over the rows indicates the fit of the model, whereas the sum of squares over the columns indicates the importance of a variable for a certain component (Wold and Kowalski, 1984; Geladi and Kowalski, 1986). Like in regression modeling, the fit of the model can be used to detect outliers. Geladi and Kowalski (1986: 15) note that these statistics can be calculated for every latent component in PLS. These statistics can be used to estimate which variables contribute mainly to the model. In this thesis, this means that these statistics can be used to understand which supply chain measurements (of their respective supply chain steps) contribute mainly to the performance of the final product (i.e., *Yield*). Having reviewed the underlying mathematical model of the PLS algorithm, the next section will introduce the data of the study.

4.2. Data of the Study

Initially, the aim of this research was to find a publicly available data set for a typical multiple process step supply chain. However, no studies had offered a complete data set to implement and test the sensitivity of the PLS approach. Thus, a manufacturing data set was obtained from an industrial resource. This study examines a single multiple-step assembly product of a silicon chip manufacturer. The product under consideration is an integrated silicon wafer chip – a complex electronics assembly product.

The contact company provided one manufacturing data set for eight major process steps in its supply chain. However, in order to test the sensitivity of the approach to differentiate types of underlying relationships, twenty two additional data sets were simulated. These twenty two simulated data sets are grouped in two clusters[31]. All data sets (i.e. the single manufacturing and twenty two simulated data sets) are analyzed to understand the nature of a typical supply chain system from the perspective of integration between process steps and completely independent process steps. Both simulated data clusters consist of eleven data sets, each including information about the same supply chain with varying relational strengths between input and output variables. Each simulated data set (i.e., Data 0 to 10 for both clusters) are essentially comprised of measurements associated with the process parameters for each process step, more specifically 51 process steps each with five process measures. Unlike the eight-process step supply chain in the manufacturing data set, a 51-process step supply chain is chosen for each simulated data set. Analyzing a more complex supply chain – a one having more process steps – will give a better indication about the

[31] Both data clusters are essentially the same in terms of supply chain structure. Since the study initially had eleven simulated data sets and a second group of eleven data sets were added later on to better test the sensitivity of PLS, a distinction has been made between data cluster 1 (the original eleven simulated data sets) and data cluster 2 (the additional eleven simulated data sets).

distinction between pursuing the *integrated* approach over the traditional *independent* approach.

Both manufacturing and simulated data sets are analyzed using the *predictive* and *causal* PLS approaches[32] to consider the extent to which process steps are dependent on each other. Although, the details of the manufacturing environment is withheld due to confidentiality reasons about the process management of the company, the following section discusses the characteristics of both manufacturing and simulated data sets in greater detail.

4.2.1. Manufacturing Facility Data

The manufacturing supply datum is made up of eight predictor variables each representing a different supply chain step and one dependent variable. The dependent variable, *Yield*, is a binary variable that keeps track of pass or fail of the product at the final quality test. The number of observations provided by the company was originally 2046, however a number of observations were missing relevant data. These observations were removed from the manufacturing data set. Consequently, the remaining number of observations is 2009 (i.e., sample size).

$\text{Data}_{\text{Manuf}}$

- Eight supply chain steps
- One metric per supply chain step
- Eight manifest variables (one metric for each supply chain step: 8 x 1 = 8)
- One binary dependent variable (i.e., *Yield*)
- 2009 observations (i.e., n = 2009)

Appendix A1/A (p. 86) illustrates a portion of the manufacturing data set[33]. The first column indicates the index number to track individual observations. Each individual observation corresponds to the process readings of a single product. Thus, this manufacturing data set records process readings of 2009 products in total. Each process step (i.e., Steps one to eight)

[32] Predictive PLS approach is pursued to test the *integrated* supply chain approach (refer to the *research model* in Section 3). Causal PLS approach is used to analyze the *independent* supply chain approach.
[33] Only the first thirty (out of 2009) observations are provided instead of the full data set due to space limitations.

has one metric, thus each column (denoted by steps 1 to 8) shows the process metric of its respective process step. The details about the units of these measurements are not provided by the manufacturer due to confidentiality of the data. However, this does not pose a problem, since we are only interested in understanding the numerical relationship between the dependent and manifest variables. Each metric is treated as a manifest variable, since we *observe* their values directly. The dependent variable, *Yield*, is a binary variable, in which "0" denotes failure and "1" denotes success of the end product at the quality test. Out of 2009 products, 1330 of them passed the quality test (representing a success rate of approximately 66.20%. Although this value seems a very low value for a technology product, this study is not interested in this ratio.

Appendix A1/C1 (p. 108) illustrates the range of values for each supply chain step of the manufacturing data set. This range is based on all 2009 observations of the manufacturing data set. Since the dependent variable of the manufacturing data is a binary variable, the minimum value is zero and the maximum value is one for the *Yield*. Table 10 on p. 109 reveals that the range of values for the first, fourth, and fifth supply chain steps are relatively narrow. However, the range of values for the second, third, sixth, seventh, and eight steps are wider. One should also note that the measurement values of the manufacturing data are integer numbers. Although, a number of values are negative, most of the measurements are positive integers. Having shown a portion of the manufacturing data, the next section will discuss the characteristics of the simulated data sets.

4.2.2. Simulated Data

The supply chain system under consideration has 51 supply chain steps and each step has five different metrics. This means that every data set in both simulated data clusters contains 255 (i.e., 51 x 5) measurements. Unlike the binary dependent variable in the manufacturing data set that indicates whether a product fails or passes a quality test, the dependent variable (again denoted by *Yield*) of every simulated data set is a continuous variable that measures the per cent of functional final product. A continuous dependent variable is chosen in simulated data sets, since a continuous variable provides more information than a binary variable that simply indicates a pass or fail. By obtaining more information from the dependent variable and using more process steps and measurements, simulated data sets of this study represent a typical supply chain better than the data set provided by the manufacturer.

$Data_{i,j}$

- 51 supply chain steps (i.e., $k = 1 \dots 51$)
- Five metrics per supply chain step (i.e., m = 5)
- 255 manifest variables (five metrics for each supply chain step: 51 x 5 = 255)
- One continuous dependent variable (i.e., *Yield*)
- 1000 observations (i.e., n = 1000)

where

$i = 1, 2$ (Simulated data cluster i)

$j = 0, \dots, 10$ (Simulated data set j)

$k = 1, \dots, 51$ (Supply chain step)

$m = 1, \dots, 5$ (Metric for a given supply chain step)

Tables 8 and 9 in Appendix A1/B illustrate a single observation from each simulated data set in the first and second data cluster, respectively. Thus, twenty two observations are presented in total. These tables reveal that each simulated data set has the same structure. The first column in Tables 8 and 9 indicates process metric of each supply chain step. Recall that each process step in a simulated data set has 5 metrics. The **S***k***P***m* notation refers process metric *m* (i.e., m = 1, …, 5) of supply chain step *k* (i.e., k = 1, …, 51). Consequently, Tables 8 and 9 have 255 rows corresponding to these measurements. The bottom line of both tables presents the value of the dependent variable, *Yield*. Thus, there are 256 values for each data set in these tables.

Tables 8 and 9 also reveal that the dependent variable of each simulated data set varies between 60 and 90. Unlike the manufacturing data set, simulated data sets include both integer and decimal numbers for measurements. However, most of the supply chain step measurements have a similar structure. Appendix A1/C2A – A1/C2B (p. 110 and p. 122) and Appendix A1/C3A – A1/C3B (p. 132 and p. 142) reveal the range of values for the simulated data clusters one and two, respectively. Accompanying tables in these appendices (Tables 12, 13, 15, and 16) reveal that apart from supply chain steps thirteen and fifty one, all supply chain steps have a similar approximate range of values. All supply chain steps (excluding steps #13 and #51) have integer values for process metrics one, two, and five between values of zero and two thousand. The process metrics three and four of these supply chain steps are decimal numbers between -4.25 and +4.25 approximately. Step #13 has similar range of values, but its process metrics one, two, three are decimals numbers within -4.00 and +4.25 range, and process metrics four and five are integers between zero and two thousand approximately. Only the process metric one of Step #51 is a decimal number between a range of -4.00 and +3.75. The remaining metrics are integers approximately between zero and two thousand. The details are provided in appendices A1/C2A, A1/C2B, A1/C3A, and A1/C3B.

Having considered the manufacturing and simulated data characteristics of the study, the next section will outline the procedure about how these data sets are examined.

4.2.3. Procedure

Each data set (both manufacturing and simulated data sets) is analyzed with respect to the *integrated* and *independent* approaches to test the hypothesis of the study. As mentioned earlier, two different software programs are used for *integrated* and *independent* supply chain approaches. *Predictive* PLS modeling perspective is pursued for the *integrated* approach by the use of Analyze/StripMiner software package. For the *independent* approach, *causal* PLS modeling is implemented by using PLS *GRAPH* 3.0. See Figure 9 for a depiction of the major steps in this study:

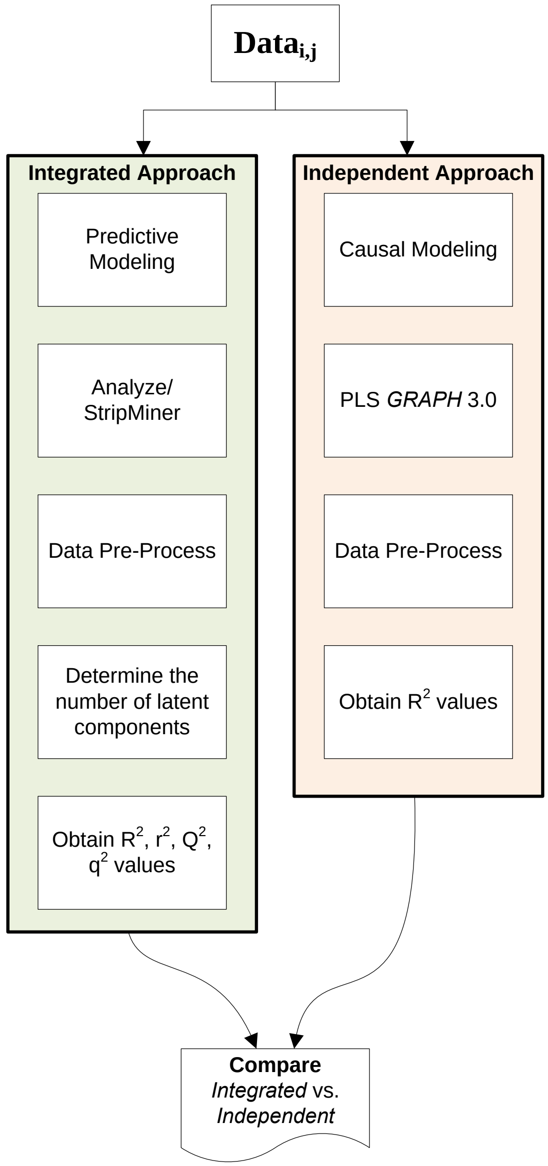

Figure 9 - Steps for Analyzing Individual Data Sets

For the *integrated* and *independent* approaches, each data set needs to be pre-processed to make the data usable for the Analyze/StripMiner and PLS *GRAPH* 3.0, respectively. The details about data preparation for Analyze/StripMiner and PLS *GRAPH* 3.0 are provided in §4.3.1.1 and §4.3.2.1, respectively.

For the *integrated* approach, the number of latent components is determined by observing the impact of individual latent components on the explanatory power of the model. The number of latent components is determined by assessing the behavior of the model based on retaining one, two, or more retained latent components. Studies show that a maximum of five retained latent components is enough for models (Geladi and Kowalski, 1986; Linton, 2004). Understanding the impact of latent components on the model is crucial to assess component loadings of manifest variables (i.e., process step measurements: 255 for simulated data sets and eight for the manufacturing data set). Further discussion about the number of latent components and component loadings are provided in §4.3.1.2.

To test the hypothesis that whether there is a difference between the *independent* and *integrated* approaches in explaining the overall supply chain performance, R^2 values from both approaches need to be compared. Both software programs provide the R^2 value for each data set. Analyze/StripMiner also provides values for r^2, Q^2, and q^2. The details about the definition and importance of these values are provided in §4.3.1.2.

Having reviewed the characteristics of both manufacturing and simulated data sets, the next section will introduce the two software tools used in this study to analyze the data sets in terms of *integrated* and *independent* approaches.

4.3. PLS Software Tools

4.3.1. Predictive PLS Modeling Software: Analyze/StripMiner™

Analyze/StripMiner[34] software is used for *predictive* data analysis in PLS (Embrechts and Bennett, 2002). It is a general purpose academic data preprocessing and modeling program for the scientific data mining of large databases[35]. The program is also capable to analyze large data sets by *predictive* PLS modeling. The *Analyze* software will be used to determine R^2 values of each data set from the perspective of the *integrated* supply chain approach. The following sections discuss data preparation, data analysis, and interpretation of results using this software.

4.3.1.1. Data Preparation

As mentioned previously, each data set needs to be converted to the appropriate format for the *Analyze* software. Each data set is first placed into a spreadsheet format to preprocess the

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[34] From now on *Analyze/StripMiner* will be simply referred as *Analyze.*
[35] An academic version of the program is available for download from the following URL link: http://www.drugmining.com/files/html_files/software.htm

data for the software. However, it is crucial to design the format of the data set according to the following rules:

- Rows: correspond to *observations*[36]
- Columns: correspond to *predictor variables*[37]
- Last Column: corresponds to the *dependent variable* (i.e., *Yield*)

The *Analyze* software only accepts numerical data, so the descriptions (i.e. the first row of each data set – "Observation", step name, and "Yield" as shown in Appendix A1/A (p. 86) were removed before feeding the data into the software. The next step is to remove all observations that are missing data[38]. After this, the file can be saved as a text file (i.e., *.txt). At this stage, the data set is ready for preprocessing. Although there are numerous options in the *Analyze* software to preprocess the data set, this study implements the steps provided in Appendix A2 (p.152).

For each analysis: 80% of the data (i.e., 800 observations for the full-set simulated data, 1637 for manufacturing data) are used for *training* data set and the remaining 20% (i.e., 200 observations for the full-set simulated data, 409 for manufacturing data) is used for testing the data[39]. After splitting the data into training and test sets, one can proceed to data analysis.

4.3.1.2. Data Analysis

The major objective in applied sciences is to generate *predictive* models rather than assessing the statistical significance in an attempt to assess causality. Linton (2004) summarizes two criteria when evaluating a model:

a) *Predictive power of the model on training data*: The main objective of the predictive PLS modeling is to offer a model that can predict the behavior of dependent variable(s) from manifest variables. The predictive power of the *training* model is measured by $\mathbf{r^2}$ and $\mathbf{R^2}$, where values range between zero and one. The value of one represents complete

[36] Observations refer to individual products. Thus, for each simulated data we have 1000 observations, meaning that we observe process measurements of 1000 individual products. For the manufacturing data set, we have 2009 observations.
[37] As explained previously, predictor variables refer to measurements for the supply chain. We have 8 predictor variables for the manufacturing data set (See Appendix A1/A) and 255 predictor variables for each simulated data set (See Appendix A1/B).
[38] It is not advised to put the mean value for the missing values (Linton, 2004).
[39] Refer to §2.2.2.3 (p. 19) and §4.3.1.2 for the discussion about *training* and *test* data.

explanatory power and zero denotes no explanatory power. Thus, good models have higher $\mathbf{r^2}$ and $\mathbf{R^2}$ values.

- $\mathbf{r^2}$ is the square of the correlation coefficient between predicted and actual values, and mathematically it is defined as follows:

$$\boldsymbol{r^2} = \frac{\sum_{i=1}^{n_{train}} (\hat{y}_i - \bar{y})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n_{train}} (\hat{y}_i - \bar{y})^2} \sqrt{\sum_{i=1}^{n_{train}} (y_i - \bar{y})^2}} \tag{33}$$

  One should note that $\mathbf{r^2}$ expresses a linear correlation.

- $\mathbf{R^2}$ is also defined as the square of the correlation coefficient between predicted and actual values, but it also considers the residual error. Thus, $\mathbf{R^2}$ is considered as a better measure than $\mathbf{r^2}$ (Golbraikh and Tropsha, 2002). Consequently, this study will primarily focus on $\mathbf{R^2}$ values. $\mathbf{R^2}$ is mathematically defined as follows:

$$\boldsymbol{R^2} = 1 - \frac{\sum_{i=1}^{n_{train}} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n_{train}} (y_i - \bar{y})^2} \tag{34}$$

  Typically, an $\mathbf{R^2}$ value is smaller than an $\mathbf{r^2}$ value, but $\mathbf{R^2}$ tends to converge to $\mathbf{r^2}$ for large data sets.

b) *Predictive power of the model on the test data*: When the model does not explain a substantial part of the dependent variable, it may be the case that the model that has been generated is very specific to the training data, which impedes its generalizability to other observations (Linton, 2004). This situation is commonly referred to as *overtraining* or *overfitting*[40]. In general, as the fit of the model improves, it becomes more difficult to fit observations outside the sample space, since patterns captured in the sample may not be generalized for the whole population. The predictive power of the testing model is represented by $\mathbf{Q^2}$ and $\mathbf{q^2}$ with values ranging from zero to one. A value of zero means

[40] In regression modeling overfitting means choosing values of model parameters that explain not only the variation the user would observe, but also the variation as a result of the noise idiosyncratic to the sample (Lattin *et al.*, 2003).

that the model perfectly predicts the test data and a value of one means no predictive power. Thus, better models have low $\mathbf{Q^2}$ and $\mathbf{q^2}$ values.

- $\mathbf{q^2}$ is defined as the square of correlation coefficient to assess the quality of the *test* set, and mathematically it is defined as follows:

$$q^2 = 1 - r_{test}^2$$

$$q^2 = 1 - \frac{\sum_{i=1}^{n_{test}} (\hat{y}_i - \bar{y})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n_{test}} (\hat{y}_i - \bar{y})^2} \sqrt{\sum_{i=1}^{n_{test}} (y_i - \bar{y})^2}} \qquad (35)$$

- $\mathbf{Q^2}$ is also defined as the square of the correlation coefficient to assess the quality of the *test* set, but it also considers the residual error. $\mathbf{Q^2}$ is mathematically defined as follows:

$$Q^2 = 1 - R_{test}^2$$

$$Q^2 = \frac{\sum_{i=1}^{n_{test}} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n_{test}} (y_i - \bar{y})^2} \qquad (36)$$

Based on these measures, one can differentiate a strong model from a weak model. For example, if the predictive power of the model is low (i.e., low R^2 and high Q^2), the relationship between dependent and manifest variables is not defined properly. Besides, there might be a problem with measurement error that may obscure important relationships. This may be due to poor measurement of manifest variables (Linton, 2004). Alternatively, when the predictive power of the model is high, the impact of measurement error on the relation between the dependent and manifest variables may not be significant. The commands for *training data set* and *testing the model* are provided in Appendix A2 (P. 152).

Each data set is analyzed with respect to the dependent variable (i.e., *Yield*). For the *integrated* approach, we analyze all predictor variables (i.e., eight for the manufacturing data and 255 for the simulated data sets) with respect to the dependent variable. In addition to retaining five latent components[41] as in the case of other analyses, the explanatory power

[41] As discussed previously, studies show that a maximum of five retained components is enough for predictive PLS models (Geladi and Kowalski, 1986; Linton, 2004). Thus, we will retain at most five latent components in

(i.e., R^2) of the model based on one, two, three and four retained components is also considered. This is a crucial step to understand the explanatory power of individual components (i.e., components one to five). By definition, the first component has the highest R^2 with each additional component having less explanatory power.

To obtain the R^2 value of components, one first analyzes using a single component – giving the explanatory power (i.e., R^2) of the first component. Next, the same steps for that full data set are performed, but two components are retained. Unsurprisingly, a greater R^2 value results as this is the sum attributed to the sum of the first and second components. This approach is repeated to obtain R^2 values of the third, fourth, and fifth components.

After calculating the R^2 values of each component, components are compared with each other based on their R^2 values. Component loadings provide valuable information about the importance of process steps, because they essentially highlight the weight of their respective process step on the dependent variable. Having reviewed the data analysis step of the Analyze software, the next section will discuss the interpretation of results to test the hypothesis of the study.

4.3.1.3. Interpretation of Results

In order to determine which manifest variables are associated to which latent variables, aforementioned steps need to be repeated for different numbers of latent variables. The number of manifest variables dictates the number of latent variables in a given model. For example, if the number of manifest variables is three in a given model, we need to check the explanatory power of the model[42] by obtaining three R^2 values for each latent component[43].

Furthermore, *Bbmatrix.txt* contains a value corresponding to each of the predictor variable. Since this value indicates the overall influence that each predictor variable has on the PLS model, values in the *Bbmatrix.txt* file can be assessed based on the highest order of magnitude. Component loadings having the highest order of magnitude signify the relative

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this study. However, we also observe how the model responds when fever latent components are retained. This is discussed in detail in §5.1.1.1 and §5.2.1.1.

[42] Based on *one, two* and *three* latent variable(s)

[43] This suggests that the number of latent variables ≤ the number of manifest variables

importance of the corresponding variable. Variables having loadings closest to one offer the greatest explanatory power to the model.

Now that the software for the *predictive* data analysis in PLS has been presented, the next section will introduce the *causal* modeling PLS software that is used to assess whether the supply chain is best described as *independent* or *integrated*.

4.3.2. Causal PLS Modeling Software: PLS GRAPH 3.0

This study pursues the *social sciences* approach of PLS to analyze the *independent* approach of the supply chain under study. This approach is intended to demonstrate the *causal* association between manifest variables, process steps, and output dependent variable. The PLS *GRAPH* 3.0 software is used to determine R^2 values of each data set from the perspective of the *independent* supply chain approach[44]. The following sections discuss data preparation, data analysis, and interpretation of results using this software.

4.3.2.1. Data Preparation

Unlike the *Analyze* software, the first row of each data file has alphanumeric variable names. Consequently, the formatting remains the same ("Observation", "Yield", and supply chain step names) as illustrated in Appendix A1/A. As in the case of the *Analyze* software, each data set is placed onto a spreadsheet according to the following format:

- Rows: correspond to *observations*
- Columns: correspond to *predictor variables*
- Last Column: corresponds to the *dependent variable* (i.e., *Yield*)

The next step is to remove all observations that are missing data, since PLS *GRAPH* does not delete or estimate missing values. After missing values of data have been addressed by deleting the entire observation, the data is ready for preprocessing.

PLS *GRAPH* allows causal latent variable path modeling by finding the best least squares fit between the specified model and data under study. To illustrate the model building process, a simple supply chain will be considered now. Figure 10 illustrates a simplified two-step supply chain system to depict path modeling in *PLS GRAPH*.

[44] To obtain an academic version of PLS *GRAPH* 3.0, one should contact Wynne Chin from wchin@uh.edu

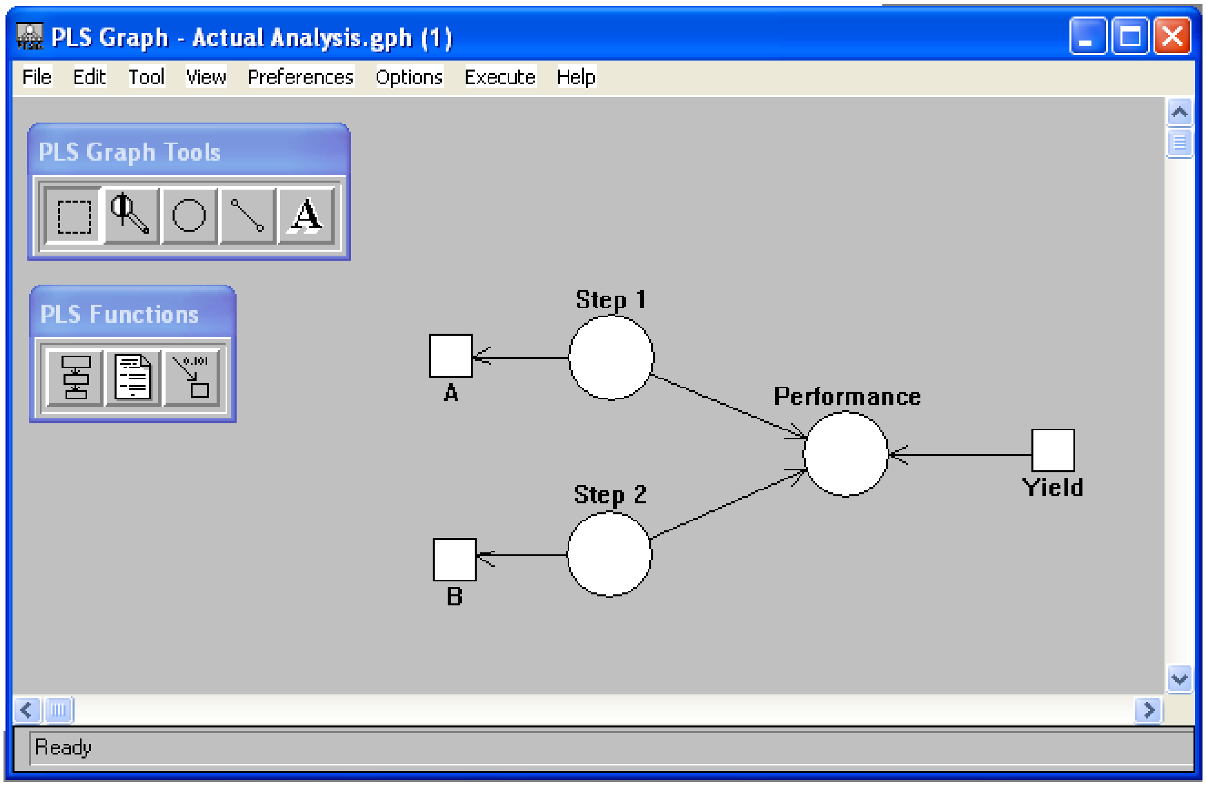


Figure 10 - A Two-Step Supply Chain Modeling using PLS *GRAPH*

The dependent variable, *Yield*, is shown on the screen as being a definition of the latent construct *Performance* (Figure 10). Since the manifest variable defines the latent construct, the arrow points from *Yield* to *Performance* (i.e., a *formative* causal structure discussed in §2.2.1 on p. 11). Both supply chain steps (i.e., Step 1 and Step 2) *define* the dependent latent construct, *Performance*, since performance of a supply chain system is typically *defined* by its individual steps. Reflections of the manifest variables (i.e., A and B) on their respective supply chain steps (i.e., Step 1 and Step 2, respectively) suggest that the manifest variables are related to the latent supply chain construct. This means that the manifest variables *reflect* or approximate the meaning of the latent construct (i.e., Step 1 or Step 2) by an arrow pointing away from the latent construct and towards the manifest variable. This relationship is analogous to the Principal Component Analysis (PCA), where the principal component represents the latent construct (Linton, 2004). After setting up the relationship between the latent constructs, the observations from the data set is linked to the model. The model is now ready for analysis.

4.3.2.2. Data Analysis

The analysis of *causal* PLS involves finding the best fit model based on the contents of the entire data set. The solution provides a set of coefficients and an explained variance associated with each construct. To obtain the best fit of the data set with the specified model visible on the work area, we select *Generate*, *Run*, *Extract* from the *Execute* pull-down menu. The results will appear on screen and are considered in the next section.

4.3.2.3. Interpretation of Results

After executing the *Generate*, *Run*, *Extract* command, numeric values appear beside each of the lines connecting variables and underneath the latent constructs that are dependent on other latent constructs. When we refer to Figure 13 in §5.1.2 (p. 56), we observe the amount of variance that is explained by the proposed model: $R^2 = 0.587$. The arrows that connect the constructs (i.e., individual supply chain steps) to the dependent construct (i.e., *Performance*) have coefficients[45] about the relationship. Alternatively, the loadings[46] of each supply chain metric (i.e. each supply chain has five metrics and the metrics of supply chain step 45 are illustrated as small square boxes in Figure 13) can be compared with all 255 metrics[47]. By comparing these loadings with each other, the contribution of each supply chain metric to the explanatory power of the model can be obtained. Supply chain metrics having higher loadings suggest that those steps are crucial for the overall supply chain performance. These loadings are analogous to the component loadings obtained from the *predictive* PLS approach as discussed in §4.3.1.3.

Now that the methodology for both *predictive* and *causal* PLS modeling have been outlined and reviewed, the next section will discuss results by examining both manufacturing and simulated data sets.

[45] These are considered as coefficients since the arrows in Figure 13 point from each supply chain step towards the dependent variable, *Performance*. This is known as a *formative* relation as discussed in §2.2.1 on page 12.
[46] These are considered as loadings since the arrows in Figure 13 point from supply chain steps towards their associated five metrics. This is known as a *reflective* relation as discussed in §2.2.1 on page 12.
[47] Recall that each simulated data set has 255 metrics (i.e. 51 supply chain steps x 5 metrics/step = 255)

5. Results

This chapter presents the results of the study to determine whether the integration of process measurement and control across a supply chain offers a substantial advantage over the *independent* approach of optimization at the firm level. Results include data sets from both manufacturing data and simulated data sets. In the following subsections, the output of PLS will be presented in detail. Included in this discussion are an overview of (5.1) simulated data results and (5.2) manufacturing data results.

5.1. Simulated Data Results

This subsection presents the results from the twenty two simulated data sets of the study. The first part (§5.1.1) will examine the results from the *integrated* supply chain perspective and the second part (§5.1.2) from the *independent* supply chain approach.

5.1.1. Integrated Supply Chain Approach

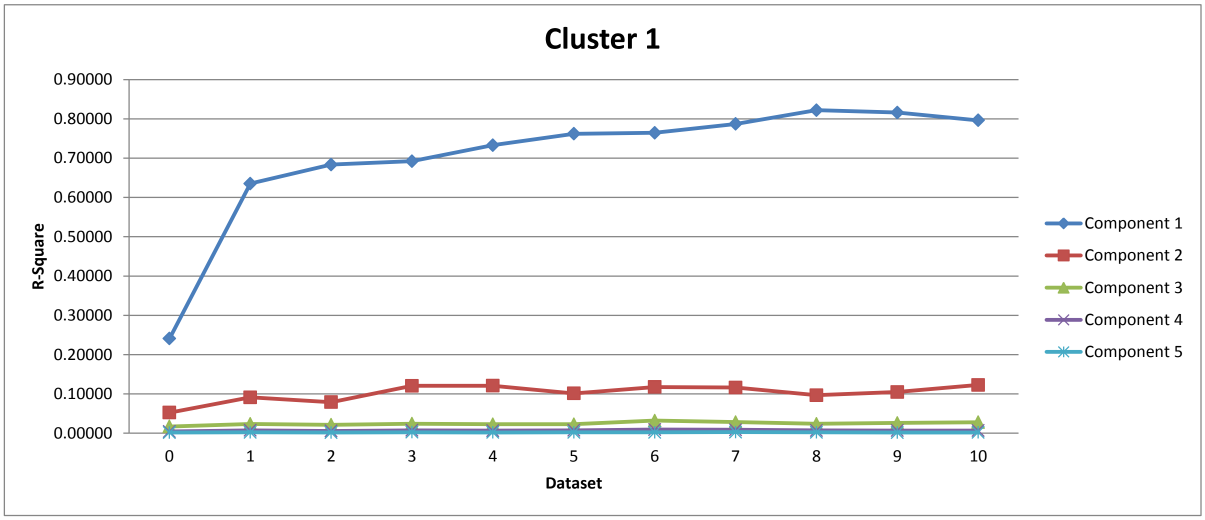
5.1.1.1. Determining the Number of Components

As discussed previously, R^2 values of each data set based on different numbers of retained components from one to five were collected (Tables are provided in *Appendix* A3/A – A3/B on p. 155 and 157, respectively). The table and the accompanying graph (Table 1 and Figure 11) highlight the dominance of the first component (R^2 values) across all eleven data sets for each data cluster. As we move from data set 0 to 10, the importance of the first component considerably increases[48]. The impact of the third component (1.6% to 3.2%), the fourth component (under 1%) and the fifth component (under 0.3%) are negligible.

[48] As discussed in Section 4.2 (p. 38), each simulated data set includes information about the same supply chain with varying relational strengths between input and output variables. The variational strength is weakest for Data 0 and strongest for Data 10 for both clusters. The strength increases gradually from Data 0 to Data 10. Thus, R^2 value of the model increases as we move from Data 0 to Data 10 for both clusters.

Table 1 - R^2 Values of Components

		R^2 Values of Component				
Cluster	Dataset	1	2	3	4	5
1	0	0.24088	0.05253	0.01699	0.00442	0.00153
	1	0.63520	0.09121	0.02353	0.00728	0.00225
	2	0.68360	0.07910	0.02139	0.00571	0.00172
	3	0.69218	0.12045	0.02431	0.00731	0.00245
	4	0.73309	0.12095	0.02284	0.00652	0.00191
	5	0.76200	0.10136	0.02295	0.00748	0.00208
	6	0.76455	0.11765	0.03217	0.00920	0.00217
	7	0.78698	0.11630	0.02832	0.00870	0.00273
	8	0.82201	0.09667	0.02402	0.00720	0.00223
	9	0.81595	0.10472	0.02619	0.00682	0.00152
	10	0.79611	0.12281	0.02799	0.00684	0.00188
2	0	0.24320	0.08734	0.01980	0.00642	0.00202
	1	0.35539	0.08043	0.02596	0.00930	0.00312
	2	0.37731	0.05859	0.01578	0.00493	0.00157
	3	0.47083	0.07057	0.02024	0.00641	0.00173
	4	0.48992	0.08481	0.02545	0.00768	0.00233
	5	0.55589	0.08146	0.02233	0.00719	0.00242
	6	0.61937	0.10109	0.02378	0.00781	0.00219
	7	0.73176	0.11079	0.02431	0.00686	0.00186
	8	0.79748	0.11583	0.02340	0.00715	0.00170
	9	0.83759	0.11281	0.02552	0.00803	0.00251
	10	0.83497	0.12708	0.02895	0.00640	0.00177



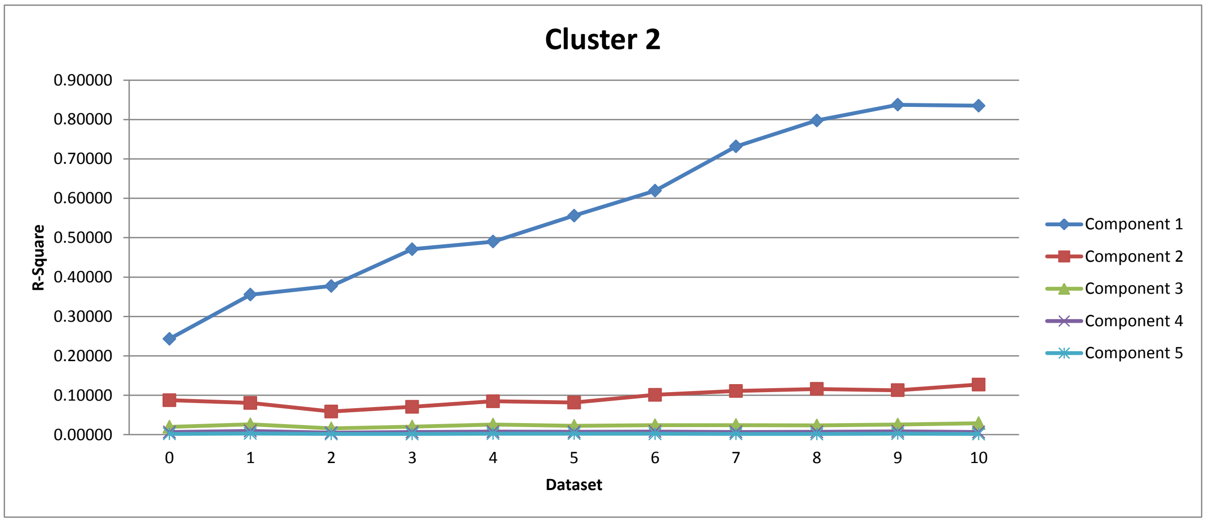


Figure 11 - Component R^2 Values Graph

Understanding the explanatory power is crucial to examine the impact of process steps on the dependent variable. Since the first component dominates the remaining components in this study, component loadings of individual variables are based on the first component.

5.1.1.2. Component Loadings

Component loadings of each process step are obtained for each data set (i.e., 51 Steps x 5 supply chain metrics = 255 loadings for each data set). Details about component loadings are provided in *Appendix* A4/A and A4/B (p. 160 and 174, respectively). These component loadings were sorted from the highest value to the lowest to determine which process steps are crucial for the model. *Appendix* A5/A and A5/B (p. 189 and 190, respectively) show the highest twenty loadings for each data set.

One can observe that even retaining five variables (having the highest loading) can provide enough explanatory power for the model by regressing process steps having highest loadings with the dependent variable (i.e., *Yield*) using linear regression in SPSS. Figure 12 illustrates this based on the R^2 values using linear modeling of SPSS. This figure highlights that even when we retain four to five predictor variables (with highest loading from the PLS test), the explanatory power of the model remains substantial. For example, for data sets 7 to 10, retaining only three variables with highest PLS loading provide R^2 values greater than 0.60. R^2 values of data sets 0 to 2 remain relatively low even when we retain twenty predictor variables, but R^2 values remain relatively constant even when five predictor variables remain in the model. The decline of R^2 values of data sets 8 to 10 is more apparent especially after retaining six or fewer predictor variables in the model. Exact R^2 values from the linear regression for each data set are provided in Appendix A6 (p. 191).

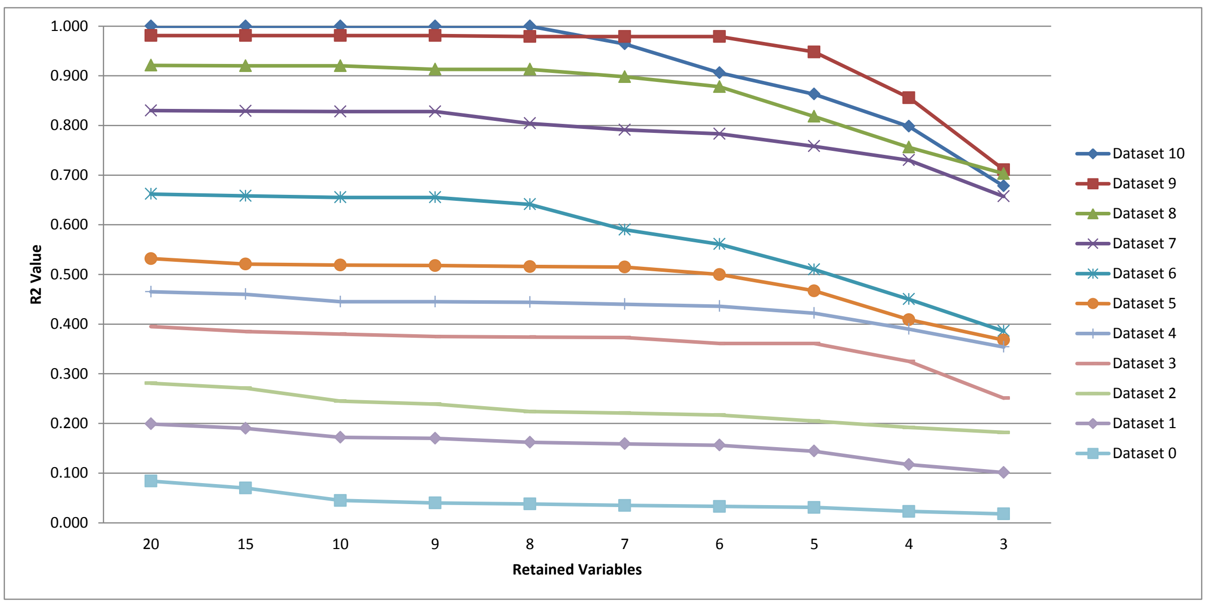
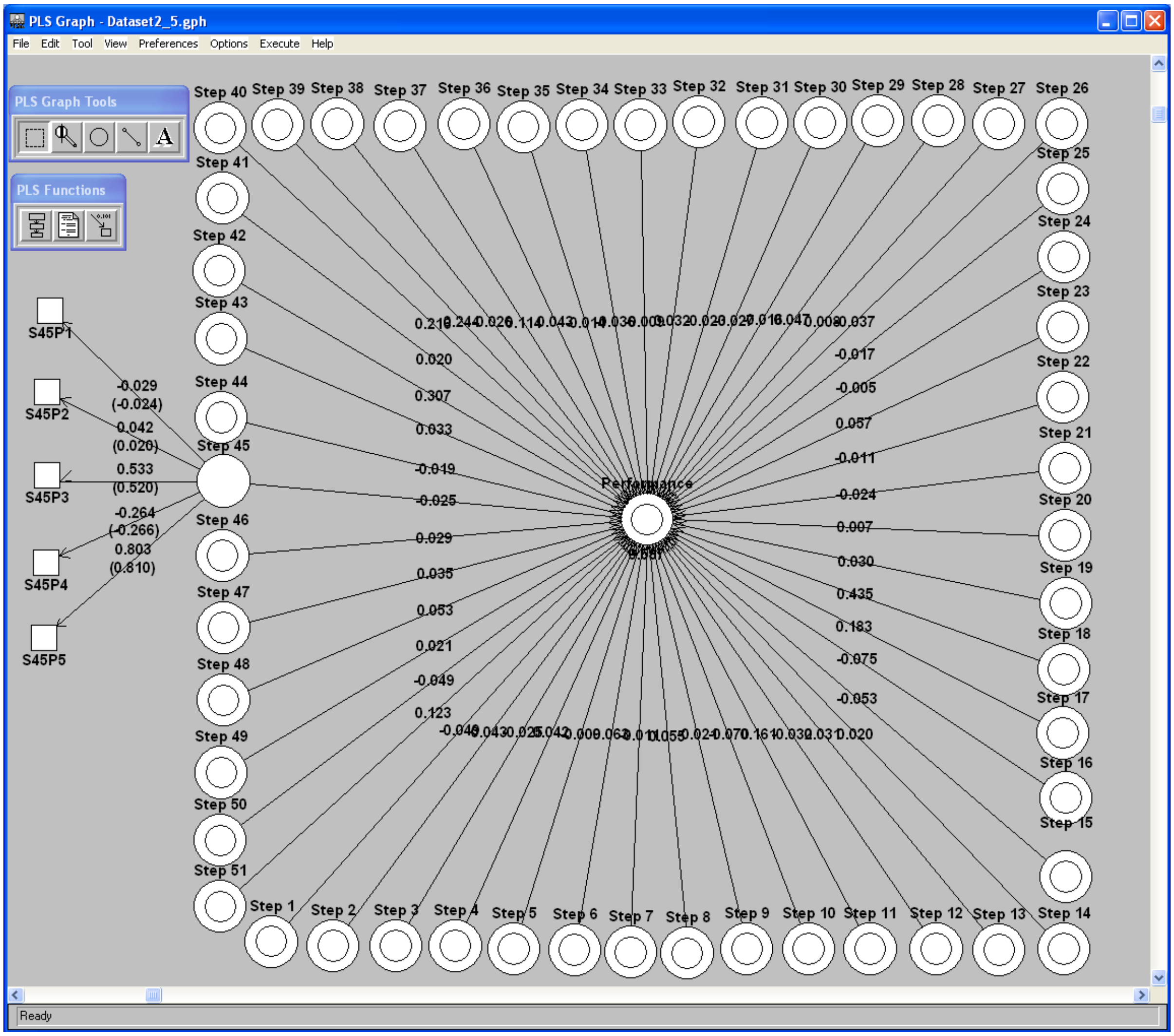


Figure 12 - R^2 Values Based on the Number of Retained Predictor Variables

5.1.2. Independent Supply Chain Approach

To illustrate the model building process, the final model of simulated data set 5 of the second cluster is shown below (Figure 13).



† *For visual clarity, indicators of each process step (i.e., five manifest variables for each process step) are toggled. Notice that process indicators of Step 45 are provided along with their component loadings for convenience.*

Figure 13 - PLS *GRAPH* Output (Simulated Data Sets)

There are 51 latent constructs for each of 51 supply chain process variables (i.e., Step 1 to Step 51). Each of the 51 latent variables reflects five metrics[49] (manifest variables are not shown in the figure since indicators are toggled for aesthetic reasons). All process latent variables point to the dependent variable, *Performance*, which is defined by a single manifest

[49] These metrics can be regarded as manifest variables since we observe their values directly.

variable, *Yield*[50]. As opposed to the manufacturing data set, the dependent variable *Yield* is a continuous variable.

Table 2 - R^2 Value Comparison between *Independent* and *Integrated* Approaches

						Improvement (value)		Improvement (%)	
Cluster	Dataset	Independent†	Integrated‡	Difference	Difference (%)	Minimum	Maximum	Minimum	Maximum
1	0	0.212	0.31635	**0.10435**	**49.22**	0.01656	0.10435	1.77	49.22
	1	0.674	0.75947	0.08547	12.68				
	2	0.727	0.79152	0.06452	8.87				
	3	0.797	0.84670	0.04970	6.24				
	4	0.833	0.88531	0.05231	6.28				
	5	0.864	0.89792	0.03392	3.93				
	6	0.898	0.92684	0.02884	3.21				
	7	0.905	0.94060	0.03560	3.93				
	8	0.934	0.95056	**0.01656**	**1.77**				
	9	0.936	0.95534	0.01934	2.07				
	10	0.936	0.95563	0.01963	2.10				
2	0	0.255	0.35878	0.10378	40.70	0.01817	0.16019	1.85	46.81
	1	0.323	0.47420	0.15120	**46.81**				
	2	0.371	0.45818	0.08718	23.50				
	3	0.478	0.56978	0.09178	19.20				
	4	0.450	0.61019	**0.16019**	35.60				
	5	0.587	0.66929	0.08229	14.02				
	6	0.683	0.75424	0.07124	10.43				
	7	0.823	0.87558	0.05258	6.39				
	8	0.892	0.94556	0.05356	6.00				
	9	0.959	0.98646	0.02746	2.86				
	10	0.981	0.99917	**0.01817**	**1.85**				

†*PLS GRAPH* software is used for the *independent* approach. *PLS GRAPH* provides R^2 values up to three significant figures

‡ *Analyze/StripMiner* software is used for the *integrated* approach. *Analyze/StripMiner* provides R^2 values up to five significant figures

Similar results are obtained from simulated data sets. For example, for data set 5 in the second cluster (Figure 13), the R^2 value of the *independent* approach is 0.587, compared to the 0.669 from the PLS *integrated* approach. This means that the *integrated* approach explains approximately 8.23% more variability in the data. Likewise, data set 0 from the second cluster reveals a similar trend (*Integrated* $R^2 = 0.359$; *Independent* $R^2 = 0.255$). Table 2 compares R^2 values between *independent* and *integrated* approaches for the remaining simulated data sets. The difference in terms of nominal value and percentage are highlighted

[50] The dependent variable, *Yield*, is considered as a definition of the latent construct *Performance. Yield* is not shown on the figure, since it is toggled under *Performance*. But, as in the case of §4.3.2.1, we have a formative construct, consequently the arrow points from *Yield* to *Performance.*

for easier comparison. Improvements of the *integrated* approach over the *independent* approach are also provided in percentage. The relevant discussion about the difference between *integrated* and *independent* approaches is provided in §6.3 (p. 78).

Having considered the results from the simulated data sets, the next section will reveal the results from the manufacturing data set.

5.2. Manufacturing Data Results

This subsection presents the results of the manufacturing data set. The first part (§5.2.1) examines the results from the *integrated* supply chain perspective and the second part (§5.2.2) from the *independent* supply chain approach.

5.2.1. Integrated Supply Chain Approach

5.2.1.1. Determining the Number of Components

As in the case of simulated data, we obtain R^2 values of the manufacturing data based on different number of retained components from 1 to 5 (Relevant tables are provided in *Appendix* A7 on p. 192). The following table summarizes R^2 values of each component. The table and the accompanying graph (Table 3 and Figure 14) highlight the importance of components. One should note that unlike the case in the simulated data sets, the first component of this manufacturing data set does not dominate the remaining components significantly. Although there is no clear cut-off value for the number of retained latent components, one can retain all five latent variables for the test[51].

Table 3 - R^2 Values of Individual Components

	Component				
	1	**2**	**3**	**4**	**5**
R^2	0.00436	0.00338	0.00281	0.00109	0.00048

[51] Studies show that a maximum of five retained components is enough for predictive PLS models (Geladi and Kowalski, 1986; Linton, 2004).

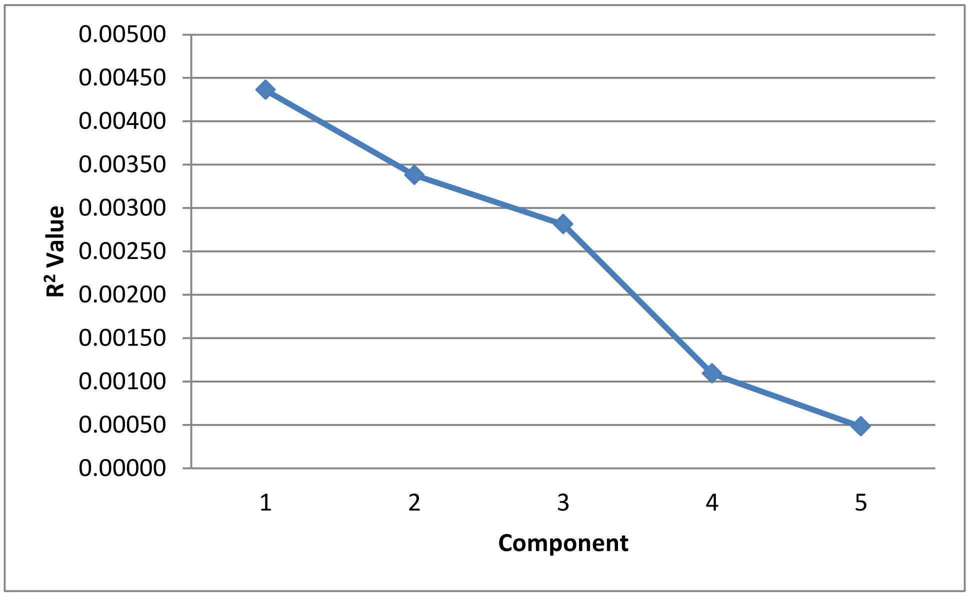


Figure 14 - Component R^2 Values Graph

In order to find the R^2 value of the model based on five retained latent components, we can simply add the individual component values in Table 3. This gives an R^2 value of 0.01212 for the manufacturing data set. Although this seems like a very low value compared to the ones obtained from the simulated data sets, we should remember that capturing information from a supply chains is a challenging task if the relationship between the manifest variables and the dependent variables is not very strong. Recall that the dependent variable of the manufacturing data set is a binary variable (i.e., 0: pass, 1: success at the quality test). Since it does not provide extensive information like the continuous dependent variable of the simulated data sets, an R^2 value of 0.01212 should not be treated as a surprise. In fact, the goal is to compare this R^2 value of the *integrated* approach with the values that will be obtained from the *independent* approach. *Independent* approach of the manufacturing data set is discussed in §5.2.2 (p. 61). The following section will now examine the component loadings prior to independent-integrated R^2 value comparison.

5.2.1.2. Component Loadings

Component loadings of each process step are obtained for the manufacturing data set (i.e., 8 supply chain steps x 1 metric/step = 8 loadings).

Table 4 - Component Loadings (Integrated Approach)

Step	Loading	Rank
1	-1.24E-01	2
2	1.96E-02	6
3	3.23E-02	5
4	-1.58E-02	8
5	-1.85E-02	7
6	-1.33E-01	1
7	6.30E-02	3
8	-5.62E-02	4

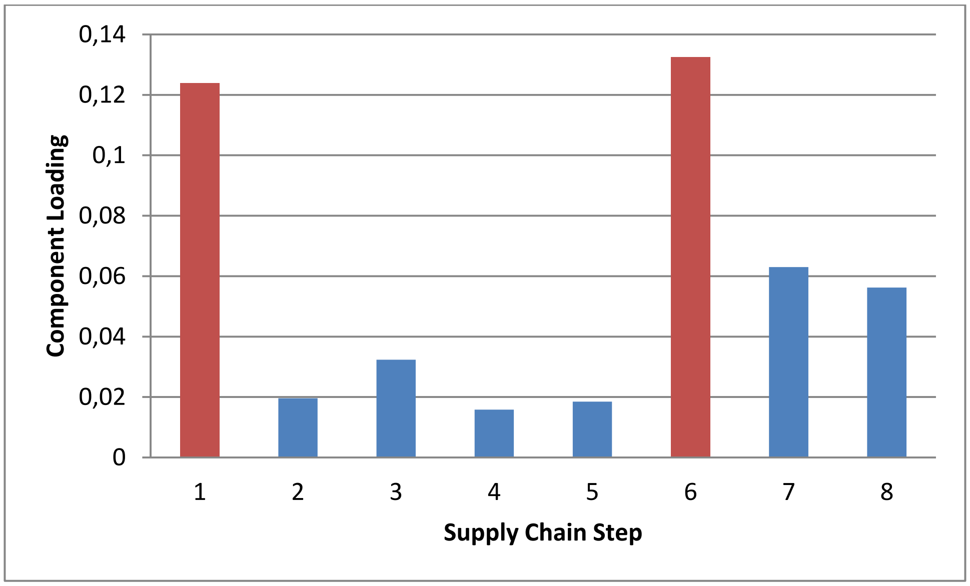


Figure 15 - Component Loadings Comparison (Integrated Approach)

These component loadings can be ranked according to the absolute value of their component loadings (Table 4). Although there is no component loading cutoff point that marks a step as either an important or insignificant, one can determine which steps to focus on by comparing the component loadings of supply chain steps with each other. The accompanying Figure 15 illustrates the relative impact of each step on the supply chain. Based on this ranking, the first and sixth steps are the most important steps, while steps two to five have relatively small impact. Consequently, focusing on the first and sixth steps will give a better indication about the supply chain performance. Now that the *integrated* approach is covered, the next section will examine the manufacturing data from the *independent* supply chain perspective.

5.2.2. Independent Supply Chain Approach

To illustrate the model building process, the final model is shown below (Figure 16). Model formulation for the manufacturing data set is similar to that of simulated data sets. As it can be seen in Figure 16, there are eight latent constructs for each of eight process variables (i.e., Step 1 to Step 8). Supply chain steps in this formulation are considered as latent constructs, each of which reflects a single manifest variable (i.e., denoted by A to H). Letters A to H represent data columns from Step 1 to Step 8 in Appendix A1/B (p. 88). All process latent variables point to the dependent variable, *Performance*, which is defined by a single manifest variable, *Yield*[52]. We should also note that *Yield* points to the *Performance* latent variable, since *Yield defines* the *Performance*.

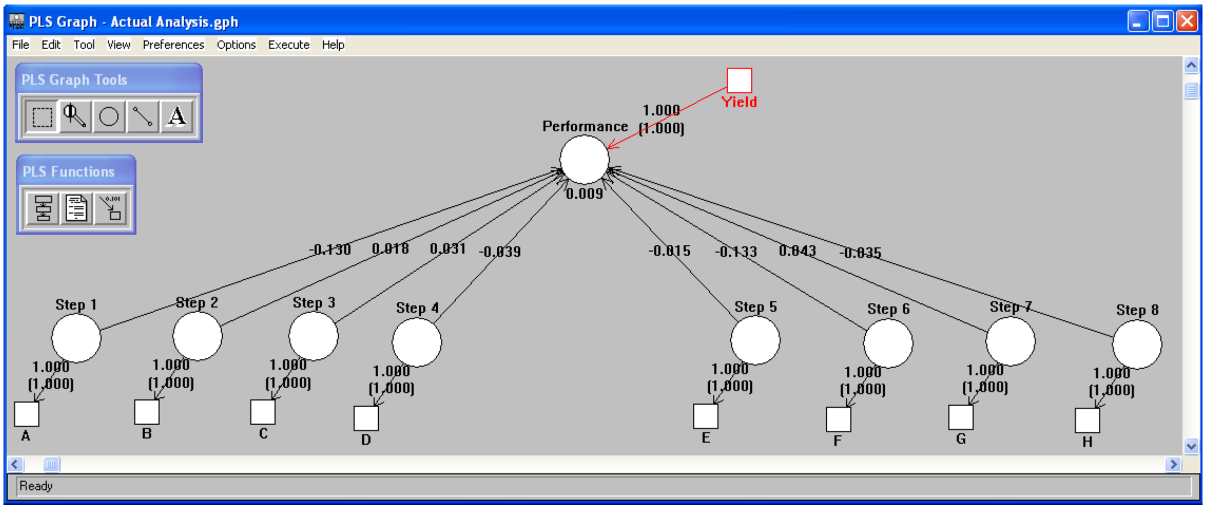


Figure 16 - PLS GRAPH Output (Manufacturing Data Set)

Coefficients[53] of each latent variable are provided on the arrow between each latent variable and the dependent variable (e.g., the coefficient linking Step 1 to Performance is -0.130 in Figure 16). These coefficients are analogous to the component loadings discussed in the previous section and we can compare them with each other to determine crucial supply chain steps.

[52] Each supply chain step and performance is constructed as a latent variable as stated above. Manifest variables that reflect or define their respective latent construct are joined by an arrow. *Yield* is treated as a manifest variable (since we have data for the yield in Appendix A1/A and A1/B) to define the *Performance* metric. Consequently, *Performance* is essentially the *Yield*.

[53] These coefficient values are associated with regression analysis, in which the arrow points away from each step towards the dependent variable. This is known as a *formative* relation as discussed in §2.2.1 on page 12.

Table 5 - Component Coefficients (Independent Approach)

Step	Coefficient	Rank
1	-0.130	2
2	0.018	7
3	0.031	6
4	-0.039	4
5	-0.015	8
6	-0.133	1
7	0.043	3
8	-0.035	5

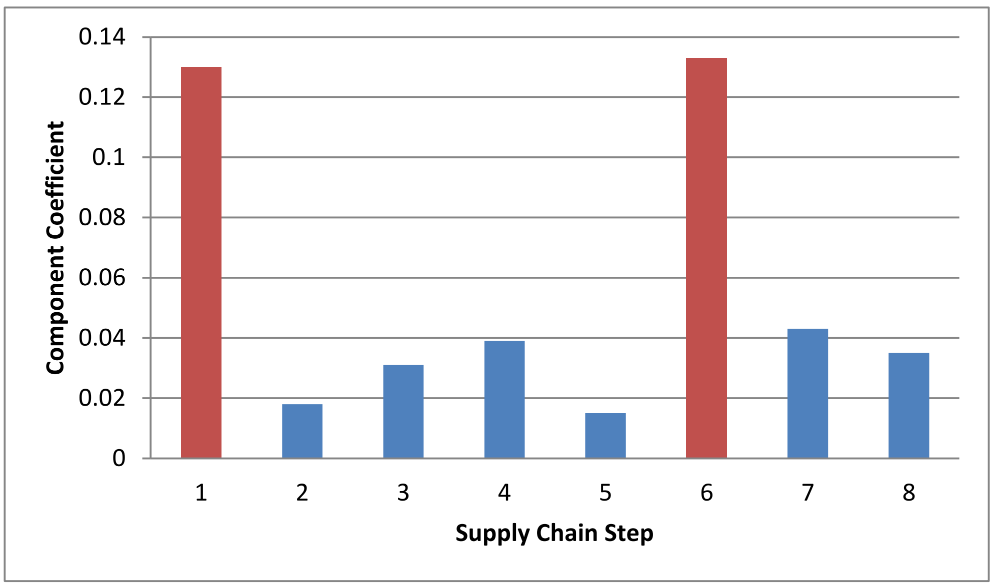


Figure 17 - Component Coefficients Comparison (Independent Approach)

These component coefficients can also be ranked according to their absolute values (Table 5). As discussed in §5.2.1.2 (p. 59), one can determine which steps to focus on by comparing the coefficients of supply chain steps with each other. The accompanying Figure 17 illustrates the relative impact of each step on the supply chain. Based on this ranking, the first and sixth steps are the most important steps, while steps two to five have relatively small impact. These values are very similar to the ones obtained from *predictive* PLS modeling in

§5.2.1.2, although the ranking is not exactly the same. Consequently, focusing on the first and sixth steps will give a better indication about the supply chain performance.

An R^2 value of 0.009 indicates that this *independent* approach (optimizing each individual step separately as opposed to the *integrated* approach) generates a weaker model. This is a lower value compared to the one obtained from the *integrated* PLS approach[54] (*integrated* R^2 = 0.01212). Although the improvement may seem small, since R^2 values of both approaches are low, pursuing the *integrated* approach provides a 34.67% improvement over the *independent* approach. This clearly indicates that the *integrated* approach is better than the *independent* approach. Thus, we reject the null hypothesis and conclude that there is a difference between *integrated* and *independent* approaches in in explaining the overall supply chain performance:

> **H_O**: There is no difference between the *integrated* and *independent* approaches in explaining overall supply chain performance based on the process settings and measures of the final product output.
>
> **H_A**: There is a difference between the *integrated* and *independent* approaches in explaining overall supply chain performance based on the process settings and measures of the final product output.

In summary, results reveal that integrating analysis and management of process data across the supply chain performs better than independent analysis of individual supply chains. These results will now be considered in the *Discussion* section.

[54] That is modeling all 8 steps simultaneously. The R^2 value is based on five-latent variable PLS analysis.

6. Discussion

The primary objective of this research is to identify whether there is a difference between the *integrated* and *independent* approaches in terms of explaining the overall performance for a given supply chain process setting. Consideration of the *integrated* approach suggests there is a significant difference in explaining the overall supply chain performance. The study reveals that *predictive* PLS is a promising approach to analyze the *integrated* approach to process management. In the following subsections, the output of PLS will be discussed thoroughly. Included in this discussion are an overview of (6.1) the *integrated* approach, (6.2) the *independent* approach, (6.3) comparison of the *independent* and *integrated* approaches, (6.4) determining the number of latent components, (6.5) contributions of the study, (6.6) limitations of the study, (6.7) further studies, and (6.8) conclusion.

6.1. Integrated Approach

Results reveal that the *integrated* approach determines the interaction among components of different process steps more accurately than the *independent* approach. This is achieved by investigating the interactions between all 51 process steps to identify the crucial components (i.e., small shaded boxes) through component loadings of each process (Figure 18).

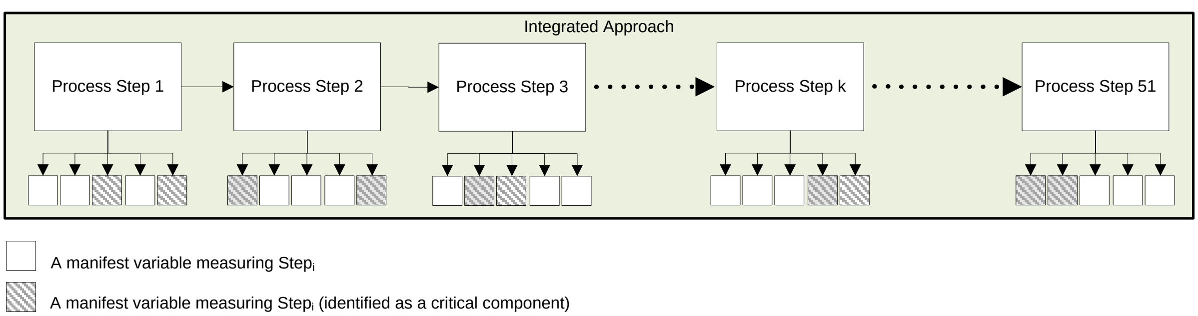


Figure 18 - Integrated Approach on a Supply Chain

By sorting the component loadings from the highest to the lowest values, we demonstrated which components are crucial for each data set. Based on the preference, one can select the number of components to retain[55].

The number of retained variables (i.e., twenty) is based on personal preference and one can retain more or less number of variables. Yet, we analyzed the performance of the model based on fewer retained variables for each data set. Results revealed that even retaining five variables, having the highest loadings, provides decent explanatory power of the model. This means that from a set of 255 measurements, focusing even on five highly influential measurements can provide valuable information about a given supply chain. Dimension reduction from 255 to five is a tremendous improvement given the complex nature of a typical supply chain system. Although, one cannot feasibly analyze a model with 255 measurements, analyzing relatively few measurements can provide enough explanatory power. Other more complex supply chains may require a greater number of retained measures, but the promising PLS approach can ensure reduced dimensionality without sacrificing the explanatory power of a given model.

This achievement ensures that treating variable loadings (i.e., 255 measurements for 51 process steps) as components affecting the performance of the end product is possible. The technique can also be used for initial variable selection. Assessing measurements (i.e., process step loadings) in terms of component loadings in PLS allows a fast approach to individually examine the impact of each step on the overall supply chain system. This methodology allows us to determine whether the components are specific to a single process step or across multiple process steps. Obtaining high loadings from different process steps signify that components are crucial across multiple process steps instead of being specific to a single process step. Thus, the research demonstrates a generalizable technique that assesses the relationship between seemingly unrelated process steps that positively or negatively affect the performance (i.e., *Yield*) of the end-product. As in the case of *integrated* supply chains, process steps extensively interact with each other, since we obtain high component loadings across different process steps.

---

[55] Recall that each data set has 51 x 5 = 255 measurements in total, where 51 is the total number of supply chain steps and 5 metrics for each supply chain step.

Obtaining high explanatory power for integrated supply chains supports the first part of the first tactic:

Tactic A: When process steps interact with other extensively, the supply chain should be examined in an *integrated* manner to avoid suboptimal solutions.

Consequently, the proposed method can be used to measure the degree at which process steps interact with each other and obtain a better understanding of the supply chain under study. This crucial finding necessitates a comparison between the *integrated* approach and the *independent* approach in explaining the overall supply chain performance. Consequently, we will discuss the results of the *independent* approach in the next section and compare both approaches in the following sub-section.

6.2. Independent Approach

To highlight the significance of the *integrated* supply chain approach, it is important to analyze the dynamics of a given supply chain under an *independent* approach. Figure 19 illustrates the *independent* supply chain approach of the study based on the simulated data sets. As in the case of the *integrated* approach, recall that the number of process steps for all simulated data sets is 51 and each process step is associated with five components that affect the quality of the final product – the variable *Yield*.

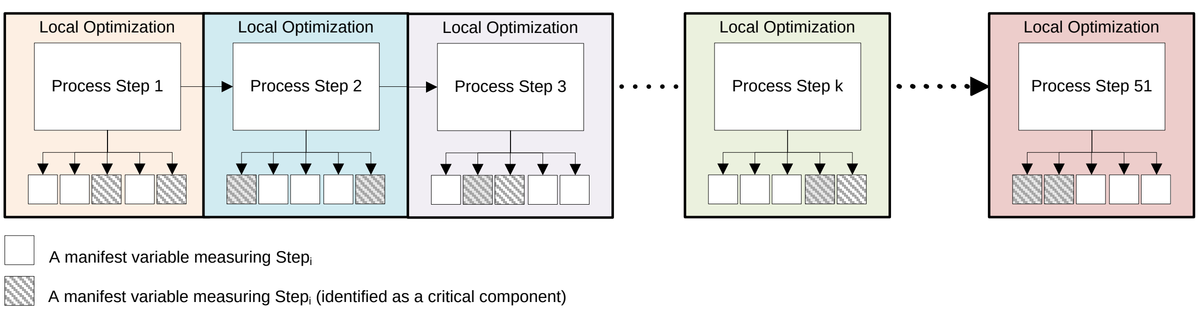


Figure 19 - Independent Supply Chain Approach

As illustrated in the *Results Section*, all data sets (i.e., simulated and manufacturing data) are also analyzed from the *independent* supply chain approach perspective. As opposed to the *integrated* approach, local optimization of the *independent* approach focuses on relating identified components (shaded square boxes) to the quality of their respective product, but not to the end-product. Since an effect on a sub-assembled product ultimately affects the quality of the final end-product, one should not consider the effects of measurables on individual steps in vacuum and then consider the impact of individual steps on the overall explanatory of the supply chain. Alternatively, one can pursue the *causal* social sciences approach of PLS (Discussed in §4.3.2 on p. 49) by using the PLS *GRAPH* software to determine the R^2 value of the *independent* approach.

Compared to the *integrated* approach, the *independent* approach reveals lower explanatory power across all data sets. This suggests that the supply chain under study (both for the manufacturing data and simulated data sets) portrays an *integrated* supply chain characteristic. Consequently, we obtain relatively lower R^2 values for the *independent* approach for all data sets. If this is the case and when the process steps have limited interaction with each other, then the *independent* approach is possible to streamline a given supply chain system. The *independent* approach may allow the system integrator to eliminate process steps that have negative effects on the quality of the end-product, thereby supporting the second tactic:

Tactic B: When process steps have limited or no interaction with each other, local optimization (*independent* approach) is possible to streamline a given supply chain system.

However, we should note that since our study is based on a single supply chain datum (i.e., one manufacturing data set) and the remaining simulated data sets are based on that single supply chain, which is found to be *closely integrated* in the previous section, we cannot directly support this tactic fully. For example, if we have a series of measurements from different supply chain – preferably ones having segregated supply chains – we most probably will obtain very similar R^2 values for both *independent* and *integrated* PLS approaches, since analyzing segregated supply chains from an *integrated* perspective does not add valuable information about the overall supply chain performance. Thus, we need to assess this tactic under different segregated supply chains. Unavailability of different supply chain structures is one of the major limitations of this study.

Nevertheless, after closer examination of the results from the simulated data sets, one can note that the degree of improvement of the *integrated* approach over the *independent* approach varies across data sets. This finding is elaborated in the following section.

6.3. Comparison of Independent and Integrated Approaches

As discussed in the preceding sub-sections, results indicate that the *integrated* approach performs better than the *independent* approach in terms of providing a greater explanatory power. Consider Table 6 that tabulates R^2 values of *independent* and *integrated* approaches for both manufacturing and simulated data set

Table 6 - R^2 Value Comparison between *Independent* and *Integrated* Approaches

							Improvement (value)		Improvement (%)	
	Cluster	Dataset	Independent	Integrated	Difference	Difference (%)	Minimum	Maximum	Minimum	Maximum
Simulated Data sets	1	**0**	0.212	0.31635	**0.10435**	**49.22**				
		1	0.674	0.75947	0.08547	12.68				
		2	0.727	0.79152	0.06452	8.87				
		3	0.797	0.84670	0.04970	6.24				
		4	0.833	0.88531	0.05231	6.28				
		5	0.864	0.89792	0.03392	3.93	**0.01656**	**0.10435**	**1.77**	**49.22**
		6	0.898	0.92684	0.02884	3.21				
		7	0.905	0.94060	0.03560	3.93				
		8	0.934	0.95056	0.01656	**1.77**				
		9	0.936	0.95534	**0.01934**	2.07				
		10	0.936	0.95563	0.01963	2.10				
	2	**0**	0.255	0.35878	0.10378	40.70				
		1	0.323	0.47420	0.15120	**46.81**				
		2	0.371	0.45818	0.08718	23.50				
		3	0.478	0.56978	0.09178	19.20				
		4	0.450	0.61019	**0.16019**	35.60				
		5	0.587	0.66929	0.08229	14.02	**0.01817**	**0.16019**	**1.85**	**46.81**
		6	0.683	0.75424	0.07124	10.43				
		7	0.823	0.87558	0.05258	6.39				
		8	0.892	0.94556	0.05356	6.00				
		9	0.959	0.98646	0.02746	2.86				
		10	0.981	0.99917	**0.01817**	**1.85**				
Manufacturing Data			0.009	0.01212	**0.00312**	**34.67**				

The table reveals that the simulated data sets are sorted with respect to R^2 values for both clusters. This shows that although some supply chains in our study are well understood (i.e., data sets having high R^2 values), some apparently are not. This range of values allows us to explore the performance of pursuing an *integrated* approach over the *independent* approach across different supply chain structures.

The shaded columns signify that in all circumstances the *integrated* approach performs better than the *independent* approach. Thus, the first proposition is supported:

Proposition 1. An *integrated* approach will allow supply chain members to have a greater understanding of the critical coordination components and use these insights to improve the overall supply chain performance.

We should also assess the degree of improvement before moving forward. The values range from small improvements as low as 1.77% to significant values as high as 49.22% for simulated data sets. One can notice that when process steps are not well understood (thereby having low R^2 values); significant improvements can be obtained by choosing the *integrated* approach. This is a significant observation, since most supply chains in real life are complex by their nature and are not well understood by their participating members. If this is the case, then pursuing an *integrated* perspective by using the outlined PLS approach can provide valuable information to streamline a given supply chain system. However, if the supply chain is already very well understood, pursuing an *integrated* approach may not provide significant additional critical information.

Although this finding is logical, real supply chains are not well understood in general, thus reveal low R^2 values if one to examine them[56]. Recall that both data clusters (i.e., twenty two data sets) are *simulated* data sets to illustrate the performance of PLS under different supply chains settings (i.e., R^2 values ranging from low to very high). In fact, the *manufacturing* data set suffers from a very low R^2 value of 0.009 for the *independent* approach (Table 6), signifying that initially, the process steps of this supply chain is not well understood. Conducting the *integrated* approach by using PLS provides a considerable 34.67% improvement in explaining the variability in the model.

This level of percentage improvement in explanatory power for the model may not necessarily yield such high levels of cost reduction in a given supply chain system. Thus, for the *manufacturing* supply chain under study, we can potentially reduce the overall cost of the supply chain when we focus on eliminating performance deficiencies that are related to critical components determined by the PLS approach. The 34.67% improvement in explaining variability in the model may not necessarily translate into 34.67% cost reduction, since the overall supply chain cost can be affected by other components that are not captured

[56] Recall that the manufacturing data set (based on an actual supply chain data) revealed relatively low R^2 values for both *independent* and *integrated* approaches: 0.009 and 0.01212, respectively.

by the model used in PLS modeling. The outlined approach of PLS simply allows us to understand the nature of a supply chain better by determining crucial components across a system and signals possible cost reductions. But, determining the amount of supply chain cost reductions is beyond the scope of this research.

Having underlined the importance of the *integrated* approach, the next section discusses other important findings of this study, namely the criteria to determine the number of latent components in PLS analysis.

6.4. Determining the Number of Latent Components

As discussed previously in §2.2.2 (p. 13), although PLS components are analogous to the PCA approach, the selection criteria for the number of components differ between two methodologies. In PCA, one can determine the number of retained components by using the *Kaiser's Rule*, *Horn's Procedure*, *eigenvalue greater than one rule* or by looking for an "elbow" in the curve of a scree plot (Lattin *et. al.*, 2003). These rules and procedures are well recognized and used frequently among researchers in quantitative modeling. Since PLS is a relatively newer approach, the field still lacks such prevalent rules and procedures, although some studies shows that selecting the first five components is usually sufficient (Geladi and Kowalski, 1986; Linton, 2004). Thus, all our analyses are conducted based on retaining five components. We also investigate the performance of the models under study by using fewer variables.

Results illustrated in §5.1.1.1 (p. 52) signify the dominance of the first principal component over the remaining components across all simulated data sets. This is especially true for data sets, in which the R^2 value is very high. When the supply chain under study is very well understood (thus having a high R^2 value), retaining even one principal component could be sufficient. This means that one can assess the component loadings of the PLS model based on only a single component, instead of more components. Supply chains having relatively lower R^2 values should retain at least three principal components to ensure high explained variability values. One should also note that depending on the complexity of the supply chain, one may need to retain more principal components to maintain decent explained variability values. Thus, researcher should retain five principal components to maximize their understanding of complex supply chain models. Determining the number of retained principal components in supply chains can be examined in future studies. Having discussed the results of PLS, the next section will consider the contribution of the study.

6.5. Contribution of the Study

This study demonstrates that the *integrated* approach performs better than the *independent* approach in terms of providing a greater explanatory power. This indicates that companies need to consider their individual process steps together to streamline their respective supply chain operations. Instead of relying on complex modeling algorithms, this study quantitatively demonstrates the advantage of the *integrated* approach by simply comparing the explanatory power (i.e., R^2) of the supply chain model based on *independent* and *integrated* approaches. This is achieved by using both *predictive* and *causal* PLS modeling approaches. This thesis is also the first study to implement the *predictive* PLS approach on a supply chain. The component loadings obtained from PLS analyses provide a quick and accurate way to determine significant process measures of a given supply chain. By focusing on these process measures, companies can identify the critical processes that affect the overall supply chain performance based on the quality of the end product. Having underlined the contribution of the study, the next section will discuss the limitations of the study.

6.6. Limitations of the Study

Although the study develops an effective empirical tool to assess a given supply chain performance, the study has a number of limitations. As discussed previously, one does not have an avenue to collect data from a sample of companies from different industries and all of our data is collected from a single company. While this sampling choice minimizes confounds by holding focal firm characteristics constant, it limits the generalizability of the results to some extent. Supply chains vary in complexity depending on the field they operate. As the complexity of the product increases, supply chains horizontally and vertically expand, thereby increasing the complexity of retrieving accurate data across supply chains. In fact, some supply chains may operate in multiple sectors, thus increasing the complexity of the system further. The supply chain under study reveals data primarily based on its internal 51 process steps. Although this allows accurate measurements, supply chains in general span across multiple companies. Capturing accurate and complete information from all external supply chain members is a challenging task by the very nature of complex supply chains.

Another major limitation of the study is the availability of an extensive real data set. As mentioned in §4.2 (p. 38), finding a publicly available supply chain data is very difficult. Although most well established companies do collect and store multiple process steps data for their respective supply chains and/or internal manufacturing operations, availability of this type of data set is a challenge, since process steps datum is considered as confidential information for commercial purposes. Thus, companies do not share this type of information on publicly available mediums such as the Internet. Even if this is the case, the available data set is either limited in information or purposefully distorted to ensure confidentiality. The electronics company provided data for a portion of its supply chain operations due to confidentiality reasons. Also, the single manufacturing data set provided by the company is not enough to assess the performance of PLS approach across different supply chain environments as discussed previously. If we had more observations of the manufacturing supply chain (instead of generating simulated data sets based on the single manufacturing data set), we might have a better understanding of the capabilities of PLS approach on different supply chain settings.

6.7. Further Studies

An interesting follow-up study would be to collect data from a number of supply chains from different industries such as the automotive or the aerospace industries. Such complex supply chains can be examined to investigate capabilities of PLS approach further. Analyzing a very complex supply chain, namely from an aerospace industries, using the outlined PLS approach may add valuable insight to this field. But, obtaining a complete, undistorted data set on such supply chains will be a very challenging task. In addition, future studies can also focus on determining the amount of supply chain cost reductions of the outlined PLS approach. Although, this study signals cost reductions across supply chains by providing greater explanatory power.

6.8. Conclusion

This study develops and tests an empirical PLS approach to determine whether optimizing across a supply chain gives significantly different outcomes than consideration at a firm level. Manufacturing-related supply chain data using a PLS procedure is analyzed to determine the crucial components and indicators that make up each component in a supply chain system. The research involves an examination of a supply chain process to determine which latent variables are crucial for a given system.

A major focus of the study is to compare the *integrated* and *independent* approaches together in explaining the overall supply chain performance. Results indicate that the *integrated* and *independent* approaches are indeed different in explaining the overall supply chain performance. The *integrated* approach always provides greater R^2 values for supply chains that have high interaction among their individual steps. The improvements in R^2 are even more significant particularly for supply chains that originally have low R^2 values. This indicates that pursuing an *integrated* approach, especially for supply chains that are less well understood, can allow supply chain members to coordinate their processes better and reduce or eliminate the impacts of any non-value adding activities along their respective supply chains.

The outlined PLS approach allows supply chain members to have a greater understanding of these critical coordination components and to use these insights to improve their overall supply chain performance. For this purpose PLS is applied to produce components that best describe the output value. The importance of measures from across supply chain partners to each component is the focus of this study. PLS offers the potential for methodological advances in analysis in supply chain studies. In summary, PLS has much to offer in the future as more researchers gain experience and continue to experiment with PLS.

7. Bibliography

Barclay, D., Higgins, C., and Thompson, R. (1995). The partial least squares (PLS) approach to causal modeling: Personal computer adoption and use as an illustration. *Technology Studies, 2*(2), 285-309.

Barros, A. I., Dekker, R., and Schoolmen, V. (1998). A two-level network for recycling sand: A case study. *European Journal of Operational Research, 110*(2), 199-214.

Ben Naylor, J., Naim, M. M., and Berry, D. (1999). Leagility: Integrating the lean and agile manufacturing paradigms in the total supply chain. *International Journal of Production Economics, 62*(1), 107-118.

Berger, A. J., Itzkan, I., and Feld, M. S. (1997). Feasibility of measuring blood glucose concentration by near-infrared Raman Spectroscopy. *Spectrochimica Acta - Part A Molecular Spectroscopy, 53*(2), 287-292.

Boute, R. N., Disney, S. M., Lambrecht, M. R. and Van Houdt, B. (2007). An integrated production and inventory model to dampen upstream demand variability in the supply chain. *European Journal of Operational Research, 178*(1), 121-142.

Braun, D. E., Maas, S. G., Zencirci, N., Langes, C., Urbanetz, N. A., and Griesser, U. J. (2010). Simultaneous quantitative analysis of Ternary mixtures of D-Mannitol polymorphs by FT-Raman Spectroscopy and multivariate calibration models. *International Journal of Pharmaceutics, 385*(1-2), 29-36.

Braunscheidel, M. J. and Suresh, N. C. (2009). The organizational antecedents of a firm's supply chain agility for risk mitigation and response. *Journal of Operations Management, 27*(2), 119-140.

Cachon, G. P. and Fisher, M. (2000). Supply chain inventory management and the value of shared information. *Management Science, 46*(8), 1032-1048.

Cannon, J. P. and Perreault Jr., W. D. (1999). Buyer-seller relationships in business markets. *Journal of Marketing Research, 36*(4), 439-460.

Chen, F., Drezner, Z., Ryan, J. K., and Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. *Management Science, 46*(3), 436-443.

Chen, I. J. and Paulraj, A. (2004). Towards a theory of supply chain management: The constructs and measurements. *Journal of Operations Management, 22*(2), 119-150.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly: Management Information Systems, 22*(1), vii-xvi.

Chin, W. W., and Newsted, P. R. (1999). Structural equation modeling analysis with small samples using partial least squares. *Statistical Strategies for Small Sample Research,* , 307-341.

Chin, W. W., Marcelin, B. L., and Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research, 14*(2), 189-217+218.

Chopra, S. and Sodhi, M. S. (2004). Managing risk to avoid: Supply-chain breakdown. *MIT Sloan Management Review, 46*(1), 53-61+87.

Christopher, M. and Holweg, M. (2011). "Supply chain 2.0": Managing supply chains in the era of turbulence. *International Journal of Physical Distribution and Logistics Management, 41*(1), 63-82.

Claassen, M. J. T., Van Weele, A. J., and Van Raaij, E. M. (2008). Performance outcomes and success factors of vendor managed inventory (VMI). *Supply Chain Management, 13*(6), 406-414.

Datta, P. P. and Christopher, M. G. (2011). Information sharing and coordination mechanisms for managing uncertainty in supply chains: A simulation study. *International Journal of Production Research, 49*(3), 765-803.

Dejonckheere, J., Disney, S. M., Lambrecht, M. R., and Towill, D. R. (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research, 147*(3), 567-590.

Delios, A., and Beamish, P. W. (1999). Geographic scope, product diversification, and the corporate performance of Japanese firms. *Strategic Management Journal, 20*(8), 711-727.

Disney, S. M. and Towill, D. R. (2003). On the bullwhip and inventory variance produced by an ordering policy. *Omega, 31*(3), 157-167.

Edwards, J. R. and Bagozzi, R. P. (2000). On the nature and direction of relationships between constructs and measures. *Psychological Methods, 5*(2), 155-174.

Embrechts, M. J. and Bennett, K. (2002). Sparse-kernel PLS for molecular drug design. *Proceedings of the Learning Workshop*, Snowbird, Utah.

Embrechts, M. J., Bress, R. A., and Kewley, R. H. (2006). Feature selection via sensitivity analysis with direct kernel PLS. *Studies in Fuzziness and Soft Computing,* 207, 447-462.

Fisher, M. L., Raman, A., and McClelland, A. S. (2000). Rocket science retailing is almost here: Are you ready? *Harvard Business Review, 78*(4), 115.

Fleischmann, M., Beullens, P., Bloemhof-Ruwaard, J. M., and Van Wassenhove, L. N. (2001). The impact of product recovery on logistics network design. *Production and Operations Management, 10*(2), 156-173.

Fleischmann, M., Bloemhof-Ruwaard, J. M., Dekker, R., Van Der Laan, E., Van Nunen, J. A. E. E., and Van Wassenhove, L. N. (1997). Quantitative models for reverse logistics: A review. *European Journal of Operational Research, 103*(1), 1-17.

Fleischmann, M., Krikke, H. R., Dekker, R., and Flapper, S. D. P. (2000). A characterization of logistics networks for product recovery. *Omega, 28*(6), 653-666.

Folan, P. and Browne, J. (2005). A review of performance measurement: Towards performance management. *Computers in Industry, 56*(7), 663-680.

Fornell, C. and Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing Research, 19* (4, Special Issue on Causal Modeling), 440-452.

Frohlich, M. T. and Westbrook, R. (2001). Arcs of integration: An international study of supply chain strategies. *Journal of Operations Management, 19*(2), 185-200.

Garvin, D. A. (1996). Competing on the eight dimensions of quality. *IEEE Engineering Management Review, 24*(1), 15-23.

Geladi, P. and Kowalski, B. R. (1986). Partial Least Squares Regression: A tutorial. *Analytica Chimica Acta, 185*(C), 1-17.

Golbraikh, A. and Tropsha, A. (2002). Beware of q2! *Journal of Molecular Graphics and Modeling, 20*(4), 269-276.

Ghoshal, S. and Bartlett, C. A. (1995). Changing the role of top management: Beyond structure to processes. *Harvard Business Review, 73*(1), 86-96.

Guide Jr., V. D. R. (2000). Production planning and control for remanufacturing: Industry practice and research needs. *Journal of Operations Management, 18*(4), 467-483.

Guide Jr., V. D. R., Jayaraman, V., and Linton, J. D. (2003). Building contingency planning for closed-loop supply chains with product recovery. *Journal of Operations Management, 21*(3), 259-279.

Gunasekaran, A. Patel, C., and Tirtiroglu, E. (2001). Performance measures and metrics in a supply chain environment. *International Journal of Operations and Production Management, 21*(1-2), 71-87.

Handfield, R. B. and Nichols, E. L. (1999). Introduction to supply chain management. *Introduction to Supply Chain Management,*

Handfield, R. B. and Bechtel, C. (2002). The role of trust and relationship structure in improving supply chain responsiveness. *Industrial Marketing Management, 31*(4), 367-382.

Hayes, R. H. and Wheelwright, S. C. (1984). Restoring our competitive edge: Competing through manufacturing. *Wiley,* New York, NY.

Helo, P. and Szekely, B. (2005). Logistics information systems: An analysis of software solutions for supply chain co-ordination. *Industrial Management and Data Systems, 105*(1), 5-18.

Hendricks, K. B., Singhal, V. R., and Stratman, J. K. (2007). The impact of enterprise systems on corporate performance: A study of ERP, SCM, and CRM system implementations. *Journal of Operations Management, 25*(1), 65-82.

Ho, L., Müller, R., Gordon, K. C., Kleinebudde, P., Pepper, M., Rades, T., *et al.* (2009). Monitoring the film coating unit operation and predicting drug dissolution using terahertz pulsed imaging. *Journal of Pharmaceutical Sciences, 98*(12), 4866-4876.

Hsieh, C., Lai, F., and Shi, W. (2006). Information orientation and its impacts on information asymmetry and e-business adoption: Evidence from China's international trading industry. *Industrial Management and Data Systems, 106*(6), 825-840.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic Management Journal, 20*(2), 195-204.

Jayaraman, V., Guide Jr., V., and Srivastava, R. (1999). A closed-loop logistics model for remanufacturing. *Journal of the Operational Research Society, 50*(5), 497-508.

Jiao, J., You, X., and Kumar, A. (2006). An agent-based framework for collaborative negotiation in the global manufacturing supply chain network. *Robotics and Computer-Integrated Manufacturing, 22*(3), 239-255.

Johnston, D. A. and Linton, J. D. (2000). Social networks and the implementation of environmental technology. *IEEE Transactions on Engineering Management, 47*(4), 465-477.

Johnston, D. A., McCutcheon, D. M., Stuart, F. I., and Kerwood, H. (2004). Effects of supplier trust on performance of cooperative supplier relationships. *Journal of Operations Management, 22*(1), 23-38.

Keim, D. A. (2002). Information visualization and visual data mining. *IEEE Transactions on Visualization and Computer Graphics, 8*(1), 1-8.

Kocabasoglu, C. and Suresh, N. C. (2006). Strategic sourcing: An empirical investigation of the concept and its practices in U.S. manufacturing firms. *Journal of Supply Chain Management, 42*(2), 4-16.

Koh, S. C. L., Demirbag, M., Bayraktar, E., Tatoglu, E., and Zaim, S. (2007). The impact of supply chain management practices on performance of SMEs. *Industrial Management and Data Systems, 107*(1), 103-124.

Kotabe, M., Martin, X., and Domoto, H. (2003). Gaining from vertical partnerships: Knowledge transfer, relationship duration, and supplier performance improvement in the U.S. and Japanese automotive industries. *Strategic Management Journal, 24*(4), 293-316.

Krumwiede, D. W. and Sheu, C. (2002). A model for reverse logistics entry by third-party providers. *Omega, 30*(5), 325-333.

Kulp, S. C., Lee, H. L. and Ofek, E. (2004). Manufacturer benefits from information integration with retail customers. *Management Science, 50*(4), 431-444.

Lambert, D. M. and Cooper, M. C. (2000). Issues in Supply Chain Management. *Industrial Marketing Management, 29*(1), 65-83.

Lattin, J. M., Carroll, J. D., and Green, P. E. (2003). Analyzing multivariate data. *Thomson Brooks/Cole*: Pacific Grove, CA.

Lee, H. L. (2004). The triple-A supply chain. *Harvard Business Review, 82*(10), 102-112.

Lee, H. L., Padmanabhan, V., and Whang, S. (1997). Information distortion in a supply chain: The bullwhip effect. *Management Science, 43*(4), 546-558.

Lee, H. L., So, K. C., and Tang, C. S. (2000). Value of information sharing in a two-level supply chain. *Management Science, 46*(5), 626-643.

Li, S., Ragu-Nathan, B., Ragu-Nathan, T. S., and Subba Rao, S. (2006). The impact of supply chain management practices on competitive advantage and organizational performance. *Omega, 34*(2), 107-124.

Li, W., Woldu, A., Araba, L., and Winstead, D. (2010). Determination of water penetration and drug concentration profiles in HPMC-based matrix tablets by near infrared chemical imaging. *Journal of Pharmaceutical Sciences, 99*(7), 3081-3088.

Liang, H., Saraf, N., Hu, Q., and Xue, Y. (2007). Assimilation of enterprise systems: The effect of institutional pressures and the mediating role of top management. *MIS Quarterly: Management Information Systems, 31*(1), 59-87.

Linton, J. D. (2004). Data analysis in a non-normal non-linear small sample size world: A Practical Guide to the use of Partial Least Squares (PLS) in the Social Sciences. Rensselaer Polytechnic Institute: Troy, NY.

Lohman, C., Fortuin, L., and Wouters, M. (2004). Designing a performance measurement system: A case study. *European Journal of Operational Research, 156*(2), 267-286.

Luco, J. M. (1999). Prediction of the Brain−Blood distribution of a large set of drugs from structurally derived descriptors using Partial Least Squares (PLS) modeling. *Journal of Chemical Information and Computer Sciences, 39*(2), 396-404.

Mantell, L. H. (1972). The systems approach and good management. an argument for the "whole" approach. *Business Horizons, 15*(5), 43-51.

Marcoulides, G. A. and Saunders, C. (2006). PLS: A silver bullet? *MIS Quarterly: Management Information Systems, 30*(2), III-IV.

Mason-Jones, R. and Towill, D. R. (1997). Information enrichment: Designing the supply chain for competitive advantage. *Supply Chain Management, 2*(4), 137-148.

Mentzer, J. T., Dewitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D. and Zacharia, Z. G. (2001). Defining supply chain management. *Journal of Business Logistics, 22*(2), 1-25.

Min, H., and Zhou, G. (2002). Supply chain modeling: Past, present and future. *Computers and Industrial Engineering, 43*(1-2), 231-249.

Norinder, U., Österberg, T., and Artursson, P. (1997). Theoretical calculation and prediction of Caco-2 cell permeability using MolSurf parameterization and PLS statistics. *Pharmaceutical Research, 14*(12), 1786-1791.

Otto, A., and Kotzab, H. (2003). Does Supply Chain Management really pay? Six perspectives to measure the performance of managing a supply chain. *European Journal of Operational Research, 144*(2), 306-320.

Pearl, J. (2000). *Causality: Models, Reasoning, and Inference,* Cambridge University Press.

Rai, A., Patnayakuni, R., and Seth, N. (2006). Firm performance impacts of digitally enabled supply chain integration capabilities. *MIS Quarterly: Management Information Systems, 30*(2), 225-246.

Ravichandran, T. and Rai, A. (2000). Quality management in systems development: An organizational system perspective. *MIS Quarterly: Management Information Systems, 24*(3), 381-410.

Reichheld, F. F., and Sasser Jr., W. E. (1990). Zero defections: Quality comes to services. *Harvard Business Review, 68*(5), 105-111.

Rosenzweig, E. D. (2009). A contingent view of e-collaboration and performance in manufacturing. *Journal of Operations Management, 27*(6), 462-478.

Sarkar, M. B., Echambadi, R. A. J., and Harrison, J. S. (2001). Alliance entrepreneurship and firm market performance. *Strategic Management Journal, 22*(6-7), 701-711.

Savaskan, R. C., Bhattacharya, S., and Van Wassenhove, L. N. (2004). Closed-loop supply chain models with product remanufacturing. *Management Science, 50*(2), 239-252.

Shafer-Peltier, K. E., Haynes, C. L., Glucksberg, M. R., and Van Duyne, R. P. (2003). Toward a glucose biosensor based on surface-enhanced Raman Scattering. *Journal of the American Chemical Society, 125*(2), 588-593.

Smith, A. D. (2005). Exploring Radio Frequency Identification technology and its impact business systems. *Information Management and Computer Security, 13*(1), 16-28.

Soliman, K. S. and Janz, B. D. (2004). An exploratory study to identify the critical factors affecting the decision to establish Internet-based inter-organizational information systems. *Information and Management, 41*(6), 697-706.

Sparling, D. (2002). Simulations and supply chains: Strategies for teaching Supply Chain Management. *Supply Chain Management, 7*(5), 334-342.

Sterman, J. D. (1989). Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management Science, 35*(3), 321-339.

Subramani, M. (2004). How do suppliers benefit from information technology use in supply chain relationships? *MIS Quarterly: Management Information Systems, 28*(1), 45-73.

Swaminathan, J. M. and Tayur, S. R. (2003). Models for supply chains in e-business. *Management Science, 49*(10), 1387-1406.

Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics, 103*(2), 451-488.

Tenenhaus, M., Vinzi, V. E., Chatelin, Y., and Lauro, C. (2005). PLS path modeling. *Computational Statistics and Data Analysis, 48*(1), 159-205.

Thissen, U., Pepers, M., Ustun, B., Melssen, W. J., and Buydens, L. M. C. (2004). Comparing support vector machines to PLS for spectral regression applications. *Chemometrics and Intelligent Laboratory Systems, 73*(2), 169-179.

Tiessen, J. H. and Linton, J. D. (2000). The JV dilemma: Cooperating and competing in joint ventures. *Canadian Journal of Administrative Sciences, 17*(3), 203-216.

Thomas, D. J. and Griffin, P. M. (1996). Coordinated Supply Chain Management. *European Journal of Operational Research, 94*(1), 1-15.

Tibben-Lembke, R. S., and Rogers, D. S. (2002). Differences between forward and reverse logistics in a retail environment. *Supply Chain Management, 7*(5), 271-282.

Van Ackere, A., Larsen, E. R., and Morecroft, J. D. W. (1993). Systems thinking and business process redesign: An application to the beer game. *European Management Journal, 11*(4), 412-423.

Vandaele, D. and Gemmel, P. (2007). Purchased business services influence downstream supply chain members. *International Journal of Service Industry Management, 18*(3), 307-321.

Wangphanich, P., Kara, S. and Kayis, B. (2010). Analysis of the bullwhip effect in multi-product, multi-stage supply chain systems – a simulation approach. *International Journal of Production Research, 48*(15), 4501-4517.

Wise, R., and Baumgartner, P. (2000). Go downstream: The new profit imperative in manufacturing. *IEEE Engineering Management Review, 28*(1), 89-96.

Wixom, B. H. and Watson, H. J. (2001). An empirical investigation of the factors affecting data warehousing success. *MIS Quarterly: Management Information Systems, 25*(1), 17-41.

Wold, H. (1974). Causal flows with latent variables. Partings of the ways in the light of NIPALS modeling. *European Economic Review, 5*(1), 67-86.

Wold, H. (1982). Soft modeling: The basic design and some extensions. *Systems under Indirect Observation, 2*, 1-54.

Wold, S. and Kowalski, B. (1984). Chemometrics: Mathematics and Statistics in Chemistry, Reidel, Dordrecht, (Editorial).

Wold, H. (1989). Introduction to the second generation of multivariate analysis. *Theoretical Empiricism,* vii-xi.

Wold, S., Sjöström, M., and Eriksson, L. (2001). PLS-regression: A basic tool of Chemometrics. *Chemometrics and Intelligent Laboratory Systems, 58*(2), 109-130.

Yoshikawa, T. and Linton, J. (2000). The applicability of North American corporate governance and investor relations practice to Japanese firms: Theoretical support and preliminary investigation. *Journal of Asian Business, 16*, 1-24.

8. Appendices

Appendix A1 – Sample Data

In this appendix, a portion of manufacturing and simulated data sets is provided for convenience to illustrate the nature of the supply chain. Because of space limitations, only the first thirty observations for the manufacturing data set (the original data has 2009 observations) and a single observation from each simulated data set – a total of twenty two observations – (each of the twenty two simulated data sets is originally comprised of thousand observations) are provided. These data sets are directly fed into *Analyze/StripMiner* and PLS *GRAPH* 3.0 software programs after making necessary preprocessing adjustments for both programs. Further discussion about data preprocessing steps is provided in Sections 4.3.1.1 (p. 44) and 4.3.2.1 (p. 49).

A1/A – Manufacturing Data set (30 Observations)

The manufacturing supply data set is made up of eight predictor variables each representing a different supply chain step and one dependent variable. The dependent variable, *Yield*, is a binary variable that keeps track of pass or fail of the product at final test. The number of observations is 2009, but Table 7 gives a snapshot of the first thirty observations.

The first line of the data file consists of alphanumeric variable names. The first column indicates the index number to track individual observations. Each individual observation (i.e. each row) corresponds to the process readings of a single product. Each process step (i.e., Steps one to eight) has one metric, thus each column (denoted by steps 1 to 8) shows the process metrics of its respective process step. As shown below, the measurements are in integer. The details about the units of these measurements are not provided by the manufacturer due to confidentiality of the data. However, this is not a problem, since we are only interested in understanding the numerical relationship between the dependent and manifest variables. Each metric is treated as a manifest variable, since we *observe* their values directly. The dependent variable, *Yield*, is a binary variable, in which "0" denotes a failure of the end product at the quality test and "1" denotes success at the quality test. Out of 2009 observations, 1330 of the products passed the quality test (representing a success rate of approximately 66.20%. Although this value seems a very low value for a technology product, this study is not interested in this ratio. This 66.20% indicates that the data of the manufacturing data set is not balanced in a 50:50 ratio for success/failure.

Table 7 - Manufacturing Data Snapshot

Observation	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Yield
1	470	349	705	587	280	320	850	697	0
2	462	353	706	588	279	314	866	697	1
3	468	347	700	584	277	316	873	709	1
4	474	348	685	566	280	313	867	699	1
5	479	340	697	579	280	314	873	709	1
6	474	346	695	575	280	311	871	708	1
7	473	344	697	578	276	320	872	717	1
8	467	340	706	589	276	313	883	724	1
9	473	345	694	575	282	315	867	704	1
10	469	350	695	574	279	319	841	683	1
11	464	356	709	585	273	317	882	723	1
12	464	343	715	597	281	325	848	693	1
13	465	333	714	594	282	311	851	690	1
14	468	348	711	593	277	316	856	696	1
15	467	347	708	588	283	307	852	693	0
16	475	336	706	584	285	312	851	684	1
17	467	339	719	600	282	309	872	701	1
18	465	342	718	600	278	319	853	708	1
19	467	329	720	601	279	306	886	727	1
20	469	340	706	588	286	310	847	684	1
21	463	348	707	588	281	318	844	686	1
22	464	338	721	601	281	311	869	705	0
23	464	353	706	585	280	314	851	701	1
24	465	351	706	589	281	310	870	710	1
25	469	353	697	578	281	320	841	683	1
26	453	354	699	582	282	306	866	702	1
27	472	350	699	582	281	318	841	686	1
28	472	340	705	585	284	309	873	711	1
29	465	346	708	589	278	316	869	706	0
30	468	335	711	591	279	309	880	719	1

A1/B – Simulated Data set

The supply chain system under consideration has 51 supply chain steps and each step has five different metrics or predictor variables. This means that every data set for both simulated data cluster one and two contains 255 (i.e., 51 x 5) measurements. Unlike the binary dependent variable in the manufacturing data set that indicates whether a product fails or passes a quality test, the dependent variable (denoted by *Yield*) of every simulated data set is a continuous variable that measures the per cent of functional final product. A continuous dependent variable is chosen in simulated data sets, since a continuous variable provides more information than a binary variable that simply indicates a pass or fail. By obtaining more information from the dependent variable and using more process steps and metrics, simulated data sets of this study represent a typical supply chain better than the data set provided by the manufacturer.

Tables 8 and 9 illustrate a single observation from each simulated data set in the first and second data cluster, respectively. Thus, twenty two observations are presented in total. These tables reveal that each simulated data set has the same structure. The first column in Tables 8 and 9 indicates process metrics of each supply chain step. Recall that each process step in a simulated data set has five metrics. The **S***k***P***m* notation refers process metric *m* (i.e., m = 1, …, 5) of supply chain step *k* (i.e., k = 1, …, 51). Consequently, Tables 8 and 9 have 255 rows corresponding to these metrics. The bottom line of both tables presents the value of the dependent variable, *Yield*. Thus, there are 256 values for each data set in these tables.

Tables 8 and 9 reveal that the dependent variable of each simulated data set varies between 60 and 90. Unlike the manufacturing data set illustrated in the previous appendix, simulated data sets include both integer and decimal numbers for measurements. However, most of the supply chain step measurements have a similar structure. When we examine Tables 8 and 9 more closely, we observe that apart from supply chain steps thirteen and fifty one, all supply chain steps have a similar approximate range of values. For example, all supply chain steps (excluding steps #13 and #51) have integer values for process metrics one, two, and five between values of zero and two thousand approximately. The process metrics three and four of these supply chain steps are decimal numbers varying between -2.00 and +2.00 approximately. Step #13 has similar range of values, but its process metrics one, two, three are decimals within -1.00 and +1.00 range, and process measurements four and five are integers between zero and 1700 approximately. Only the process metric one of Step #51 is a decimal number varying between -2.00 and +1.50. The remaining metrics are integers approximately between ten and 1650.

Table 8 - Simulated Data Cluster 1

	Cluster 1										
Step	**Data Set 0**	**Data Set 1**	**Data Set 2**	**Data Set 3**	**Data Set 4**	**Data Set 5**	**Data Set 6**	**Data Set 7**	**Data Set 8**	**Data Set 9**	**Data Set 10**
S1P1	1128	86	5	373	105	91	592	74	495	1173	374
S1P2	0.7835	-1.37043	1.842146	0.2119323	1.4919912	0.6834108	-0.236984	-0.685277	-0.644153	-1.86736	-0.8355272
S1P3	0.7011	-0.91474	-0.567839	-0.925527	-1.022244	1.1339704	0.3344061	1.4452101	2.1985414	0.860004	-0.8844185
S1P4	9	66	307	63	949	535	785	1007	134	240	156
S1P5	89	1482	634	343	1138	58	895	1505	1397	1001	447
S2P1	100	446	41	575	38	80	360	216	1217	123	21
S2P2	-2.703	1.3610762	-0.253707	-0.339914	0.6602806	-0.72933	1.0505518	-0.424189	-2.284703	1.1975876	-0.7001233
S2P3	-1.4201	-0.741477	1.0992312	1.5598397	0.6909358	0.3594349	0.8875877	2.2247551	0.6412188	-1.465039	0.81869742
S2P4	168	39	161	305	1608	41	1463	14	545	403	752
S2P5	95	151	11	130	47	1023	274	36	276	45	59
S3P1	99	437	605	231	613	129	999	871	478	650	896
S3P2	-1.3718	-0.152732	-0.751231	1.5292745	-0.702142	-0.957819	0.8732557	-1.592842	-1.194604	-0.402162	-1.0364649
S3P3	-0.8484	0.2712548	-0.902776	-0.158557	0.6280325	-0.124341	1.9420225	-0.684489	-0.496767	0.3792489	0.52919557
S3P4	32	65	150	19	842	579	1104	1073	786	1132	158
S3P5	876	203	771	676	342	51	219	595	781	98	196
S4P1	405	953	155	6	1263	101	387	168	1495	107	465
S4P2	-1.3477	1.6481103	0.4483268	1.0980408	-0.521354	-0.806247	0.1126218	-0.57362	1.3023154	0.1187543	-1.9474104
S4P3	-0.9721	-1.922807	0.8533437	-2.22626	-0.494877	-0.422833	0.1692215	0.2853729	-0.572446	1.0887717	0.73289366
S4P4	896	42	193	337	405	1519	1303	19	1102	435	132
S4P5	796	1260	757	27	115	583	3	158	669	38	647
S5P1	123	540	30	851	980	551	39	823	145	1039	421
S5P2	-0.3701	-0.028034	-0.954913	-0.167057	-0.996643	0.3814666	-1.292562	0.0778058	0.5900135	0.318273	-1.4067641
S5P3	1.4567	-0.254389	0.7402626	0.0659368	0.9956034	-0.924282	-0.259753	-0.978716	-0.759482	-0.176259	-0.852224
S5P4	651	415	59	1153	76	120	528	1191	970	102	1037
S5P5	776	1620	211	495	179	1856	22	272	453	1624	277

S6P1	598	1495	4	114	173	37	427	1164	321	600	1530
S6P2	-0.4715	0.4066336	-0.756278	0.5051162	-0.739187	1.2552031	0.805471	0.3366703	-0.481966	1.1403544	-0.4662257
S6P3	-0.0607	1.2665882	2.1113213	-0.044895	0.3025467	0.7682544	-0.25797	1.5878583	2.4788897	0.432739	-0.5435939
S6P4	61	299	402	843	857	190	625	307	834	258	183
S6P5	495	70	212	45	1876	69	183	630	611	944	612
S7P1	12	86	1319	36	340	1390	611	141	609	58	217
S7P2	-0.6437	-0.640046	-0.586404	0.5081411	-0.265879	2.0338096	-0.44333	0.1654415	-1.807547	0.2619047	-1.7708509
S7P3	-0.4005	-1.108149	-0.803313	-0.020062	-0.831315	1.6389167	0.990975	-0.236808	-0.230093	-1.088499	2.20930491
S7P4	74	149	778	261	739	844	26	382	255	1029	89
S7P5	191	130	1032	74	525	335	702	782	12	370	121
S8P1	11	701	836	1470	89	772	194	24	1413	456	583
S8P2	-2.115	0.0372208	-0.228967	2.4626181	0.4885558	0.4100902	0.549458	-0.386318	0.0537474	-0.357829	1.58268233
S8P3	0.258	-2.101311	0.2103504	-1.831198	0.77868	0.024111	1.6137516	-0.258356	-1.481712	0.1517672	-1.4225014
S8P4	1498	397	416	716	1125	69	586	996	406	1006	678
S8P5	387	155	1018	372	127	23	159	982	390	167	50
S9P1	156	470	157	298	599	425	31	30	541	360	153
S9P2	0.0319	0.2291483	0.6523847	0.6288549	-0.470898	0.5196075	-1.505775	0.4607468	1.4164633	-0.402201	0.3557784
S9P3	0.146	0.4426297	-2.296936	0.0697731	0.8750719	0.4710923	0.065553	-0.569308	-0.416882	-1.380034	0.02933627
S9P4	1110	213	153	360	769	164	455	334	420	175	522
S9P5	341	874	209	75	734	1110	754	1480	367	63	1113
S10P1	1181	13	186	323	481	813	246	434	385	1052	271
S10P2	-0.9116	2.3396008	-1.486523	0.2315927	-0.101984	-0.160656	1.6546305	-0.496333	0.0211619	0.0074708	0.58392304
S10P3	0.3589	-0.004208	-1.022361	1.5588643	-1.185963	-1.019227	-0.777933	0.698876	0.8571805	0.6189407	-0.1656624
S10P4	883	648	1185	88	1496	244	273	112	169	878	44
S10P5	380	894	670	133	338	1242	670	612	24	763	92
S11P1	911	350	458	511	63	884	151	1172	713	28	168
S11P2	-0.6278	0.8038124	-0.627567	-1.015192	-1.316676	-0.86845	0.57232	0.4637689	0.7463526	0.7141388	-0.0846196
S11P3	-1.0224	-1.386239	0.697709	-1.437693	0.2398201	0.2985404	-0.668498	-0.877923	-1.274698	0.9652982	0.21375405

S11P4	64	11	1303	746	739	1004	593	901	1911	74	1527
S11P5	279	9	557	668	312	264	100	16	907	135	600
S12P1	226	1654	706	796	30	16	278	457	891	875	613
S12P2	-0.3865	0.8192671	1.4665273	0.8091338	1.8561983	-0.451624	0.3619108	0.1837011	-0.515121	-1.624479	-0.0270586
S12P3	-0.0289	-0.795548	-0.54232	0.1010911	0.2229604	0.1955337	-0.838429	-0.06778	-0.06762	0.9656266	0.65804482
S12P4	341	871	47	122	97	82	571	946	1127	1129	218
S12P5	402	776	862	103	649	571	1140	294	1110	283	639
S13P1	167	26	560	90	196	840	554	90	110	147	244
S13P2	56	386	731	1606	269	184	564	683	312	994	397
S13P3	356	312	226	1063	210	111	1325	158	386	1887	266
S13P4	1.159	-0.961417	-0.57563	0.2349008	0.3725164	-0.548867	-0.535258	1.0548701	0.5079653	-0.129233	0.88989902
S13P5	0.7573	-0.401114	-0.648234	-0.289982	0.1130177	0.7723702	-0.280861	0.1975608	-0.106074	0.8306222	0.89283233
S14P1	418	39	155	129	352	51	1352	537	25	673	26
S14P2	-1.2575	-0.534527	0.006414	-0.92902	-0.533533	-0.885385	0.9381745	0.7905572	-0.589858	0.9919118	-1.1141321
S14P3	-0.0515	0.7202009	0.9782934	0.2697111	-0.846558	1.4562125	1.1415028	1.8117992	1.3369121	1.4216422	-1.014205
S14P4	1168	818	1348	124	133	432	511	1415	629	8	198
S14P5	369	286	264	1240	1035	105	846	123	372	125	195
S15P1	168	775	514	16	1182	404	326	41	646	1083	161
S15P2	1.4489	-0.695771	1.8424302	-0.835426	-0.439972	-2.004992	-1.29723	0.9004415	0.3030974	-1.29063	0.42123816
S15P3	-0.423	-1.115206	-0.097184	0.8007802	-1.655215	-0.712468	-0.541041	-0.267955	-1.023744	-0.188781	-0.3861492
S15P4	1623	65	1090	1928	31	540	513	1123	96	347	236
S15P5	1126	1614	271	825	431	663	616	40	1285	869	610
S16P1	1707	1948	616	844	306	411	332	924	945	320	232
S16P2	0.9952	0.8292185	-0.005943	1.3881123	-1.747431	0.1245686	1.2608413	0.4228284	-0.553492	1.6617214	-2.0424908
S16P3	-0.6784	2.0961887	0.3615262	-0.52441	2.3691978	0.437952	-1.81639	0.0789893	0.0620682	1.3618763	-1.3195194
S16P4	73	368	310	1333	179	29	1261	171	7	837	74
S16P5	344	187	668	41	339	1141	783	267	1653	130	3
S17P1	628	5	33	670	178	234	899	631	56	46	18

S17P2	0.7304	-0.921452	1.3916563	0.4950028	0.1509314	0.3879781	-0.347032	-0.298359	-0.105213	-0.736733	0.55878284
S17P3	1.2299	-0.690867	1.7426714	0.5502265	-0.131574	-3.208267	0.5417959	0.9091198	1.0881775	-0.821295	-1.3218724
S17P4	180	562	342	385	441	46	198	297	1640	118	389
S17P5	286	947	499	23	1422	50	641	453	650	983	11
S18P1	1137	1288	620	67	875	1106	606	503	399	567	214
S18P2	-0.1891	0.8158669	-1.130092	0.1690187	1.328329	-0.191496	0.9397802	0.6278705	0.1296156	0.0139176	-0.6680825
S18P3	-0.7072	0.6135453	-0.000618	-0.40594	-0.471329	-0.88454	0.8447879	1.9031169	-0.770737	-0.309573	0.14848478
S18P4	41	361	108	89	419	79	173	69	300	417	111
S18P5	507	262	732	317	361	52	570	56	1208	404	231
S19P1	183	132	1266	251	323	62	1246	86	250	377	115
S19P2	1.5554	-0.967453	0.6192742	0.3579952	-1.270952	0.6936866	-0.771554	-0.168332	-0.973155	0.1886756	-1.4922217
S19P3	-0.1204	0.3165345	-0.014795	1.1347896	0.2543183	2.2763717	1.3307407	1.5629797	0.3167886	0.6131496	-1.7238865
S19P4	96	322	753	54	493	209	508	514	69	200	346
S19P5	113	632	15	927	1561	407	268	155	207	102	88
S20P1	68	79	36	904	734	741	377	385	678	198	736
S20P2	-0.6342	-0.164257	-0.2814	-0.52191	1.3707374	-1.374214	1.5552936	0.8518255	-0.564397	0.1447129	-1.3135685
S20P3	0.1501	-0.626055	1.505878	-1.445116	1.1806088	0.8747067	-0.41763	0.6940823	-2.030821	0.5510767	-0.9473646
S20P4	1068	57	187	524	393	28	1447	797	117	883	663
S20P5	29	25	440	556	83	440	159	568	346	599	938
S21P1	88	61	115	485	548	385	787	175	7	59	395
S21P2	-0.0652	-0.239973	-1.658889	-0.65276	-1.586157	1.2598683	0.1724542	-0.056346	0.0625446	-0.63701	0.61849063
S21P3	0.3913	0.599816	-0.116324	-0.071808	-1.598337	0.4962174	1.6427592	-1.121784	-0.697274	2.5648902	1.70894534
S21P4	498	1315	1830	99	88	51	305	862	357	436	708
S21P5	298	399	593	1211	212	93	561	314	308	883	98
S22P1	1142	585	568	218	398	631	719	707	212	310	222
S22P2	-0.4666	0.7468511	0.6304185	1.5712272	1.0133587	1.2635365	1.2822843	-0.025958	0.7409608	0.357259	1.49114427
S22P3	-0.5812	-0.821849	-0.194244	1.9509946	-1.990459	-1.969327	-0.342946	-0.010633	0.6458077	-0.251766	1.88646463
S22P4	964	357	98	161	65	506	523	8	420	375	47
S22P5	1284	1727	543	379	406	205	77	621	151	844	265

S23P1	1333	237	1346	1029	351	1485	953	505	97	1572	794
S23P2	-1.3557	1.3128708	2.1768213	0.0698572	0.6653291	-0.503302	-1.012029	0.4334714	-0.030083	-1.398957	1.27324198
S23P3	0.0183	0.0566723	-0.882375	1.6156267	2.3073244	1.5752043	-1.043964	-1.426042	-0.677453	-2.22175	-0.4417787
S23P4	350	772	1026	206	884	279	206	192	1351	685	137
S23P5	444	140	447	657	924	568	44	241	134	408	298
S24P1	374	441	236	310	399	109	717	61	1207	210	23
S24P2	0.4834	0.4003538	-0.094253	-0.258209	0.0447982	0.0356409	-1.321968	0.1079657	0.1918529	1.0402461	-1.379068
S24P3	-0.1293	0.3939084	0.6713242	-1.296629	0.552027	-0.212135	1.1360212	-0.67484	-0.961713	0.2861623	-1.44559
S24P4	1446	341	104	616	176	117	980	1150	177	906	268
S24P5	332	680	82	1257	202	1323	51	754	19	998	1184
S25P1	303	46	1429	404	411	468	154	816	1758	56	667
S25P2	-0.3303	-1.466263	-9.54E-06	5.63E-01	1.45E+00	1.36E+00	1.13E+00	-1.28E+00	-4.87E-01	-7.78E-01	-1.20E+00
S25P3	0.6692	-0.525069	0.7862843	0.5006696	0.8250937	0.7502983	0.3962905	0.0503402	0.2339211	0.7159311	0.62284249
S25P4	278	489	1198	61	339	152	62	816	788	48	227
S25P5	467	311	50	262	180	139	236	3	98	933	128
S26P1	217	21	637	570	404	393	350	303	964	97	71
S26P2	-0.0506	0.8819718	1.141363	2.0152976	0.2054224	0.3558646	-0.065904	-0.488288	0.5056427	-1.873799	-0.3601872
S26P3	-1.1986	0.2169197	-0.088024	0.0585927	-0.741141	1.7264388	0.3509809	-0.254995	-1.24095	0.6965774	-0.3070736
S26P4	16	224	317	461	493	1405	34	148	304	196	947
S26P5	440	347	40	681	382	131	44	551	328	801	140
S27P1	86	137	11	344	19	1080	24	838	31	255	376
S27P2	-0.0122	-0.299867	-1.000215	-1.394831	0.2674031	0.1312875	-0.289527	-0.33007	0.616628	-0.612016	-0.3918969
S27P3	-1.7226	1.1956372	0.7206138	-0.628144	0.2892023	1.7819487	-0.643898	-2.012539	-0.122185	-1.077582	0.31015372
S27P4	294	93	69	54	80	101	161	178	1634	225	1185
S27P5	544	44	660	97	707	103	837	887	1344	55	207
S28P1	550	351	214	289	496	721	331	547	597	110	441
S28P2	-0.7785	0.7084487	0.8916215	0.7837139	0.1554395	-0.609144	0.5693876	-0.948989	-0.863979	-0.033563	1.18158233
S28P3	0.0584	1.7352018	0.3841401	-0.092565	-0.691146	1.3127829	0.1698033	1.0649724	-0.893915	1.5869464	2.07585353

S28P4	148	269	448	774	87	57	593	96	972	483	552
S28P5	414	1098	5	142	827	91	693	753	913	415	43
S29P1	713	203	949	75	714	519	220	167	609	317	84
S29P2	-1.5242	0.757315	-2.108525	-0.230672	0.9945169	-0.739146	-0.756136	0.2655808	0.6300687	-0.475706	0.17424848
S29P3	0.0138	-0.592109	-0.465828	-1.249069	-0.097605	-1.593114	-0.161075	0.1787616	0.8136127	-1.068961	0.75278519
S29P4	594	456	642	1201	138	14	1386	303	166	1903	481
S29P5	28	1548	598	319	81	1245	32	303	625	709	190
S30P1	22	514	1211	181	808	668	693	851	63	334	43
S30P2	-2.0122	-1.032141	0.5882648	-0.561857	0.8011873	-0.883568	0.3053723	-0.385966	1.2309509	0.3234817	-0.7295449
S30P3	-0.3664	-0.295909	-1.452745	0.599791	-0.28272	0.3159421	-0.960484	1.9557804	0.482418	-0.869106	0.43648335
S30P4	737	170	611	1003	1204	39	5	1499	394	365	281
S30P5	1373	841	101	888	641	203	801	61	83	6	47
S31P1	34	6	32	146	158	700	223	629	898	303	334
S31P2	0.5908	-0.041213	-0.191498	0.2392029	1.4410485	-0.386253	-1.057892	-0.391845	-2.304493	0.4223165	0.95478726
S31P3	-0.7966	0.3107029	1.2186732	0.5545135	-0.622753	1.5029095	-0.690591	0.2651927	-1.767165	-0.761386	0.09168461
S31P4	823	340	297	79	218	378	287	30	404	191	603
S31P5	628	355	43	1826	843	933	378	447	696	117	136
S32P1	441	656	594	273	262	1432	66	110	121	813	969
S32P2	0.0527	0.1256727	0.8769766	1.5815678	-2.734807	-0.431828	1.0886261	0.2419125	-0.833478	-1.986182	0.78750983
S32P3	-0.8142	-0.022443	-0.304834	-0.6077	0.1662056	0.2360932	-2.765894	0.0293714	-1.280318	-0.739297	0.05691842
S32P4	691	597	410	472	560	136	221	913	293	213	141
S32P5	409	292	756	522	1495	154	161	1262	1376	208	21
S33P1	188	369	176	145	263	686	193	545	295	1350	226
S33P2	1.0585	0.1712914	1.7034482	0.5369249	1.3842785	-0.439835	-1.022595	-0.183568	-1.636996	-0.654112	0.01621553
S33P3	-1.9562	-0.396765	-0.49163	0.6816048	-0.147451	1.2377356	-0.398696	0.0638945	0.5901742	-1.430943	1.10389624
S33P4	132	572	425	694	1506	78	17	112	242	372	952
S33P5	196	450	10	1462	112	1598	156	27	997	108	11
S34P1	344	364	936	587	218	1331	1472	499	37	697	1033

S34P2	2.1174	0.3090986	0.6593404	-1.83598	0.6165486	-1.20678	-0.729264	-0.125453	0.8123844	-1.013858	-0.0161897
S34P3	0.3726	-0.142543	-0.413916	-0.011274	0.015705	-1.243576	-2.449389	-0.597774	-0.970222	-2.573008	-0.9922018
S34P4	219	66	1084	222	18	1089	67	286	818	634	198
S34P5	633	59	341	53	301	93	27	274	950	492	502
S35P1	325	309	31	216	1345	502	433	1019	244	239	61
S35P2	-0.6874	0.3812487	-0.436282	0.8689697	-0.279129	0.4424921	0.8371484	0.3111261	0.5709987	1.8776277	2.3733581
S35P3	-1.2353	0.1539202	0.3911826	1.5227033	1.0840782	-0.311871	0.3358748	0.2448579	-1.202716	1.4355237	-0.1275953
S35P4	293	24	21	605	124	100	118	984	348	1135	790
S35P5	24	563	1076	670	986	414	1659	251	236	327	108
S36P1	171	122	430	177	63	16	90	708	630	45	84
S36P2	-1.4658	-0.143063	-0.724703	1.6533618	-0.540138	-0.311329	1.5638742	0.8175013	0.0693839	0.0499398	-0.4649806
S36P3	0.4389	0.5911554	-0.265514	3.4808935	-1.809556	-0.123453	-0.33328	1.4111317	-0.143291	0.616513	-0.1339615
S36P4	2	489	292	89	162	373	787	332	928	12	158
S36P5	368	466	471	768	1553	541	1580	1248	223	643	227
S37P1	866	851	65	71	254	188	1172	8	1018	356	26
S37P2	-1.4734	0.0890307	0.0686525	-1.822041	-0.586063	2.0708298	-1.38394	0.9857137	0.3731438	0.4461413	1.25802841
S37P3	0.6278	0.0431853	0.5671882	1.1723726	0.3111482	-1.733635	-1.044283	-0.258797	-0.390494	-0.691359	0.19300108
S37P4	633	230	908	32	1163	772	874	386	1766	279	741
S37P5	90	1215	211	810	714	275	576	301	39	1069	107
S38P1	104	274	1630	906	569	1278	1177	432	270	24	921
S38P2	-0.2432	0.4354243	-0.304171	0.395208	-1.152066	0.5771881	0.6085525	-1.286944	-1.233524	0.8962816	0.72952989
S38P3	0.3438	-0.730758	-0.497623	-1.614492	-0.633432	0.4563425	0.2465691	0.0082083	-1.227495	2.0448943	0.80912571
S38P4	453	1040	1339	678	92	1372	45	1154	59	544	1280
S38P5	1489	114	482	1283	429	165	419	725	279	8	483
S39P1	356	23	47	301	25	818	1132	483	115	184	609
S39P2	0.0647	-0.276448	-0.082608	-0.739455	1.5650382	-0.648496	0.3762017	-0.643519	1.1992248	-0.776912	-0.3922748
S39P3	2.1789	-1.557924	0.909188	-1.268354	-0.775161	0.7543067	-0.084798	0.5608437	0.6581751	-1.200633	-1.0599685
S39P4	1126	1519	148	123	1803	571	287	1198	795	489	510

S39P5	476	196	923	259	177	46	501	125	1551	165	850
S40P1	796	213	279	1226	409	2	225	13	47	438	174
S40P2	0.2838	1.5450848	-1.469306	1.8125083	1.6613028	0.7495543	-0.535523	-0.730109	0.0205357	-0.802731	0.46801012
S40P3	-3.2101	1.7960483	1.5781484	0.7848788	-0.355013	0.1103235	2.0249364	-0.356164	0.2384113	0.07333	-1.6275644
S40P4	629	185	661	353	1794	366	602	1101	273	137	1485
S40P5	150	1667	675	646	1626	753	1489	560	1357	46	1132
S41P1	300	67	243	75	280	520	75	476	1301	40	1594
S41P2	-0.312	-1.565877	-0.772363	0.7175587	0.8491899	-1.581571	1.6019953	0.9605284	1.7221752	-1.091216	-1.2219255
S41P3	0.2252	1.1451896	1.8498649	0.8203206	-0.073664	-0.868782	-2.213575	-0.734118	0.2912302	2.3321049	-0.8988726
S41P4	19	504	52	1295	10	12	225	438	419	126	655
S41P5	52	814	992	340	173	45	121	1549	130	148	144
S42P1	29	334	801	112	797	1143	902	746	442	10	212
S42P2	0.4096	1.063879	0.374967	-0.663662	0.2226462	1.3784555	-1.084929	0.1689079	-0.175795	0.2385867	0.681291
S42P3	0.8324	-0.221563	1.1689348	0.2317272	-0.142969	-0.129231	0.6926514	0.862084	0.3864545	0.8003569	0.48428378
S42P4	728	321	907	99	1520	745	89	1078	1796	172	12
S42P5	358	190	96	706	343	410	508	575	469	790	195
S43P1	257	112	997	79	198	181	104	736	62	1401	991
S43P2	0.2545	1.6160236	0.651772	2.0396337	0.0162494	0.8476197	0.0747744	-0.167746	-1.406841	0.5338959	-1.3307394
S43P3	0.1246	-0.63928	-0.563052	0.0751496	-0.698507	0.559489	-1.168622	-0.169858	0.4684607	-0.825429	-1.3930768
S43P4	41	462	130	184	541	154	1259	247	193	201	19
S43P5	667	1006	1410	621	684	1207	241	21	475	109	52
S44P1	1202	499	333	477	982	653	617	1108	583	55	18
S44P2	1.2805	-0.334535	2.3083108	0.0242763	0.3072001	-0.215277	1.0584263	-1.472457	-0.67835	0.5884096	0.55135255
S44P3	-0.7756	0.5585627	-1.05608	0.6553003	1.2131471	-1.799775	1.1754291	0.8977955	-0.927799	-0.598607	-0.1012119
S44P4	735	47	1086	10	920	908	65	13	591	548	166
S44P5	773	78	1028	240	146	214	328	262	70	477	393
S45P1	773	411	927	555	194	1407	577	1115	485	7	337
S45P2	-0.7685	0.6436327	-0.259986	-0.811298	0.7205572	-0.094485	-1.098246	-0.196529	0.988758	-0.292429	1.13883646

S45P3	-0.7443	1.0356889	0.3454543	-0.139125	0.0510379	-0.205835	0.326093	-1.521556	-0.629816	0.1879135	-1.1450182
S45P4	273	842	28	54	511	575	257	169	135	247	119
S45P5	715	199	241	441	1090	522	3	310	369	793	79
S46P1	81	279	939	208	521	717	675	168	490	419	1879
S46P2	0.8077	-0.013407	-0.795164	-0.480647	0.2226776	-0.337772	1.4071082	-1.162178	-1.119997	-0.701531	1.15947918
S46P3	-0.8944	-0.777388	0.0530791	-0.294332	0.0686192	-0.967002	-0.354349	0.3987366	0.9379233	1.4676741	-0.1606124
S46P4	1373	513	198	1165	198	415	1580	855	227	800	1162
S46P5	690	174	120	288	74	114	116	716	303	806	99
S47P1	217	326	10	942	172	687	390	37	214	284	809
S47P2	-1.5177	-0.080512	-0.310288	-1.586704	-0.294516	0.1299148	-1.019816	-0.003986	1.1994238	1.0604833	0.0915676
S47P3	1.1751	0.5746036	1.9005763	1.5553459	0.7783899	-0.086702	-0.458352	0.2350228	-0.851826	1.0811821	-0.0845008
S47P4	590	32	873	306	261	47	983	66	392	28	959
S47P5	43	235	1061	170	213	56	1211	1007	118	20	1439
S48P1	1140	75	720	223	22	1199	52	756	84	897	83
S48P2	0.5928	1.1170151	0.7236886	1.2624507	-2.249702	-0.992593	-0.484363	0.6053742	0.5267202	-0.483404	-0.1034848
S48P3	0.4719	-0.405698	0.8356697	-0.132386	0.4344965	-0.715663	1.620969	-1.408172	0.4873185	-0.022819	-1.0870338
S48P4	13	451	1752	246	157	396	772	87	841	19	218
S48P5	56	28	718	126	225	544	175	236	507	694	233
S49P1	479	31	31	1182	1265	555	201	46	555	284	240
S49P2	0.5964	-2.139754	-0.113389	0.3606372	-1.050558	-1.388916	-0.157356	-1.85737	0.9108907	0.9432325	0.51741748
S49P3	-2.0636	0.6155341	1.5262456	1.1489292	-1.757055	-2.051691	0.9567439	0.7948173	-3.113388	-1.111266	0.57227588
S49P4	1248	37	322	460	880	1355	699	233	75	149	56
S49P5	499	331	899	425	71	12	324	208	1192	28	293
S50P1	704	367	1682	1780	14	155	342	991	570	293	1757
S50P2	-0.4703	1.2903677	-1.400299	1.102817	1.5462557	0.1272854	0.5414824	-0.719401	0.4380874	-0.02759	1.62019684
S50P3	-0.2074	1.3055189	0.3887662	1.649974	-0.680949	1.2247712	-0.205019	0.5511764	1.1508813	-0.789888	-0.0451251
S50P4	1040	101	483	26	1198	1622	1003	186	10	409	85
S50P5	0.0513	0.8246646	-0.794393	0.6044304	0.9224027	1.3358422	-0.123182	-0.680445	-0.14502	0.1882941	-0.6480463

S51P1	0.2532	0.6507039	-0.958811	-0.057526	1.5194352	-1.007387	1.5399028	0.9691864	-0.220843	-1.750181	1.10983404
S51P2	24	720	212	378	1299	90	228	71	234	266	19
S51P3	93	202	436	155	182	9	82	245	550	408	622
S51P4	1357	1050	1561	12	451	156	877	236	176	1267	143
S51P5	281	10	635	605	782	991	62	876	73	937	46
Yield	85.7353	60.746855	67.896016	65.325771	73.466646	61.678741	78.260393	72.04351	62.034628	88.667859	62.3070864

Table 9 - Simulated Data Cluster 2

	Cluster 2										
Step	**Data Set 0**	**Data Set 1**	**Data Set 2**	**Data Set 3**	**Data Set 4**	**Data Set 5**	**Data Set 6**	**Data Set 7**	**Data Set 8**	**Data Set 9**	**Data Set 10**
S1P1	483	585	447	1065	574	187	335	522	32	1082	54
S1P2	-0.377365	-0.468614	0.8829891	-2.187313	-0.848539	0.5101905	1.9562827	0.4456409	0.0325141	0.3213909	0.67377724
S1P3	-0.525827	0.6175405	1.107002	0.3099604	-1.707732	-0.104656	0.1052104	-0.646868	1.1168587	1.8862927	0.51717894
S1P4	409	381	137	15	880	1020	525	123	182	226	788
S1P5	6	239	237	591	10	118	440	558	26	49	751
S2P1	655	473	628	656	189	61	468	193	14	59	512
S2P2	0.2379911	-1.133374	-0.062997	-0.472225	-0.591078	-1.824893	-0.253663	0.911472	0.1086644	1.4208075	0.34578115
S2P3	1.2076444	0.8519479	0.1628873	0.5261564	-0.199423	-0.322295	-1.615626	2.9149275	2.3791231	-0.666257	0.75536665
S2P4	23	983	874	423	873	661	374	763	115	516	24
S2P5	577	838	889	226	443	1181	938	355	157	832	1277
S3P1	758	862	49	1803	56	14	1386	1230	716	205	25
S3P2	0.4530786	0.198671	-0.776257	0.8203606	-0.386351	0.3110053	0.6530524	1.9137434	-0.616268	1.3469951	-1.2148036
S3P3	1.3244444	-1.458185	-0.420738	0.5946551	-0.080628	-1.412787	1.7286922	-0.276201	-0.04604	-0.444479	0.27156426
S3P4	144	1005	152	458	641	710	309	1365	204	909	675
S3P5	412	165	181	260	35	633	51	39	287	78	273
S4P1	221	55	1634	180	141	55	238	553	355	124	739
S4P2	-0.652342	0.5875374	0.0355765	-1.276924	0.2853213	0.1886541	1.6366709	-1.076443	0.7460346	0.8740373	-0.0851517
S4P3	1.7911662	-0.250227	-0.337681	1.2254706	0.2934736	-1.051063	0.9318387	1.2680692	0.2762575	0.0034294	0.71718136
S4P4	304	698	685	673	119	35	767	849	278	411	59
S4P5	30	490	641	35	113	935	12	606	59	1699	16
S5P1	1519	72	72	181	426	253	519	211	1828	230	645
S5P2	0.0919956	1.8384484	0.5268201	1.9397441	-1.002939	0.9102511	-0.387358	-1.232846	0.5827712	0.1654527	0.81657328
S5P3	-0.826588	0.4235478	-0.577215	-1.088057	-1.283891	1.3223336	-0.708388	0.4524405	-1.407013	-0.759732	0.38222498
S5P4	53	40	1295	125	126	695	915	167	163	736	1151
S5P5	121	1217	90	1552	797	379	319	1210	15	382	1360
S6P1	839	150	797	413	626	781	1478	583	222	65	329
S6P2	0.8491853	-0.44288	0.2781594	1.2986389	-0.673482	-0.027044	0.1421989	-0.089194	1.5413636	-0.371994	0.60800852
S6P3	1.3309557	0.8919317	0.821859	1.5579651	0.0844518	0.0412784	0.2010953	0.7628665	-2.026403	0.2331858	0.07814367
S6P4	489	383	1834	81	346	746	870	152	282	138	733

S6P5	390	698	379	637	65	25	348	1250	39	598	703
S7P1	102	798	330	98	100	416	156	74	218	1204	194
S7P2	0.5278051	-0.567547	-1.65736	-1.091871	-0.222315	0.8196368	0.028041	-0.377645	-0.770157	-0.699902	-0.2790238
S7P3	0.0067182	-1.321139	-2.004652	-0.421501	0.3379501	1.974994	-0.558644	0.7110954	-1.124669	-0.20938	-0.7003812
S7P4	433	830	31	194	864	568	997	557	18	964	844
S7P5	717	1105	656	355	1091	400	243	154	586	80	1814
S8P1	63	396	648	88	34	420	294	1738	450	1498	1176
S8P2	-1.254427	-1.533729	0.0285337	2.1275139	0.1389255	-0.900669	0.7919379	1.1304523	-0.786335	-0.298156	-0.9924471
S8P3	-1.249642	0.0637752	1.1628506	-0.356927	1.9935218	0.7973789	-0.213693	0.3095848	0.7825389	-1.258901	0.90333259
S8P4	217	408	1310	430	89	428	1839	998	1279	1049	45
S8P5	1133	208	460	1325	176	1452	849	517	1421	94	594
S9P1	725	704	1658	453	479	133	54	39	1113	965	291
S9P2	0.7840336	0.4441355	1.0668701	-0.213384	-0.136012	1.720239	-0.454489	0.6929815	-0.565685	-1.625214	-0.082786
S9P3	1.1401259	0.8114097	0.4053048	-1.109525	-0.926202	-0.192752	1.0115839	1.6224892	0.7042965	0.9986646	-2.2138838
S9P4	367	230	448	1557	1037	79	204	106	871	1162	864
S9P5	255	8	1180	196	177	131	283	40	164	678	9
S10P1	120	694	675	728	39	381	686	1484	501	1161	669
S10P2	-0.843432	-1.132117	-1.435611	-1.549346	0.3861902	-0.225689	0.2929718	-0.394642	0.4091753	-0.671013	1.10533333
S10P3	-1.105438	1.1974428	1.5409429	1.5279318	-0.944947	-0.841214	-1.004132	-1.583751	2.075936	-0.702911	-0.9943599
S10P4	549	889	960	1531	11	33	214	869	444	435	240
S10P5	165	7	84	455	104	108	180	48	1441	1248	615
S11P1	588	1609	700	75	938	1299	118	1393	1045	270	487
S11P2	0.029134	-0.283372	-0.081966	-0.939196	-0.121075	-1.60341	0.6962815	-0.220946	0.334425	0.7051447	1.15822613
S11P3	0.3332121	-0.738403	-0.098589	-0.106475	-0.350049	1.0010642	2.0189739	-0.314334	-0.404453	1.1156797	1.21872284
S11P4	583	741	611	363	5	573	1373	420	643	142	456
S11P5	272	566	630	169	56	273	118	395	97	1467	1252
S12P1	266	130	708	245	592	288	495	548	55	76	56
S12P2	1.6030034	-0.55939	0.3658397	-1.025483	0.2549543	0.0023229	-0.949986	1.0407787	-0.844338	-0.654386	-1.8514868
S12P3	-0.178933	0.2949944	0.5900516	-0.806122	1.8233035	0.1847593	-0.610841	0.7154479	-1.131629	1.3397937	0.14252024
S12P4	226	1139	185	62	63	131	198	351	504	504	1106
S12P5	162	904	166	51	1623	395	527	633	514	708	1452
S13P1	780	1690	478	1098	481	1020	1035	966	507	138	907
S13P2	1173	254	1546	281	1230	1460	42	1881	7	160	399

S13P3	1064	42	436	727	298	975	622	615	310	34	901
S13P4	0.642758	0.0649481	-0.429095	1.3972071	0.4610453	0.5560154	0.9804152	0.1030374	-0.076406	-0.744786	-1.0594605
S13P5	-0.832105	-0.622036	-0.121327	-1.264644	0.2725402	-0.58784	-1.504128	-0.479216	0.514827	-1.707197	0.34816469
S14P1	116	957	331	109	19	216	156	1008	842	1369	60
S14P2	-0.645131	1.7103765	-0.23238	0.5644626	-0.246673	0.4271892	-0.480199	0.1591742	-0.923997	0.4674448	1.3912243
S14P3	1.9400576	0.0372122	0.8576839	0.0902113	0.6056095	-0.137487	0.4436263	-1.103131	1.136557	-0.16716	0.44539139
S14P4	367	224	1420	417	409	736	492	280	1078	281	1086
S14P5	882	48	318	1102	297	1528	505	18	129	456	797
S15P1	63	827	66	615	1037	166	350	1029	306	552	129
S15P2	0.0989856	0.3333288	-1.022755	-0.204357	-0.793373	-1.36424	-1.554163	-0.463544	-0.377403	-1.131341	-0.9511922
S15P3	0.4843583	0.337058	-1.325248	1.7860434	0.1718665	-0.873857	-1.372933	0.6839529	-2.026471	-0.520374	1.33543699
S15P4	239	28	68	414	744	565	76	125	227	70	154
S15P5	156	41	493	343	7	106	104	217	160	376	1036
S16P1	824	20	749	53	496	1290	1188	1501	154	820	42
S16P2	-1.035379	0.2953084	1.2787934	-0.785914	0.5912369	-0.583984	1.4963583	-0.241704	0.5882739	-0.477722	-0.6342672
S16P3	2.1312047	0.4071376	0.9446261	-1.314489	2.0759054	-0.425893	0.7554863	0.0482117	-1.334573	-0.244506	0.56494008
S16P4	115	415	335	183	1424	726	236	1024	19	18	54
S16P5	1081	329	1517	259	842	221	1104	304	61	187	88
S17P1	469	168	56	367	1150	702	956	117	22	1077	421
S17P2	0.6164598	-1.056617	-0.462959	0.229544	1.1352937	0.3606505	0.0363303	1.1206769	-2.535802	-0.053426	-0.9007024
S17P3	-0.530208	-1.99642	1.6904196	-1.170472	-1.306833	-1.406525	-0.994637	-0.369839	-1.432597	1.7506162	-1.8002894
S17P4	310	51	902	590	15	365	86	52	38	431	350
S17P5	249	1799	39	139	823	564	220	45	1204	295	242
S18P1	223	746	910	1550	185	355	354	95	791	96	1585
S18P2	0.7230937	0.3963054	-1.29306	0.0211287	0.8064573	0.0532838	0.2112753	-0.517517	-1.449854	-0.536246	0.19078133
S18P3	0.1705134	-0.637505	0.3565661	1.2338193	0.3377784	0.3607291	-0.609465	3.0476261	-0.070823	0.0145814	0.75256372
S18P4	183	384	894	1456	101	745	1749	148	225	128	328
S18P5	298	593	65	137	365	685	521	5	394	1163	1699
S19P1	1100	567	194	77	44	955	1562	1019	304	48	333
S19P2	-0.806194	-0.665277	2.0909935	0.0446541	-1.068625	0.1008966	0.6407073	1.8805234	0.8621448	1.4200689	-0.5339407
S19P3	-0.670651	-0.949823	-0.627431	0.6703989	0.3525575	-0.702473	-1.130922	-0.436921	-1.317453	0.1206191	0.69843572
S19P4	57	249	86	104	671	589	756	745	908	150	448
S19P5	556	35	962	373	1199	648	216	1153	1709	70	439

S20P1	782	832	130	1103	868	351	241	654	18	1035	1092
S20P2	-1.028113	-1.387975	0.3724922	0.5372628	0.6534579	-0.056795	-0.496995	-0.447102	-0.121763	0.0372531	1.00808454
S20P3	-0.211201	0.7564932	0.4661348	1.3828471	-0.034215	1.5965767	1.7213381	-0.785364	-0.024066	0.6064545	1.66192786
S20P4	225	528	157	49	946	1022	88	469	1222	175	72
S20P5	660	577	442	147	993	250	45	960	377	408	172
S21P1	1070	115	84	615	344	297	313	277	697	626	294
S21P2	2.0389244	-0.2741	0.5603736	-0.948296	1.2957971	0.1518068	-0.559866	-1.441618	-0.59234	0.5132644	-0.4036242
S21P3	0.1976414	1.6756286	0.5234849	0.3425973	0.0428927	0.0259462	-0.465347	-0.564434	-1.061453	1.4338964	-0.1423517
S21P4	689	321	1375	1360	76	84	1691	498	460	472	538
S21P5	859	44	572	319	22	176	848	709	326	185	84
S22P1	31	19	144	401	571	130	23	355	86	704	705
S22P2	0.2913546	1.21952	2.4170761	0.7823308	0.2186044	1.5076563	1.9419944	0.2750339	0.2576995	1.1195502	-0.0708683
S22P3	-1.907912	0.7623031	-0.03004	1.3417106	-0.115083	1.0978939	-0.531781	-1.152126	0.1169147	-0.069923	0.00193445
S22P4	1757	875	175	860	460	80	264	296	192	103	35
S22P5	457	169	1232	657	524	37	354	446	113	1334	272
S23P1	105	850	147	471	192	564	316	592	8	154	296
S23P2	-1.304702	2.2992445	1.6381966	0.0157018	1.0445575	-0.085672	-0.077969	0.8989247	-1.401129	-0.603553	2.40545557
S23P3	0.4316104	0.2470977	1.3248134	-0.340495	1.1477464	-2.360759	-0.689872	0.7732816	1.1494773	1.986774	-0.3019824
S23P4	111	308	30	627	190	465	130	221	11	718	321
S23P5	1179	722	201	84	57	141	81	109	536	146	1257
S24P1	495	48	1551	1086	464	175	547	375	254	322	810
S24P2	-2.647716	0.0158553	-1.002657	0.0133316	-0.782811	0.9541906	0.6949336	-0.383304	0.4470039	-1.07564	1.6203586
S24P3	0.1967555	-0.432461	0.1413098	0.1755398	-1.152732	-1.67998	-0.053594	-1.044943	-0.357821	1.1904952	-0.4236782
S24P4	418	1135	126	965	461	1110	1277	125	968	1408	902
S24P5	581	17	455	321	162	42	392	905	376	820	1099
S25P1	1346	752	354	1371	633	15	678	55	453	20	404
S25P2	-1.484117	-0.855289	4.99E-02	7.80E-01	-3.85E-01	1.39E+00	-4.44E-01	3.05E-01	-4.27E-01	-9.43E-01	-1.57E-01
S25P3	1.2544343	2.329525	1.1155685	1.3985343	0.7337088	-0.298725	-0.589306	0.3274643	-0.148212	0.354	-0.5276087
S25P4	237	76	102	1335	510	32	409	278	206	249	909
S25P5	191	703	869	254	296	947	456	333	90	427	99
S26P1	1681	413	772	599	954	62	1278	123	76	305	65
S26P2	0.3155946	-0.404294	-0.022591	0.7131651	-0.761341	2.3866456	1.0986309	0.6698216	0.2956924	0.0201754	-2.0579133
S26P3	0.1296477	0.1520461	-1.753724	-0.624578	0.1050962	0.1695228	-0.308669	-1.263008	1.5971098	-1.760287	-0.2906747

S26P4	1156	121	934	1248	1193	375	491	1397	613	108	233
S26P5	149	339	437	669	545	165	182	243	56	513	249
S27P1	299	18	48	191	586	154	692	1457	483	12	1201
S27P2	-0.386301	0.3217055	0.148356	-0.166291	0.5562619	0.8122876	0.7407802	-0.057593	1.6167561	0.1496316	0.54345622
S27P3	-0.141412	-0.141097	0.2621812	-0.631723	-1.240112	-0.996765	0.8355239	-1.092182	1.1698562	0.0387571	0.5116501
S27P4	764	347	1406	6	138	3	163	703	120	24	256
S27P5	214	835	79	327	335	1853	1089	11	142	880	281
S28P1	1087	704	649	479	965	394	158	928	410	19	314
S28P2	-0.464086	-1.424525	0.428235	-0.161042	0.8776091	0.2106522	1.4461465	0.2574086	0.5736925	1.0855926	-0.4211025
S28P3	-0.703485	1.768213	2.3645959	0.4898182	-0.017964	0.0013575	-2.187163	0.067368	-0.679859	-0.785816	-1.5975404
S28P4	195	867	161	1439	626	395	7	978	158	762	582
S28P5	254	73	130	239	109	113	95	720	154	1258	159
S29P1	454	1216	705	299	402	1652	646	52	170	5	114
S29P2	-0.427507	-2.192094	1.4076066	-0.505714	0.5869453	-1.14479	0.7849867	0.9792461	0.8408727	-0.100289	0.05614383
S29P3	-1.615756	-0.906567	-0.868444	0.1202801	0.6038983	-1.042385	1.0122552	-0.511557	-0.28941	-0.402487	-0.0099233
S29P4	147	283	231	246	207	70	905	535	7	644	557
S29P5	484	1037	352	353	1792	169	335	794	592	741	215
S30P1	129	434	151	1749	942	390	1089	451	161	1119	1869
S30P2	-1.797954	-0.831099	-0.785887	-0.722596	-1.694815	0.1211131	-0.1363	1.2058316	1.5085266	-0.168271	0.26049168
S30P3	2.645509	0.9793318	-0.032511	-1.321272	-0.076491	-0.008145	-0.929648	1.1669061	-0.248337	0.6137034	0.41898718
S30P4	564	560	10	401	6	479	480	61	416	70	939
S30P5	201	784	1163	314	355	225	73	1103	222	179	456
S31P1	124	642	119	500	321	925	699	1049	592	1832	915
S31P2	-0.226855	0.2625264	1.4127314	-0.254141	-0.768375	1.2880079	1.2792213	-2.318815	0.0586544	-0.086238	2.12222935
S31P3	-0.699907	-2.61362	0.3101852	0.160861	-0.107368	-0.286047	0.3919296	1.3483568	0.1276284	0.4308245	0.48893762
S31P4	4	503	106	177	201	1448	1007	548	888	1416	474
S31P5	1465	127	70	14	499	151	89	9	259	1142	465
S32P1	82	823	701	156	1534	907	529	976	1163	249	1138
S32P2	1.5544511	-0.201433	0.7018515	0.0071511	0.7858979	0.1073655	-1.318088	1.2978993	-1.026532	0.4109559	-2.0289613
S32P3	-0.265708	0.1034867	-0.642447	-1.129198	1.146531	-1.110818	-0.393637	-0.989704	0.5473271	-1.302834	-0.6306225
S32P4	10	544	523	1698	479	101	542	228	312	1118	178
S32P5	747	239	44	1110	37	234	149	53	1146	21	1099
S33P1	876	384	173	242	1812	636	1580	153	13	919	88

S33P2	-0.302262	0.7480464	0.0312186	1.0747347	0.2128729	3.2506198	0.7982822	0.3848862	0.3669223	-0.228413	-0.7388973
S33P3	0.8059212	-2.260731	0.084967	0.2180112	-0.275527	0.0176019	-0.391888	0.9803747	-0.321632	-0.707309	0.09655623
S33P4	1567	1089	91	713	836	550	664	366	884	307	1162
S33P5	826	11	30	324	182	96	561	185	573	398	571
S34P1	636	1054	1367	75	830	320	102	231	893	365	1039
S34P2	-0.403774	0.4473131	0.7055648	-1.455268	0.0730142	0.1717858	-1.924345	-1.894059	-2.039717	-1.705636	-0.9279472
S34P3	0.2116354	0.8478057	0.2909281	0.1320396	-0.098763	-0.050522	0.7188736	0.3044178	0.364321	0.1661043	1.16782773
S34P4	223	198	587	274	1160	77	334	188	59	14	214
S34P5	603	72	169	1244	1179	1367	1324	795	1204	351	68
S35P1	1198	201	39	1152	435	193	396	1861	287	740	60
S35P2	-0.797821	-1.604999	-0.117878	1.0280188	-0.487604	-0.05448	0.4361156	0.3522383	0.8401973	-1.005158	-0.7834501
S35P3	1.4724692	0.0494288	-0.156554	-1.089173	-0.081983	-1.122607	0.3893158	-1.400121	-0.09144	-0.509117	0.45605688
S35P4	72	495	320	1176	943	103	412	325	1218	672	454
S35P5	859	514	16	93	288	616	121	741	228	603	321
S36P1	491	412	72	388	549	847	256	563	358	47	467
S36P2	0.2444794	1.1398922	0.4673362	1.5658489	-1.510636	1.4643763	-1.027303	-1.291607	-0.46195	0.0780392	0.8785066
S36P3	-0.565184	-1.177181	0.2033424	-0.584229	0.7233651	1.7896873	1.7691929	-1.656063	-1.440273	0.0233127	-0.3975087
S36P4	49	101	326	64	744	71	711	1653	211	106	58
S36P5	549	253	102	360	362	981	150	752	416	1265	686
S37P1	202	432	49	1115	27	194	1633	779	281	247	651
S37P2	-1.500768	-1.091319	-1.867972	0.2123579	0.1153255	0.9294343	0.2159727	0.3614661	-0.399504	0.7303027	1.09999072
S37P3	-0.95343	1.9530148	-1.19073	-0.005433	0.368982	0.1199499	-1.327319	0.4392948	-0.177459	-1.133481	-0.9952571
S37P4	16	374	1086	741	546	11	1218	1407	222	30	483
S37P5	170	43	518	866	1219	880	47	216	12	862	159
S38P1	313	252	358	1093	519	669	104	280	220	126	466
S38P2	-0.331315	1.9858385	0.2674617	0.4309071	-1.220501	0.3631648	1.237772	-0.426838	-1.004492	-0.22892	-1.484436
S38P3	0.8497378	0.5091261	-0.136122	1.6153674	1.1818399	1.0315414	-0.003199	-0.250176	0.0664575	2.0898523	-1.028224
S38P4	53	251	285	540	343	432	619	869	1185	286	212
S38P5	443	645	4	909	295	858	334	390	966	42	68
S39P1	1509	981	85	36	385	366	325	181	193	24	1015
S39P2	1.0742689	0.1266007	-1.310377	-0.76607	0.1915659	0.2318394	-0.072071	-1.607301	0.6803209	-0.061104	-1.294824
S39P3	0.5932174	-1.757607	0.3842044	1.3463816	-0.96158	-0.273848	-1.445759	-1.748982	-1.078954	-0.600591	0.14499974
S39P4	24	202	1712	853	104	832	627	121	1090	145	341

S39P5	1250	6	36	474	1073	276	123	22	295	49	380
S40P1	110	690	1375	76	175	491	1238	565	400	232	790
S40P2	1.3974199	0.1180634	-1.918866	1.9420238	-0.627855	-0.259209	-0.359569	1.4777295	1.4381168	1.0419845	-0.1098493
S40P3	1.121328	1.002671	0.2331743	-0.447827	-0.94286	-1.497099	1.0754016	-0.056068	1.4697212	2.0553775	-0.0855519
S40P4	124	469	394	297	712	304	31	561	1170	108	372
S40P5	946	29	411	168	128	696	1760	873	260	487	666
S41P1	11	303	161	133	109	181	27	23	43	822	192
S41P2	-1.170099	1.1047372	-2.445696	0.88379	-0.728425	0.6834235	-1.78352	-0.33597	1.5764298	0.4153116	0.19571169
S41P3	0.4493137	-0.276937	-0.962804	0.6630055	0.4429359	0.6603624	-0.129189	-0.605225	0.5072156	-0.829631	1.4268128
S41P4	1450	197	737	1404	13	861	532	313	858	491	19
S41P5	1322	1419	211	675	689	780	506	651	107	1018	395
S42P1	631	473	11	51	553	1028	238	535	457	16	18
S42P2	-0.030069	-1.048199	0.4247603	-0.731494	-1.215983	-0.370916	0.8725048	-1.611058	0.4641977	-0.309325	-0.3022157
S42P3	-0.370033	0.9301682	0.8001931	-0.219738	1.0277748	0.9392094	-0.325393	0.7697372	0.8080446	0.5438746	1.0275182
S42P4	249	1065	1409	39	347	22	479	430	55	752	205
S42P5	780	238	371	308	211	1759	1487	530	570	61	386
S43P1	1455	93	380	756	29	106	94	137	510	356	800
S43P2	-0.743553	0.6895986	-0.013737	0.2361719	0.2593869	1.0389362	0.7083916	1.6839471	2.1180594	0.2143297	-0.4537162
S43P3	0.8057398	-0.334429	1.0268544	0.2916446	-0.540363	-0.587404	-1.556063	-0.070781	0.6823505	-1.017366	-0.4865875
S43P4	291	646	1164	4	844	145	7	1394	334	1415	56
S43P5	245	851	946	1151	428	225	80	796	213	3	214
S44P1	419	552	616	280	201	823	448	74	76	976	584
S44P2	-0.358351	-0.047156	-0.060662	1.0765895	0.8547151	-0.793392	0.3063152	1.0358819	-0.484865	-0.641316	-1.048646
S44P3	-0.547749	0.3249928	-0.031849	0.5094794	-1.062401	0.2279069	0.6100951	0.6232624	0.0237523	0.0307221	-1.8150769
S44P4	1158	382	856	22	69	766	610	104	516	205	170
S44P5	138	383	46	838	369	7	334	185	203	690	938
S45P1	930	19	80	748	165	886	563	237	322	523	791
S45P2	-1.497412	-2.232386	0.6538994	-0.796915	0.2810476	1.2276958	1.3536238	-0.483172	0.2913761	-0.096365	0.50760352
S45P3	0.6976342	-1.660154	-0.002778	1.0853252	-1.326761	-0.87388	0.3676253	-1.022815	-1.238539	-2.190876	-0.2860993
S45P4	95	1286	305	819	566	36	816	26	91	1278	148
S45P5	882	1753	1477	1224	386	163	54	129	1399	169	879
S46P1	568	64	261	926	32	512	147	410	358	761	176
S46P2	-0.149886	-1.789315	-0.719179	0.1389963	0.6166633	0.5067034	1.5915453	1.3554247	0.2086968	-0.071751	0.19790547

S46P3	0.79692	-1.556175	1.445225	-1.058055	-0.07936	-0.384475	0.43169	0.4616008	-1.874539	-0.155382	0.80348307
S46P4	122	1173	13	80	767	42	747	793	74	206	211
S46P5	356	1168	386	867	895	892	53	508	65	37	27
S47P1	553	57	42	94	464	892	1266	11	1291	1183	521
S47P2	-0.450663	0.3517828	-0.831783	-0.875178	1.2129853	-0.905012	-0.269641	-1.067699	-1.020225	0.1859488	-1.3964002
S47P3	0.7895021	-0.134404	-0.77927	-0.277338	-0.688716	0.1263915	0.6741161	0.0221488	-0.225583	0.2429002	0.92488994
S47P4	1537	843	137	475	574	57	1256	562	61	66	841
S47P5	654	712	12	63	24	10	91	185	123	55	23
S48P1	86	161	583	47	136	604	1026	541	1554	414	1026
S48P2	-0.767393	0.7830597	-3.211454	0.0332242	-2.598986	0.7986856	1.781147	0.9884683	0.2191504	-0.616534	-0.7676149
S48P3	-0.16857	-0.418873	0.4944447	0.680971	0.3139904	0.0703149	-0.335901	1.673345	-0.026758	-0.212921	0.11831765
S48P4	504	1099	349	1654	407	89	35	261	82	343	130
S48P5	276	1227	172	653	230	124	1150	261	169	838	482
S49P1	1116	363	202	1158	13	1341	104	17	171	811	159
S49P2	0.9844694	1.666628	-0.421851	-1.8544	0.8632055	-1.256883	-0.891895	-1.638051	1.1249441	-0.362943	-1.2161197
S49P3	-0.042456	1.8609136	0.7539457	1.673694	-0.280773	0.5998993	-1.753492	-1.335898	-1.288588	1.5339298	0.85261512
S49P4	157	1335	302	345	216	205	479	958	632	121	435
S49P5	813	86	298	873	615	1118	300	356	334	852	667
S50P1	108	120	1307	1184	709	842	20	170	724	1209	1051
S50P2	-0.557047	-0.445576	0.3633647	0.2531385	-1.373695	-0.837193	-0.406468	0.6590574	2.3458975	0.481995	0.57623271
S50P3	1.1595035	0.1801133	0.4688275	0.1252707	0.2036235	0.5176733	1.6642529	0.6540473	0.8927296	0.1455452	-1.7177191
S50P4	226	150	82	904	636	1421	881	27	568	280	825
S50P5	0.5625301	-1.243165	0.3757579	0.5185579	0.8588879	-0.027675	0.0402712	-0.498438	0.7277026	-0.369493	1.67724049
S51P1	1.2942999	-0.405805	-1.28138	-1.743978	-2.049477	0.0252096	1.6623737	0.9795326	-0.366509	-0.791604	-0.4093096
S51P2	491	337	1170	150	622	635	519	347	238	141	73
S51P3	29	1053	407	815	501	132	91	847	158	485	337
S51P4	1461	614	405	796	29	266	1470	252	183	22	177
S51P5	163	445	180	281	572	132	202	287	429	147	563
Yield	89.7676	81.995067	66.695142	75.032406	76.151954	80.156882	80.606791	75.440835	72.279359	67.876873	80.7747989

A1/C – Range of Values for Supply Chain Step Measurements

In this appendix, the range of measurement values for both manufacturing and simulated data sets are given. Theses ranges give an indication about the nature of each data set. Recall that the manufacturing data set has eight metrics (i.e. 8 supply chain steps x 1 metric/step = 8 measurements in total) and each simulated data set has 255 measurements in total (i.e. 51 supply chain steps x 5 metric/step = 255 measurements in total). In addition, the range of values for the dependent variable, Yield, is given for both the manufacturing and simulated data sets. Included in this appendix are: (A1/C1) range of values for the manufacturing data set; (A1/C2A) range of values for the first simulated data cluster (Data sets 0 to 5); (A1/C2B) range of values for the first simulated data cluster (Data sets 6 to 10); (A1/C3A) range of values for the second simulated data cluster (Data sets 0 to 5); and (A1/C3B) range of values for the second data cluster (Data sets 6 to 10).

A1/C1 – Range of Values for the Manufacturing Data Set

In this section the minimum and maximum values for each supply chain step of the manufacturing data set are presented. This range is based on all 2009 observations of the manufacturing data set. Since the dependent variable of the manufacturing data is a binary variable (0: fail at the quality test, 1: success at the quality test), the minimum value is zero and the maximum value is one for the *Yield*. Table 10 reveals that the range of values for the first, fourth, and fifth supply chain steps is relatively narrow. However, the range of values for the second, third, sixth, seventh, and eight steps are wider. One should also note that the measurement values of the manufacturing data are integer numbers. Although, a number of values are negative, most of the measurements are positive integers. As mentioned previously, the units of these measurements are not provided by the manufacturer due to confidentially of the data. However, this does not pose a problem since we are only interested in the numerical relationship between the measurement values and the dependent variable.

Table 10 - Manufacturing Data Range of Values

	Step 1	Step 2	Step 3	Step 4	Step 5	Step 6	Step 7	Step 8	Yield
Minimum	337	-9522	670	547	129	170	762	161	0
Maximum	479	815	3699	671	310	884	3052	872	1

A1/C2A – Range of Values for the Simulated Data Set (Cluster 1: Data Sets 0 – 5)

In this section the minimum and maximum values for each supply chain step of the first simulated data cluster are presented. Due to space limitations only the values from data sets zero to five are given (the remaining data sets six to ten of the first simulated data cluster are provided in the next appendix – A1/C2B). This range is based on all thousand observations of each manufacturing data set.

The range of the dependent variable of each simulated data set is between 60 and 90. This range is provided at the bottom line of Tables 11 and 12. Unlike the manufacturing data set, simulated data sets include both integer and decimal numbers for measurements. However, most of the supply chain step measurements have a similar range. Table 12 reveals that apart from supply chain steps thirteen and fifty one, all supply chain steps have a similar approximate range of values. All supply chain steps (excluding steps #13 and #51) have integer values for process metrics one, two, and five between values of zero and two thousand (Table 11). The process metrics three and four of these supply chain steps have decimal values between -4.25 and +4.25 approximately. Step #13 has similar range of values, but its process metrics one, two, three are decimals within -4.00 and +4.25 range, and process measurements four and five are integers between zero and two thousand approximately. Only the process metric one of Step #51 is a decimal between a range of -4.00 and +3.75. The remaining metrics are integers approximately between zero and two thousand. The details are provided in Table 11 as follows:

Table 11 - Range of Values Summary (Cluster 1)

	Process Measurement	Type	Minimum	Maximum
All Supply Chain Steps (excluding Step #13 and #51)	1	Integer	0	2000
	2	Integer	0	2000
	3	Decimal	-4.25	4.25
	4	Decimal	-4.25	4.25
	5	Integer	0	2000
Supply Chain Step #13	1	Integer	0	1450
	2	Integer	0	1800
	3	Integer	0	1950
	4	Decimal	-4	4.25
	5	Decimal	-3.75	3.75
Supply Chain Step #51	1	Integer	-4	3.75
	2	Integer	0	1700
	3	Decimal	0	1350
	4	Decimal	0	2000
	5	Integer	0	1600
Yield		Decimal	60	90

Table 12 - Simulated Data Range of Values (Cluster 1: Data Sets 0 - 5)

		Cluster 1											
Step	**Measure**	**Data Set 0**		**Data Set 1**		**Data Set 2**		**Data Set 3**		**Data Set 4**		**Data Set 5**	
		Min	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**	**Min**	**Max**
1	**1**	9	1828	8	755	2	192	10	1315	2	158	1	188
	2	-2.8705	4.2823	-3.73368	3.00266	-3.83901	2.930572	-3.31021	3.332418	-3.39389	2.87537	-3.23793	3.237826
	3	-3.4713	3.1702	-3.01851	2.950803	-3.08391	3.276471	-2.96848	2.844888	-3.55766	3.078343	-2.85595	3.198502
	4	3	17	11	1869	1	1626	3	485	6	1762	3	1677
	5	1	1326	10	1498	6	746	0	629	2	1226	4	1214
2	**1**	7	284	5	1519	3	47	9	1198	7	49	3	544
	2	-3.1678	2.876	-3.52283	3.764243	-3.01306	3.612469	-3.14288	3.756968	-3.60034	2.792616	-3.46443	4.296153
	3	-3.2427	2.5236	-3.16326	2.837689	-3.31078	3.543285	-3.3609	3.063688	-3.03067	2.927233	-3.72321	3.824427
	4	1	380	6	302	2	677	7	918	2	1653	9	744
	5	7	613	0	721	6	77	10	156	2	900	2	1043
3	**1**	9	115	3	1148	3	1367	1	588	5	1949	5	839
	2	-3.2276	4.0562	-2.79825	3.425612	-2.77473	3.011159	-3.37093	3.352182	-2.69267	3.633711	-3.31221	3.715377
	3	-3.4897	2.9606	-3.43706	3.387944	-2.97074	3.37532	-3.04736	2.981722	-2.659	3.555135	-3.0933	3.440249
	4	3	222	14	1151	4	436	6	29	4	1750	10	1670
	5	7	1614	7	934	4	916	5	1185	9	1368	7	736
4	**1**	1	641	5	1256	7	508	5	1673	3	1682	6	433
	2	-3.2785	3.0639	-2.90513	3.157792	-2.78075	2.83588	-3.6256	3.846084	-2.76625	3.404556	-2.84769	3.302328
	3	-3.5083	3.2022	-3.30002	2.820522	-3.21028	3.413904	-2.99192	3.292748	-3.17638	4.079889	-3.20522	3.721754
	4	10	1378	4	440	6	346	7	910	5	467	14	1718
	5	1	1027	4	1434	8	1429	0	874	8	1766	6	716
5	**1**	6	148	6	635	6	426	5	1009	7	1109	0	731
	2	-3.5224	3.1143	-2.92045	2.889168	-3.02389	3.300374	-3.14606	4.162019	-3.65198	3.393903	-2.7959	2.917074
	3	-4.0614	3.5267	-3.94094	3.286837	-3.49876	3.383169	-3.03207	3.170984	-3.38539	2.868817	-3.13731	3.142182
	4	9	1529	2	1337	6	77	11	1682	5	1328	7	804

	5	10	1583	11	1688	5	1045	0	1424	7	447	7	1961
6	1	7	956	10	1572	4	89	0	163	3	183	10	191
	2	-3.0341	3.1613	-3.45943	3.210981	-3.35268	3.754159	-3.05474	2.875813	-3.41145	4.101041	-3.00225	2.655317
	3	-2.8754	2.9829	-3.60345	3.49939	-2.9233	3.182158	-3.16002	3.192865	-3.5553	2.628775	-4.38559	3.252771
	4	5	70	10	442	1	409	1	918	1	1235	0	1206
	5	10	1415	5	168	5	282	0	227	5	1970	5	546
7	1	4	79	12	873	7	1495	10	1213	9	1241	6	1818
	2	-3.1299	2.9043	-3.28031	2.658847	-3.05345	3.407073	-2.96092	3.646668	-3.21479	2.943124	-3.22234	3.38064
	3	-2.6769	2.8608	-3.68365	2.831324	-4.07504	2.95096	-2.81983	4.186393	-3.42812	2.786374	-3.00986	3.442875
	4	3	117	12	1489	7	1910	2	1601	7	1717	12	1124
	5	7	396	8	189	6	1860	6	271	3	1433	2	770
8	1	8	17	8	1158	13	1996	12	1696	0	401	9	1041
	2	-3.0042	3.1232	-3.09344	2.972027	-3.72081	3.309512	-2.90403	2.723344	-3.5985	3.212053	-2.94925	2.920434
	3	-3.0692	3.3542	-3.61859	3.586658	-3.23414	3.736216	-3.00521	3.729309	-2.9236	3.0995	-3.42116	3.471327
	4	8	1963	10	1333	3	1620	9	804	8	1717	3	72
	5	1	563	6	797	4	1274	10	876	4	556	6	696
9	1	10	1588	1	819	6	203	1	764	7	1788	7	1596
	2	-3.1738	4.2803	-2.7726	3.90271	-3.53325	2.665502	-3.68908	2.781969	-3.10941	3.010279	-2.67217	2.870721
	3	-3.1146	3.467	-2.99632	3.3117	-3.39284	3.48024	-2.9529	2.599327	-3.24578	2.837423	-3.37792	3.359619
	4	11	1609	1	536	5	1926	2	443	16	1561	2	1910
	5	4	381	8	1279	5	1855	5	374	1	1541	0	1152
10	1	9	1868	9	197	8	1962	10	1132	8	496	7	1042
	2	-3.4856	3.1918	-4.11043	3.233392	-2.84279	3.188849	-3.12259	3.091359	-3.32358	3.707399	-2.95457	2.952894
	3	-3.4578	3.2065	-3.62266	2.775426	-3.01878	3.112497	-2.74597	2.863668	-3.08443	3.696726	-2.89254	2.919761
	4	6	1666	0	1015	2	1686	5	1577	7	1604	9	461
	5	11	1997	8	915	9	1368	2	318	4	396	9	1301
11	1	12	1239	4	636	11	741	9	1133	4	73	11	1156
	2	-2.9154	3.0045	-3.19089	3.396485	-3.75794	2.834857	-3.08401	3.075491	-3.57898	3.62925	-2.90859	3.125418

	3	-3.0759	3.1103	-2.96966	3.802303	-2.94457	3.108438	-3.03498	3.718884	-2.95899	3.269305	-3.11979	3.749664
	4	8	563	10	521	9	1501	5	1943	10	874	1	1785
	5	5	338	0	144	6	1930	4	995	1	412	3	451
12	**1**	8	340	6	1838	6	753	5	1572	8	1729	5	54
	2	-2.782	2.9386	-4.13336	3.528648	-3.15609	3.394825	-2.83134	3.419402	-2.70469	4.434539	-3.04389	3.250852
	3	-2.9448	2.9445	-3.30553	3.115099	-3.12631	3.516165	-2.61564	3.69744	-3.45206	3.307057	-2.86234	3.528473
	4	6	746	5	1507	10	1323	9	144	7	190	7	1677
	5	5	1334	9	1196	9	1011	2	1125	7	1081	5	1361
13	**1**	9	486	10	231	4	577	9	620	0	958	7	1469
	2	4	1733	8	570	9	1022	7	1825	9	1154	10	1207
	3	3	1732	5	686	7	1332	6	1392	9	1341	5	199
	4	-3.5012	2.9965	-3.31156	3.93474	-3.58214	3.67413	-3.44447	3.393044	-3.06779	3.306633	-2.89114	3.390126
	5	-3.392	2.6734	-3.04236	3.37165	-2.8841	3.106136	-3.38552	3.382246	-3.75952	3.220932	-3.13927	3.381479
14	**1**	2	1596	2	260	5	1289	8	1175	10	1038	10	638
	2	-3.9839	2.7573	-3.25155	3.208014	-3.5005	2.973416	-2.86135	3.817648	-2.95291	3.176889	-3.38225	2.930515
	3	-2.9119	3.6109	-3.69794	3.737302	-3.07845	3.081051	-2.82296	3.675888	-3.28865	2.972122	-3.32483	3.344035
	4	0	1648	3	1623	10	1588	0	170	0	146	5	1628
	5	15	1943	5	1437	7	543	1	1794	9	1275	7	730
15	**1**	2	521	6	798	3	1034	10	31	7	1244	10	639
	2	-2.9722	3.5961	-3.06502	3.331555	-4.14225	3.783949	-2.8823	2.852241	-2.95444	3.450299	-4.74319	3.062768
	3	-3.3719	2.6873	-3.71136	3.482924	-3.05965	3.583487	-2.97393	3.85719	-3.04533	3.421997	-3.0951	3.349566
	4	5	1855	1	1096	9	1960	3	1937	10	189	5	718
	5	10	1477	4	1663	8	302	6	1203	9	969	2	737
16	**1**	4	1873	10	1986	10	743	6	1904	8	706	6	747
	2	-3.3628	2.9036	-3.40314	2.953149	-3.3498	2.76494	-3.09389	2.824409	-3.07922	2.856827	-3.54302	3.493749
	3	-3.0538	2.8685	-3.63609	3.305653	-3.06041	2.746587	-2.98922	3.116777	-3.31442	3.061504	-3.38262	3.201098
	4	9	727	6	415	0	468	9	1360	7	394	8	32
	5	4	344	9	1148	9	1868	5	1488	7	577	0	1860

17	**1**	6	704	3	356	2	375	6	684	8	1433	11	516
	2	-3.0924	3.2491	-3.12927	3.2315	-3.5956	3.644248	-3.90259	2.864567	-2.67338	2.913696	-3.43071	2.814967
	3	-3.1644	3.2129	-2.65971	3.577566	-2.99614	3.360057	-3.30865	2.942115	-4.2646	3.204629	-3.39877	3.357036
	4	1	1098	9	1635	10	422	6	1661	7	1029	6	66
	5	6	723	7	1825	2	1103	7	1752	10	1790	7	115
18	**1**	4	1684	9	1357	4	1746	5	258	8	949	8	1765
	2	-3.3843	3.9202	-3.58424	2.939534	-3.307	3.719964	-4.37328	2.640021	-2.91318	3.172119	-3.17056	3.512099
	3	-3.1371	2.8453	-3.05012	3.605382	-3.6756	3.372117	-3.61133	3.381359	-2.95958	3.09047	-3.31938	3.19851
	4	5	83	1	985	12	930	4	747	1	1003	5	104
	5	6	1198	1	336	4	1078	7	358	9	1063	4	250
19	**1**	2	500	3	300	8	1761	1	1268	3	704	8	113
	2	-2.8256	3.0533	-2.80463	3.547289	-2.68368	2.992371	-3.12121	3.286891	-3.38628	3.446105	-3.66849	3.523754
	3	-2.7613	3.9676	-3.75727	2.881736	-2.56193	3.09427	-2.79852	3.068244	-3.1811	4.21634	-3.38799	2.932299
	4	7	143	5	377	4	815	3	78	6	992	2	1516
	5	6	128	5	1210	6	39	4	1127	9	1973	4	772
20	**1**	8	195	2	803	2	461	5	1492	12	1817	6	1520
	2	-2.5181	3.0502	-3.3724	3.285688	-3.25638	2.897739	-2.9589	3.187892	-2.80725	3.588349	-3.30483	3.007875
	3	-3.4122	3.6848	-3.36287	2.6901	-2.94477	3.966769	-3.37963	2.90028	-3.19	3.622263	-3.37815	3.512703
	4	12	1083	4	74	0	1153	5	558	7	543	8	100
	5	7	144	3	222	5	1476	10	875	5	254	4	1554
21	**1**	1	132	10	89	1	739	7	1285	5	1839	3	642
	2	-3.0607	4.407	-3.09086	3.565206	-4.17539	3.431449	-3.97766	3.53946	-4.1889	2.711474	-3.32905	3.070526
	3	-3.9063	3.5989	-3.2381	2.643321	-2.81271	3.020316	-3.42179	3.377638	-4.18808	2.764892	-3.20909	3.402309
	4	4	1459	8	1547	5	1998	5	1318	5	252	0	83
	5	5	381	12	1852	3	800	9	1992	10	622	8	1447
22	**1**	0	1587	2	1589	8	1156	8	572	8	1204	10	1570
	2	-3.2526	3.2655	-3.26998	3.088581	-4.21565	3.352373	-3.19175	2.966171	-2.99217	3.205393	-3.36925	2.920268
	3	-3.6593	3.6872	-2.97443	3.125964	-2.50289	2.843597	-3.38516	2.786016	-4.02383	2.944998	-3.63959	3.023544

	4	5	1796	8	1404	2	1424	1	560	12	1666	1	562
	5	3	1674	6	1885	7	849	1	1054	3	1773	6	674
23	**1**	11	1970	10	1112	10	1503	1	1306	5	1585	1	1807
	2	-3.2082	3.7523	-3.22354	3.234178	-3.50428	3.552983	-3.46429	3.408506	-3.13	2.810372	-2.92489	3.71305
	3	-3.2793	3.3558	-2.94011	3.154593	-2.98484	3.223257	-3.35543	2.938689	-3.32486	3.341686	-3.74039	3.33272
	4	8	1582	1	1135	8	1222	9	1089	10	1918	2	1210
	5	8	729	12	1661	11	1791	11	1706	7	1740	1	1606
24	**1**	3	640	6	890	1	316	6	764	4	951	1	575
	2	-3.7155	3.0258	-3.15691	3.203981	-3.50107	3.158793	-3.0979	3.118843	-3.19424	3.720419	-3.23809	3.155464
	3	-3.5709	3.6307	-3.4904	3.847513	-3.02946	3.437186	-3.24489	3.042071	-3.29824	3.744492	-3.70532	3.550672
	4	12	1540	7	1995	1	675	2	1438	6	277	1	1178
	5	10	395	0	1013	7	416	5	1811	6	357	9	1553
25	**1**	4	573	2	408	9	1868	8	757	8	878	9	1264
	2	-3.0495	3.2249	-3.70359	2.999073	-3.27719	3.317707	-3.71679	3.375622	-3.77031	3.155324	-4.19215	3.211467
	3	-3.3177	3.1079	-3.32413	2.684211	-3.30533	3.057567	-3.06023	2.778799	-3.47774	3.564404	-3.37997	2.998878
	4	10	1733	2	857	5	1755	8	61	9	1376	9	1814
	5	0	1452	4	1075	2	738	8	552	7	1062	1	1654
26	**1**	1	300	1	950	6	1774	6	1393	8	1563	8	1690
	2	-3.4991	3.4475	-2.47841	3.760299	-3.69445	2.858714	-3.87663	2.95613	-3.14368	3.116741	-2.90142	3.451866
	3	-3.36	3.5513	-2.79082	3.595165	-2.92561	3.324615	-3.56966	2.854797	-3.24623	2.759376	-3.19976	3.132615
	4	10	656	7	1202	5	437	2	1099	0	636	15	1797
	5	9	992	7	800	2	90	6	1550	8	701	0	248
27	**1**	10	134	5	1899	1	92	6	1906	2	1641	1	1270
	2	-3.3497	3.7393	-2.79801	3.026968	-3.30429	3.060001	-2.97376	3.313557	-3.15779	2.941754	-3.02053	2.833811
	3	-3.3144	2.8539	-3.43494	3.630121	-3.09896	3.352943	-3.20102	3.618866	-3.73661	3.441265	-3.50272	3.362823
	4	6	1257	7	933	1	133	3	276	8	1507	11	1109
	5	5	912	8	352	7	1965	9	398	3	1685	2	1387
28	**1**	2	553	5	457	7	1573	17	1589	1	863	2	895

	2	-2.9363	3.2312	-3.06187	3.915852	-3.07344	2.684568	-2.58512	3.119512	-3.07098	3.372222	-3.11528	3.572231
	3	-3.946	3.3034	-2.8364	3.025967	-2.78553	3.247182	-3.92635	3.21768	-3.13283	2.939482	-3.1458	2.979209
	4	4	960	10	1384	7	1130	12	1068	5	1363	10	850
	5	10	708	11	1367	4	172	4	839	4	1971	9	682
29	**1**	2	1202	4	610	5	1554	8	165	6	1532	4	531
	2	-3.1093	2.9889	-2.69313	3.060278	-3.19217	3.049776	-2.95145	3.397952	-3.32012	2.8005	-4.58542	3.302943
	3	-3.7386	3.4784	-2.84684	3.451849	-2.84913	3.067424	-2.94625	2.563144	-3.0831	3.321888	-2.80699	3.113198
	4	5	690	2	1214	4	807	5	1812	9	210	9	79
	5	4	93	4	1997	10	759	4	1195	6	973	8	1302
30	**1**	5	29	10	1586	5	1606	6	1124	1	1826	8	1804
	2	-3.0399	3.1021	-2.8917	3.504122	-3.08516	3.445516	-3.52257	3.11396	-2.72923	3.901885	-2.91103	3.592806
	3	-3.3906	3.1154	-3.12784	3.064523	-2.80738	3.865536	-3.4102	3.56299	-3.37697	2.663646	-3.1821	3.143142
	4	1	1269	0	203	5	659	9	1720	5	1712	6	100
	5	8	1378	2	1633	6	1248	7	1696	10	1410	0	279
31	**1**	7	301	6	14	7	75	3	229	6	373	5	793
	2	-3.0453	4.589	-3.20812	2.858824	-2.79865	3.034098	-3.74452	3.025288	-3.50809	3.589595	-2.88954	3.346968
	3	-2.8825	2.8859	-3.31141	3.378971	-3.01806	3.00452	-3.32258	3.371657	-3.84783	3.165722	-3.08897	3.259939
	4	5	1684	7	1752	0	694	8	400	10	1855	10	1563
	5	3	629	1	1703	6	204	5	1988	2	1063	6	1635
32	**1**	6	456	10	1086	10	663	8	572	6	1545	6	1791
	2	-2.6939	2.8717	-3.03046	2.601029	-2.88198	3.300685	-3.16736	2.665669	-2.7927	3.370886	-3.11399	3.186269
	3	-3.0641	3.0748	-3.18626	2.97944	-3.05249	3.796394	-2.92902	3.554382	-2.81419	3.290021	-2.89376	2.401686
	4	8	1102	10	948	1	1881	1	512	7	907	1	1450
	5	3	908	5	1246	5	1372	5	1927	11	1890	8	1058
33	**1**	5	200	10	431	15	1199	13	1747	10	1077	7	1320
	2	-3.8583	2.7805	-3.10315	3.46806	-2.80828	3.582302	-2.95466	2.880186	-3.16681	2.853034	-3.13809	3.299305
	3	-2.9586	2.8194	-3.4936	2.615278	-2.96519	3.579133	-4.04678	3.873718	-2.85594	3.369131	-3.65366	2.716452
	4	8	636	8	633	6	909	2	1320	5	1593	10	494

	5	9	462	10	712	4	77	12	1774	7	1448	10	1970
34	**1**	3	876	11	1768	7	1941	7	1090	0	373	1	1762
	2	-3.1549	2.6711	-2.84312	2.756303	-3.30667	3.067723	-3.32999	3.809351	-3.21471	3.007598	-2.94696	3.267111
	3	-3.2839	3.2711	-3.14808	3.093979	-3.02531	2.996318	-3.0569	2.71739	-3.19407	2.953683	-3.02633	3.275956
	4	0	512	2	119	11	1125	2	323	2	1222	2	1652
	5	7	966	10	677	9	674	7	347	5	1957	0	143
35	**1**	2	420	11	1423	11	1858	1	222	7	1368	4	955
	2	-3.1491	3.9623	-2.77007	2.931396	-3.17901	3.23571	-3.11912	3.734679	-2.97832	2.998685	-3.37698	2.881483
	3	-3.0559	2.9841	-2.94461	3.622314	-3.86594	2.926138	-3.3598	3.264724	-3.12081	3.1588	-3.52188	3.696739
	4	1	374	5	74	7	144	8	1652	9	851	6	648
	5	1	52	5	1966	8	1482	10	1578	3	1122	7	546
36	**1**	5	1435	5	239	7	572	3	626	4	436	6	36
	2	-2.7655	2.5921	-2.84952	3.037222	-2.92946	2.996434	-3.05946	3.059027	-3.20055	3.796668	-3.34405	3.754998
	3	-3.0635	3.0223	-3.09896	3.476881	-3.20541	2.750001	-3.49838	3.480894	-3.33818	3.211785	-3.26277	2.910867
	4	2	1526	8	965	10	830	1	198	5	1900	1	899
	5	10	431	4	729	7	553	1	873	8	1728	9	1033
37	**1**	2	1909	10	1356	10	309	4	309	9	1021	3	1234
	2	-4.1127	3.2412	-3.4489	3.154993	-3.134	2.929639	-2.75727	3.180062	-3.31315	2.98737	-3.57396	2.682718
	3	-3.1994	3.1026	-3.82535	3.677091	-2.72465	3.540183	-2.92817	2.917092	-3.25437	3.142696	-3.80335	3.518289
	4	7	1611	2	289	7	1720	9	36	7	1877	2	1245
	5	5	357	5	1913	7	227	2	902	2	1464	2	1774
38	**1**	3	210	3	875	7	1794	2	1015	9	659	1	1789
	2	-2.7968	2.9494	-3.08877	3.039912	-3.4293	2.944538	-3.052	3.332023	-4.12027	3.059322	-4.1635	3.956701
	3	-2.6484	3.1678	-3.55538	3.468315	-3.65512	3.099527	-3.30376	3.485215	-3.23927	2.887108	-3.0948	3.180471
	4	9	977	13	1373	7	1571	2	1150	8	600	9	1695
	5	0	1735	5	337	10	544	7	1823	7	619	5	1036
39	**1**	6	1266	0	1303	7	1498	9	1472	6	25	7	1744
	2	-3.3923	3.137	-2.79471	3.033658	-2.94867	3.157999	-3.30655	3.254988	-3.58623	3.972541	-3.47522	3.462234

	3	-3.2872	3.2448	-2.89963	3.323539	-3.68566	3.082495	-3.23061	3.462157	-2.78109	3.106458	-3.36155	3.88783
	4	0	1430	3	1922	0	532	7	802	3	1970	6	618
	5	10	1387	7	268	4	1453	6	903	2	1518	0	262
40	**1**	5	1360	7	255	4	767	0	1856	10	812	2	59
	2	-2.9433	4.0802	-2.99139	3.072044	-2.61007	3.079077	-3.86637	4.018672	-3.42699	3.315915	-2.94887	3.133404
	3	-3.2101	2.869	-3.17486	3.69501	-3.51952	2.962434	-2.93741	3.381907	-3.59547	3.127177	-3.28954	3.093189
	4	5	820	3	276	3	784	4	1021	6	1967	3	601
	5	8	690	6	1957	10	748	6	1910	7	1626	9	810
41	**1**	1	862	3	981	2	405	4	496	6	505	2	1616
	2	-3.4865	3.4906	-3.12351	3.114727	-3.22223	3.086029	-3.1913	3.27291	-3.0674	3.481806	-3.39847	3.199316
	3	-3.4009	3.109	-3.82665	3.179716	-3.64587	3.016112	-3.33997	3.51786	-3.3349	3.334999	-3.4026	3.339331
	4	1	193	8	1004	10	1804	3	1580	0	361	7	14
	5	4	56	0	1395	5	1871	8	1974	3	240	10	78
42	**1**	11	697	6	407	4	1528	10	675	8	1443	2	1527
	2	-2.9154	3.1547	-3.31431	3.342275	-3.11331	3.129668	-2.86274	3.128465	-2.75273	2.978473	-2.91604	2.590534
	3	-3.5381	2.9319	-2.95468	3.13638	-3.05671	2.704559	-3.38321	3.246329	-3.1382	3.027228	-3.16646	3.655696
	4	9	894	11	702	8	1417	3	309	2	1581	9	949
	5	2	1636	4	290	2	1519	2	1756	8	393	9	643
43	**1**	6	1745	6	143	5	1002	8	196	6	1057	9	760
	2	-3.5567	3.1802	-3.42866	3.605564	-2.9526	3.183013	-3.06286	3.4401	-3.06888	2.777668	-3.78074	3.41106
	3	-3.0925	3.2783	-3.29456	3.177984	-3.07331	2.660869	-2.98788	3.695625	-2.92845	2.6867	-3.42889	3.140597
	4	3	275	10	1715	4	1622	3	1556	6	1223	9	372
	5	6	1028	7	1496	17	1655	2	1578	8	1141	8	1537
44	**1**	5	1750	5	1010	7	606	7	1771	7	1430	11	1842
	2	-3.526	3.4644	-3.78825	2.917355	-2.67556	3.291762	-3.42294	3.467567	-3.19704	3.11915	-2.92714	3.305237
	3	-3.4392	3.2093	-3.29068	2.907726	-3.17986	3.115334	-2.81387	2.841738	-3.724	3.074158	-2.97109	3.590373
	4	8	1586	3	518	3	1358	7	958	9	1128	1	1220
	5	14	1241	7	1837	2	1105	10	421	8	1477	6	879

45	**1**	7	1057	0	932	4	1858	1	1174	7	432	4	1693
	2	-3.0005	3.0597	-2.66941	3.311036	-2.90789	3.285442	-2.96776	3.113754	-2.79204	2.731586	-3.32549	2.928062
	3	-3.1967	3.0873	-3.23723	3.344967	-2.80723	2.885912	-4.05115	3.562706	-3.18334	3.772254	-3.84098	2.942287
	4	5	972	3	1297	2	109	7	352	1	1972	6	1496
	5	4	1972	6	255	10	672	10	799	3	1670	4	1031
46	**1**	1	165	0	295	10	1037	10	251	3	1524	7	1709
	2	-3.513	2.975	-3.08923	3.653871	-3.87064	3.692922	-3.13502	2.931417	-3.26609	3.746357	-3.33302	3.183139
	3	-3.347	2.8343	-3.92034	2.942881	-3.238	3.484686	-2.84594	2.839147	-3.46204	3.478754	-3.25775	2.786562
	4	0	1409	2	1656	2	291	1	1448	1	351	6	1355
	5	3	1424	14	1568	2	132	6	1111	6	718	2	309
47	**1**	4	651	4	1311	4	1222	9	1872	6	1158	0	775
	2	-3.0589	3.1879	-3.03721	3.147059	-3.02368	2.932759	-3.43013	2.871322	-3.02362	2.775818	-3.03436	4.215124
	3	-2.927	3.6144	-2.90023	3.660983	-2.9476	3.336748	-3.74624	2.961047	-3.14883	2.841771	-4.24477	3.574215
	4	7	977	5	124	20	1994	8	1068	9	272	5	166
	5	2	1655	11	1391	0	1861	11	1332	3	317	4	945
48	**1**	6	1572	10	150	7	1231	3	412	4	1732	3	1719
	2	-2.8409	2.963	-2.76027	3.509916	-3.4104	2.926806	-3.1932	3.757587	-3.34644	3.109846	-2.96296	3.228708
	3	-3.1895	2.9878	-2.73683	2.885102	-2.97739	2.861954	-3.27033	3.152392	-2.8233	2.829764	-3.23064	3.283356
	4	5	46	10	1802	0	1945	5	371	4	1208	7	503
	5	2	506	5	745	5	1171	5	296	4	1247	9	728
49	**1**	14	1348	0	492	5	411	9	1677	4	1491	9	1398
	2	-3.3016	4.4472	-3.05684	3.306436	-3.17304	2.786711	-2.9622	3.014447	-2.96272	3.34948	-3.78163	4.200939
	3	-3.7214	3.1843	-3.6655	2.969099	-2.82365	3.505201	-2.77497	3.942451	-3.63867	2.91085	-3.60413	2.918305
	4	6	1957	2	1536	6	1453	9	710	12	1712	0	1379
	5	2	878	7	483	10	1026	6	900	5	401	5	37
50	**1**	2	1988	11	850	5	1969	2	1975	6	17	1	1171
	2	-2.937	3.5447	-3.71221	2.950821	-3.06444	2.824897	-3.41612	2.878287	-3.28909	3.430239	-4.10013	2.955828
	3	-3.1015	3.5058	-2.94872	3.710394	-3.24414	3.047971	-2.73453	3.718292	-3.22544	3.594279	-2.59727	3.510003

	4	7	1642	8	250	4	1485	0	321	17	1789	2	1737
	5	-3.4247	3.3157	-3.00891	3.034792	-3.30231	3.045854	-3.02932	3.076635	-3.87035	3.132308	-3.96831	3.125786
51	**1**	-3.0586	2.889	-3.20474	2.937688	-3.01065	3.165226	-2.72104	3.514584	-3.38073	3.021512	-2.76973	3.27433
	2	6	35	6	818	4	398	9	578	10	1556	7	538
	3	10	622	0	457	10	619	4	177	10	342	7	41
	4	12	1674	4	1273	1	1734	5	24	6	943	5	895
	5	2	848	4	38	9	1610	4	1384	10	1561	5	1205
YIELD		60.0163	89.9509	60.00141	90	60.00662	90	60.00268	90	60.11978	90	60.70012	90

A1/C2B – Range of Values for the Simulated Data Set (Cluster 1: Data Sets 6 – 10)

In this section the minimum and maximum values for each supply chain step of the remaining data sets (Data sets 6 to 10) of the first simulated data cluster are presented. The range of values of these remaining data sets is very similar to the ones covered in the previous section (i.e. A1/C2A). Again, the range of the dependent variable of each simulated data set is between 60 and 90. Illustrated simulated data sets in Table 13 include both integer and decimal numbers for measurements and as in the case of the previous six data sets in the first cluster. Table 13 reveals that apart from supply chain steps thirteen and fifty one, all supply chain steps have a similar approximate range of values as in the case of Table 12. All supply chain steps (excluding steps #13 and #51) have integer values for process metrics one, two, and five between values of zero and two thousand (Table 11). The process metrics three and four of these supply chain steps have decimal values between -4.25 and +4.25 approximately. Step #13 has similar range of values, but its process metrics one, two, three are decimals within -4.00 and +4.25 range, and process metrics four and five are integers between zero and two thousand approximately. Only the process metric one of Step #51 is a decimal between a range of -4.00 and +3.75. The remaining metrics are integers approximately between zero and two thousand. The shaded columns provided in Table 13 reveal the range across all eleven data sets of the first cluster.

Table 13 - Simulated Data Range of Values (Cluster 1: Data Sets 6 - 10)

		Cluster 1											
Step	Measure	Data Set 6		Data Set 7		Data Set 8		Data Set 9		Data Set 10		Across All Sets	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1	1	7	1330	7	1660	1	1605	12	1219	7	721	1	1828
	2	-3.15677	2.687421	-3.47539	3.250856	-3.3508	3.664001	-3.93546	3.177195	-2.97993	3.237569	-3.93546	4.2823
	3	-3.24969	2.982929	-3.1382	2.896973	-2.91662	3.474834	-3.17518	3.163983	-3.30358	3.101388	-3.55766	3.474834
	4	11	976	6	1876	9	435	5	530	1	215	1	1876
	5	7	1800	8	1803	2	1773	9	1829	9	991	0	1829
2	1	0	492	10	758	8	1305	3	180	7	40	0	1519
	2	-3.4829	3.921735	-3.44417	3.450962	-3.42488	2.780167	-2.95513	3.053516	-2.94688	2.799695	-3.60034	4.296153
	3	-3.52871	3.582707	-3.90062	3.227814	-2.7507	3.256473	-3.18526	3.222596	-3.46572	3.391599	-3.90062	3.824427
	4	15	1885	7	80	5	1734	1	525	4	1251	1	1885
	5	5	892	6	55	2	442	4	904	3	655	0	1043
3	1	8	1131	10	1703	9	1956	5	1759	10	902	1	1956
	2	-3.13732	3.089267	-2.77194	3.331401	-2.89182	3.079787	-3.49487	3.24476	-3.83272	2.806988	-3.83272	4.0562
	3	-3.93512	3.532969	-3.72762	3.8594	-2.9014	3.582626	-3.04933	3.013611	-3.04609	3.312865	-3.93512	3.8594
	4	11	1614	12	1560	5	1822	7	1574	1	1173	1	1822
	5	4	1980	4	1308	10	1323	8	506	6	779	4	1980
4	1	4	1393	9	290	8	1872	0	132	6	1265	0	1872
	2	-3.65309	2.999979	-3.16531	3.01488	-3.15816	3.667986	-3.11121	3.006385	-3.9283	2.995812	-3.9283	3.846084
	3	-3.09803	3.497452	-3.1177	3.279767	-2.86591	2.791993	-3.58796	3.124035	-3.03021	3.19849	-3.58796	4.079889
	4	7	1553	8	1320	5	1102	2	584	4	542	2	1718
	5	0	38	5	504	2	1090	6	157	2	684	0	1766
5	1	3	448	10	1023	5	1558	2	1460	5	926	0	1558
	2	-3.15669	3.927514	-3.61371	3.351509	-2.71582	3.037867	-2.79637	3.620573	-3.10898	2.633274	-3.65198	4.162019
	3	-3.1245	3.482912	-3.17587	2.833688	-2.78414	2.801273	-2.95942	3.084854	-3.31595	3.019678	-4.0614	3.5267
	4	8	1580	0	1900	8	1185	1	585	5	1080	0	1900
	5	1	859	9	867	6	1706	6	1627	4	1216	0	1961
6	1	1	439	9	1693	7	506	3	1013	9	1949	0	1949
	2	-2.87312	3.025486	-3.1564	3.095715	-3.26819	3.00741	-3.0608	2.956155	-2.78254	2.893217	-3.45943	4.101041

	3	-3.11645	3.852398	-3.4574	3.178704	-3.11534	3.128258	-2.80842	3.887522	-2.76964	2.80293	-4.38559	3.887522
	4	0	1583	7	1217	4	1735	1	368	4	1163	0	1735
	5	7	409	8	644	8	750	1	1957	3	1159	0	1970
7	**1**	9	800	5	291	10	708	7	871	4	269	4	1818
	2	-2.89838	3.177195	-3.04052	2.922288	-2.53317	3.07148	-3.49273	3.885709	-2.92474	3.664242	-3.49273	3.885709
	3	-3.11529	3.017093	-2.91154	3.524258	-2.8964	3.701026	-3.1812	3.215637	-2.97284	2.821684	-4.07504	4.186393
	4	7	1477	0	1349	2	1616	6	1061	8	1017	0	1910
	5	3	747	0	1515	4	56	13	1391	8	244	0	1860
8	**1**	1	1774	0	34	2	1458	4	1887	1	960	0	1996
	2	-2.93228	3.424935	-3.26865	3.051676	-3.26813	3.192447	-3.10738	3.700705	-3.59396	3.059167	-3.72081	3.700705
	3	-3.05836	4.39158	-3.23394	3.162922	-3.45002	3.459753	-3.01944	2.901625	-3.1674	4.267893	-3.61859	4.39158
	4	7	1544	11	1142	9	675	8	1076	10	1357	3	1963
	5	6	163	8	1827	7	1037	1	348	10	1231	1	1827
9	**1**	1	747	9	285	9	1606	4	954	9	661	1	1788
	2	-3.41202	3.419536	-2.8601	3.577442	-3.12508	4.036172	-3.16616	3.295627	-3.32337	3.203529	-3.68908	4.2803
	3	-3.6319	3.075189	-3.41877	3.011726	-3.66281	3.280901	-2.86248	3.224311	-3.69339	2.686384	-3.69339	3.48024
	4	11	1512	3	1457	5	469	6	278	5	1714	1	1926
	5	6	874	2	1903	11	1891	6	93	0	1711	0	1903
10	**1**	11	1025	3	1238	9	629	3	1182	8	298	3	1962
	2	-3.20182	3.578618	-2.93732	2.828794	-3.38965	3.044885	-3.18187	3.585188	-3.04348	3.12876	-4.11043	3.707399
	3	-2.95139	2.816517	-3.19539	3.185221	-3.09151	3.532956	-3.73883	2.6169	-2.98597	3.077551	-3.73883	3.696726
	4	0	458	4	257	3	872	3	1975	2	1270	0	1975
	5	6	949	2	1919	1	499	12	774	4	97	1	1997
11	**1**	3	1063	8	1200	6	952	8	80	4	1091	3	1239
	2	-3.61825	3.010451	-3.22675	2.919059	-3.11309	3.649479	-3.60841	2.927294	-3.91052	3.087515	-3.91052	3.649479
	3	-3.48591	3.033211	-3.91285	4.054496	-2.94728	3.660928	-2.94518	3.258197	-3.13925	3.875452	-3.91285	4.054496
	4	5	1847	2	1786	8	1958	2	1013	10	1574	1	1958
	5	10	119	3	1253	0	966	9	271	0	843	0	1930
12	**1**	1	1652	6	1444	1	1416	4	1264	7	1076	1	1838
	2	-2.96696	3.858917	-3.27632	3.094668	-3.55372	3.588789	-3.06588	3.426074	-2.84334	2.927584	-4.13336	4.434539
	3	-3.77073	3.083997	-3.11368	3.597511	-2.86653	2.936053	-2.99254	3.664288	-2.98968	4.456738	-3.77073	4.456738
	4	5	754	7	1982	13	1174	2	1919	8	618	2	1982

	5	3	1625	6	1115	9	1676	1	467	9	1045	1	1676
13	**1**	9	873	9	108	1	546	3	1054	1	617	0	1469
	2	2	1136	1	850	1	612	3	1212	7	1606	1	1825
	3	12	1468	9	1180	6	512	1	1941	1	486	1	1941
	4	-3.33409	3.220941	-3.93128	3.223977	-3.01932	2.898099	-2.90604	4.191357	-3.11242	2.986342	-3.93128	4.191357
	5	-3.10092	2.893975	-3.27422	3.578837	-3.53815	3.264029	-3.13748	2.888351	-3.32017	3.770217	-3.75952	3.770217
14	**1**	4	1740	9	1479	1	49	8	838	0	639	0	1740
	2	-3.28141	2.773846	-3.46349	3.422478	-2.95719	3.34489	-3.61848	2.928065	-3.60584	4.042006	-3.9839	4.042006
	3	-3.23574	2.7867	-3.35692	3.029176	-3.49927	3.561553	-3.09232	3.451214	-3.77388	3.472268	-3.77388	3.737302
	4	1	760	9	1779	8	910	6	23	10	696	0	1779
	5	2	1479	3	1165	7	1364	2	1739	10	395	1	1943
15	**1**	8	1385	1	1137	7	737	2	1746	1	250	1	1746
	2	-3.39301	3.162871	-3.55014	3.707721	-3.25604	2.954477	-2.66731	2.907645	-3.17101	3.898649	-4.74319	3.898649
	3	-3.08547	3.001531	-2.866	3.460851	-3.62701	3.079705	-3.21037	4.087142	-3.38081	3.525217	-3.71136	4.087142
	4	2	1477	8	1365	6	118	0	1007	3	551	0	1960
	5	6	1212	4	99	8	1367	8	1665	7	1489	2	1665
16	**1**	10	1154	7	1161	9	1913	2	392	3	331	2	1986
	2	-3.16872	2.981528	-3.134	3.043721	-3.75858	3.356885	-2.68349	3.224541	-2.95692	2.660236	-3.75858	3.493749
	3	-3.24619	3.582646	-2.92368	3.070291	-3.35808	3.444572	-2.55517	3.324628	-2.83462	4.070553	-3.63609	4.070553
	4	3	1575	2	269	3	225	8	1121	10	342	0	1575
	5	11	1526	6	728	7	1680	6	306	3	139	0	1868
17	**1**	5	1804	8	966	1	1820	0	245	10	350	0	1820
	2	-3.61918	3.09089	-2.92561	3.364015	-3.00538	3.056174	-2.89044	3.484412	-3.53979	3.259517	-3.90259	3.644248
	3	-3.27519	3.63451	-3.60059	3.139122	-2.96065	3.571493	-3.81732	3.416163	-3.58971	4.244454	-4.2646	4.244454
	4	10	282	10	568	12	1985	9	1540	1	405	1	1985
	5	6	1436	2	1212	9	1085	7	1036	8	29	2	1825
18	**1**	2	1854	11	1606	4	1372	10	1853	5	1422	2	1854
	2	-3.16027	2.858145	-3.37605	2.775173	-3.17073	3.43062	-4.38225	3.45181	-3.4992	3.215433	-4.38225	3.9202
	3	-2.82967	3.090107	-3.10547	3.708803	-2.89343	2.884071	-3.70049	3.031379	-3.0435	3.291948	-3.70049	3.708803
	4	7	534	8	806	1	1894	6	834	4	128	1	1894
	5	8	741	9	1484	5	1296	9	1937	7	257	1	1937
19	**1**	4	1380	1	179	6	312	6	1553	7	1053	1	1761

	2	-2.9244	3.044391	-2.70123	3.490341	-3.35823	3.394002	-3.25619	3.094717	-2.69738	3.496124	-3.66849	3.547289
	3	-2.82199	3.395408	-2.87745	3.133547	-3.34039	3.599086	-3.35203	3.358705	-3.13393	2.74659	-3.75727	4.21634
	4	3	917	2	1205	3	72	9	1531	1	548	1	1531
	5	1	509	2	370	5	1574	11	998	12	1409	1	1973
20	**1**	6	640	4	1317	4	1658	7	1716	0	1217	0	1817
	2	-3.62821	3.698595	-2.80984	3.717825	-3.4344	3.472238	-3.67887	3.249966	-3.46309	3.613522	-3.67887	3.717825
	3	-3.16467	3.46183	-2.8334	2.992207	-2.8441	3.149803	-3.84145	2.893744	-3.13936	3.379066	-3.84145	3.966769
	4	12	1515	1	943	7	1913	7	1477	8	1278	0	1913
	5	6	228	2	990	4	1195	3	1057	8	1153	2	1554
21	**1**	2	993	3	531	4	392	5	947	0	570	0	1839
	2	-4.0209	2.848255	-2.90568	3.210404	-2.88954	3.497994	-2.92817	3.403538	-2.91129	3.216388	-4.1889	4.407
	3	-3.56607	3.198048	-3.14477	2.970558	-3.6118	3.434351	-3.51458	3.327647	-3.02234	3.813153	-4.18808	3.813153
	4	8	1108	7	1954	7	1359	1	841	11	1950	0	1998
	5	5	1227	6	445	10	792	4	1450	10	1054	3	1992
22	**1**	7	872	6	832	4	908	7	626	5	1305	0	1589
	2	-2.72363	3.790309	-3.16834	4.167161	-3.45231	2.722077	-4.12791	3.34471	-3.28139	3.285759	-4.21565	4.167161
	3	-2.81253	3.716727	-2.92765	2.666134	-3.15102	2.991022	-2.91198	3.07976	-3.11813	4.644241	-4.02383	4.644241
	4	1	1642	7	123	5	504	9	1417	2	72	1	1796
	5	0	83	8	1679	16	1943	2	1167	10	1277	0	1943
23	**1**	0	1019	6	573	0	297	3	1845	7	1028	0	1970
	2	-3.49774	2.744973	-2.67535	3.083161	-3.2322	3.415534	-3.02543	2.920338	-4.0325	3.247955	-4.0325	3.7523
	3	-3.20361	2.862039	-3.32166	2.842924	-3.18442	2.936625	-3.20775	2.749122	-3.62077	4.501557	-3.74039	4.501557
	4	9	436	5	275	7	1437	8	1309	3	247	1	1918
	5	2	78	7	973	6	1605	5	440	6	402	1	1791
24	**1**	4	845	3	1376	12	1542	7	405	1	215	1	1542
	2	-3.35009	3.074402	-3.25839	3.229677	-3.23286	2.941201	-2.95557	3.631337	-2.8031	3.275825	-3.7155	3.720419
	3	-2.74631	3.074389	-3.01073	2.733409	-3.05293	3.049948	-4.13916	2.910768	-3.46651	2.881661	-4.13916	3.847513
	4	0	1953	9	1313	5	201	2	1103	2	607	0	1995
	5	2	61	8	1122	0	1621	6	1998	9	1650	0	1998
25	**1**	9	332	10	864	1	1855	9	148	9	1372	1	1868
	2	-3.44976	3.18326	-2.85645	3.170889	-3.14578	3.778065	-3.04351	2.990038	-3.20889	3.233148	-4.19215	3.778065
	3	-2.85443	3.529678	-2.96598	2.698721	-3.42069	3.37665	-3.1755	3.534145	-2.8358	3.112399	-3.47774	3.564404

	4	0	531	3	850	10	1134	1	1761	6	857	0	1814
	5	2	809	2	36	0	278	7	1429	7	1095	0	1654
26	**1**	2	650	11	668	10	1589	10	183	3	154	1	1774
	2	-3.85166	2.927532	-3.12072	2.482249	-3.04737	2.896268	-3.68616	3.23338	-3.26325	4.626021	-3.87663	4.626021
	3	-3.85884	3.00339	-2.85861	3.3078	-3.39529	3.374338	-3.47804	3.179107	-3.91931	3.268914	-3.91931	3.595165
	4	5	72	8	1488	10	1299	8	269	2	1038	0	1797
	5	0	360	3	551	8	939	4	1075	7	678	0	1550
27	**1**	9	26	6	1453	2	378	4	888	7	540	1	1906
	2	-2.55848	3.364896	-2.74532	3.275846	-2.95052	3.220222	-2.71724	3.292636	-3.21382	2.967017	-3.3497	3.7393
	3	-3.022	3.974569	-3.40759	2.98512	-3.39255	3.520583	-3.78401	3.003524	-2.93047	3.665399	-3.78401	3.974569
	4	5	314	2	199	10	1736	4	1762	5	1437	1	1762
	5	12	1754	11	1654	6	1523	6	268	1	234	1	1965
28	**1**	5	1802	4	1218	5	1123	5	715	0	700	0	1802
	2	-2.88962	2.955077	-3.78838	3.42676	-4.20311	2.785981	-2.90495	2.983259	-3.88031	2.872438	-4.20311	3.915852
	3	-2.82681	3.011327	-3.39894	3.029751	-3.04669	2.786606	-2.60121	3.275357	-3.152	3.762597	-3.946	3.762597
	4	3	1498	1	104	4	1156	8	1520	6	1685	1	1685
	5	3	897	6	1847	8	1393	5	918	5	46	3	1971
29	**1**	5	1965	7	1473	5	1008	3	1332	5	905	2	1965
	2	-2.79751	3.259663	-3.7304	2.936352	-3.37125	3.42736	-3.20669	3.243785	-2.95854	2.982484	-4.58542	3.42736
	3	-2.99453	3.103291	-2.89624	3.152126	-2.84085	3.949766	-2.97434	2.914587	-3.10272	3.008608	-3.7386	3.949766
	4	4	1516	7	448	2	588	2	1918	5	1734	2	1918
	5	5	460	4	737	6	801	5	1784	4	309	4	1997
30	**1**	6	1052	8	1402	7	110	8	678	11	1045	1	1826
	2	-2.92329	2.863542	-3.13581	2.860945	-3.5709	3.215769	-3.38126	2.453532	-3.04518	3.401264	-3.5709	3.901885
	3	-2.81799	3.181138	-2.97681	3.364859	-2.99933	2.990326	-2.90763	3.113024	-3.00543	3.193462	-3.4102	3.865536
	4	2	708	9	1568	13	1210	1	859	1	800	0	1720
	5	5	1126	3	613	4	97	0	24	0	508	0	1696
31	**1**	4	452	4	1581	10	1481	0	519	7	1679	0	1679
	2	-3.49217	3.115415	-3.19869	3.357054	-3.16988	2.876949	-3.33016	3.14665	-3.8419	2.849624	-3.8419	4.589
	3	-3.78482	3.03399	-2.90754	3.30597	-2.81237	3.423167	-3.06714	2.719784	-2.9869	3.097331	-3.84783	3.423167
	4	4	509	3	484	1	1236	3	1492	0	1077	0	1855
	5	1	1968	6	1904	7	858	8	127	10	1684	1	1988

32	**1**	10	1932	0	702	10	356	7	1367	2	1780	0	1932
	2	-3.89372	3.561447	-3.16684	2.656122	-3.53422	3.734214	-2.99606	3.000565	-2.88467	2.820245	-3.89372	3.734214
	3	-3.42754	3.13448	-2.85027	3.752774	-3.56858	3.44583	-2.91079	3.104642	-3.57527	2.957059	-3.57527	3.796394
	4	5	343	8	1714	5	298	9	1384	2	1778	1	1881
	5	10	285	6	1728	2	1611	11	314	11	1278	2	1927
33	**1**	11	993	8	1422	6	525	5	1834	4	1088	4	1834
	2	-2.79074	3.849358	-3.03354	3.291139	-2.87367	3.151507	-3.09626	4.188637	-2.99182	3.358831	-3.8583	4.188637
	3	-2.92937	3.318967	-3.68928	3.57621	-2.88455	2.702423	-3.18723	3.026979	-3.08528	3.815452	-4.04678	3.873718
	4	0	310	7	952	4	303	9	1489	11	1746	0	1746
	5	7	191	0	79	6	1168	8	1301	10	58	0	1970
34	**1**	9	1718	8	1231	1	94	8	793	2	1583	0	1941
	2	-2.93289	3.18631	-3.19386	3.034394	-2.94331	3.300126	-3.15096	3.793626	-3.30035	3.767956	-3.32999	3.809351
	3	-3.96743	3.220446	-2.58663	3.212988	-2.58751	2.876636	-3.42139	2.693456	-2.90507	2.580761	-3.96743	3.275956
	4	10	155	5	723	10	1977	7	1366	1	1230	0	1977
	5	1	387	2	747	6	1173	2	727	10	617	0	1957
35	**1**	2	1810	10	1582	5	507	4	293	5	482	1	1858
	2	-3.04802	3.481223	-3.14066	3.157513	-2.5246	3.344773	-3.66382	3.319093	-3.68368	3.279821	-3.68368	3.9623
	3	-2.68433	3.83956	-2.76096	2.899041	-3.05603	3.604589	-3.31813	3.526622	-2.95825	3.578382	-3.86594	3.83956
	4	1	393	3	1279	6	533	7	1803	4	867	1	1803
	5	2	1828	3	712	6	349	5	730	5	1030	1	1966
36	**1**	10	125	9	1407	13	974	6	150	2	1696	2	1696
	2	-2.95502	2.83921	-3.24915	3.286006	-3.03065	2.892822	-3.21869	3.073786	-3.54305	3.064803	-3.54305	3.796668
	3	-3.03425	3.265051	-3.12179	3.082754	-2.85712	3.935945	-2.68422	3.117456	-3.31091	3.994293	-3.49838	3.994293
	4	10	822	12	1936	4	962	7	463	2	1795	1	1936
	5	2	1645	1	1588	0	803	14	1591	6	906	0	1728
37	**1**	10	1412	4	437	3	1821	2	563	6	453	2	1909
	2	-3.17061	3.268737	-3.71731	3.657297	-3.52363	3.556566	-3.09521	2.946942	-3.40812	3.634016	-4.1127	3.657297
	3	-2.72905	3.047699	-2.70698	2.684319	-2.82831	2.871122	-3.04753	2.663113	-3.21435	3.186269	-3.82535	3.677091
	4	0	874	2	1708	5	1824	4	348	0	1043	0	1877
	5	5	1210	4	370	8	201	0	1342	5	390	0	1913
38	**1**	4	1923	0	1484	6	774	2	1076	6	1830	0	1923
	2	-2.98014	2.948169	-3.62893	3.447555	-2.92448	3.366354	-2.91812	3.6871	-3.28763	3.134038	-4.1635	3.956701

	3	-3.59852	2.971669	-2.99391	3.083112	-3.12306	3.485349	-4.02157	3.392979	-3.42057	3.269435	-4.02157	3.485349
	4	1	912	10	1849	4	157	2	1448	7	1531	1	1849
	5	2	487	8	1683	8	413	0	99	8	1827	0	1827
39	**1**	2	1977	1	980	3	616	9	1399	4	1953	0	1977
	2	-3.14359	3.467184	-3.1638	3.765681	-2.68911	3.186878	-3.45503	3.136258	-3.13073	3.499408	-3.58623	3.972541
	3	-3.13043	3.522071	-2.60584	4.011889	-2.87642	3.078093	-3.06087	3.754072	-3.08787	2.820586	-3.68566	4.011889
	4	9	320	10	1895	6	1477	1	553	0	878	0	1970
	5	7	896	9	299	13	1632	2	166	8	1907	0	1907
40	**1**	6	456	0	999	1	805	11	919	0	194	0	1856
	2	-3.20385	2.99591	-3.1359	3.088127	-3.19286	2.994324	-2.94249	3.26555	-2.67922	2.857936	-3.86637	4.0802
	3	-3.29879	3.051316	-3.84308	2.65896	-2.9834	3.090193	-3.46866	3.513994	-3.50081	3.656517	-3.84308	3.69501
	4	9	646	6	1878	3	399	7	426	5	1531	3	1967
	5	13	1551	6	1243	3	1563	0	302	10	1722	0	1957
41	**1**	2	1034	3	751	1	1592	4	181	11	1647	1	1647
	2	-3.18012	3.182567	-3.11737	3.209423	-3.09197	2.795338	-3.69326	2.760367	-3.52325	3.194444	-3.69326	3.4906
	3	-2.73572	3.605466	-2.91062	3.533041	-2.95181	2.892105	-3.49487	3.418503	-3.23209	3.519542	-3.82665	3.605466
	4	3	1676	2	1447	2	932	5	259	4	691	0	1804
	5	8	532	5	1868	8	175	2	870	11	996	0	1974
42	**1**	8	1178	12	1637	7	487	8	72	6	466	2	1637
	2	-3.33551	3.22723	-3.18654	3.187018	-3.8832	3.388224	-2.9723	3.00585	-3.18575	3.464271	-3.8832	3.464271
	3	-2.7757	2.93902	-3.34965	3.719317	-3.76562	3.760238	-2.98818	3.458636	-3.16837	2.73971	-3.76562	3.760238
	4	5	1241	6	1761	2	1803	4	292	4	25	2	1803
	5	3	1242	4	1346	9	1226	0	1330	3	681	0	1756
43	**1**	4	876	12	1921	4	81	9	1492	1	1704	1	1921
	2	-3.51109	3.302789	-3.65484	3.210757	-2.85093	3.19422	-2.99934	3.636403	-2.94069	2.73212	-3.78074	3.636403
	3	-3.43724	3.043156	-3.9944	3.686549	-3.82645	2.980425	-3.1505	3.015513	-2.9729	3.469358	-3.9944	3.695625
	4	8	1693	6	1944	7	725	10	523	3	20	3	1944
	5	10	686	5	46	9	872	1	393	7	114	1	1655
44	**1**	6	1380	3	1644	2	1768	10	803	0	1968	0	1968
	2	-3.25099	2.74774	-2.71579	2.743686	-3.28377	3.857531	-3.23138	2.735483	-3.41978	3.051063	-3.78825	3.857531
	3	-2.97698	2.836346	-2.54091	3.462057	-3.209	3.556883	-3.42117	2.98675	-3.37714	3.48246	-3.724	3.590373
	4	10	820	0	1559	3	639	2	742	8	1786	0	1786

	5	9	1246	4	1205	6	802	5	1548	8	1953	2	1953
45	**1**	10	725	11	1613	9	1199	6	285	1	480	0	1858
	2	-3.02501	3.245735	-3.00689	3.565349	-2.80728	3.011144	-3.17975	2.833385	-3.97061	3.486528	-3.97061	3.565349
	3	-2.9591	3.083903	-3.12753	3.331814	-3.34494	3.327219	-3.24481	3.341371	-3.19634	3.218482	-4.05115	3.772254
	4	3	356	5	555	3	237	2	1042	1	642	1	1972
	5	0	17	4	677	3	472	11	828	10	315	0	1972
46	**1**	2	1010	0	441	1	872	5	1153	7	1885	0	1885
	2	-3.15584	3.093806	-3.48011	2.693859	-2.50706	3.443158	-3.34317	2.770118	-2.93463	3.740781	-3.87064	3.746357
	3	-2.95458	4.740115	-2.97284	2.8816	-3.35265	2.896028	-2.98297	3.309826	-3.01453	2.970468	-3.92034	4.740115
	4	4	1743	1	1143	9	1315	8	824	5	1586	0	1743
	5	7	1071	7	1357	9	999	0	1151	6	140	0	1568
47	**1**	12	1741	10	63	6	267	4	606	7	816	0	1872
	2	-3.01473	3.193874	-3.11421	2.705474	-3.69081	3.262596	-3.26507	2.742795	-2.72298	3.224334	-3.69081	4.215124
	3	-3.32939	3.260046	-3.44625	3.313827	-3.95784	3.339276	-3.77196	2.812872	-3.17856	3.204427	-4.24477	3.660983
	4	3	1267	7	199	10	529	6	36	11	1157	3	1994
	5	6	1673	12	1467	7	1687	6	1525	3	1705	0	1861
48	**1**	8	333	15	1528	6	1578	10	1263	0	1505	0	1732
	2	-3.10027	3.698684	-3.88117	2.916961	-3.19835	3.323544	-3.55994	3.288399	-3.2492	3.268879	-3.88117	3.757587
	3	-2.9293	3.118174	-3.20656	2.819288	-2.9643	3.651866	-3.55125	3.329034	-3.32089	3.094781	-3.55125	3.651866
	4	10	800	6	156	1	911	5	118	8	1684	0	1945
	5	7	1711	8	414	0	624	4	720	9	749	0	1711
49	**1**	1	284	4	942	5	771	8	287	5	517	0	1677
	2	-4.0809	2.884332	-2.83502	2.794669	-3.10214	3.173154	-3.07219	3.223359	-3.32573	3.108497	-4.0809	4.4472
	3	-2.82587	3.079662	-2.96029	3.150851	-3.60559	3.368006	-3.49853	2.983755	-3.86125	3.902156	-3.86125	3.942451
	4	8	1267	8	319	3	260	1	535	1	491	0	1957
	5	0	1126	9	361	5	1801	2	98	9	1632	0	1801
50	**1**	7	1655	1	1700	3	1185	9	1437	2	1963	1	1988
	2	-3.13398	3.339697	-3.42175	3.150806	-2.33071	3.044421	-3.46502	3.144563	-3.32186	3.562407	-4.10013	3.562407
	3	-3.11015	2.911291	-3.23189	2.582997	-2.71808	2.688647	-3.02965	3.400808	-3.18371	3.391972	-3.24414	3.718292
	4	2	1906	5	319	2	118	4	1723	8	1675	0	1906
	5	-2.8511	2.759247	-2.92239	3.131666	-3.23064	3.160441	-3.23612	3.338195	-3.41305	2.706028	-3.96831	3.338195
51	**1**	-3.923	2.758365	-3.20272	2.970147	-3.01512	3.75034	-3.29995	3.55441	-3.04004	3.253826	-3.923	3.75034

	2	7	297	6	521	7	879	21	1758	4	148	4	1758
	3	12	754	6	1340	4	1060	5	504	7	666	0	1340
	4	10	1592	0	985	2	979	1	1335	8	1995	0	1995
	5	5	85	8	909	3	96	2	969	3	278	2	1610
YIELD		60.00451	90	60.03953	90	60.02502	90	60.00189	90	60.00277	90	60.00141	90

A1/C3A – Range of Values for the Simulated Data Set (Cluster 2: Data Sets 0 – 5)

In this section the minimum and maximum values for each supply chain step of the second simulated data cluster are presented. Due to space limitations only the values from data sets zero to five are given (the remaining data sets six to ten of the first simulated data cluster are provided in the next appendix – A1/C3B). This range is based on all thousand observations of each manufacturing data set.

Similar to the first data cluster, the range of the dependent variable of each simulated data set is between 60 and 90. This range is provided at the bottom line of Tables 14 and 15. Second cluster simulated data sets also include both integer and decimal numbers for measurements. Table 15 reveals that apart from supply chain steps thirteen and fifty one, all supply chain steps have a similar approximate range of values. All supply chain steps (excluding steps #13 and #51) have integer values for process metric one, two, and five between values of zero and two thousand (Table 14). The process metrics three and four of these supply chain steps have decimal values between -4.25 and +4.25 approximately. Step #13 has similar range of values, but its process metrics one, two, three are decimals within -4.00 and +4.25 range, and process metrics four and five are integers between zero and two thousand approximately. Only the process metric one of Step #51 is a decimal between a range of -3.75 and +4.25. The remaining metrics are integers approximately between zero and two thousand. The details are provided in Table 14 as follows:

Table 14 - Range of Values Summary (Cluster 2)

	Process Measurement	Type	Minimum	Maximum
All Supply Chain Steps (excluding Step #13 and #51)	1	Integer	0	2000
	2	Integer	0	2000
	3	Decimal	-4.25	4.25
	4	Decimal	-4.25	4.25
	5	Integer	0	2000
Supply Chain Step #13	1	Integer	0	1900
	2	Integer	0	2000
	3	Integer	0	1800
	4	Decimal	-4	3.75
	5	Decimal	-4	4.25
Supply Chain Step #51	1	Integer	-3.75	4.25
	2	Integer	0	2000
	3	Decimal	0	1700
	4	Decimal	0	2000
	5	Integer	0	1400
Yield		Decimal	60	90

Table 15 - Simulated Data Range of Values (Cluster 2: Data Sets 0 - 5)

		Cluster 2											
Step	Measure	Data Set 0		Data Set 1		Data Set 2		Data Set 3		Data Set 4		Data Set 5	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1	1	4	1275	3	735	6	468	2	1067	2	750	0	1948
	2	-3.82999	3.31953	-3.08901	3.072862	-3.14388	3.351003	-2.9292	2.798884	-2.98538	3.316222	-3.62533	3.156301
	3	-3.6491	3.257933	-3.59307	3.248213	-2.78561	3.091558	-3.18184	3.504827	-3.29834	3.185316	-3.69845	3.242179
	4	1	1670	1	689	10	396	4	140	6	1185	0	1423
	5	4	14	8	455	2	1190	4	1541	9	749	5	236
2	1	3	1693	10	580	6	666	4	1057	10	232	8	455
	2	-3.71991	2.640055	-3.12494	3.321318	-3.32481	2.834351	-3.10672	3.515697	-3.19128	3.228764	-2.75201	3.275848
	3	-2.94568	2.814209	-2.72829	2.841249	-3.51333	2.836759	-3.36794	3.457576	-2.71377	2.942599	-3.39601	2.834856
	4	3	44	6	1350	3	1321	1	652	15	1819	10	662
	5	4	1467	10	1523	4	1206	6	1367	1	710	9	1672
3	1	4	806	6	907	10	79	10	1902	9	1033	1	914
	2	-3.33196	3.532472	-3.69494	2.784171	-3.70294	3.609711	-3.05632	2.954576	-3.44273	3.427374	-2.91398	3.074369
	3	-3.54795	2.855332	-3.58375	3.709249	-3.13166	2.921651	-3.46876	3.195524	-3.43864	3.601367	-3.46928	3.40102
	4	0	883	0	1005	6	527	4	906	7	1416	4	1231
	5	7	1780	9	623	9	1038	10	266	2	65	8	1146
4	1	0	313	2	862	9	1922	0	211	5	1307	7	208
	2	-2.86644	3.63473	-3.91461	3.775723	-3.17703	3.854072	-3.801	3.213663	-3.41955	3.832162	-3.18334	2.848292
	3	-3.29797	3.014019	-3.15143	2.78691	-2.69737	3.062909	-2.8637	2.877916	-3.0976	2.769209	-3.22979	2.983502
	4	10	642	2	1593	8	1509	6	1974	5	1024	9	161
	5	1	1769	6	1820	7	1015	5	87	1	1217	8	1251
5	1	12	1848	8	1267	7	86	0	1627	10	1693	2	1066
	2	-3.27572	3.3945	-3.25951	3.547284	-3.05825	3.005767	-3.19635	3.189947	-3.74339	3.201989	-3.23672	3.0988
	3	-2.94623	3.225512	-2.70948	3.100485	-3.12943	2.879274	-3.21973	3.305628	-3.16382	3.19393	-3.23214	3.573792
	4	5	91	3	53	1	1715	0	313	10	1341	6	941
	5	3	686	8	1404	6	1015	5	1644	3	868	0	865
6	1	4	1958	1	907	8	1933	5	741	9	1265	11	1767
	2	-2.9599	3.162491	-2.98716	3.152254	-3.74058	4.443486	-3.54028	3.064842	-3.12838	3.211956	-3.22935	3.47269
	3	-3.33839	2.965885	-3.33464	3.415396	-3.2365	3.034808	-3.38748	3.01681	-2.997	2.651351	-2.98035	3.258574
	4	0	542	0	888	6	1859	7	114	9	629	8	1087
	5	3	854	6	1651	2	442	6	1042	0	1084	9	87

7	**1**	6	219	6	860	8	1474	6	1065	1	1835	1	469
	2	-2.55816	3.76831	-3.22449	3.102073	-2.8507	2.843729	-2.64869	2.920903	-3.19166	3.127289	-2.92425	2.773862
	3	-2.70135	3.084373	-3.61184	2.93776	-4.14599	4.201091	-3.33505	2.940107	-3.10777	4.584726	-3.56194	2.472594
	4	5	1494	2	1515	0	37	6	857	4	1405	10	1148
	5	5	1336	2	1822	2	851	4	1434	12	1401	6	1789
8	**1**	2	1757	1	1267	3	1363	8	842	1	61	2	1742
	2	-2.68568	4.435865	-3.93326	3.514488	-3.16515	3.10456	-3.291	2.86765	-2.88591	2.67535	-3.3178	3.329749
	3	-3.21154	3.61392	-2.61177	3.164237	-3.79693	3.394893	-3.07467	4.205232	-3.58373	3.442937	-2.79777	3.480817
	4	10	462	0	1176	4	1367	2	613	7	383	5	601
	5	12	1698	5	1980	8	1730	9	1401	2	609	9	1700
9	**1**	9	1118	1	989	9	1790	8	648	8	929	2	930
	2	-3.03168	3.031386	-3.20117	3.06259	-3.30155	3.177387	-3.02424	2.685249	-2.93638	2.901705	-3.25848	2.913997
	3	-3.35614	4.077099	-3.0601	2.830298	-3.28043	3.046172	-3.43058	2.811771	-2.83174	3.027299	-2.71359	3.279314
	4	5	1528	6	919	3	1962	11	1583	8	1429	8	1873
	5	9	1976	4	541	4	1289	1	407	2	299	3	245
10	**1**	0	906	13	1648	9	748	1	1223	12	1218	3	777
	2	-3.61012	3.103185	-3.5413	4.937591	-2.84844	2.968057	-4.63624	3.146027	-3.10408	3.217397	-3.418	3.73988
	3	-3.10516	4.121653	-2.8401	3.020769	-3.59669	2.790706	-3.24433	3.365908	-3.07451	3.070215	-3.26311	2.902896
	4	3	569	1	949	10	1840	1	1708	9	1425	11	451
	5	6	790	4	11	8	1143	2	1184	9	769	3	740
11	**1**	7	1030	12	1847	9	818	2	579	2	1232	4	1353
	2	-4.07252	3.575747	-3.10588	3.478531	-3.4447	3.163286	-2.9446	3.721276	-3.29766	3.333302	-2.99064	3.304959
	3	-2.86982	3.036707	-3.0391	3.38907	-2.92348	2.870183	-2.8967	3.073356	-3.81788	3.148954	-4.14183	3.429343
	4	5	1679	10	1497	4	866	9	417	6	776	9	963
	5	7	389	5	953	6	949	9	839	7	1986	4	1286
12	**1**	8	288	2	858	7	1770	3	780	3	782	8	1634
	2	-2.78974	2.976021	-3.17748	3.590722	-2.97552	3.271888	-3.08773	3.558941	-3.50835	3.319256	-3.06835	3.067134
	3	-2.98448	2.72853	-2.94083	2.829965	-3.7341	2.978306	-3.08162	3.653397	-3.12366	3.393478	-3.36361	2.850783
	4	9	1074	2	1850	0	268	2	138	4	309	2	270
	5	6	388	11	1727	6	512	10	69	1	1630	6	1703
13	**1**	5	857	4	1851	4	860	7	1397	10	1368	1	1062
	2	6	1211	4	1110	3	1749	10	383	8	1847	5	1788
	3	10	1298	3	678	6	554	4	1558	2	1230	8	1624
	4	-3.01562	3.01349	-3.03691	3.449307	-2.762	3.638152	-3.88976	2.725857	-3.01831	2.788011	-3.317	3.207335
	5	-2.84472	3.232798	-2.84956	3.213226	-2.95941	2.888288	-3.37135	3.255163	-2.91937	2.986161	-3.23755	4.130961

14	**1**	11	673	9	1438	10	899	8	1405	10	44	6	672
	2	-2.91208	3.235787	-2.73802	2.935587	-2.47026	3.602709	-3.09299	3.146783	-3.00102	3.089044	-3.2243	3.579029
	3	-2.97791	3.096682	-2.8143	2.831796	-2.97528	3.898474	-3.06384	2.874403	-2.63687	4.096106	-3.25895	3.020665
	4	9	413	0	1135	5	1428	9	1839	6	622	4	1175
	5	2	1415	1	1633	0	406	5	1579	1	1108	9	1657
15	**1**	10	72	10	1068	4	1746	11	1888	3	1451	2	216
	2	-2.95971	3.178655	-3.37839	2.870229	-3.12071	3.978762	-3.37453	3.461249	-3.12155	3.004405	-3.21627	3.532154
	3	-3.10219	3.003754	-3.375	2.852017	-3.23947	3.145951	-4.24808	2.761529	-3.32802	3.151193	-3.2151	3.161316
	4	0	1759	8	1346	5	249	6	1472	7	1844	10	779
	5	6	167	2	257	10	1505	1	1473	0	24	2	345
16	**1**	9	1064	8	804	4	941	6	283	4	1619	4	1457
	2	-3.36167	3.431819	-3.30425	3.063808	-2.94262	3.228115	-3.40211	3.234856	-3.23347	2.868436	-3.11735	3.154157
	3	-3.18151	3.831752	-3.14898	3.750323	-3.54297	3.65607	-2.95751	3.267783	-3.50829	3.104815	-3.75382	3.648806
	4	2	138	6	1354	10	697	10	998	7	1727	8	729
	5	8	1793	9	1783	12	1915	1	325	1	1330	2	1529
17	**1**	1	788	0	288	4	155	3	1917	9	1191	9	804
	2	-2.90027	3.228452	-2.82783	3.502879	-3.18047	3.895129	-3.16929	3.413501	-3.31802	2.565043	-3.16188	3.163522
	3	-2.95957	3.178797	-3.32864	3.380034	-3.57301	2.755253	-3.17166	3.6709	-3.95656	3.593893	-3.25939	3.624201
	4	2	1470	4	555	11	1181	5	1176	9	83	8	799
	5	3	1640	11	1821	4	192	5	261	1	1780	9	1320
18	**1**	0	1435	4	1249	4	1455	5	1973	5	1729	2	1417
	2	-3.1606	3.014508	-3.49497	3.371273	-3.79448	3.68608	-3.37223	3.231051	-3.31885	3.213831	-3.12775	2.918525
	3	-3.17487	3.422543	-3.0884	3.304061	-3.21271	3.058594	-4.12872	2.972526	-3.63459	3.132088	-3.0757	3.328715
	4	7	1103	1	606	7	957	6	1486	10	324	3	1907
	5	2	847	11	976	7	252	7	225	3	1065	7	1549
19	**1**	6	1370	3	751	0	862	10	166	8	273	6	1526
	2	-3.33952	3.258071	-3.18979	2.753764	-2.91834	2.842208	-3.04474	3.249254	-3.97874	3.564938	-3.28716	3.267417
	3	-3.35684	3.481987	-2.82008	3.110238	-3.26714	2.953076	-2.59558	3.729277	-3.02729	3.119997	-3.02873	2.853511
	4	7	65	2	1085	3	976	0	124	8	1340	1	1180
	5	1	717	4	156	8	1374	10	765	8	1268	5	888
20	**1**	0	1882	4	1721	8	171	10	1537	7	1189	4	765
	2	-2.71298	3.302182	-3.7203	3.120201	-3.61969	3.614704	-3.13539	3.577331	-3.50267	3.334181	-2.85105	3.362572
	3	-3.2294	3.423929	-3.24376	3.727091	-2.96006	3.215454	-4.31066	2.769791	-2.89699	2.930976	-3.52004	3.607087
	4	3	1999	4	1202	7	212	6	129	8	1795	5	1240
	5	6	723	8	1467	6	975	6	159	1	1006	8	775

21	**1**	4	1662	10	1314	5	90	2	1804	10	1053	3	398
	2	-3.25567	3.464607	-3.21161	3.16886	-3.05705	3.055585	-3.72622	2.942751	-3.0194	2.721886	-3.08114	3.333934
	3	-3.16272	3.07317	-3.63144	3.005535	-3.08267	3.17791	-3.92004	3.479575	-3.0789	2.597307	-3.54742	3.474239
	4	10	1525	7	970	1	1830	1	1435	7	1053	3	121
	5	8	1166	10	1173	10	1116	1	584	3	771	1	1088
22	**1**	9	1901	7	40	5	1128	0	698	7	746	4	237
	2	-3.59572	3.000871	-3.31024	3.122716	-3.00202	3.163983	-3.27154	3.321384	-3.22479	2.970249	-3.11745	2.969105
	3	-3.50085	3.725478	-3.23833	3.231165	-3.60031	2.892997	-3.02139	2.702618	-2.92843	3.404239	-3.3251	2.603296
	4	2	1835	11	1450	10	584	5	1060	10	595	8	937
	5	10	1638	10	593	2	1437	1	840	2	1149	6	590
23	**1**	8	375	7	1138	3	947	8	712	5	651	8	654
	2	-3.68041	2.959417	-3.17127	3.012935	-2.74719	3.295066	-4.25613	3.031542	-3.41349	2.725521	-3.02679	3.289655
	3	-3.00418	3.0954	-3.26839	2.881448	-3.25902	3.337024	-3.37198	3.099695	-3.39874	3.505482	-2.78824	2.902054
	4	6	1621	2	335	4	593	4	1265	4	890	9	1901
	5	6	1298	1	1709	7	993	10	420	6	64	8	864
24	**1**	8	745	5	106	2	1884	2	1329	3	1006	0	1167
	2	-2.64772	3.229329	-2.74904	2.832968	-3.12036	3.429621	-3.59124	3.467608	-3.5764	3.564576	-3.6719	3.104123
	3	-3.2738	2.996004	-3.64265	3.178972	-3.30922	3.428156	-3.22938	3.528318	-2.48878	3.364113	-3.08448	3.779962
	4	10	1364	4	1851	6	191	3	1395	1	469	0	1486
	5	7	1217	4	1709	9	1175	3	384	10	857	9	243
25	**1**	3	1775	11	780	9	415	7	1956	10	790	6	19
	2	-3.80375	2.937205	-3.13267	3.292267	-2.86528	2.831665	-2.68132	3.163067	-3.05971	2.812481	-2.8996	3.044991
	3	-2.86806	3.324163	-2.78164	3.258367	-3.22751	3.858406	-3.1529	3.349252	-3.5519	4.177462	-3.72484	3.178173
	4	6	1074	5	95	10	123	9	1629	7	863	10	181
	5	2	1501	2	1584	6	1516	6	820	7	307	9	1666
26	**1**	11	1954	4	605	10	1317	9	917	6	1132	1	68
	2	-3.08084	3.747656	-3.2049	3.229447	-3.21777	2.936604	-3.2239	3.452128	-3.01098	2.582499	-3.7321	3.105295
	3	-2.98486	2.662397	-2.88383	3.744333	-3.30124	3.171468	-2.98262	3.055201	-2.90201	2.690026	-3.07189	3.263299
	4	8	1995	7	1548	5	1005	5	1591	1	1214	1	1083
	5	6	247	10	398	8	976	10	1249	5	935	6	972
27	**1**	7	1360	3	1718	7	730	10	1281	0	1600	8	415
	2	-2.92335	2.750109	-3.41361	3.141554	-3.13004	3.33988	-2.91179	4.645035	-3.04545	2.907698	-3.00422	3.366699
	3	-2.93085	2.915695	-3.30562	3.014626	-2.84759	3.367952	-3.21402	4.169138	-2.91078	3.272953	-3.28767	3.226221
	4	11	1974	10	512	1	1541	5	32	3	1462	3	60
	5	6	1993	14	1737	1	108	2	457	4	1601	4	1961

28	**1**	4	1109	4	982	7	654	11	1601	3	1273	5	1662
	2	-3.53325	3.728867	-4.08613	3.5285	-3.6303	2.691869	-2.92527	3.37072	-2.87658	2.959109	-3.21797	2.96686
	3	-2.6987	3.262465	-3.0673	2.938384	-2.74044	3.111828	-2.92013	3.455942	-3.31157	3.996062	-3.46095	3.031991
	4	7	1406	8	1052	7	1111	12	1950	2	1233	10	491
	5	0	274	7	166	5	306	8	370	4	445	10	247
29	**1**	8	707	6	1352	8	1175	7	1847	3	504	10	1856
	2	-3.05182	3.489948	-3.1086	3.776465	-3.25971	3.958526	-3.21867	3.202841	-3.39568	3.901854	-2.99702	2.993463
	3	-3.17472	3.114382	-3.16832	2.78156	-3.06695	3.040657	-2.94525	3.343291	-3.29435	3.476985	-3.05994	2.861075
	4	8	1546	6	1380	3	1033	4	669	3	253	9	210
	5	0	1327	0	1087	3	356	7	596	7	1794	7	805
30	**1**	0	498	7	908	10	1259	9	1924	3	1357	13	1871
	2	-3.05059	3.656791	-2.63079	3.559386	-3.16174	3.350707	-2.79963	3.807198	-3.13073	3.514813	-3.20169	3.274617
	3	-4.23415	3.480259	-3.63272	2.534433	-3.12549	2.97343	-2.96967	3.139387	-3.87353	2.639591	-3.29705	3.365544
	4	7	910	0	1086	2	206	4	1819	6	267	0	813
	5	6	922	9	907	1	1265	6	405	6	868	5	343
31	**1**	7	348	8	1229	7	999	0	1322	6	1125	3	1305
	2	-3.61149	3.365019	-3.01434	3.161746	-3.61121	3.202966	-2.92501	3.200461	-3.87702	3.200881	-3.855	3.462754
	3	-3.45485	2.911958	-3.69401	3.453798	-3.11478	3.677586	-2.76931	3.448467	-3.0053	3.228618	-2.96796	3.835946
	4	1	712	5	1669	3	1485	11	812	10	602	7	1637
	5	6	1753	2	716	2	84	9	19	6	2000	1	1509
32	**1**	4	96	6	938	8	1385	1	1670	3	1799	3	1305
	2	-2.94512	2.72206	-3.56195	3.485342	-2.90575	3.252412	-3.72442	3.24825	-3.32272	3.406712	-2.67248	2.822377
	3	-3.56997	3.070127	-3.48122	3.445181	-3.29436	3.822171	-2.761	3.307646	-3.86514	3.671261	-3.43523	3.262134
	4	4	1968	3	1609	0	1332	10	1970	4	1771	0	591
	5	4	936	7	1912	8	212	6	1656	5	85	9	237
33	**1**	5	917	1	419	2	317	4	279	4	1828	9	995
	2	-3.41956	3.14747	-2.85051	3.6157	-3.35246	3.117063	-3.41125	3.841226	-2.95797	3.200739	-3.8518	2.722074
	3	-3.04874	3.276649	-3.15758	3.15968	-3.5166	3.495562	-3.44759	3.066279	-3.19984	2.957825	-2.79936	2.766459
	4	4	1833	9	1952	8	258	6	1069	10	1147	10	647
	5	8	1416	9	12	9	536	3	830	5	1654	0	1967
34	**1**	2	757	6	1495	4	1496	9	332	2	1230	8	1408
	2	-3.42019	3.207766	-3.42661	3.808905	-3.87926	3.551199	-2.77081	3.14296	-2.89601	3.033675	-3.38592	3.019812
	3	-3.66463	2.877445	-2.97033	3.054584	-3.57305	3.585534	-3.25007	3.466911	-3.39901	3.066693	-3.30603	3.327664
	4	3	932	1	675	3	1189	1	683	11	1472	8	156
	5	10	1676	0	280	7	703	7	1986	15	1434	7	1935

35	**1**	1	1345	10	600	2	153	12	1747	6	1827	7	569
	2	-3.09541	3.436188	-2.84227	2.996399	-4.16945	3.242718	-3.23964	2.811683	-3.11729	3.58367	-3.6376	3.161002
	3	-2.77309	3.333441	-4.09142	2.875396	-3.02309	3.358725	-3.51844	3.443533	-3.00019	3.135251	-3.428	3.135246
	4	9	878	3	862	5	365	8	1658	11	1064	8	381
	5	6	1773	4	1023	9	98	8	1473	2	967	9	1357
36	**1**	5	1269	4	487	0	189	5	942	4	685	2	1380
	2	-3.73961	3.261965	-3.28272	3.82452	-3.64021	3.118186	-3.37458	3.297347	-3.2252	3.492082	-2.82448	3.245306
	3	-3.02464	3.562641	-2.99795	3.142054	-3.02935	3.831455	-3.8271	2.897869	-2.95504	3.165125	-2.76103	3.167467
	4	10	1631	9	816	7	446	1	100	3	1485	10	817
	5	7	1059	0	1702	5	132	6	991	3	591	11	1639
37	**1**	1	1428	1	567	5	109	9	1574	10	51	6	456
	2	-4.2732	3.148631	-3.04847	3.083326	-3.08853	3.257533	-3.23307	3.747843	-2.78169	3.039918	-3.01936	3.452907
	3	-3.03814	3.462019	-2.55041	3.6953	-2.67907	3.23139	-2.66885	3.514084	-3.16916	3.173094	-2.93894	2.73205
	4	2	134	4	1793	8	1523	7	886	10	1866	4	11
	5	11	1169	1	298	8	525	4	989	4	1954	7	921
38	**1**	1	894	5	597	10	748	7	1686	5	1079	10	1247
	2	-3.26977	3.748462	-3.17898	3.200899	-3.16307	2.866221	-2.73924	3.685292	-3.26899	2.801583	-3.04444	3.299744
	3	-3.57782	3.476666	-2.91122	2.994137	-3.06335	2.864826	-3.5109	2.931727	-3.70468	3.338864	-3.35326	3.296705
	4	9	420	7	955	7	1589	8	987	7	893	5	584
	5	9	574	3	1727	4	362	4	1748	8	368	3	1802
39	**1**	4	1624	1	1789	4	567	9	205	0	553	12	1133
	2	-3.04	3.025932	-3.01938	2.786615	-3.83787	2.765224	-3.0513	3.645284	-3.40038	3.519765	-3.23266	3.695326
	3	-3.06119	3.004495	-3.34898	2.726241	-3.50391	3.190546	-3.3367	3.338049	-3.30007	2.916283	-4.48737	2.766672
	4	4	252	7	263	6	1970	0	867	9	129	5	1250
	5	8	1616	6	1374	0	156	7	1487	10	1733	7	1871
40	**1**	6	1856	5	1785	3	1711	6	120	1	221	7	1091
	2	-2.89325	3.307045	-3.30639	3.045575	-3.43264	3.527817	-3.60328	3.477795	-3.12041	3.249651	-2.90159	2.887796
	3	-3.22548	3.232066	-3.41072	3.790371	-3.04549	3.64924	-3.49707	3.557127	-2.76849	2.826471	-2.95568	3.780684
	4	3	151	5	512	0	1032	5	307	7	1874	8	1433
	5	0	961	7	506	8	467	10	265	1	939	7	939
41	**1**	7	1145	7	1862	5	1765	5	261	0	514	5	185
	2	-2.99918	3.415139	-3.8545	2.784204	-3.37322	3.068424	-2.75701	3.417557	-3.00673	3.690001	-3.28085	3.833767
	3	-3.36494	2.663297	-2.67063	3.327263	-2.94679	3.146306	-3.0669	3.020896	-2.60312	2.664022	-3.47739	2.98629
	4	11	1839	8	1530	5	1916	7	1651	2	113	7	1810
	5	1	1525	11	1507	5	598	9	1592	4	1228	15	1833

42	**1**	1	1918	10	984	6	600	3	381	4	698	6	1367
	2	-2.83376	3.335356	-3.67441	4.025528	-3.07096	3.130602	-3.00703	3.411416	-3.24105	3.166041	-3.35267	3.462767
	3	-3.4575	3.375622	-2.76004	2.565518	-2.98096	3.095204	-3.14337	3.176008	-3.11048	3.450051	-2.56707	3.624753
	4	1	1346	7	1746	10	1752	4	627	1	512	5	292
	5	1	930	1	962	0	593	7	1957	7	1208	4	1771
43	**1**	2	1786	4	614	3	384	2	1899	8	35	5	359
	2	-3.45723	2.983402	-3.02637	3.081239	-4.03108	2.91205	-3.67332	3.40678	-3.28008	3.185919	-3.1725	3.228933
	3	-3.3015	4.050105	-2.92006	3.046903	-2.95494	2.716812	-3.90866	2.972384	-2.61954	3.322187	-3.53495	3.204859
	4	6	1482	3	851	12	1169	1	922	4	1489	10	195
	5	0	386	10	1981	5	1373	7	1264	8	583	1	321
44	**1**	10	1096	9	961	4	822	6	745	7	376	2	1180
	2	-3.34223	3.092287	-3.31399	3.161941	-2.95884	2.932357	-3.22857	3.08633	-3.54952	3.138706	-3.04079	4.025234
	3	-3.02117	3.492922	-3.46872	3.179162	-2.68566	3.34479	-2.671	3.683657	-3.34265	2.948548	-2.72772	3.43633
	4	3	1571	5	567	6	933	1	357	7	83	4	1577
	5	12	837	5	566	7	1832	5	1547	6	974	2	389
45	**1**	8	1749	2	209	7	289	12	1547	7	1230	5	1484
	2	-3.61386	3.525558	-2.94794	3.544837	-2.6138	2.735545	-3.62646	3.334761	-2.96787	2.868994	-4.02402	2.991153
	3	-3.47478	4.422972	-3.05079	3.083858	-3.36571	3.798695	-3.80856	2.875126	-3.1958	3.442863	-4.17929	2.756458
	4	1	143	4	1330	7	1525	5	1119	0	637	8	240
	5	7	1083	6	1772	10	1641	10	1578	2	522	7	1798
46	**1**	9	825	9	144	9	276	2	932	9	90	0	929
	2	-3.04992	2.894936	-3.62361	3.714295	-3.11687	3.016641	-2.98793	2.82924	-2.90673	3.020568	-3.40726	3.464705
	3	-3.1516	3.455375	-3.41099	3.184129	-3.21513	3.392461	-2.84271	2.772399	-3.23291	3.071861	-4.13577	2.980223
	4	9	641	5	1414	2	32	3	165	9	1251	5	260
	5	10	428	1	1489	5	396	3	1438	10	1557	9	1787
47	**1**	2	1088	5	237	3	43	2	482	2	844	10	943
	2	-2.76187	3.291123	-3.7814	3.188717	-3.34762	3.060839	-3.83818	3.095538	-3.48986	2.99989	-3.32256	3.302105
	3	-3.61065	3.123018	-2.8404	3.184547	-2.95058	3.238143	-3.35827	3.214371	-3.21763	3.107796	-2.79855	2.84496
	4	7	1827	9	1336	3	907	10	1328	5	688	3	145
	5	2	957	3	764	8	29	8	332	0	128	1	921
48	**1**	1	1835	6	1652	0	908	2	1220	7	789	10	1228
	2	-3.73605	3.164398	-3.18628	2.959329	-3.21145	2.722052	-3.52207	3.52448	-3.32931	3.212936	-3.72929	3.601462
	3	-4.01641	3.380237	-2.83256	3.304751	-2.86063	3.086608	-3.0841	3.89918	-3.08321	3.235774	-3.20884	3.268555
	4	16	1856	2	1359	2	1395	9	1675	5	564	2	1455
	5	2	1880	3	1229	9	1039	2	940	7	791	2	172

49	**1**	6	1121	1	512	7	491	12	1888	3	15	7	1383
	2	-3.81875	3.045563	-3.07616	2.83105	-3.68072	3.602304	-2.66779	3.291995	-3.23681	2.846445	-3.1391	3.371533
	3	-3.26336	3.802997	-4.08148	3.175465	-2.7614	2.65853	-3.38858	2.833904	-3.15887	3.420353	-3.03769	3.058072
	4	7	514	6	1507	5	355	3	392	10	576	6	303
	5	2	1514	8	626	2	1634	10	969	6	1131	6	1461
50	**1**	4	1864	5	645	5	1589	7	1581	7	1829	0	1448
	2	-2.77607	2.863048	-3.09107	3.49229	-3.20895	3.30379	-2.8601	3.451586	-3.62134	4.194018	-3.24625	4.101994
	3	-3.33853	2.639084	-3.38302	2.971023	-3.5044	3.270261	-2.89048	3.053165	-3.12413	4.084139	-3.11569	2.920142
	4	7	253	1	409	2	382	9	936	10	1693	10	1556
	5	-4.10905	3.007127	-3.09799	2.893784	-3.30851	2.679812	-2.93177	3.423861	-3.22032	3.294491	-3.23937	3.362673
51	**1**	-3.22192	2.827413	-2.72349	3.210808	-3.0496	2.938435	-3.66633	2.78033	-3.38104	3.112602	-3.69801	2.636166
	2	1	720	0	381	1	1575	4	1925	11	1681	10	1493
	3	8	221	4	1603	9	408	5	1669	3	514	11	859
	4	8	1477	6	705	5	980	4	1950	3	258	1	612
	5	4	485	4	814	9	1385	0	655	7	872	2	1037
YIELD		60.0047	89.9699	61.4517 6	90	62.87185	90	62.4358	90	63.6505 6	90	65.0815 2	90

A1/C3B – Range of Values for the Simulated Data Set (Cluster 2: Data Sets 6 – 10)

In this section the minimum and maximum values for each supply chain step of the remaining data sets (Data sets 6 to 10) of the second simulated data cluster are presented. The range of values of these remaining data sets is very similar to the ones covered in the previous section (i.e. A1/C3A). Again, the range of the dependent variable of each simulated data set is between 60 and 90. Illustrated simulated data sets in Table 16 include both integer and decimal numbers for measurements and as in the case of the previous six data sets in the first cluster. Table 16 reveals that apart from supply chain steps thirteen and fifty one, all supply chain steps have a similar approximate range of values as in the case of Table 15. All supply chain steps (excluding steps #13 and #51) have integer values for process metrics one, two, and five between values of zero and two thousand (Table 11). The process metrics three and four of these supply chain steps have decimal values between -4.25 and +4.25 approximately. Step #13 has similar range of values, but its process metrics one, two, three are decimals within -4.00 and +4.25 range, and process metrics four and five are integers between zero and two thousand approximately. Only the process metric one of Step #51 is a decimal between a range of -3.75 and +4.25. The remaining metrics are integers approximately between zero and two thousand. The shaded columns provided in Table 16 reveal the range across all eleven data sets of the first cluster.

Table 16 - Simulated Data Range of Values (Cluster 2: Data Sets 6 - 10)

		Cluster 2											
Step	Measure	Data Set 6		Data Set 7		Data Set 8		Data Set 9		Data Set 10		Across All Sets	
		Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
1	1	3	1730	1	543	7	67	8	1341	0	381	0	1948
	2	-2.8424	3.092671	-3.29542	3.45287	-3.52723	4.227454	-3.34496	3.66265	-2.7866	3.260096	-3.82999	4.227454
	3	-3.69042	3.167812	-3.35418	2.953883	-3.57917	3.514984	-3.0506	2.927013	-3.56061	3.375143	-3.69845	3.514984
	4	1	1036	9	128	6	408	4	1309	8	1400	0	1670
	5	6	935	8	590	8	462	6	865	2	1018	2	1541
2	1	10	1288	0	1183	7	515	4	176	3	815	0	1693
	2	-2.75086	2.900296	-3.25601	3.479039	-3.53755	3.913087	-2.96877	3.57975	-2.73085	3.328545	-3.71991	3.913087
	3	-3.69699	3.090077	-2.67676	2.95361	-3.50156	3.695369	-2.88123	3.403203	-4.04155	3.596664	-4.04155	3.695369
	4	1	543	11	1414	0	814	10	616	2	103	0	1819
	5	10	971	5	623	2	808	7	1814	8	1735	1	1814
3	1	9	1555	1	1499	9	875	9	1767	3	261	1	1902
	2	-3.20152	3.906265	-3.18517	2.908165	-3.50865	2.84495	-3.34153	3.534982	-3.34302	4.25331	-3.70294	4.25331
	3	-3.40095	4.143879	-2.98532	3.826666	-2.86046	3.401609	-3.32765	2.950624	-3.22627	3.453568	-3.58375	4.143879
	4	8	755	10	1476	6	436	5	1800	10	733	0	1800
	5	11	1603	2	191	8	442	5	1229	7	1075	2	1780
4	1	3	1507	7	574	0	518	7	315	3	1289	0	1922
	2	-3.20868	3.278044	-3.636	4.004233	-3.11891	3.665884	-3.1384	3.052671	-3.44143	3.023311	-3.91461	4.004233
	3	-4.2469	3.119792	-3.57843	3.46804	-3.6013	2.909944	-3.29801	2.999392	-2.97518	3.739632	-4.2469	3.739632
	4	9	1309	13	1533	6	319	7	996	4	142	2	1974
	5	6	108	8	1539	13	1139	7	1788	1	196	1	1820
5	1	9	1947	2	409	25	1883	1	1016	11	899	0	1947
	2	-3.07626	2.64314	-3.63849	2.851531	-2.77772	3.166858	-3.11591	3.211249	-3.05543	3.057547	-3.74339	3.547284
	3	-3.37982	3.321403	-3.00176	2.560606	-3.09195	3.179351	-3.00192	3.206366	-2.65825	2.919697	-3.37982	3.573792
	4	6	1845	10	740	8	173	10	1744	10	1402	0	1845
	5	10	1013	4	1354	7	97	0	1299	11	1740	0	1740
6	1	3	1667	10	1777	3	657	3	395	7	467	1	1958
	2	-3.99322	2.963179	-3.11247	2.663292	-3.30889	3.506834	-2.84931	2.930678	-2.71359	4.038747	-3.99322	4.443486

	3	-2.72061	3.232027	-2.94498	3.126638	-2.58067	3.297757	-3.68478	3.829003	-2.78403	3.189972	-3.68478	3.829003
	4	1	1056	3	259	9	796	11	1735	4	1902	0	1902
	5	3	1131	7	1951	8	279	6	1157	0	783	0	1951
7	**1**	2	591	6	698	6	421	7	1815	2	921	1	1835
	2	-3.28646	2.839351	-3.24576	3.200334	-3.02769	3.448944	-3.13553	2.919196	-3.17149	3.352873	-3.28646	3.76831
	3	-2.53542	2.948104	-3.06273	2.772666	-3.24764	3.415861	-3.06778	3.00933	-2.80236	3.634182	-4.14599	4.584726
	4	2	1297	9	711	10	105	1	1638	2	1194	0	1638
	5	0	1091	2	1638	8	961	6	571	5	1976	0	1976
8	**1**	9	1656	9	1809	9	1150	6	1551	6	1673	1	1809
	2	-3.18735	3.204366	-3.35579	3.412558	-3.55123	3.556584	-3.10543	2.981685	-3.08869	3.521467	-3.93326	4.435865
	3	-2.66897	3.30404	-2.99827	3.296769	-2.92389	3.409009	-3.10681	2.683407	-3.02883	2.654814	-3.79693	4.205232
	4	2	1960	4	1442	9	1290	0	1053	0	352	0	1960
	5	10	1976	5	575	3	1432	9	160	4	1405	2	1980
9	**1**	10	84	0	616	10	1129	5	1627	8	924	0	1790
	2	-3.194	3.442671	-3.21436	2.971913	-3.4451	3.543653	-3.40747	3.284725	-3.60195	3.187534	-3.60195	3.543653
	3	-2.967	3.005626	-3.94934	2.721133	-3.32345	3.043908	-2.91522	2.730241	-3.28464	3.530568	-3.94934	4.077099
	4	9	1106	9	946	4	1250	4	1462	8	1132	3	1962
	5	3	867	9	550	9	1874	4	1591	9	53	1	1976
10	**1**	2	1365	8	1870	2	1582	11	1523	5	1271	0	1870
	2	-4.45824	3.147377	-2.8873	2.978115	-2.73259	3.219572	-3.18708	3.074589	-3.35307	3.457318	-4.63624	4.937591
	3	-2.83856	3.05978	-3.28051	2.85126	-2.85686	3.116687	-2.60178	3.845867	-3.28747	2.923771	-3.59669	4.121653
	4	9	626	3	1283	9	1909	2	1017	10	421	1	1909
	5	6	896	10	749	10	1922	14	1279	7	1343	2	1922
11	**1**	5	218	9	1455	6	1307	1	514	1	722	1	1847
	2	-2.7954	2.724723	-3.48772	2.932273	-3.06963	3.156697	-4.06042	2.772701	-3.05633	3.180542	-4.07252	3.721276
	3	-3.00251	3.800208	-3.16449	3.201781	-3.48099	3.467178	-2.95667	3.439768	-3.02227	3.708089	-4.14183	3.800208
	4	7	1498	2	564	3	751	9	1758	7	622	2	1758
	5	0	123	1	685	9	399	11	1859	10	1536	0	1986
12	**1**	9	923	2	1912	12	1687	3	252	0	140	0	1912
	2	-3.55208	2.744208	-3.12257	3.195263	-2.88078	2.924602	-3.0264	3.183018	-3.51815	2.850081	-3.55208	3.590722
	3	-2.8739	3.65532	-4.57458	2.936651	-3.16487	3.161638	-2.91757	3.470571	-3.07306	2.743528	-4.57458	3.65532
	4	7	1362	5	563	5	1582	4	1072	8	1758	0	1850

	5	8	815	1	1502	0	1027	7	808	11	1467	0	1727
13	**1**	6	1346	3	1230	12	957	6	533	4	959	1	1851
	2	4	100	8	1968	2	101	7	309	12	1421	2	1968
	3	11	898	2	1196	6	1236	0	331	16	1800	0	1800
	4	-3.45445	2.98551	-3.40112	3.356641	-3.85271	3.45314	-3.18023	2.788721	-3.37034	2.770932	-3.88976	3.638152
	5	-2.83644	3.327614	-2.76144	3.318973	-4.08892	3.427568	-3.0135	3.509387	-2.9796	3.373196	-4.08892	4.130961
14	**1**	2	898	10	1356	2	1410	3	1904	6	974	2	1904
	2	-3.01057	3.213622	-3.47691	2.981461	-3.17135	3.474016	-3.16944	3.32096	-3.15266	2.911141	-3.47691	3.602709
	3	-3.49946	3.113373	-2.99166	3.197927	-3.22815	3.873561	-3.53677	2.985513	-3.42084	3.530025	-3.53677	4.096106
	4	5	1068	0	661	7	1712	4	482	11	1130	0	1839
	5	9	1028	2	448	5	1742	9	963	8	1487	0	1742
15	**1**	11	1083	6	1273	11	1780	11	1592	9	680	2	1888
	2	-4.31422	3.182428	-3.29401	3.137433	-3.28773	3.524668	-3.19436	2.988451	-2.76356	3.081852	-4.31422	3.978762
	3	-2.74431	3.017348	-2.76458	2.730957	-2.98198	3.496193	-3.39759	3.464332	-4.05298	3.203168	-4.24808	3.496193
	4	6	791	0	145	10	362	5	504	7	328	0	1844
	5	6	186	2	1880	3	948	2	912	6	1502	0	1880
16	**1**	6	1353	6	1526	1	342	2	1752	1	332	1	1752
	2	-3.49149	3.299323	-2.55591	3.638316	-4.00164	3.544023	-3.43821	3.616813	-2.65707	3.392098	-4.00164	3.638316
	3	-3.31089	3.019382	-3.52068	3.141073	-3.35183	3.314157	-3.23374	3.242447	-2.77642	3.074427	-3.75382	3.831752
	4	0	291	4	1223	4	303	1	68	0	163	0	1727
	5	1	1192	5	1359	10	850	7	1587	5	1271	1	1915
17	**1**	6	1731	9	596	8	435	5	1785	7	1062	0	1917
	2	-3.04745	2.757621	-3.17217	3.435805	-3.36951	3.203106	-3.75302	3.38385	-2.93326	3.657205	-3.75302	3.895129
	3	-3.53676	3.160135	-3.19846	3.390579	-3.73842	3.027502	-3.07905	3.700321	-3.23596	3.822501	-3.95656	3.822501
	4	1	635	1	118	4	87	3	900	5	986	1	1470
	5	2	748	5	68	9	1625	8	1013	6	530	1	1821
18	**1**	9	1524	7	969	3	849	12	1179	1	1602	0	1973
	2	-3.40862	3.769782	-3.62211	3.537087	-4.24129	3.09225	-3.53277	3.524931	-3.01511	2.915551	-4.24129	3.769782
	3	-2.75335	3.371141	-3.13696	2.732718	-3.26493	3.180195	-3.01356	2.997196	-3.67003	2.730576	-4.12872	3.422543
	4	1	1929	6	1511	7	643	11	1848	2	664	1	1929
	5	4	966	1	29	4	1319	8	1336	9	1871	1	1871
19	**1**	10	1610	8	1796	5	1595	8	119	2	1203	0	1796

	2	-3.24895	3.101176	-3.18324	3.54508	-3.63904	3.824368	-3.37817	3.037042	-4.00368	2.951583	-4.00368	3.824368
	3	-3.994	3.777474	-2.79374	3.197104	-3.23308	3.22562	-3.19214	2.917153	-3.22708	2.945898	-3.994	3.777474
	4	2	844	7	1410	12	1850	3	567	0	480	0	1850
	5	7	306	5	1269	0	1796	5	1245	3	1766	0	1796
20	**1**	3	532	4	1359	0	190	3	1110	1	1390	0	1882
	2	-3.28617	2.862114	-3.14641	2.924034	-2.98284	3.174317	-3.29503	3.407118	-2.95589	3.131361	-3.7203	3.614704
	3	-3.6022	3.245195	-2.85693	3.077823	-4.01002	3.059731	-3.17047	4.015574	-3.00439	3.283024	-4.31066	4.015574
	4	3	122	10	504	7	1873	7	311	6	666	3	1999
	5	8	173	1	1138	10	515	1	853	3	1645	1	1645
21	**1**	2	356	5	813	4	1497	3	1360	10	958	2	1804
	2	-3.0391	2.850739	-3.45887	3.574581	-3.67066	3.784926	-3.13256	3.336598	-3.00505	2.966482	-3.72622	3.784926
	3	-3.46688	2.874235	-3.00581	3.113935	-3.06335	3.111147	-3.25505	3.527912	-3.19584	3.44426	-3.92004	3.527912
	4	10	1768	7	714	7	710	0	738	8	661	0	1830
	5	12	1114	8	1137	3	1437	9	438	4	1694	1	1694
22	**1**	9	246	0	1938	0	1056	8	1939	11	1688	0	1939
	2	-3.52198	3.120753	-3.3218	3.105742	-2.83183	3.42328	-3.36533	3.09693	-3.62907	3.070469	-3.62907	3.42328
	3	-3.45558	3.030901	-3.3322	3.504165	-3.43474	3.241193	-3.11769	4.221846	-3.54696	3.067859	-3.60031	4.221846
	4	1	297	10	383	10	1253	8	146	6	106	1	1835
	5	3	520	0	643	3	139	10	1601	8	673	0	1638
23	**1**	0	1960	1	734	8	164	7	247	12	768	0	1960
	2	-2.71486	3.289443	-2.76761	3.356893	-2.96481	3.804389	-2.85623	3.230332	-3.2152	3.689965	-4.25613	3.804389
	3	-3.5315	2.983595	-3.74457	2.972794	-3.28686	3.382734	-2.96113	2.831337	-3.02928	3.58463	-3.74457	3.58463
	4	10	641	3	459	2	245	2	1239	5	1550	2	1901
	5	5	497	4	174	9	554	8	734	12	1989	1	1989
24	**1**	7	649	2	1317	12	1457	3	385	9	1007	0	1884
	2	-2.81025	3.302062	-2.76141	2.897593	-4.74512	2.843004	-3.08078	3.275954	-3.02973	3.361194	-4.74512	3.564576
	3	-2.81268	3.532203	-3.43976	2.894632	-3.06366	2.767597	-3.27793	3.191203	-3.17537	2.828557	-3.64265	3.779962
	4	0	1577	4	634	2	1541	10	1503	5	1503	0	1851
	5	1	918	7	1601	8	907	11	1417	1	1796	1	1796
25	**1**	3	1194	7	72	2	1578	3	65	6	1879	2	1956
	2	-3.48817	2.969453	-2.97524	3.194408	-2.94646	3.456939	-3.80778	2.552992	-2.87488	2.520622	-3.80778	3.456939
	3	-3.26863	3.708468	-3.60797	2.8677	-3.37544	3.395743	-2.64525	3.72227	-3.1235	3.161886	-3.72484	4.177462

	4	4	1936	6	339	1	472	0	250	10	1724	0	1936
	5	6	683	5	1488	3	1127	1	979	3	455	1	1666
26	**1**	5	1538	9	1594	8	139	12	1397	1	1181	1	1954
	2	-3.01576	3.04538	-3.30559	3.458063	-3.47133	3.392048	-2.74573	3.043079	-3.1014	3.374081	-3.7321	3.747656
	3	-3.63373	2.663468	-3.02333	3.121115	-2.85385	3.107284	-3.58893	3.107538	-2.99228	3.787676	-3.63373	3.787676
	4	2	698	10	1993	2	1067	10	398	8	303	1	1995
	5	9	198	10	1063	8	1180	1	1074	5	434	1	1249
27	**1**	2	1664	4	1820	3	711	10	326	9	1783	0	1820
	2	-2.84353	4.335766	-2.99327	3.3201	-3.73824	2.886481	-3.32707	3.948125	-3.27275	3.428853	-3.73824	4.645035
	3	-3.14245	3.612576	-3.67738	3.142934	-3.00468	2.829863	-2.98978	3.053193	-3.48046	3.13699	-3.67738	4.169138
	4	10	584	5	1828	5	379	10	62	8	888	1	1974
	5	2	1326	5	23	6	160	10	1618	5	494	1	1993
28	**1**	1	207	10	1239	1	593	2	131	10	368	1	1662
	2	-3.33351	3.374845	-3.36069	3.077543	-3.08727	3.80503	-3.38017	3.306871	-3.04014	2.83012	-4.08613	3.80503
	3	-3.48033	3.449634	-2.98633	3.159349	-2.79811	2.565311	-3.54155	3.252542	-2.96027	3.249231	-3.54155	3.996062
	4	6	663	0	1323	9	1283	1	1241	12	1501	0	1950
	5	1	599	9	827	6	832	6	1790	6	420	0	1790
29	**1**	5	698	1	76	0	322	1	367	3	914	0	1856
	2	-3.53686	3.041841	-3.25498	3.027078	-3.44397	2.769575	-3.68171	3.032192	-3.09043	3.070777	-3.68171	3.958526
	3	-3.39143	3.220505	-2.63725	3.400029	-2.87358	3.198505	-2.82556	2.856143	-3.29614	3.037569	-3.39143	3.476985
	4	12	1428	10	649	3	92	6	720	9	1223	3	1546
	5	3	419	3	988	8	754	3	1403	0	1486	0	1794
30	**1**	7	1252	8	1682	2	1248	3	1524	5	1930	0	1930
	2	-3.36167	2.861846	-3.10646	2.92064	-3.51771	3.440099	-3.10135	3.533432	-2.67741	2.988278	-3.51771	3.807198
	3	-3.59197	3.111254	-3.47281	3.004972	-2.90163	2.792789	-3.08676	3.395491	-3.39502	3.384318	-4.23415	3.480259
	4	8	875	4	309	3	432	9	97	3	1120	0	1819
	5	7	1514	1	1577	3	256	7	1006	7	1923	1	1923
31	**1**	7	940	10	1506	10	696	11	1876	13	980	0	1876
	2	-3.34729	2.825684	-3.41031	2.936869	-3.12711	3.662225	-2.971	3.004812	-3.72745	3.216838	-3.87702	3.662225
	3	-3.42708	3.196923	-3.32512	3.017075	-3.05412	3.105118	-3.36254	2.918497	-2.83712	3.039076	-3.69401	3.835946
	4	4	1092	0	1410	11	1689	12	1772	1	940	0	1772
	5	5	399	8	11	9	1213	6	1283	5	790	1	2000

32	**1**	8	1333	4	1029	4	1399	0	277	2	1816	0	1816
	2	-3.12994	2.680196	-3.13701	3.251333	-3.15868	3.018442	-3.32793	3.396163	-3.61574	2.892867	-3.72442	3.485342
	3	-3.19325	3.275283	-3.61336	2.904663	-4.33862	3.170566	-2.87576	3.090017	-3.20024	2.899372	-4.33862	3.822171
	4	2	718	4	316	4	702	5	1852	2	471	0	1970
	5	2	214	2	1411	9	1259	10	33	5	1706	2	1912
33	**1**	3	1618	4	237	12	680	6	1375	3	1686	1	1828
	2	-3.10658	3.067406	-2.84855	3.334034	-3.46537	2.788543	-3.75465	2.813865	-3.07798	2.763414	-3.8518	3.841226
	3	-3.35748	3.68611	-3.90848	3.818938	-3.30823	2.83778	-3.36965	3.15663	-2.91227	3.197241	-3.90848	3.818938
	4	7	1009	4	553	9	897	5	811	3	1413	3	1952
	5	8	1374	5	1406	4	1141	3	1053	7	1470	0	1967
34	**1**	3	178	2	467	0	906	8	999	11	1485	0	1496
	2	-2.96454	2.934032	-3.69793	3.840089	-3.31371	3.144528	-3.22788	3.197992	-2.98992	3.069004	-3.87926	3.840089
	3	-3.16245	2.935787	-3.56236	2.785379	-4.16033	3.298264	-3.13903	2.754938	-3.37596	3.471691	-4.16033	3.585534
	4	13	842	5	189	8	494	5	348	6	917	1	1472
	5	4	1511	4	1401	12	1480	10	864	6	1142	0	1986
35	**1**	9	1749	11	1902	0	1081	7	1287	3	601	0	1902
	2	-3.07268	3.392453	-3.22476	3.102267	-2.90429	3.106415	-3.30958	3.085241	-3.23061	2.77905	-4.16945	3.58367
	3	-3.28388	2.985153	-2.58045	3.268862	-3.43018	2.896273	-3.54819	3.06704	-3.04585	4.278637	-4.09142	4.278637
	4	6	1779	8	840	6	1609	8	1631	8	455	3	1779
	5	8	1158	3	1447	7	922	8	634	0	1033	0	1773
36	**1**	8	639	8	1160	9	509	4	253	10	538	0	1380
	2	-3.46841	3.27053	-2.85571	3.839835	-3.31445	2.894883	-2.69364	3.045197	-3.17044	3.708905	-3.73961	3.839835
	3	-2.73819	3.363085	-2.92016	3.488023	-2.86497	3.375588	-3.48673	2.844612	-2.91551	3.449357	-3.8271	3.831455
	4	5	761	4	1665	8	1058	2	392	4	123	1	1665
	5	8	1077	3	1733	8	888	3	1660	8	1888	0	1888
37	**1**	8	1731	3	1776	1	705	4	1409	10	1323	1	1776
	2	-3.014	3.706687	-3.44802	3.009401	-3.1313	2.893174	-3.30784	2.79891	-3.02667	3.303651	-4.2732	3.747843
	3	-3.19934	3.342559	-3.39022	3.366187	-3.26493	2.329056	-4.12599	3.639145	-2.81669	3.18337	-4.12599	3.6953
	4	5	1217	0	1605	2	943	2	359	8	623	0	1866
	5	10	432	8	733	6	1522	7	1695	1	850	1	1954
38	**1**	3	192	4	857	7	1785	10	148	9	757	1	1785
	2	-3.51051	3.462399	-3.21626	2.812435	-2.7367	3.609861	-3.27946	3.004881	-3.34282	3.539339	-3.51051	3.748462

	3	-4.89693	3.30749	-3.04589	3.326571	-2.89901	3.891253	-2.69598	3.150735	-3.2485	2.966191	-4.89693	3.891253
	4	1	911	10	1056	5	1873	4	1467	7	1023	1	1873
	5	7	979	3	522	8	1482	2	127	4	130	2	1802
39	**1**	8	1105	1	886	7	1605	5	113	7	1540	0	1789
	2	-3.60585	3.002748	-3.00701	3.39085	-2.83529	2.794232	-3.11078	3.540404	-2.81218	3.493166	-3.83787	3.695326
	3	-3.77704	3.443503	-4.0965	2.919931	-3.28259	3.251381	-3.18886	2.724473	-2.76145	3.275771	-4.48737	3.443503
	4	10	1667	6	482	5	1161	5	719	8	361	0	1970
	5	4	1421	0	167	6	336	6	100	4	1404	0	1871
40	**1**	4	1393	10	1392	5	1006	10	1124	0	1140	0	1856
	2	-3.21122	2.919415	-2.83977	3.215687	-4.97406	3.548824	-3.1001	2.899947	-2.5184	2.77699	-4.97406	3.548824
	3	-3.43077	3.755342	-3.49712	3.643345	-3.04966	2.866598	-3.40284	2.864309	-3.71731	3.371156	-3.71731	3.790371
	4	5	1431	6	832	2	1692	4	567	12	949	0	1874
	5	5	1785	2	1956	10	806	3	763	7	746	0	1956
41	**1**	7	833	15	1641	10	739	4	1848	10	498	0	1862
	2	-2.9416	3.081404	-2.97967	3.087624	-3.82341	3.555589	-3.39107	3.972098	-2.714	3.04965	-3.8545	3.972098
	3	-3.21206	3.039754	-3.33218	3.161681	-2.86475	3.596555	-3.21281	3.142865	-3.20626	3.34383	-3.47739	3.596555
	4	7	1812	4	680	1	1580	8	967	4	418	1	1916
	5	8	1102	9	1127	9	975	9	1608	7	1668	1	1833
42	**1**	1	553	2	651	8	1379	3	156	6	60	1	1918
	2	-3.52889	3.308518	-3.48904	3.359107	-3.32964	3.143016	-3.57994	3.399696	-3.20386	2.723214	-3.67441	4.025528
	3	-3.68508	3.414254	-3.71153	3.177194	-3.23667	3.053395	-3.452	3.283903	-3.10983	3.312552	-3.71153	3.624753
	4	0	568	6	578	10	1437	8	1865	6	312	0	1865
	5	17	1588	9	910	4	609	7	64	11	718	0	1957
43	**1**	4	584	5	887	9	1362	1	471	4	1488	1	1899
	2	-3.31685	3.458807	-2.84279	3.424136	-3.07823	2.739903	-3.41051	2.817865	-3.37683	3.071531	-4.03108	3.458807
	3	-3.20407	3.319699	-3.41983	3.55677	-3.21294	3.725755	-3.19134	3.375942	-3.18261	2.836453	-3.90866	4.050105
	4	2	148	12	1634	7	463	4	1428	8	659	1	1634
	5	8	1023	7	1351	4	242	3	38	8	354	0	1981
44	**1**	5	1532	10	74	4	76	5	1995	9	624	2	1995
	2	-2.8117	3.3168	-3.05812	3.396561	-3.79717	3.557004	-3.54171	2.997048	-3.04767	3.058097	-3.79717	4.025234
	3	-2.69928	3.063243	-3.55582	3.335976	-3.16195	3.911308	-3.11461	2.914286	-3.2369	2.952606	-3.55582	3.911308
	4	5	1464	10	206	8	1457	8	616	10	619	1	1577

	5	1	693	3	1483	5	260	4	1899	3	1666	1	1899
45	**1**	5	1848	2	858	9	566	6	542	4	1118	2	1848
	2	-3.33069	3.190843	-3.74067	3.299248	-2.95392	3.449203	-3.00213	3.691708	-3.13393	3.073347	-4.02402	3.691708
	3	-3.11657	3.251741	-4.05234	3.015897	-3.03722	3.044222	-3.72854	3.226704	-2.98742	3.55951	-4.17929	4.422972
	4	4	1405	2	1380	5	578	1	1478	0	336	0	1525
	5	6	234	2	232	6	1805	6	437	9	1132	2	1805
46	**1**	4	468	6	498	3	768	10	1914	2	323	0	1914
	2	-3.23487	3.067356	-3.38403	3.276421	-3.59437	3.236525	-3.59534	3.197988	-3.3682	2.934349	-3.62361	3.714295
	3	-3.3596	2.834801	-3.41931	3.396006	-3.36281	3.02297	-3.59612	3.118436	-3.10606	2.917715	-4.13577	3.455375
	4	6	1709	9	1579	1	509	1	381	6	339	1	1709
	5	3	85	4	592	8	162	4	46	8	1909	1	1909
47	**1**	6	1360	8	1399	9	1700	9	1258	8	931	2	1700
	2	-2.99185	3.071843	-3.27408	3.051991	-2.99804	3.054469	-3.83362	2.945168	-2.93847	3.609961	-3.83818	3.609961
	3	-2.45157	3.040337	-3.15725	3.23621	-3.86851	2.553137	-3.12637	3.472413	-2.93186	2.926304	-3.86851	3.472413
	4	10	1411	8	1241	12	868	10	112	11	1938	3	1938
	5	4	227	0	188	9	182	10	1795	7	106	0	1795
48	**1**	3	1569	7	1399	2	1983	5	1202	4	1764	0	1983
	2	-2.76538	2.964342	-3.12633	2.778353	-2.81029	2.746292	-3.05002	2.705281	-3.38616	2.90503	-3.73605	3.601462
	3	-2.9749	2.813571	-2.91511	3.161282	-4.0295	3.113373	-3.42793	3.874947	-3.73138	2.86636	-4.0295	3.89918
	4	5	1170	10	450	6	629	5	345	5	509	2	1856
	5	5	1374	7	293	4	1454	3	1627	3	815	2	1880
49	**1**	3	950	0	21	11	494	10	1221	10	391	0	1888
	2	-3.57005	3.96699	-3.73099	2.983824	-2.91895	2.864885	-3.85821	3.010895	-3.59166	3.046737	-3.85821	3.96699
	3	-3.71283	3.533235	-3.50686	3.142721	-3.2979	3.02426	-3.06725	2.903744	-3.46127	3.16247	-4.08148	3.802997
	4	0	741	1	968	10	1013	5	222	11	868	0	1507
	5	2	543	3	563	9	1236	3	1495	11	1177	2	1634
50	**1**	10	196	3	1667	4	1162	1	1984	6	1359	0	1984
	2	-2.93525	3.121391	-3.39843	3.14857	-2.87544	3.481179	-3.00188	3.338107	-3.03559	2.956348	-3.62134	4.194018
	3	-3.33783	3.039811	-3.04072	3.431637	-3.10001	3.491795	-3.11001	3.520332	-3.15883	3.395003	-3.5044	4.084139
	4	1	1026	1	111	2	1179	10	731	7	877	1	1693
	5	-3.09198	3.037894	-2.7545	2.918435	-2.89933	3.251233	-3.12	3.357836	-3.10535	2.951535	-4.10905	3.423861
51	**1**	-3.43382	2.85569	-2.87175	3.144405	-3.30165	3.670374	-3.12902	4.168309	-3.12706	2.957697	-3.69801	4.168309

	2	8	608	4	1519	3	1943	9	1788	9	86	0	1943
	3	4	149	1	992	7	1113	8	1359	5	1114	1	1669
	4	1	1515	9	509	7	331	10	41	4	717	1	1950
	5	7	341	5	331	1	434	9	1119	1	722	0	1385
YIELD		66.7523 9	90	65.1713 4	90	64.74662	90	67.2643 7	90	67.39639	90	60.0047	90

Appendix A2 – Data Preparation and Data Analysis in Analyze/StripMiner™

This appendix provides information about how to examine each data set by pursuing the *predictive* PLS approach to understand the information provided by the *integrated* supply chain approach. Before feeding the raw data into the Analyze/StripMiner software, each data set needs to be preprocessed. In the first part, preprocessing steps that are implemented to all data files (the manufacturing data set and twenty two simulated data sets) before applying any predictive PLS analysis are considered. The second part discusses the analysis of data using the *Analyze* software. All critical results (i.e., R^2 values and component loadings) are obtained in this section.

A. Data Preprocessing Steps

Step 1 – *Adding identifier tags to every observation*: This is a customary approach to track individual observations in each data set. Since the *Analyze* software only expects values for variables in the data set, the "observation" column illustrated in Appendix A1/A (p. 86) needs to be removed before feeding the data to the program. By adding identifier tags to every observation, we overcome the problem of not having a column to track observations. The *Analyze* command for this is: *Analyze [file_name].txt 1070*

Step 2 – *Indicating whether the dependent variable is dichotomous or binary*: Recall that the dependent variable of the manufacturing data set (i.e., *Yield*) is a binary variable (Appendix A1/A). Consequently, the following command should be entered to analyze the manufacturing data set: *Analyze [file_name].txt.txt -414159*

This step is not required to analyze the simulated data sets, since the dependent variable is continuous (Appendix A1/B on p. 88).

Step 3 – *Standardizing the data*: Since there will be differences in scale between variables in a given supply chain system, the data set should be scaled by centering and descaling[57]. The command for this process is: *Analyze [file_name].txt.txt.txt 3*

Step 4 – *Splitting the data set into a test and training set*: As discussed in §4.3.1.2 (p.45), there is a need to subdivide the data set into *training* and *test* sets to assess the predictive accuracy of the model. In all our studies, we will retain 80% of the data under consideration

[57] This process of normalizing is sometimes referred as Mahalanobis scaling (Linton, 2004).

for the *test* set, and the remaining 20% for the *training* data set. The command for this is: *Analyze [file_name].txt.txt.txt*.txt 20

Step 5 – *Indicating the number of latent components*: As discussed in §5.1.1.1 (p. 52), the number of retained latent component should be identified by the user. This way, we can explore the impacts of individual latent components on the model. As illustrated in §5.1.1.1, we obtained the values for up to five retained latent variables. Thus, the whole PLS analysis needs to be repeated five times for each data set with different number of retained latent variables (i.e., from one to five). The command for this is: *Analyze num_eg.txt 105*

After indicating the number of retained variables, the training and test data subsets from the fourth step needs to be stored:

Copy cmatrix.txt [file_name].pat (for the training data set)

Copy dmatrix.txt [file_name].tes (for the test data set)

Now that the preprocessing steps are outlined, the next section will present the data analysis steps in predictive PLS.

B. Data Analysis Steps

As discussed in §4.3.1.2 (p. 45), the major objective in applied sciences is to generate *predictive* models rather than assessing the statistical significance in an attempt to assess causality. Recall the two criteria to evaluate the model: (1) predictive power of the model on *training* data, and (2) predictive power of the model on *test* data. The latter criterion is more crucial, since we retain 80% of the data for *testing* the data and the remaining 20% to determine the power of the *training* data.

Step 6 – *Training data set:* The following command is entered to obtain the PLS model for the *training* data set:

Analyze [file_name].pat 31

By typing this command, the program generates a loading matrix that contains a single value for each of the predictor variable (i.e., *Bbmatrix.txt*). These values are essentially component loadings for each supply chain measurement. The values indicate the overall influence of each predictor variable on the PLS model. These loadings can be compared with each other since they are generated from a scaled data. By observing the component loadings, one can identify crucial supply chain steps and their corresponding measurements.

Step 7 – *Testing data set:* The following command is entered to *test* the PLS model:

Analyze [file_name].tes 18

This command provides R^2, r^2, Q^2, and q^2 values that measure quality of the training and test sets. Since the major criterion is determining the predictive power of the model on *training* data, greater attention is given to the R^2 value[58]. The minor criterion of determining the predictive power of the model on *test* data is measured by observing Q^2 and q^2 values, but as in the case of R^2 and r^2, Q^2 is preferred over q^2, since Q^2 considers the residual error.

[58] As discussed in §4.3.1.2, $\mathbf{R^2}$ is considered as a better measure than $\mathbf{r^2}$ since $\mathbf{R^2}$ also considers the residual error. (Golbraikh and Tropsha, 2002).

Appendix A3 – Latent Component Summary Statistics (Simulated Data sets)

Summary statistics to test the predictive power of the *training* data (r^2 and R^2) and *test* data (q^2 and Q^2) for each latent component are provided in this appendix. These measures signify whether a model is weak or strong as discussed in §4.3.1.2 (p. 45). For each data set, these summary statistics are provided for different number of retained latent variables. Obviously, as we retain more latent variables the predictive power of the training data (r^2 and R^2) increases. However, we limit the number of retained latent components to five, since studies show that a maximum of five retained components is enough for models (Geladi and Kowalski, 1986; Linton, 2004). The first block ("1 Latent Variable") gives the values for the first component for each data set. To calculate the impact of the second latent component individually, R^2 values from "1 Latent Variables" can be subtracted from the corresponding value in the "2 Latent Variable". For example, for data set 0, R^2 of 0.29341 from "2 Latent Variables" can be subtracted from 0.24088 of "1 Latent Variable" to obtain an R^2 value of 0.05253 for the second component. Similarly, the third latent component can be calculated by subtracting "2 Latent Variables" from "3 Latent Variables" block. The accompanying graphs signify the impact of individual components (excluding to first component) on the model. The relevant discussion is provided in §5.1.1.1 (p. 52).

A3/A – Summary Statistics Based on the Number of Retained Latent Components (Cluster 1 – Simulated Data)

Table 17 presents the summary statistics of the first simulated data cluster for the *training* data (r^2 and R^2) and *test* data (q^2 and Q^2) under different number of retained latent variables. The table highlights the dominance of the first component (R^2 values) across all eleven data sets.

Table 17 - Summary Statistics about Individual Components (Cluster 1)

	1 Latent Variable				2 Latent Variables				3 Latent Variables				4 Latent Variables				5 Latent Variables			
Dataset	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2
0	0.24090	0.24088	0.99992	1.15375	0.29351	0.29341	0.99997	1.28114	0.31048	0.31040	0.99987	1.34382	0.31493	0.31482	0.99990	1.38505	0.31646	0.31635	0.99998	1.41378
1	0.63555	0.63520	0.63089	0.64318	0.72672	0.72641	0.58022	0.61152	0.75029	0.74994	0.55891	0.62088	0.75765	0.75722	0.55205	0.63463	0.75988	0.75947	0.54365	0.63550
2	0.68378	0.68360	0.59069	0.59395	0.76276	0.76270	0.49705	0.50432	0.78411	0.78409	0.46604	0.47618	0.78980	0.78980	0.46524	0.47973	0.79152	0.79152	0.46938	0.48758
3	0.69234	0.69218	0.44195	0.44706	0.81285	0.81263	0.33219	0.33765	0.83738	0.83694	0.29914	0.31178	0.84475	0.84425	0.28853	0.30605	0.84719	0.84670	0.29093	0.31088
4	0.73326	0.73309	0.39768	0.40343	0.85415	0.85404	0.26686	0.27410	0.87701	0.87688	0.24905	0.26298	0.88353	0.88340	0.24790	0.26681	0.88542	0.88531	0.24901	0.27008
5	0.76207	0.76200	0.37380	0.38258	0.86336	0.86336	0.23566	0.23571	0.88631	0.88631	0.19887	0.20125	0.89380	0.89379	0.18572	0.19158	0.89589	0.89587	0.18347	0.19116
6	0.76463	0.76455	0.27280	0.30568	0.88236	0.88220	0.17713	0.18332	0.91453	0.91437	0.13891	0.14128	0.92374	0.92357	0.13199	0.13427	0.92589	0.92574	0.13235	0.13463
7	0.78698	0.78698	0.35379	0.37110	0.90331	0.90328	0.21237	0.21481	0.93165	0.93160	0.14858	0.14964	0.94034	0.94030	0.13725	0.13799	0.94307	0.94303	0.13500	0.13642
8	0.82201	0.82201	0.26147	0.27261	0.91870	0.91868	0.13627	0.13775	0.94271	0.94270	0.10028	0.10044	0.94991	0.94990	0.09233	0.09320	0.95214	0.95213	0.08834	0.08955
9	0.81596	0.81595	0.34421	0.34479	0.92067	0.92067	0.15574	0.15645	0.94689	0.94686	0.09686	0.09744	0.95372	0.95368	0.08627	0.08709	0.95523	0.95520	0.08594	0.08694
10	0.79617	0.79611	0.26142	0.27321	0.91894	0.91892	0.15006	0.15080	0.94692	0.94691	0.10530	0.10583	0.95375	0.95375	0.08701	0.08827	0.95563	0.95563	0.07932	0.08170

The following graph illustrates the impact of individual components on the model, excluding the first latent component. The graph including the first component is provided in §5.1.1.1.

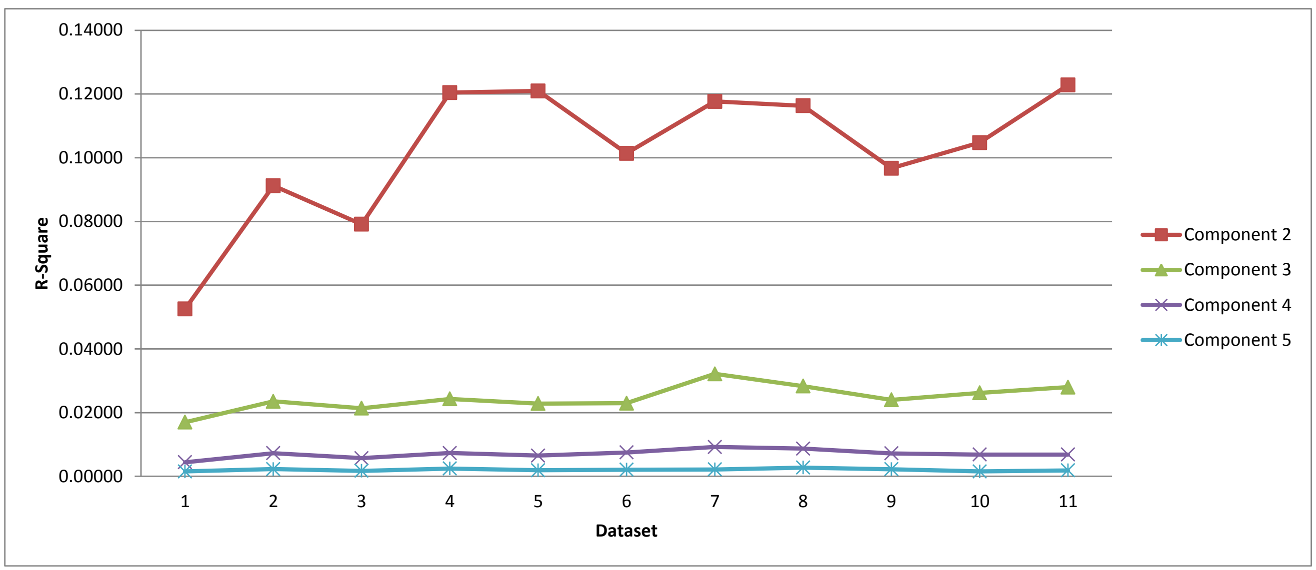


Figure 20 - Component R^2 Values (Cluster 1 – excluding the first component)

A3/B – Summary Statistics Based on the Number of Retained Latent Components (Cluster 2 – Simulated Data)

The following table presents the summary statistics of the second simulated data cluster for the *training* data (r^2 and R^2) and *test* data (q^2 and Q^2) under different number of retained latent variables. Like the case in the first simulated data cluster, this table highlights the dominance of the first component (R^2 values) across all eleven data sets.

Table 18 - Summary Statistics about Individual Components (Cluster 2)

	1 Latent Variable				2 Latent Variables				3 Latent Variables				4 Latent Variables				5 Latent Variables			
Dataset	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2	r^2	R^2	q^2	Q^2
0	0.27326	0.24320	0.96959	1.03742	0.33072	0.33054	0.97735	1.17818	0.35068	0.35034	0.98422	1.30296	0.35717	0.35676	0.98625	1.35068	0.35917	0.35878	0.98860	1.38574
1	0.35540	0.35539	0.94297	0.99055	0.43582	0.43582	0.95142	1.08832	0.46178	0.46178	0.95932	1.16930	0.47110	0.47108	0.96639	1.23633	0.47422	0.47420	0.96569	1.25915
2	0.37736	0.37731	0.87561	0.90607	0.43606	0.43590	0.87499	0.98617	0.45176	0.45168	0.87460	1.04447	0.45665	0.45661	0.88104	1.08602	0.45822	0.45818	0.88636	1.11113
3	0.47086	0.47083	0.81910	0.83941	0.54147	0.54140	0.78691	0.84382	0.56172	0.56164	0.78511	0.87020	0.56815	0.56805	0.78811	0.89200	0.56989	0.56978	0.78751	0.89902
4	0.49010	0.48992	0.74887	0.75652	0.57493	0.57473	0.71673	0.76632	0.60030	0.60018	0.68598	0.77705	0.60797	0.60786	0.67661	0.79252	0.61033	0.61019	0.67463	0.80312
5	0.55591	0.55589	0.65638	0.65716	0.63738	0.63735	0.30294	0.61787	0.65971	0.65968	0.59466	0.62349	0.66693	0.66687	0.60501	0.65114	0.66934	0.66929	0.60365	0.65677
6	0.61938	0.61937	0.48507	0.49060	0.72048	0.72046	0.42623	0.43161	0.74426	0.74424	0.42802	0.44799	0.75206	0.75205	0.43377	0.46263	0.75425	0.75424	0.43465	0.46621
7	0.73192	0.73176	0.39881	0.42030	0.84271	0.84255	0.26504	0.26836	0.86710	0.86686	0.22079	0.22436	0.87396	0.87372	0.21301	0.21759	0.87584	0.87558	0.20982	0.21505
8	0.79750	0.79748	0.29408	0.30454	0.91334	0.91331	0.15779	0.15928	0.93671	0.93671	0.13434	0.13487	0.94387	0.94386	0.12382	0.12550	0.94557	0.94556	0.11966	0.12158
9	0.83761	0.83759	0.33441	0.35113	0.95040	0.95040	0.11793	0.12592	0.97592	0.97592	0.06446	0.06665	0.98397	0.98395	0.04024	0.04109	0.98647	0.98646	0.03148	0.03204
10	0.83499	0.83497	0.19852	0.23375	0.96205	0.96205	0.05914	0.06674	0.99100	0.99100	0.01615	0.01812	0.99740	0.99740	0.00503	0.00547	0.99917	0.99917	0.00206	0.00216

The following graph illustrates the impact of individual components in the second simulated data cluster on the model, excluding the first latent component. The graph including the first component (Figure 11) is provided on p. 54.

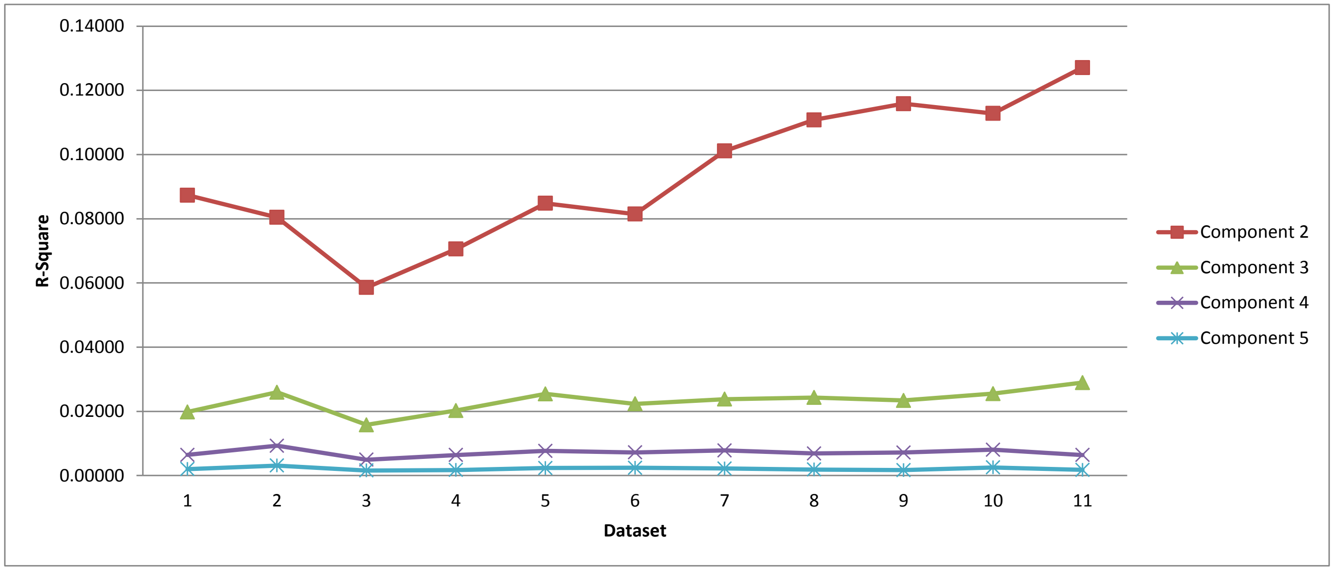


Figure 21 - Component R^2 Values (Cluster 2 – excluding the first component)

Appendix A4 – Process Step Component Loadings

In this appendix, *component loading* values of each process step for simulated data sets are provided. *Component loading* in PLS is analogous to *factor loading* in Explanatory Factor Analysis, where loadings refer to the correlations between the attributes and the factors. In this PLS context, we try to determine the relationship between each process step metric (i.e., each row denoted as **S***k***P***m* notation that refers process metric *m* (i.e., m = 1, …, 5) of supply chain step *k* (i.e., k = 1, …, 51) and the dependent variable, *Yield*. A higher component loading indicates that metric of the supply chain step has a significant impact on the overall model (i.e., the dependent variable, *Yield*). As mentioned previously, these loadings of different supply chain steps can be compared with each other since they are generated from a scaled data[59].

[59] The loadings are generated from *Mahalanobis* scaled data. Thus, there are no scale effects distorting the relative importance of the variables (Linton, 2004).

A4/A –Component Loading Values of Process Steps (Cluster 1)

The following table provides the component loading values for each simulated data set in the first cluster. The values indicate the relationship between each process step metric and the dependent variable, *Yield*.

Table 19 - Component Loading Values (Cluster 1)

	LOADINGS										
Step #	**Dataset 0**	**Dataset 1**	**Dataset 2**	**Dataset 3**	**Dataset 4**	**Dataset 5**	**Dataset 6**	**Dataset 7**	**Dataset 8**	**Dataset 9**	**Dataset 10**
S1P1	-2.52E-04	2.60E-05	4.59E-05	-3.58E-06	6.92E-06	-7.33E-05	3.52E-05	-2.22E-05	-1.66E-05	1.59E-05	2.10E-05
S1P2	-3.57E-04	-3.07E-05	1.10E-05	2.70E-05	2.20E-05	1.59E-05	1.27E-05	2.52E-05	4.68E-05	-2.95E-05	2.09E-05
S1P3	6.71E-05	-9.15E-05	5.45E-05	5.70E-05	-4.34E-05	9.70E-06	2.21E-05	-3.75E-05	6.74E-06	2.17E-05	-3.13E-05
S1P4	1.51E-04	-5.45E-05	3.02E-05	4.13E-05	-1.35E-05	5.56E-05	3.23E-05	-4.82E-05	1.84E-05	-1.51E-05	-3.05E-05
S1P5	2.09E-05	5.37E-05	4.22E-06	-3.39E-05	1.13E-05	6.10E-05	-2.48E-05	-4.54E-05	4.11E-05	-2.36E-05	3.37E-05
S2P1	2.42E-05	3.37E-05	7.85E-06	9.23E-05	2.12E-05	4.20E-05	2.01E-05	-1.27E-05	8.00E-06	-3.36E-05	1.54E-05
S2P2	-1.64E-04	6.10E-05	-4.12E-05	2.62E-05	-8.53E-05	4.46E-07	1.86E-05	2.72E-05	-1.66E-05	2.75E-05	9.39E-05
S2P3	-2.21E-04	9.80E-06	-3.12E-05	2.44E-05	-3.30E-05	-2.80E-05	1.80E-05	3.36E-05	2.97E-05	-3.24E-05	-5.09E-06
S2P4	1.82E-05	-4.07E-05	-1.72E-05	1.98E-05	2.51E-05	2.22E-05	6.70E-05	-1.54E-05	2.08E-05	-6.98E-05	1.68E-05
S2P5	-3.40E-05	-1.72E-05	-2.45E-05	-3.88E-05	6.73E-06	-3.55E-05	5.45E-05	-2.94E-05	2.94E-05	-2.92E-05	2.76E-06
S3P1	4.67E-05	2.32E-05	2.45E-05	-2.65E-05	7.17E-05	1.61E-05	-3.83E-05	2.75E-05	7.24E-05	5.45E-05	-1.29E-05
S3P2	-4.59E-05	3.59E-05	-1.41E-05	-4.59E-06	-4.89E-05	6.84E-05	1.14E-05	1.80E-06	9.70E-06	3.78E-05	-1.77E-05
S3P3	1.20E-04	-1.62E-05	1.09E-04	7.51E-06	6.00E-05	-5.70E-06	5.53E-05	3.32E-05	-2.96E-05	-7.17E-06	-4.64E-05

S3P4	-1.34E-04	-3.40E-06	5.12E-05	1.04E-04	3.69E-05	-4.59E-05	2.35E-05	2.04E-05	-2.75E-05	-3.71E-05	5.97E-05
S3P5	-1.66E-05	-1.47E-05	2.26E-05	-6.42E-05	1.75E-05	2.10E-05	-1.08E-05	2.21E-05	-7.95E-05	-4.99E-05	-9.39E-05
S4P1	-1.68E-04	-6.21E-05	-3.02E-05	2.66E-05	4.03E-05	6.82E-05	1.24E-05	-1.54E-05	6.90E-06	-4.07E-06	-3.00E-05
S4P2	-1.11E-04	-3.26E-05	1.83E-05	-6.00E-05	4.56E-05	-7.46E-05	4.57E-05	-5.82E-05	2.33E-05	2.15E-05	4.08E-05
S4P3	1.31E-04	2.44E-05	-3.64E-05	-4.64E-06	-2.23E-06	-3.80E-05	4.38E-05	-6.89E-05	-2.84E-05	-1.15E-05	1.57E-05
S4P4	-1.78E-04	-4.65E-05	-1.23E-04	4.37E-05	4.00E-06	-4.99E-05	5.93E-06	3.14E-05	2.34E-05	3.95E-05	-2.70E-06
S4P5	8.32E-05	3.07E-05	-5.20E-06	-1.98E-05	1.49E-05	5.71E-05	6.20E-06	-1.76E-05	3.44E-05	-2.26E-05	-9.35E-06
S5P1	-6.60E-05	1.45E-05	-1.11E-05	8.38E-06	1.43E-06	-7.64E-05	-2.59E-05	4.73E-05	3.35E-05	-8.50E-06	1.25E-05
S5P2	4.21E-05	1.57E-05	5.89E-05	1.83E-06	1.18E-08	-2.71E-05	-1.89E-05	3.06E-05	4.45E-06	1.41E-05	6.63E-06
S5P3	1.60E-04	-5.82E-05	5.31E-06	6.34E-05	-4.21E-05	1.31E-05	-6.00E-06	2.11E-05	2.61E-06	-3.18E-07	1.16E-05
S5P4	-2.57E-04	5.63E-05	9.53E-07	1.73E-05	2.95E-05	1.06E-05	-4.21E-05	-4.45E-05	-4.81E-05	-1.84E-05	2.14E-05
S5P5	-1.03E-04	-9.75E-06	-5.47E-05	5.89E-06	5.89E-05	5.07E-05	4.75E-05	1.32E-05	8.41E-06	2.23E-05	2.08E-05
S6P1	-1.08E-04	-3.15E-06	-3.21E-05	-7.24E-05	-6.22E-05	-3.57E-05	-2.77E-06	2.32E-05	-1.08E-05	-4.20E-05	-3.49E-05
S6P2	-1.78E-05	4.05E-05	-2.10E-05	2.56E-05	8.64E-06	-8.17E-06	3.43E-05	7.20E-05	3.63E-05	2.10E-05	1.27E-05
S6P3	1.58E-04	2.30E-05	-4.54E-05	-7.20E-06	7.33E-06	1.53E-05	1.35E-05	-1.39E-06	1.69E-05	1.47E-05	-4.30E-06
S6P4	7.89E-05	-1.00E-05	3.87E-05	3.10E-05	-6.64E-06	-2.43E-05	-3.21E-05	-2.56E-05	4.12E-05	5.45E-05	-1.70E-05
S6P5	1.21E-04	2.12E-05	-4.11E-05	-1.65E-05	-2.31E-05	-3.46E-05	1.56E-05	-2.47E-06	-1.80E-05	3.31E-05	5.14E-05
S7P1	-1.48E-05	-5.68E-05	-2.40E-05	8.15E-05	-2.10E-06	-1.95E-05	-4.88E-05	2.95E-06	-6.16E-05	-3.60E-05	-1.33E-05
S7P2	3.41E-04	-3.69E-05	-6.84E-06	-2.05E-05	3.59E-05	-1.81E-05	-4.89E-05	-3.43E-05	-2.30E-06	-3.46E-05	3.96E-05
S7P3	-2.85E-04	-9.81E-06	3.74E-05	-4.40E-05	1.91E-05	-1.08E-05	-2.34E-05	8.91E-05	-1.40E-05	-1.79E-05	-3.21E-06

S7P4	1.50E-04	-3.61E-05	2.20E-05	-2.10E-05	-8.01E-05	2.21E-05	-3.42E-05	5.35E-05	3.37E-05	-2.00E-05	-3.21E-05
S7P5	-5.40E-05	-9.78E-05	6.98E-05	-1.19E-04	1.44E-05	-1.53E-06	-8.01E-06	5.68E-06	5.57E-06	-4.38E-05	1.28E-05
S8P1	2.18E-04	5.13E-05	-8.68E-06	-4.64E-05	8.59E-06	-3.84E-05	1.57E-05	7.20E-06	9.86E-06	8.41E-06	-1.22E-05
S8P2	1.69E-04	1.67E-05	-8.76E-06	-8.02E-06	5.39E-07	-3.20E-05	-1.01E-05	-2.03E-05	-6.13E-05	-1.81E-05	-7.62E-05
S8P3	-1.29E-04	-3.64E-06	-3.78E-05	8.76E-06	4.58E-05	3.04E-05	7.07E-05	1.16E-05	4.94E-05	-8.46E-05	-7.28E-06
S8P4	-1.02E-04	-1.77E-05	-3.50E-05	5.38E-05	-1.99E-05	1.81E-05	-4.09E-05	1.92E-05	4.91E-05	4.75E-05	3.92E-05
S8P5	1.49E-04	2.65E-06	1.02E-04	-7.75E-05	1.05E-04	-1.06E-05	-4.45E-05	-5.14E-05	-4.09E-05	6.28E-05	-4.55E-05
S9P1	1.15E-04	1.10E-04	-3.59E-05	7.79E-05	1.25E-05	5.94E-06	1.26E-05	-2.12E-05	-1.61E-05	-1.50E-05	3.01E-05
S9P2	-1.09E-04	1.01E-05	-4.06E-05	-2.58E-05	-2.85E-05	2.86E-05	1.17E-06	-9.41E-05	6.85E-06	1.84E-05	-2.92E-05
S9P3	1.42E-05	-2.51E-05	-3.55E-05	3.34E-05	-4.80E-05	-8.38E-06	-1.86E-05	8.67E-06	-2.61E-05	-9.10E-06	-5.17E-05
S9P4	3.72E-05	-3.41E-05	9.84E-06	-2.33E-05	-2.62E-05	-1.86E-05	-7.85E-05	2.72E-05	-7.84E-06	6.69E-05	1.57E-05
S9P5	2.46E-04	-7.38E-05	-2.62E-05	4.92E-05	2.39E-05	-2.83E-05	5.94E-06	4.61E-05	4.05E-05	-2.15E-06	-4.44E-05
S10P1	-3.66E-05	-7.99E-05	3.20E-05	-1.81E-05	5.84E-06	-3.83E-05	1.20E-05	2.75E-06	-1.39E-07	-2.44E-05	-2.73E-05
S10P2	1.04E-05	-1.20E-05	4.01E-05	4.82E-05	1.40E-05	2.86E-06	1.82E-05	2.12E-06	3.64E-05	3.96E-05	-3.89E-05
S10P3	2.83E-04	-3.33E-05	-3.88E-05	-4.22E-07	2.86E-05	4.34E-05	-3.94E-05	-5.14E-05	-4.15E-05	1.49E-05	-6.36E-05
S10P4	2.13E-04	-1.07E-04	-3.08E-05	-4.04E-05	2.07E-05	-3.90E-05	4.50E-05	-2.43E-05	-1.22E-05	8.71E-06	6.24E-06
S10P5	-2.92E-05	2.44E-05	8.16E-05	-3.24E-05	-2.39E-05	-3.80E-06	3.97E-05	7.29E-06	5.03E-05	7.33E-06	7.34E-06
S11P1	-2.16E-05	1.35E-05	1.65E-05	-2.51E-06	-1.74E-05	-1.36E-05	3.28E-05	-1.65E-05	-4.28E-05	-5.57E-05	-2.54E-05
S11P2	-1.94E-04	-9.61E-06	-3.63E-05	7.61E-05	-2.72E-05	-1.25E-06	-1.71E-05	-2.69E-05	-2.54E-05	-2.25E-05	6.68E-05
S11P3	1.55E-04	-3.08E-05	7.20E-05	-2.03E-05	-3.56E-05	-4.76E-06	-3.80E-05	-3.74E-05	-5.03E-05	1.15E-05	1.26E-05

S11P4	-5.72E-05	-6.12E-05	4.11E-06	5.21E-05	-2.20E-05	4.31E-05	-2.16E-05	-1.01E-05	3.45E-06	-2.15E-05	-2.89E-05
S11P5	-7.95E-05	2.57E-06	8.15E-05	8.65E-06	-9.92E-06	4.73E-05	1.85E-05	-4.50E-05	6.97E-05	7.49E-06	7.33E-05
S12P1	-1.61E-04	-3.50E-05	-2.70E-05	2.45E-05	4.31E-05	2.76E-05	-1.93E-05	-1.62E-05	-1.91E-05	-1.78E-05	-8.00E-06
S12P2	-6.11E-05	-4.53E-06	-5.08E-05	4.77E-07	1.09E-05	-3.88E-05	-4.13E-05	3.03E-05	-6.47E-06	-3.73E-05	-6.77E-06
S12P3	1.61E-04	-4.61E-05	3.85E-05	-3.16E-05	6.16E-05	3.74E-05	-2.07E-05	2.01E-05	-2.54E-05	4.83E-06	9.80E-06
S12P4	-5.77E-05	-1.48E-05	3.95E-06	1.63E-05	-2.89E-06	-2.17E-05	-8.02E-06	-3.99E-05	-2.35E-05	5.42E-06	4.66E-05
S12P5	-1.35E-05	-8.87E-05	-8.14E-06	2.65E-05	-5.18E-06	3.86E-05	2.08E-05	9.76E-06	-5.05E-05	-3.63E-06	5.46E-05
S13P1	-8.47E-05	4.71E-05	5.35E-05	-5.85E-05	7.26E-06	-9.17E-06	-1.69E-04	7.04E-05	3.74E-05	-2.32E-05	-1.16E-05
S13P2	1.97E-04	8.48E-05	-1.08E-04	-5.50E-06	5.91E-05	2.67E-06	-4.70E-05	2.97E-05	-2.61E-05	-1.01E-05	3.20E-05
S13P3	1.25E-04	4.39E-05	5.24E-05	-7.51E-06	1.32E-06	2.57E-05	-1.51E-05	-3.91E-06	1.41E-05	2.48E-05	-3.59E-05
S13P4	-1.19E-04	-2.84E-05	3.62E-05	4.90E-05	-6.56E-05	-1.04E-05	6.52E-05	2.59E-05	3.44E-05	-6.09E-05	4.28E-05
S13P5	-1.18E-04	2.17E-06	-2.81E-05	-5.07E-05	-2.81E-05	-3.35E-05	8.40E-05	1.93E-05	-6.75E-06	-5.02E-05	5.60E-05
S14P1	-2.03E-04	-3.49E-05	5.76E-05	-5.00E-05	3.36E-05	5.32E-05	-7.58E-06	2.72E-05	3.89E-05	1.04E-05	-1.50E-05
S14P2	7.40E-05	2.22E-05	5.45E-05	-1.65E-05	-4.96E-05	-6.26E-05	9.41E-06	-4.15E-05	4.43E-05	-2.30E-05	-4.34E-06
S14P3	1.38E-04	-2.97E-05	-5.91E-05	-3.29E-06	-2.48E-05	-2.72E-05	1.08E-05	-3.64E-05	8.44E-06	5.59E-05	-1.05E-05
S14P4	-1.85E-04	7.50E-07	-9.51E-06	1.67E-05	-1.27E-05	2.49E-06	2.92E-05	3.99E-06	-1.47E-05	6.80E-05	3.01E-05
S14P5	-1.32E-04	-6.67E-07	-2.23E-05	-3.71E-05	-2.68E-05	5.31E-05	4.76E-05	-4.90E-05	-1.26E-05	2.67E-05	-8.77E-06
S15P1	-6.79E-05	-3.81E-05	-1.01E-05	4.28E-05	-4.96E-05	-1.55E-05	1.16E-05	-5.13E-06	-1.13E-05	1.61E-05	-5.90E-05
S15P2	1.25E-05	1.25E-05	5.27E-05	-2.13E-05	-4.08E-05	2.99E-07	4.20E-05	-1.34E-05	1.25E-05	-7.01E-06	6.63E-05
S15P3	-2.31E-04	-5.75E-06	-5.96E-05	1.80E-05	5.03E-05	-3.56E-05	-3.08E-05	1.47E-05	4.03E-05	7.12E-05	-2.67E-05

S15P4	-5.63E-05	-1.88E-05	9.54E-06	-2.00E-05	-3.35E-05	-5.11E-05	-8.49E-05	-1.26E-05	4.37E-05	-6.42E-05	7.96E-05
S15P5	-1.50E-04	-2.52E-05	5.39E-05	3.19E-05	6.54E-05	1.26E-05	-3.12E-05	-1.26E-05	2.81E-05	-3.42E-05	4.53E-05
S16P1	-5.85E-05	5.75E-05	-3.57E-05	-3.56E-05	4.51E-05	6.25E-06	-6.75E-05	-9.00E-06	1.74E-05	-1.51E-05	1.03E-04
S16P2	-1.01E-04	-3.65E-05	-4.97E-05	-6.72E-05	4.97E-05	-1.71E-06	7.28E-05	-4.07E-07	-3.44E-05	-3.34E-05	2.93E-05
S16P3	-1.33E-04	-3.55E-05	6.44E-07	-3.23E-06	-1.29E-05	-5.22E-06	-3.48E-05	1.26E-05	-3.65E-05	5.54E-05	5.82E-05
S16P4	1.08E-04	-2.95E-05	3.69E-06	1.83E-06	2.32E-05	3.24E-05	-1.18E-05	1.24E-05	6.46E-06	1.27E-05	3.39E-06
S16P5	-3.75E-05	1.08E-04	-1.83E-05	-1.36E-05	2.50E-06	6.53E-05	9.07E-05	-6.41E-06	-2.44E-05	-3.98E-06	1.00E-06
S17P1	-2.34E-04	3.44E-05	-5.82E-05	-6.64E-05	1.76E-05	3.07E-05	4.80E-05	1.33E-05	1.05E-06	1.80E-05	-6.07E-05
S17P2	-4.72E-05	5.41E-06	3.48E-05	8.83E-05	2.20E-05	-1.70E-05	1.87E-05	-2.14E-05	5.41E-05	1.75E-05	6.77E-06
S17P3	1.34E-04	-1.03E-04	-3.71E-05	5.73E-05	-4.84E-05	-2.35E-05	2.35E-05	-5.03E-05	2.21E-05	3.50E-05	-7.03E-06
S17P4	1.09E-04	-1.19E-05	-3.14E-05	-5.84E-05	-4.28E-06	-9.50E-05	-6.15E-06	4.62E-05	-5.84E-06	-9.25E-05	4.20E-05
S17P5	-2.38E-04	8.79E-05	-1.19E-05	1.57E-05	2.39E-06	3.32E-05	-4.54E-05	2.78E-05	-7.72E-06	7.68E-05	3.34E-05
S18P1	1.29E-04	-5.94E-05	7.48E-05	-2.79E-05	-1.67E-05	-6.87E-06	4.04E-05	9.28E-06	-2.89E-05	6.42E-06	-1.85E-05
S18P2	-1.34E-04	1.41E-06	-3.62E-05	2.50E-05	-1.16E-05	-1.14E-05	3.10E-05	3.72E-05	1.24E-06	5.20E-06	-8.40E-06
S18P3	1.55E-04	-4.31E-05	9.28E-05	-5.02E-05	-3.00E-05	2.96E-05	-5.00E-06	-2.82E-05	-4.89E-05	-1.28E-06	2.42E-05
S18P4	-3.79E-05	-8.59E-05	-3.69E-05	7.19E-06	1.27E-05	2.80E-05	-5.45E-05	4.83E-06	-1.19E-05	4.60E-05	2.06E-05
S18P5	1.33E-04	3.63E-05	1.60E-05	6.68E-05	-4.40E-05	-2.89E-06	2.85E-06	3.73E-05	-2.73E-05	-6.27E-05	-8.12E-05
S19P1	-1.20E-04	-6.59E-05	1.55E-05	1.14E-05	-5.11E-05	-1.30E-05	7.75E-05	-4.44E-05	1.63E-05	-1.59E-05	-2.21E-05
S19P2	1.37E-06	-3.90E-05	-4.25E-05	8.43E-05	3.17E-05	-4.87E-05	3.50E-05	-3.03E-05	-6.80E-05	-4.82E-05	-8.02E-06
S19P3	-2.52E-04	4.27E-05	-9.30E-06	-1.76E-05	5.61E-05	3.88E-06	-5.52E-05	-6.73E-06	-2.84E-05	-4.65E-05	-8.64E-06

S19P4	5.87E-06	1.19E-05	-4.85E-05	3.13E-06	2.94E-06	-2.30E-05	5.06E-05	-3.66E-05	-7.15E-06	-1.32E-05	-3.34E-05
S19P5	-1.70E-05	-7.12E-05	2.35E-05	4.20E-05	1.91E-05	-3.04E-05	-5.00E-06	-3.45E-05	3.15E-08	-1.98E-05	-1.73E-05
S20P1	-8.51E-05	9.88E-07	2.19E-05	-4.62E-06	6.04E-05	-5.26E-05	5.33E-06	7.61E-06	6.78E-05	1.20E-05	-3.06E-07
S20P2	-4.05E-04	-1.49E-05	-2.46E-05	2.51E-05	2.83E-06	4.00E-05	5.30E-05	4.45E-05	6.35E-06	-2.09E-06	-2.14E-05
S20P3	-1.53E-05	-3.39E-05	-1.14E-05	3.10E-06	1.16E-04	-6.65E-06	-4.47E-05	-3.02E-05	3.47E-05	-9.06E-05	9.44E-06
S20P4	2.01E-04	5.61E-06	3.87E-05	-9.12E-05	-2.28E-05	3.21E-05	-6.47E-05	-1.51E-05	-7.03E-06	4.10E-05	1.25E-05
S20P5	-1.35E-04	3.29E-05	1.86E-05	3.14E-05	-7.72E-05	7.41E-05	3.00E-05	-3.68E-05	1.02E-04	-8.18E-07	-2.19E-05
S21P1	2.74E-04	6.14E-05	-4.10E-05	-3.16E-05	2.58E-05	-2.68E-05	3.10E-05	-5.20E-05	5.47E-05	-1.72E-05	-7.60E-05
S21P2	-3.19E-04	-4.18E-05	2.08E-05	4.52E-06	2.60E-05	-4.06E-05	4.10E-05	-1.92E-05	-2.33E-05	2.48E-05	-3.44E-05
S21P3	-3.07E-04	-4.30E-05	1.13E-04	-1.28E-05	2.03E-05	2.22E-05	1.34E-06	-3.84E-05	-7.81E-05	3.63E-05	1.40E-05
S21P4	-1.76E-05	-2.65E-05	3.99E-05	-5.35E-05	9.23E-06	-5.21E-05	-7.91E-07	-3.70E-05	-6.34E-05	-2.89E-05	1.84E-05
S21P5	-6.69E-05	3.79E-05	1.50E-05	-2.86E-05	2.50E-05	-9.71E-06	1.61E-06	3.49E-05	1.15E-05	-1.58E-05	5.37E-05
S22P1	1.90E-04	-3.86E-05	-1.51E-05	-6.78E-06	-3.71E-05	3.60E-05	-5.47E-05	-4.64E-05	1.32E-05	-4.29E-06	-8.16E-05
S22P2	-5.69E-05	8.11E-06	-5.58E-06	1.50E-05	3.04E-05	-2.31E-05	-4.52E-05	-1.02E-05	3.98E-06	-4.46E-05	-2.82E-05
S22P3	-1.33E-04	6.18E-06	-3.28E-05	1.81E-05	-8.27E-05	-7.63E-05	-7.48E-05	2.14E-05	5.05E-05	-8.32E-06	2.24E-05
S22P4	1.81E-04	-1.08E-05	-7.95E-05	-1.86E-05	-1.48E-05	7.13E-06	-3.21E-05	1.14E-05	-4.29E-05	-5.01E-05	-2.51E-05
S22P5	6.70E-05	-2.48E-05	-3.76E-05	-4.48E-05	4.72E-05	-1.13E-05	1.32E-05	-2.42E-05	7.68E-05	-8.77E-06	7.62E-06
S23P1	4.78E-07	-2.62E-05	-3.41E-05	1.70E-05	2.35E-05	-2.63E-05	5.30E-05	2.71E-05	6.27E-06	3.45E-05	-6.14E-05
S23P2	1.72E-04	-3.98E-05	6.05E-05	5.27E-05	7.99E-05	-7.06E-05	5.53E-05	6.00E-06	5.85E-05	-7.64E-06	1.33E-05
S23P3	-1.36E-04	3.07E-05	-5.25E-05	-6.76E-06	5.29E-05	2.35E-05	2.74E-05	-2.59E-05	-9.53E-06	-7.94E-06	-5.07E-05

S23P4	1.48E-04	-2.22E-08	-2.11E-05	-2.03E-05	4.68E-05	-9.85E-06	5.11E-05	-2.41E-05	-2.77E-05	8.24E-05	1.80E-05
S23P5	1.63E-04	-5.76E-05	1.22E-05	3.11E-05	-8.61E-05	-1.59E-05	3.83E-05	-3.32E-05	-7.91E-06	-2.63E-06	-1.52E-06
S24P1	5.87E-05	4.62E-06	-4.27E-06	8.34E-05	5.89E-06	3.40E-05	-1.93E-06	-8.53E-05	-7.38E-06	-1.54E-06	1.60E-05
S24P2	2.15E-05	-4.95E-05	-5.24E-05	-1.88E-05	7.52E-05	2.55E-05	-3.48E-05	3.26E-05	3.33E-05	4.70E-06	1.81E-05
S24P3	8.16E-05	-7.20E-05	-2.57E-05	-1.55E-05	-7.96E-06	-6.68E-05	-1.85E-05	8.42E-05	-1.58E-06	-1.01E-06	-3.02E-05
S24P4	1.10E-04	-4.42E-05	1.29E-05	-4.61E-05	1.00E-04	1.82E-05	2.48E-05	-9.92E-06	2.68E-05	-8.31E-06	-2.88E-05
S24P5	-6.34E-05	1.31E-05	9.89E-06	-3.83E-05	7.65E-05	-1.62E-05	-5.90E-05	-3.34E-07	-1.20E-05	1.64E-05	7.76E-06
S25P1	-1.43E-04	4.88E-06	4.90E-05	-4.43E-05	-2.44E-06	5.16E-05	-3.30E-05	2.48E-05	5.35E-05	-4.44E-05	-4.91E-05
S25P2	-5.08E-05	6.96E-05	8.17E-06	3.73E-05	1.66E-05	-1.15E-05	3.14E-06	-1.28E-05	1.82E-05	4.83E-06	3.66E-05
S25P3	-7.32E-06	-1.76E-05	5.77E-05	3.18E-05	-1.27E-05	-2.47E-05	7.17E-05	4.69E-05	4.68E-05	5.08E-05	-2.19E-06
S25P4	1.15E-04	9.10E-06	-9.67E-05	-4.59E-05	3.44E-05	4.10E-05	2.03E-05	-2.68E-05	9.08E-05	-1.55E-05	5.29E-06
S25P5	-1.60E-04	4.92E-05	-2.40E-05	-3.37E-05	4.29E-06	1.80E-05	-5.18E-05	1.05E-05	-5.22E-05	2.83E-05	-6.71E-05
S26P1	-4.37E-05	1.71E-05	-1.95E-05	-4.92E-05	1.68E-05	-4.61E-05	1.42E-05	-5.78E-05	2.37E-06	7.67E-06	1.44E-05
S26P2	1.33E-04	-1.05E-04	2.91E-05	7.90E-06	7.91E-05	7.66E-08	1.46E-05	-1.86E-06	-4.15E-05	-1.02E-05	1.64E-05
S26P3	-4.06E-05	-1.16E-05	3.34E-05	6.22E-05	-3.26E-05	-2.77E-05	4.61E-05	-1.80E-07	9.95E-05	-8.05E-06	1.43E-05
S26P4	3.07E-05	5.31E-05	4.42E-05	-5.41E-05	-5.67E-06	-3.98E-05	-5.41E-05	-2.01E-05	2.33E-05	1.22E-05	1.48E-05
S26P5	8.42E-05	-2.87E-05	-3.10E-05	2.64E-05	-2.90E-05	-1.33E-05	-5.40E-05	7.60E-05	5.78E-06	-2.66E-05	-2.72E-05
S27P1	-1.33E-05	-1.48E-06	-3.10E-05	9.35E-08	3.47E-05	1.86E-05	3.03E-05	-2.47E-05	1.08E-05	3.44E-05	-4.38E-05
S27P2	-4.51E-05	-1.61E-05	1.19E-06	6.02E-05	1.62E-05	7.33E-05	-2.49E-06	1.96E-05	4.05E-06	-2.97E-05	-1.09E-05
S27P3	-9.63E-05	-5.27E-05	6.70E-06	-1.48E-05	-6.32E-05	2.76E-05	1.80E-05	-2.23E-05	-2.93E-05	1.88E-05	-1.65E-05

S27P4	-1.84E-04	-7.47E-05	3.47E-05	-6.02E-05	3.37E-05	4.02E-05	-1.87E-05	2.91E-06	5.44E-05	-2.93E-05	1.11E-05
S27P5	5.47E-05	1.56E-05	-9.74E-05	-6.95E-05	-4.78E-05	-1.62E-06	6.68E-05	2.62E-05	5.86E-05	8.49E-06	1.11E-04
S28P1	2.55E-04	-4.51E-05	-7.46E-05	-8.78E-05	-5.68E-06	-4.52E-05	2.87E-05	2.62E-05	2.93E-05	-5.49E-05	-3.20E-05
S28P2	-1.73E-04	-5.19E-05	-4.11E-05	-9.92E-06	-3.64E-05	3.05E-05	-3.46E-05	-6.47E-05	3.67E-05	2.84E-06	4.13E-05
S28P3	5.34E-06	-3.56E-06	-1.09E-04	-1.31E-05	-3.56E-05	-3.32E-05	-4.47E-05	2.75E-05	-1.36E-05	-2.25E-05	-4.98E-05
S28P4	-5.83E-05	1.58E-07	-3.39E-05	1.93E-05	-1.88E-05	-1.17E-05	4.18E-05	4.36E-05	-2.23E-05	-2.54E-05	-1.29E-05
S28P5	1.37E-05	4.61E-05	-1.41E-05	-2.10E-05	3.73E-05	4.51E-05	-4.33E-05	4.99E-05	-1.48E-05	-4.18E-06	-3.14E-05
S29P1	1.63E-04	1.81E-05	2.08E-05	4.34E-06	1.15E-05	2.15E-05	-5.29E-05	-3.13E-05	-6.32E-05	1.51E-05	2.79E-05
S29P2	3.08E-05	2.79E-06	1.06E-05	6.02E-05	-4.38E-05	-2.83E-05	9.87E-06	5.05E-05	-2.65E-05	2.15E-05	8.10E-05
S29P3	-2.45E-04	-2.57E-05	8.52E-05	-6.35E-06	3.33E-05	-4.42E-05	7.93E-06	1.58E-06	-1.99E-05	-2.11E-05	1.02E-05
S29P4	2.38E-04	9.95E-04	1.04E-03	9.91E-04	1.00E-03	1.02E-03	1.01E-03	9.77E-04	9.85E-04	9.90E-04	9.57E-04
S29P5	-2.04E-04	-1.18E-05	-3.47E-05	-4.14E-05	4.28E-05	2.66E-05	1.50E-05	-1.23E-04	1.13E-05	9.50E-06	-8.54E-07
S30P1	-2.12E-05	2.95E-05	-3.33E-05	9.27E-07	-6.31E-05	-3.43E-05	1.52E-05	1.54E-05	-1.14E-05	-4.03E-07	5.24E-05
S30P2	-4.56E-05	-1.29E-05	-4.36E-05	7.21E-05	-7.57E-05	5.82E-06	-3.83E-06	-1.79E-05	3.46E-06	-3.98E-05	2.38E-05
S30P3	-8.81E-05	-3.22E-05	-1.64E-05	4.94E-05	3.72E-05	1.08E-05	3.18E-05	2.73E-05	4.30E-06	2.08E-05	-2.05E-06
S30P4	-1.52E-04	-2.50E-05	-3.09E-05	1.32E-05	3.18E-06	-4.15E-05	-1.52E-05	2.68E-05	-5.01E-05	-3.44E-05	-1.85E-05
S30P5	2.59E-04	-4.76E-05	-1.64E-05	3.10E-05	-2.30E-05	2.06E-05	-1.80E-05	-1.73E-05	-2.21E-06	-1.13E-05	2.70E-05
S31P1	-1.17E-04	-2.43E-05	-2.94E-05	2.10E-05	1.79E-05	-9.08E-06	1.99E-05	1.82E-05	-6.75E-05	4.09E-06	4.39E-05
S31P2	-2.30E-04	-7.82E-05	-6.67E-06	-1.28E-04	-4.36E-05	2.51E-05	-1.56E-05	3.92E-05	7.43E-06	7.43E-06	-2.37E-05
S31P3	-3.35E-05	-6.24E-05	1.21E-05	9.91E-07	7.65E-06	2.06E-05	-3.12E-05	-3.66E-05	-6.30E-06	2.91E-05	-1.41E-05

S31P4	-5.59E-05	-1.50E-05	3.20E-06	4.56E-05	-6.01E-05	-9.99E-06	3.01E-05	-5.18E-05	-2.25E-05	-3.52E-05	-4.72E-05
S31P5	2.50E-06	8.30E-06	-4.55E-06	-5.84E-05	-3.27E-05	3.58E-05	8.03E-05	-1.37E-05	1.11E-05	-2.40E-05	-4.29E-07
S32P1	1.43E-04	5.15E-05	-1.57E-05	8.90E-05	-2.99E-07	6.49E-05	3.66E-05	2.54E-05	-5.78E-05	2.36E-05	-3.11E-06
S32P2	-1.48E-04	-6.54E-05	2.39E-05	-6.43E-05	-3.18E-05	-1.58E-05	7.69E-06	5.18E-05	3.32E-05	-2.22E-05	-2.39E-05
S32P3	8.03E-06	1.32E-06	-1.52E-05	7.41E-06	-4.29E-05	1.43E-05	-5.60E-06	4.71E-05	-5.84E-06	8.51E-06	-1.53E-05
S32P4	6.40E-05	1.39E-05	4.32E-06	3.01E-05	7.65E-06	-3.61E-05	-8.34E-06	-6.06E-05	-4.71E-05	-9.71E-06	-5.68E-05
S32P5	-2.76E-05	-4.81E-07	4.24E-05	-4.83E-05	-5.59E-05	-4.07E-05	4.34E-06	1.33E-05	-7.12E-06	8.12E-06	-1.05E-05
S33P1	1.89E-05	-7.06E-05	-2.39E-07	-2.94E-06	-8.42E-05	3.50E-05	-2.15E-05	1.48E-05	7.94E-05	4.13E-05	5.41E-06
S33P2	-2.71E-05	5.37E-05	-5.76E-05	2.67E-05	2.51E-05	5.98E-05	-1.10E-05	1.49E-06	3.22E-05	5.83E-06	9.49E-06
S33P3	3.41E-05	-9.06E-06	1.41E-05	4.71E-07	1.31E-05	1.48E-05	6.22E-06	9.76E-06	-3.27E-05	-1.05E-05	-4.09E-05
S33P4	-9.58E-05	1.80E-05	-5.09E-05	6.22E-05	1.84E-05	-1.67E-05	-2.11E-05	-5.51E-05	4.46E-05	-5.25E-05	-1.56E-05
S33P5	1.78E-04	1.31E-05	-1.73E-05	-4.62E-05	-2.77E-06	4.00E-05	-2.32E-05	1.35E-05	1.36E-05	3.50E-05	1.49E-05
S34P1	-8.80E-05	-4.29E-05	2.44E-05	5.07E-05	6.14E-05	4.98E-05	-3.22E-05	-9.74E-06	3.33E-05	1.84E-05	-2.54E-05
S34P2	8.25E-05	5.72E-07	-3.12E-06	-2.63E-05	2.49E-05	3.15E-05	4.38E-05	-8.62E-07	9.86E-07	-6.04E-05	4.44E-05
S34P3	4.59E-05	5.24E-06	-1.40E-05	-1.31E-05	4.62E-05	-4.47E-06	-2.47E-05	2.84E-05	4.61E-05	3.57E-05	-8.23E-06
S34P4	-4.81E-05	7.90E-06	6.65E-05	1.00E-04	-4.25E-05	-3.67E-05	-7.17E-05	1.27E-05	-1.90E-05	2.42E-05	-1.61E-05
S34P5	-4.08E-05	6.22E-06	-1.91E-05	-1.47E-05	-7.28E-05	1.60E-05	1.69E-05	1.94E-05	-2.14E-05	7.88E-05	-4.46E-05
S35P1	-7.51E-05	-1.66E-05	3.78E-06	1.79E-05	-2.76E-05	-3.59E-05	-5.56E-05	3.78E-05	-1.43E-05	-1.97E-05	2.11E-05
S35P2	2.29E-04	-4.36E-06	1.01E-05	-6.30E-05	-3.20E-05	5.29E-06	-2.10E-05	4.45E-05	6.13E-05	4.97E-05	-5.10E-05
S35P3	-2.84E-05	-6.90E-06	-2.46E-05	1.33E-05	3.20E-05	-3.30E-05	-1.00E-05	-4.65E-05	7.24E-06	-4.81E-05	1.69E-06

S35P4	-2.14E-04	2.04E-05	3.58E-05	-9.23E-06	3.51E-05	1.20E-05	-3.21E-05	-2.66E-05	-3.58E-05	-1.14E-05	9.06E-06
S35P5	7.35E-05	1.93E-05	4.61E-05	-8.22E-06	-2.14E-05	2.62E-05	-2.00E-05	-1.96E-05	4.62E-05	3.05E-05	1.75E-06
S36P1	-1.03E-04	8.29E-05	-1.93E-05	-5.06E-05	1.84E-05	-3.07E-05	1.32E-05	-2.64E-05	-1.38E-05	-2.44E-05	6.16E-05
S36P2	-3.42E-06	2.15E-05	1.83E-05	-9.04E-05	2.71E-05	-3.14E-05	6.73E-07	1.19E-05	5.09E-05	-2.28E-05	3.11E-05
S36P3	-8.05E-05	-1.02E-04	2.46E-05	-6.42E-06	1.96E-05	-6.34E-05	-2.39E-05	-3.49E-05	-1.90E-05	2.48E-05	-1.50E-05
S36P4	-7.67E-05	5.05E-05	4.91E-05	8.17E-05	-2.86E-05	-1.17E-05	-3.48E-05	-8.42E-06	2.20E-05	-2.24E-06	-4.36E-05
S36P5	7.17E-05	-5.02E-05	-9.60E-06	-3.73E-05	-2.72E-05	4.39E-05	2.70E-05	3.84E-05	-1.51E-05	-3.10E-05	-4.02E-05
S37P1	-3.75E-04	5.28E-05	1.99E-05	-3.01E-05	-7.66E-06	3.66E-05	-2.18E-05	2.92E-06	-3.35E-05	-4.77E-05	2.40E-05
S37P2	-7.48E-05	2.49E-05	-3.62E-05	1.47E-05	2.10E-05	-3.14E-05	6.85E-05	-3.30E-06	8.64E-07	6.33E-05	-6.99E-06
S37P3	-1.64E-04	7.20E-06	-3.23E-05	-2.02E-05	-2.83E-06	-5.96E-05	7.68E-05	-1.76E-05	-4.45E-05	-2.25E-05	6.87E-06
S37P4	-6.35E-05	1.57E-05	6.33E-05	8.34E-05	-3.74E-05	2.25E-05	2.43E-06	4.99E-05	1.12E-06	-1.95E-05	-4.98E-05
S37P5	6.72E-05	4.13E-05	1.88E-05	-5.60E-06	6.73E-05	1.03E-05	-1.98E-05	-4.58E-05	-4.46E-05	4.21E-06	6.09E-06
S38P1	2.43E-06	7.15E-05	2.06E-05	-3.64E-06	-4.78E-05	-6.78E-05	3.52E-05	-4.91E-05	1.58E-05	-1.97E-05	3.12E-05
S38P2	-1.37E-04	2.95E-05	5.95E-05	5.33E-05	6.13E-05	-1.16E-05	4.24E-05	-1.07E-05	5.31E-06	-5.25E-06	-3.79E-05
S38P3	1.24E-04	4.21E-05	-3.26E-06	-1.02E-05	-1.65E-05	2.76E-05	5.69E-05	3.66E-06	3.21E-05	3.49E-05	1.86E-05
S38P4	-1.07E-04	6.35E-05	2.22E-05	-2.77E-05	-1.04E-05	-5.70E-05	-5.07E-05	1.89E-05	3.31E-05	3.54E-06	-1.26E-05
S38P5	1.77E-04	-1.06E-04	-5.58E-05	-8.35E-06	-6.95E-07	-2.13E-05	-4.77E-07	-3.60E-06	7.59E-05	-5.47E-05	1.88E-06
S39P1	-8.63E-05	7.10E-05	3.04E-05	2.44E-05	-2.87E-05	-1.17E-05	-3.40E-06	-6.47E-05	-3.93E-05	2.50E-05	2.74E-05
S39P2	5.50E-05	1.88E-05	7.26E-05	2.64E-05	2.74E-05	-4.25E-06	-6.09E-06	-8.73E-06	-3.16E-05	1.82E-05	2.51E-05
S39P3	1.00E-05	-5.91E-05	4.66E-05	5.21E-06	-4.39E-05	-1.57E-05	-5.16E-05	-3.96E-05	8.38E-05	1.30E-05	7.80E-06

S39P4	5.16E-05	-8.29E-06	-3.69E-05	-1.40E-05	-1.40E-05	-1.10E-05	3.50E-06	-4.24E-06	-8.25E-05	-4.34E-05	-1.29E-05
S39P5	-7.44E-05	5.41E-05	7.21E-05	-8.75E-06	-4.75E-05	-1.52E-05	-3.07E-06	1.81E-05	2.57E-05	2.68E-05	-1.06E-06
S40P1	9.31E-05	-1.10E-04	-2.96E-05	-1.09E-05	4.55E-05	5.17E-05	2.53E-05	-6.15E-05	-3.93E-06	1.16E-05	-2.74E-06
S40P2	1.09E-04	-4.89E-05	1.14E-05	-1.27E-05	3.04E-05	-1.44E-05	-1.67E-05	-6.19E-05	-1.66E-05	-2.61E-05	-4.38E-05
S40P3	-1.21E-04	6.45E-05	-3.17E-05	-1.95E-05	-2.05E-05	-3.16E-05	-2.33E-05	-4.95E-05	1.02E-06	-2.05E-05	-1.51E-05
S40P4	2.13E-05	8.12E-05	2.72E-05	-1.30E-05	-2.36E-05	-3.22E-06	7.92E-06	3.15E-05	8.62E-05	-1.20E-05	-5.87E-06
S40P5	1.47E-04	-5.88E-07	-4.88E-06	4.85E-05	2.54E-05	-7.51E-05	2.00E-05	-5.53E-05	-3.66E-06	-4.74E-05	2.80E-05
S41P1	6.77E-05	-8.76E-06	1.68E-05	3.65E-06	-7.16E-05	-1.87E-05	4.85E-05	5.34E-05	6.24E-06	-1.73E-05	3.04E-05
S41P2	1.96E-05	-5.32E-05	3.35E-05	4.98E-05	5.65E-06	-2.67E-05	4.39E-05	2.82E-06	-5.40E-05	3.14E-05	2.79E-05
S41P3	-6.86E-05	-4.95E-05	4.67E-05	-3.85E-05	9.23E-06	-4.78E-05	3.27E-05	-1.56E-05	-3.10E-05	4.04E-05	1.05E-05
S41P4	-2.39E-04	-1.44E-05	1.36E-05	5.42E-05	2.01E-05	2.48E-05	-3.48E-05	-3.39E-06	4.85E-05	-2.52E-05	-1.38E-06
S41P5	1.42E-04	-2.75E-05	-1.85E-06	2.02E-05	-4.52E-06	-1.79E-06	-4.59E-05	-1.76E-05	-1.43E-05	-5.81E-06	-7.60E-05
S42P1	1.21E-04	1.54E-05	-4.76E-05	5.75E-05	-2.30E-05	-1.09E-05	2.07E-05	-4.56E-05	-3.18E-05	-2.31E-05	-3.78E-05
S42P2	-3.64E-05	3.19E-05	-2.80E-05	-8.81E-05	4.87E-05	4.49E-05	-1.31E-05	-2.74E-05	-4.96E-06	-2.43E-05	-1.78E-05
S42P3	-1.33E-04	5.96E-05	-5.29E-05	2.12E-05	-1.59E-05	4.13E-05	-4.16E-05	-1.91E-05	9.49E-06	1.35E-05	-6.87E-06
S42P4	6.52E-05	-8.76E-06	7.39E-06	-2.06E-05	2.59E-05	-5.30E-05	3.44E-05	-7.25E-06	-4.09E-05	6.50E-07	-1.49E-05
S42P5	4.23E-05	5.58E-06	-1.52E-05	3.15E-06	5.56E-06	-9.45E-05	1.28E-05	-3.87E-05	1.76E-05	2.75E-05	-3.20E-06
S43P1	-2.07E-04	-4.28E-05	5.42E-06	4.71E-05	4.89E-05	-2.09E-05	2.06E-05	-3.34E-06	1.57E-05	-7.44E-06	2.03E-05
S43P2	-6.68E-05	2.83E-05	-5.16E-05	2.65E-05	-2.26E-05	-6.04E-05	2.89E-05	1.37E-05	1.25E-06	-6.62E-05	-2.25E-05
S43P3	-6.79E-05	-1.01E-04	-4.15E-05	4.83E-05	-9.88E-06	7.59E-05	4.81E-05	1.02E-04	-9.72E-06	-4.16E-05	1.25E-05

S43P4	-1.17E-04	3.65E-05	-5.54E-05	2.02E-05	-2.89E-05	5.29E-05	-6.18E-05	3.03E-05	-9.76E-07	8.16E-06	1.80E-05
S43P5	-9.41E-05	9.22E-06	-4.17E-05	3.05E-05	-8.36E-05	6.47E-06	-4.57E-05	2.17E-05	-2.08E-05	-2.43E-05	-1.80E-06
S44P1	-3.30E-05	2.74E-06	-4.04E-05	-2.64E-05	-1.31E-05	-2.43E-05	-6.58E-05	2.20E-05	-8.70E-06	-2.56E-05	-1.15E-06
S44P2	1.35E-04	-3.27E-06	5.22E-06	5.81E-05	-1.80E-05	-2.05E-05	-2.07E-06	-2.67E-05	6.88E-05	1.36E-05	8.12E-05
S44P3	1.44E-04	-7.22E-05	-2.93E-05	-5.92E-05	-7.13E-06	4.49E-06	-2.97E-05	4.44E-05	-2.90E-06	-1.85E-05	1.92E-05
S44P4	9.94E-05	-1.18E-05	2.40E-05	-3.06E-05	-5.18E-06	4.34E-05	7.77E-05	1.13E-05	-2.17E-05	1.17E-05	3.47E-05
S44P5	4.38E-06	-1.03E-05	-4.01E-05	3.59E-05	-7.08E-06	3.14E-05	1.23E-05	-8.42E-06	-5.68E-06	4.76E-05	2.75E-05
S45P1	1.01E-04	3.93E-06	1.31E-04	-7.02E-06	6.37E-06	2.61E-05	1.88E-05	-6.97E-06	2.18E-05	-9.03E-06	-1.68E-05
S45P2	-2.37E-04	2.57E-05	-6.46E-05	7.51E-05	-7.12E-06	1.02E-04	3.07E-05	-1.85E-05	-4.29E-05	6.26E-06	3.75E-06
S45P3	4.02E-06	-5.55E-07	1.58E-05	-2.07E-05	-3.20E-05	4.90E-06	2.10E-07	6.48E-07	-4.79E-05	1.49E-05	-3.59E-05
S45P4	-7.87E-05	5.33E-06	4.37E-05	4.39E-05	6.65E-06	1.95E-05	-1.03E-06	3.48E-06	2.82E-05	-5.88E-06	-8.73E-06
S45P5	3.20E-06	4.03E-05	-1.43E-05	2.27E-05	2.73E-05	2.34E-06	1.25E-05	2.11E-05	-6.33E-05	-6.72E-05	-4.22E-05
S46P1	1.31E-05	2.14E-05	-5.08E-05	-2.48E-05	4.09E-06	-6.97E-05	-3.08E-05	-4.95E-05	-1.51E-05	-3.74E-05	-5.50E-05
S46P2	-1.95E-04	-4.22E-06	4.99E-05	-6.86E-05	-5.50E-06	2.41E-06	4.27E-05	4.34E-05	-7.17E-06	4.80E-05	-3.82E-06
S46P3	-5.01E-05	-3.35E-05	-5.67E-05	7.10E-06	6.94E-05	-6.07E-05	-4.55E-05	4.53E-06	-3.16E-05	-1.72E-05	1.75E-05
S46P4	-1.12E-04	7.23E-05	-4.28E-05	6.11E-05	3.40E-05	5.13E-06	-3.07E-05	-1.18E-05	4.01E-05	3.70E-05	-2.94E-05
S46P5	1.69E-05	-2.96E-05	-1.63E-05	-1.15E-05	6.00E-06	-3.02E-05	7.38E-06	2.25E-05	-2.35E-05	-5.16E-05	-4.70E-06
S47P1	-4.24E-05	-8.51E-05	9.43E-05	-5.08E-05	-1.94E-05	3.76E-05	-2.36E-05	-3.51E-06	-5.17E-05	6.88E-05	1.14E-05
S47P2	-1.11E-04	-1.52E-05	3.01E-05	3.97E-06	-4.63E-05	2.57E-05	3.53E-05	-2.69E-05	-4.08E-05	-1.78E-05	-2.88E-05
S47P3	1.67E-04	8.02E-05	-2.94E-05	1.81E-06	5.65E-05	-2.88E-05	2.24E-05	7.97E-05	-1.25E-05	3.27E-05	3.44E-05

S47P4	-3.88E-05	-1.80E-05	-1.49E-04	-6.01E-05	4.22E-05	5.70E-05	6.77E-05	4.95E-05	5.92E-05	-4.84E-05	3.03E-05
S47P5	-2.63E-04	-9.78E-06	-1.80E-05	2.69E-05	1.53E-05	4.45E-05	3.73E-05	2.06E-05	2.06E-05	-3.61E-05	2.75E-05
S48P1	-3.40E-05	7.26E-05	2.40E-05	-1.18E-05	2.46E-06	1.05E-05	7.96E-06	3.25E-05	-2.39E-06	-4.75E-06	4.93E-05
S48P2	-7.09E-05	-1.75E-05	1.67E-05	6.43E-05	-7.69E-05	-3.78E-05	8.37E-05	1.45E-05	-2.64E-05	-4.43E-05	-4.75E-05
S48P3	-4.05E-05	2.07E-05	5.06E-05	-1.39E-05	1.96E-05	3.63E-05	2.04E-05	-5.23E-05	-2.67E-05	5.43E-07	4.42E-05
S48P4	-2.21E-06	6.19E-06	-4.47E-05	4.81E-05	-3.54E-05	2.38E-05	5.78E-05	1.64E-05	-2.69E-05	-5.07E-05	1.47E-05
S48P5	-7.31E-05	7.31E-06	2.69E-05	-1.15E-04	3.91E-05	3.89E-05	4.13E-05	-2.23E-05	1.86E-05	5.77E-05	-3.49E-06
S49P1	4.92E-05	8.18E-05	-6.67E-05	3.25E-05	-1.98E-05	7.33E-05	-4.03E-05	5.49E-05	-1.25E-06	-7.63E-05	-3.69E-05
S49P2	-1.97E-04	-5.43E-06	9.92E-06	1.69E-05	-3.36E-05	5.58E-07	6.42E-06	2.27E-05	7.29E-06	-8.17E-06	-3.40E-05
S49P3	-1.74E-04	4.80E-05	5.26E-05	-1.46E-05	-3.60E-05	3.03E-05	-4.33E-05	2.37E-05	-9.12E-06	7.91E-05	-5.09E-05
S49P4	4.43E-05	-6.74E-05	2.21E-05	6.67E-05	-9.71E-06	-2.09E-05	4.06E-05	-2.57E-05	-1.64E-05	3.31E-05	-1.78E-05
S49P5	-8.87E-05	3.56E-05	-1.08E-05	6.59E-05	-1.32E-05	3.94E-05	4.69E-05	4.47E-05	5.93E-05	3.36E-05	1.08E-05
S50P1	-1.36E-04	1.62E-06	-7.97E-05	5.25E-05	1.05E-05	-2.37E-06	2.75E-05	8.01E-05	-7.80E-06	-4.09E-05	2.17E-06
S50P2	-9.47E-06	-8.79E-06	4.41E-05	-8.08E-06	5.24E-06	8.06E-06	-2.21E-05	-9.04E-06	-5.77E-05	7.10E-06	-6.11E-05
S50P3	-2.35E-04	-6.75E-05	3.42E-05	-7.20E-05	-4.72E-05	-4.24E-06	1.60E-05	-3.74E-06	7.77E-06	6.11E-05	-1.13E-05
S50P4	-3.16E-04	-1.16E-04	-4.26E-05	-5.23E-05	5.21E-05	-3.44E-05	7.66E-05	1.93E-05	-3.37E-05	4.29E-05	1.06E-04
S50P5	-2.11E-06	3.91E-05	-5.60E-06	-8.36E-06	-6.30E-05	1.12E-05	-4.04E-05	4.23E-05	-1.22E-05	7.74E-06	6.68E-06
S51P1	-3.13E-05	-4.67E-05	-7.55E-05	2.93E-05	6.50E-05	-4.84E-05	4.10E-05	1.07E-04	1.89E-05	-6.05E-06	-5.17E-05
S51P2	1.69E-05	1.19E-04	-9.24E-06	-7.08E-06	-1.91E-05	-3.29E-08	5.94E-05	3.45E-05	-4.60E-06	7.79E-06	5.34E-06
S51P3	-3.13E-04	4.88E-05	4.20E-05	1.16E-05	-2.14E-05	-2.08E-06	-3.74E-05	-3.51E-05	-5.89E-06	-4.88E-05	4.56E-05

S51P4	1.78E-04	-3.99E-05	2.79E-05	-6.90E-05	9.41E-06	-1.24E-05	-5.77E-06	3.97E-05	3.62E-06	4.79E-05	3.37E-05
S51P5	-5.31E-05	-2.76E-06	7.09E-06	6.06E-05	5.32E-05	-9.39E-05	1.45E-05	3.42E-05	9.42E-06	2.46E-06	-1.23E-05

† **S***k***P***m* notation that refers process metric *m* (i.e., m = 1, …, 5) of supply chain step *k* (i.e., k = 1, …, 51)

‡ Higher loadings signify the importance of metric (S*P*) for a given data set. These values can be sorted to determine which metrics are more important than others.

A4/B – Component Loading Values of Process Steps (Cluster 2)

The following table provides the component loading values for each simulated data set in the second cluster. The values indicate the relationship between each process step metric and the dependent variable, *Yield*.

Table 20 - Component Loading Values (Cluster 2)

	LOADINGS										
Step ID	**Dataset 0**	**Dataset 1**	**Dataset 2**	**Dataset 3**	**Dataset 4**	**Dataset 5**	**Dataset 6**	**Dataset 7**	**Dataset 8**	**Dataset 9**	**Dataset 10**
S1P1	1.69E-04	7.42E-06	3.08E-05	3.67E-06	-4.06E-05	-9.35E-05	-5.27E-05	1.86E-05	-5.36E-05	3.87E-05	-2.57E-05
S1P2	-2.21E-04	1.04E-04	-3.89E-05	-8.30E-05	7.93E-05	5.13E-05	3.78E-05	6.96E-06	-2.71E-05	-3.04E-05	5.07E-05
S1P3	1.17E-04	1.46E-05	-4.63E-05	-2.27E-05	5.07E-05	4.01E-05	1.96E-05	3.43E-05	-3.29E-05	6.95E-06	4.17E-05
S1P4	1.32E-04	9.65E-05	-5.01E-05	8.60E-05	2.82E-05	5.99E-05	-3.48E-06	-2.18E-05	4.34E-05	5.00E-05	-4.19E-05
S1P5	6.68E-05	1.53E-04	4.80E-04	3.39E-04	2.69E-04	6.94E-05	2.43E-04	1.11E-04	1.07E-04	1.76E-04	2.09E-04
S2P1	2.38E-06	3.63E-05	5.12E-05	-2.06E-05	7.16E-05	5.31E-05	4.93E-05	-3.75E-05	8.43E-07	6.01E-05	3.65E-05
S2P2	3.55E-05	-1.47E-05	-6.07E-05	-2.12E-06	6.97E-06	3.08E-05	-3.34E-06	5.11E-05	-8.63E-06	2.15E-05	5.13E-06
S2P3	-6.73E-05	-1.48E-04	-1.02E-04	-7.81E-05	2.33E-05	-2.38E-05	-3.16E-05	-5.42E-05	6.32E-05	1.40E-05	2.17E-05
S2P4	-3.14E-04	2.74E-05	-4.46E-05	-1.47E-04	-1.14E-05	2.21E-05	5.05E-05	6.27E-05	-7.91E-06	3.33E-05	2.95E-05
S2P5	-1.36E-04	-3.30E-05	1.77E-04	8.53E-05	-5.93E-05	8.70E-05	-3.48E-06	3.01E-05	4.00E-05	4.41E-05	4.99E-05
S3P1	4.96E-05	-6.25E-05	7.54E-05	-2.52E-05	2.76E-05	-6.47E-05	-6.30E-05	-7.06E-06	2.72E-05	-4.04E-05	1.40E-05
S3P2	2.61E-04	6.32E-05	-2.90E-05	6.03E-06	-3.43E-05	4.88E-05	1.43E-05	-8.64E-06	2.12E-05	-7.22E-05	-7.59E-05
S3P3	1.13E-04	9.84E-05	-1.55E-05	-3.81E-05	-8.31E-05	-1.08E-05	-1.90E-05	-4.41E-05	-4.87E-05	-2.27E-05	1.65E-05
S3P4	9.42E-06	-4.88E-05	9.31E-05	-1.52E-05	-3.35E-06	8.19E-05	-5.84E-05	1.03E-05	4.27E-05	-2.22E-05	4.50E-05

S3P5	-8.68E-05	-1.47E-04	-7.04E-05	4.59E-05	-3.00E-05	-2.32E-05	-6.50E-05	4.40E-05	-2.75E-05	-2.57E-05	-1.64E-05
S4P1	2.30E-05	1.44E-05	-7.73E-05	-3.54E-05	-5.66E-05	2.97E-05	-9.21E-05	-7.04E-05	-4.12E-05	7.01E-06	-4.88E-05
S4P2	-4.08E-05	-1.10E-04	-1.25E-05	3.04E-05	-2.15E-05	6.68E-05	9.31E-05	6.52E-05	2.02E-05	-5.27E-05	4.04E-06
S4P3	-9.09E-05	-5.92E-05	-8.20E-05	2.02E-05	9.94E-05	5.90E-05	1.13E-04	3.58E-05	1.32E-05	-6.06E-06	-1.32E-05
S4P4	2.98E-04	-4.04E-05	-3.55E-05	-3.00E-05	5.17E-05	1.34E-05	-1.95E-05	5.02E-05	-1.74E-05	-2.79E-05	-3.38E-05
S4P5	-7.68E-05	-6.90E-05	-7.84E-05	-5.09E-05	-1.98E-05	6.21E-05	1.18E-04	-6.75E-06	2.41E-06	3.13E-06	-1.15E-05
S5P1	3.30E-06	4.14E-05	3.67E-05	1.99E-05	-4.98E-06	2.46E-05	8.89E-05	-4.98E-05	3.12E-05	-1.70E-05	2.45E-05
S5P2	-8.57E-05	-4.94E-07	4.78E-06	6.06E-05	-2.27E-05	3.80E-05	5.10E-05	6.59E-07	2.70E-06	2.35E-05	3.19E-06
S5P3	-8.35E-07	1.40E-04	-1.83E-06	-7.19E-05	-3.32E-05	8.33E-07	1.71E-05	-6.12E-05	-4.08E-05	-5.05E-05	4.97E-05
S5P4	-9.93E-05	-7.61E-05	8.00E-05	2.40E-05	-6.91E-05	6.26E-05	1.86E-06	4.73E-06	-4.62E-05	-6.85E-05	-2.28E-05
S5P5	-1.79E-04	-3.80E-05	4.45E-05	-7.98E-05	2.92E-05	-1.45E-05	5.15E-05	-4.72E-05	1.56E-05	4.83E-06	6.07E-06
S6P1	-3.27E-05	-5.38E-05	-2.61E-05	8.11E-06	-1.28E-04	-6.16E-05	3.74E-05	-4.44E-06	-2.54E-05	-5.82E-05	1.17E-05
S6P2	7.35E-05	-6.41E-05	-3.93E-05	1.06E-04	6.03E-05	2.83E-05	-4.16E-05	4.09E-05	1.44E-06	2.35E-05	-4.15E-05
S6P3	-2.80E-04	-6.54E-05	8.34E-05	8.49E-05	-2.05E-05	-5.15E-06	3.33E-05	3.63E-05	-1.92E-05	-1.53E-05	5.28E-05
S6P4	-1.12E-04	2.20E-05	-1.31E-05	4.98E-05	4.36E-05	1.08E-05	5.35E-05	-3.88E-05	6.62E-05	-6.63E-05	2.21E-06
S6P5	-1.36E-04	7.40E-05	-1.64E-04	4.74E-05	-5.98E-06	3.67E-05	7.54E-05	8.21E-05	-2.52E-05	-6.11E-05	-2.70E-05
S7P1	-1.21E-04	4.91E-05	-4.71E-05	-4.60E-05	-2.26E-05	-7.41E-05	-9.83E-06	3.30E-05	2.90E-05	1.68E-05	-9.33E-06
S7P2	-5.97E-05	-1.18E-06	4.28E-05	3.61E-06	-4.08E-05	-3.27E-05	-1.47E-05	-3.46E-05	-1.26E-05	4.88E-05	-3.45E-05
S7P3	-2.09E-04	-1.31E-05	-8.30E-05	3.99E-05	-1.43E-04	5.70E-05	7.97E-06	-5.91E-05	-3.38E-05	-7.51E-05	4.79E-05
S7P4	-2.30E-05	-8.45E-05	7.19E-06	1.12E-04	-3.87E-05	4.03E-05	3.75E-05	-1.49E-05	2.96E-05	4.53E-05	-3.54E-05

S7P5	-1.32E-04	-4.10E-05	-8.96E-05	-4.67E-05	-2.95E-05	-6.73E-05	-1.64E-05	-1.76E-06	5.73E-05	-2.47E-05	7.05E-06
S8P1	-5.53E-05	-7.71E-07	8.68E-05	-6.81E-05	-2.95E-05	8.95E-05	-1.83E-05	3.31E-05	-1.99E-05	-5.60E-05	-6.31E-05
S8P2	-8.07E-05	-1.74E-04	-9.22E-06	2.25E-05	-8.55E-05	-2.67E-05	-2.23E-05	8.97E-06	-4.37E-05	-1.80E-05	1.01E-05
S8P3	1.51E-04	-1.19E-04	-9.42E-05	-1.50E-04	1.14E-04	-6.67E-05	-4.00E-05	-9.40E-05	-2.21E-05	5.63E-06	3.60E-05
S8P4	-6.24E-05	1.68E-05	-4.10E-06	2.94E-05	5.23E-05	6.93E-05	-1.18E-04	-6.79E-05	-7.28E-06	-4.23E-05	-4.60E-06
S8P5	1.67E-04	-3.56E-05	-1.43E-05	7.07E-05	-3.97E-05	-2.07E-05	-5.90E-05	5.88E-05	9.65E-06	3.89E-05	1.51E-05
S9P1	1.60E-04	5.03E-05	-1.07E-06	1.28E-04	-3.74E-05	3.51E-05	1.34E-05	1.40E-05	-1.24E-05	4.83E-07	-9.24E-05
S9P2	8.04E-06	7.41E-05	-3.51E-05	-6.21E-05	3.01E-05	-1.26E-04	2.74E-05	-1.72E-06	-5.54E-05	4.10E-05	-6.28E-05
S9P3	-1.04E-04	1.34E-05	-5.00E-05	4.63E-05	-1.28E-04	5.10E-05	-3.01E-05	-7.62E-05	-1.05E-05	-3.68E-05	-1.52E-09
S9P4	-1.23E-04	-1.19E-04	-3.12E-05	-1.62E-05	1.06E-04	-1.68E-05	-4.00E-05	-2.81E-05	-4.63E-05	3.08E-05	4.18E-05
S9P5	5.86E-05	8.23E-05	4.11E-05	1.05E-05	1.96E-05	1.49E-05	1.42E-05	-4.46E-05	-4.02E-05	-1.35E-05	-3.98E-05
S10P1	2.10E-04	-1.16E-05	6.60E-07	-8.27E-06	2.65E-05	-3.77E-05	8.96E-05	2.70E-06	2.35E-05	-8.02E-06	-1.74E-06
S10P2	-5.65E-05	-7.53E-05	1.08E-05	5.90E-05	-1.97E-05	-1.43E-04	-1.11E-04	-3.60E-05	-3.88E-05	7.89E-07	-6.53E-05
S10P3	1.41E-04	-6.56E-05	-1.48E-04	5.81E-05	2.67E-05	7.13E-05	-1.60E-05	-3.80E-05	3.91E-05	-5.49E-05	-4.15E-05
S10P4	6.58E-05	-1.16E-05	4.36E-06	-1.62E-05	-2.43E-05	-5.12E-05	2.43E-05	6.52E-05	3.55E-05	-3.19E-06	-1.44E-05
S10P5	1.72E-04	-9.39E-06	1.66E-04	1.36E-04	2.97E-05	-7.67E-05	1.42E-05	6.83E-06	1.68E-05	-4.08E-05	-6.61E-05
S11P1	-2.51E-05	-9.05E-06	3.37E-04	2.04E-05	-1.14E-04	2.46E-05	3.75E-05	-1.81E-05	-1.26E-05	5.83E-05	-6.60E-06
S11P2	-9.24E-05	4.02E-05	-1.11E-05	6.86E-06	1.45E-05	-4.61E-06	-1.03E-05	-3.41E-05	-6.31E-05	-8.98E-06	1.92E-05
S11P3	2.51E-04	-4.05E-05	7.17E-05	-6.25E-05	-4.62E-06	-2.51E-06	1.26E-05	4.68E-05	-8.87E-06	-3.92E-06	-2.60E-05
S11P4	1.16E-04	3.36E-04	2.22E-04	1.23E-04	4.50E-04	2.39E-04	3.26E-04	1.55E-04	2.29E-04	4.62E-04	2.00E-04

S11P5	-3.06E-04	7.30E-05	8.83E-05	3.87E-05	3.55E-05	-5.24E-05	4.37E-05	-2.31E-05	-3.48E-05	5.25E-06	6.85E-06
S12P1	-8.02E-05	6.16E-05	1.53E-05	1.10E-05	9.84E-06	-8.62E-06	-5.72E-05	-5.14E-05	-3.85E-05	4.52E-05	3.21E-05
S12P2	-3.52E-05	5.29E-05	-7.52E-06	-4.60E-05	-5.40E-06	-4.54E-05	7.97E-05	1.09E-05	9.18E-06	-4.74E-06	-1.98E-05
S12P3	1.55E-04	9.59E-05	2.80E-05	-1.17E-04	3.04E-05	-6.10E-05	-1.24E-05	-5.26E-06	1.42E-06	3.85E-06	-1.67E-05
S12P4	2.31E-05	-3.26E-05	-1.19E-05	-6.10E-05	-9.23E-06	3.49E-05	-4.58E-05	-4.58E-06	2.53E-06	-1.53E-05	-1.96E-05
S12P5	-1.30E-04	-5.95E-05	3.77E-05	6.60E-05	-2.46E-05	-3.94E-05	-8.14E-05	-1.83E-05	-5.41E-06	-1.58E-05	-4.68E-05
S13P1	-5.56E-05	1.40E-04	-2.80E-05	-4.11E-05	1.63E-05	2.04E-05	6.86E-05	4.78E-05	3.58E-05	-2.42E-06	-1.40E-05
S13P2	5.09E-05	-1.01E-04	-8.21E-05	-3.04E-05	-8.22E-05	-1.06E-04	7.19E-05	5.16E-05	1.29E-05	-4.54E-05	1.64E-06
S13P3	-1.55E-04	5.84E-06	-4.93E-05	2.62E-05	-1.00E-05	1.74E-05	-5.79E-05	1.64E-06	7.56E-05	2.23E-05	8.62E-06
S13P4	9.85E-06	6.32E-05	1.54E-04	-3.18E-05	1.95E-05	-2.25E-05	3.96E-05	-2.23E-05	-6.95E-06	3.19E-05	-9.20E-06
S13P5	-1.62E-05	7.18E-05	-6.04E-06	6.33E-05	-3.28E-05	8.65E-05	-9.98E-05	3.72E-06	-2.59E-05	-1.90E-05	1.12E-05
S14P1	-7.79E-05	-3.28E-05	-7.27E-05	5.03E-05	-5.59E-05	9.40E-06	-7.24E-05	4.56E-05	3.60E-05	-9.06E-06	-1.99E-05
S14P2	-7.09E-05	1.72E-04	1.41E-04	4.62E-05	-6.03E-05	-6.99E-05	7.58E-05	3.95E-05	2.87E-05	-2.03E-05	5.50E-05
S14P3	-8.62E-05	2.87E-05	-1.67E-05	3.67E-05	-2.48E-05	4.35E-05	-4.82E-05	-1.58E-05	6.96E-05	1.06E-05	-1.07E-05
S14P4	-9.41E-05	5.28E-05	5.09E-05	3.07E-05	-1.62E-05	-8.74E-05	-9.10E-06	4.00E-06	1.44E-05	2.10E-05	5.25E-05
S14P5	-3.88E-05	3.24E-05	7.83E-05	2.29E-05	1.35E-05	-1.72E-05	-3.28E-05	2.98E-05	2.63E-07	-5.22E-05	-5.17E-05
S15P1	2.67E-05	1.69E-04	-5.21E-05	7.01E-05	6.14E-05	-3.31E-06	-6.75E-05	-2.95E-05	5.81E-05	1.98E-05	2.14E-05
S15P2	1.15E-04	-3.13E-05	7.79E-05	3.30E-05	6.61E-05	3.75E-05	2.12E-05	-8.24E-05	-4.48E-05	-5.77E-05	2.91E-05
S15P3	-1.69E-05	-1.20E-05	7.87E-05	-5.08E-05	-7.36E-05	1.97E-05	-2.07E-05	2.63E-05	3.44E-05	-5.45E-06	-7.46E-06
S15P4	1.87E-04	-1.08E-04	-3.27E-05	2.10E-05	1.21E-05	-6.59E-05	1.60E-05	5.27E-06	-7.00E-06	-5.73E-05	5.16E-06

S15P5	-1.60E-05	-6.90E-05	-1.15E-04	-6.22E-05	6.06E-05	-1.20E-05	-5.01E-05	4.85E-06	3.92E-05	-2.48E-05	4.02E-05
S16P1	2.50E-04	-1.19E-04	-3.02E-06	-5.89E-05	5.51E-05	-1.11E-04	-7.63E-05	7.42E-05	7.00E-06	2.12E-07	1.67E-05
S16P2	3.08E-05	2.82E-05	6.76E-06	-2.72E-05	-7.59E-05	-2.98E-05	5.45E-05	4.45E-05	8.20E-06	-7.68E-05	-5.97E-06
S16P3	-3.39E-05	1.01E-04	4.30E-05	6.41E-05	1.21E-05	-4.97E-05	1.87E-05	-1.59E-05	-6.74E-05	1.11E-06	5.65E-05
S16P4	6.28E-05	-5.30E-05	6.01E-05	-2.75E-05	4.54E-05	3.51E-05	3.29E-05	4.61E-05	-6.68E-05	-6.23E-06	-1.97E-05
S16P5	9.22E-05	1.62E-04	2.72E-05	1.85E-06	-3.86E-05	9.99E-05	8.37E-06	7.03E-05	3.52E-05	3.01E-05	-8.97E-06
S17P1	1.91E-05	-3.35E-05	2.16E-04	5.24E-04	7.58E-04	3.61E-04	4.31E-04	1.11E-04	1.12E-04	4.64E-04	3.20E-04
S17P2	-1.50E-04	-2.64E-04	-1.05E-04	-4.22E-07	7.90E-05	3.90E-05	2.10E-05	-9.29E-06	5.13E-05	3.29E-05	5.78E-06
S17P3	2.58E-05	-3.67E-05	-3.51E-05	5.18E-05	-9.00E-06	-6.84E-05	3.54E-05	-1.05E-04	-2.46E-05	9.89E-06	-7.25E-06
S17P4	-7.84E-06	-1.23E-04	3.25E-05	6.69E-05	6.60E-05	-2.16E-05	4.03E-05	1.01E-06	-1.78E-05	4.21E-05	-8.89E-06
S17P5	-1.70E-04	5.47E-05	8.92E-05	7.27E-05	3.95E-05	-1.01E-05	-6.07E-05	-1.92E-05	-7.57E-05	-5.36E-05	1.94E-05
S18P1	-1.67E-04	-1.59E-05	5.34E-05	1.10E-05	-2.48E-05	-3.30E-05	8.95E-06	-1.66E-06	-5.31E-05	2.57E-05	8.85E-06
S18P2	-6.93E-05	1.47E-04	-4.83E-05	3.24E-05	-2.33E-05	-5.45E-06	1.88E-05	1.95E-05	-2.01E-05	2.31E-05	2.22E-05
S18P3	-1.61E-04	-8.29E-05	1.17E-04	-7.23E-05	6.92E-05	2.39E-06	5.89E-05	-2.81E-05	-1.45E-05	2.99E-05	-4.77E-06
S18P4	-4.73E-05	3.06E-04	3.25E-04	5.31E-04	2.63E-04	7.59E-04	5.98E-04	5.43E-04	2.15E-04	5.47E-04	1.89E-04
S18P5	1.25E-04	1.53E-04	3.97E-05	-4.28E-05	7.58E-05	-5.95E-05	8.89E-06	5.46E-05	3.26E-05	-3.75E-05	-1.84E-05
S19P1	-1.99E-05	-7.92E-05	2.40E-05	1.03E-05	4.61E-05	2.31E-05	5.83E-05	3.00E-05	1.03E-05	7.38E-05	5.28E-05
S19P2	1.41E-04	1.95E-04	6.92E-05	-2.62E-05	-1.01E-04	-6.02E-06	1.88E-05	6.31E-06	8.90E-06	-3.64E-05	-1.45E-05
S19P3	1.05E-04	-4.76E-05	8.10E-05	-8.28E-05	-1.99E-05	2.77E-05	-6.28E-05	1.04E-05	5.80E-05	3.57E-05	1.63E-05
S19P4	-1.98E-04	-4.34E-05	-1.02E-04	1.56E-04	-2.25E-05	-6.54E-05	8.38E-06	-1.59E-05	8.60E-08	2.74E-05	3.56E-05

S19P5	1.37E-04	-5.24E-05	-1.23E-04	-6.14E-05	7.32E-05	2.68E-05	4.48E-05	-7.94E-06	-1.37E-05	3.43E-05	2.94E-06
S20P1	2.14E-04	-1.68E-04	6.95E-05	1.96E-05	1.13E-05	6.86E-05	1.61E-05	-1.00E-05	4.66E-05	-3.31E-05	-1.36E-05
S20P2	-1.27E-04	-1.34E-04	-1.01E-06	-4.05E-05	-7.23E-05	-6.42E-05	-5.85E-05	-5.28E-05	1.08E-05	5.29E-05	-3.41E-05
S20P3	-1.45E-04	-6.25E-05	-4.97E-06	5.68E-05	5.25E-05	2.37E-05	-8.73E-06	-4.94E-05	1.60E-05	4.91E-05	9.86E-06
S20P4	1.06E-04	-3.32E-05	-2.19E-05	7.07E-05	-1.50E-04	4.98E-05	1.36E-05	4.47E-05	-1.30E-05	2.67E-05	1.65E-05
S20P5	5.22E-05	-7.31E-05	-5.17E-07	1.34E-04	-7.44E-05	2.63E-05	1.01E-04	-3.31E-05	-6.04E-06	7.10E-06	3.77E-05
S21P1	1.55E-04	-1.23E-04	-1.29E-05	-5.69E-05	-2.16E-05	-5.62E-05	-2.78E-05	2.73E-05	2.77E-06	3.78E-05	2.41E-05
S21P2	2.23E-04	-3.18E-05	1.18E-04	-3.95E-05	3.43E-05	-1.28E-05	-5.48E-05	-4.29E-05	-2.85E-05	6.89E-05	-1.88E-05
S21P3	-1.30E-04	-5.97E-06	1.09E-04	4.21E-05	-1.23E-05	-2.85E-05	9.20E-05	-1.29E-05	-6.20E-05	-1.27E-05	-2.79E-05
S21P4	1.34E-04	-9.54E-05	5.06E-05	2.67E-05	-2.22E-05	-3.72E-05	-9.16E-05	-3.06E-05	-5.11E-05	3.33E-05	1.93E-05
S21P5	-5.27E-05	-6.31E-05	1.79E-04	6.41E-05	2.09E-05	-4.95E-05	1.92E-05	-1.60E-05	-2.80E-05	-4.01E-05	3.28E-05
S22P1	6.47E-05	-1.34E-04	-4.78E-05	-3.69E-05	-2.64E-05	-5.83E-05	2.74E-05	2.36E-05	3.29E-05	-3.49E-05	4.85E-05
S22P2	-1.63E-04	-1.23E-05	8.03E-05	1.24E-04	-3.00E-05	3.85E-05	7.31E-06	-2.42E-05	-4.04E-05	-2.30E-05	2.10E-05
S22P3	-8.43E-05	3.55E-05	2.77E-05	-1.04E-04	9.02E-06	-2.36E-05	-6.56E-06	-1.00E-05	9.03E-06	-2.70E-05	4.53E-05
S22P4	2.48E-04	-1.01E-04	-6.25E-05	7.64E-05	-1.31E-04	1.38E-05	-2.04E-05	8.91E-06	-3.36E-05	-1.73E-05	4.10E-05
S22P5	1.04E-04	-1.75E-04	-1.43E-04	1.84E-05	6.47E-05	-1.18E-05	6.64E-05	-1.21E-05	-2.51E-06	1.56E-05	4.84E-05
S23P1	3.40E-05	-1.01E-04	5.06E-05	-6.29E-05	1.56E-05	9.45E-05	-8.43E-05	6.96E-05	-3.31E-05	-8.91E-06	-2.53E-06
S23P2	1.61E-04	8.88E-05	7.34E-05	-3.99E-05	6.77E-05	2.86E-05	2.15E-05	8.99E-05	6.11E-05	-4.16E-05	2.49E-05
S23P3	-2.50E-04	-1.49E-04	-6.21E-05	-1.85E-05	-7.68E-05	-6.43E-06	4.31E-05	3.71E-05	1.74E-05	-8.33E-05	-2.39E-05
S23P4	1.19E-05	3.13E-06	-4.53E-05	1.97E-05	4.97E-05	-1.25E-04	-5.47E-05	2.63E-05	4.22E-05	6.65E-06	3.01E-05

S23P5	9.54E-05	-1.04E-04	8.02E-05	-1.52E-04	6.03E-05	5.40E-05	2.41E-05	3.16E-05	-6.19E-06	1.61E-05	-1.50E-05
S24P1	2.36E-04	5.73E-05	5.21E-05	7.23E-05	1.37E-05	1.81E-05	4.81E-05	2.95E-05	-1.53E-05	3.08E-05	-4.01E-05
S24P2	2.50E-05	-3.24E-05	-7.38E-05	-3.22E-05	8.83E-05	-7.13E-06	6.98E-05	-1.56E-06	-1.28E-05	-4.88E-05	1.78E-05
S24P3	-1.17E-04	-5.55E-05	1.21E-05	1.21E-04	-3.29E-05	-9.45E-05	5.69E-05	-9.12E-05	-6.63E-05	-1.53E-05	2.79E-05
S24P4	-1.35E-04	1.83E-04	-3.94E-05	-4.86E-05	7.56E-05	9.98E-06	9.75E-06	-3.05E-05	-3.23E-05	1.21E-05	-3.48E-05
S24P5	2.81E-05	-1.39E-04	1.09E-04	1.29E-04	1.46E-05	-2.43E-05	-4.03E-05	-6.42E-05	-5.91E-06	-9.52E-06	-4.13E-05
S25P1	2.36E-04	2.05E-05	1.33E-04	5.78E-05	-1.47E-05	8.54E-06	3.83E-05	-7.05E-06	-1.54E-05	-2.49E-05	5.98E-06
S25P2	-6.71E-05	-6.71E-05	7.43E-06	4.98E-05	-1.07E-05	-4.47E-05	9.10E-07	1.51E-07	-2.84E-05	-2.14E-05	-1.17E-05
S25P3	8.92E-05	2.64E-05	3.99E-05	-8.94E-05	-4.14E-05	-5.17E-05	-4.13E-05	1.30E-05	-7.40E-06	3.33E-05	6.04E-05
S25P4	1.85E-06	-1.31E-05	-3.56E-05	7.04E-05	9.81E-07	-5.68E-05	-1.01E-05	4.81E-05	-1.77E-05	-5.14E-05	3.59E-05
S25P5	-1.22E-04	1.53E-04	-3.56E-05	-9.02E-05	8.88E-06	2.83E-05	4.08E-05	5.02E-05	-1.35E-06	-1.52E-06	-1.22E-05
S26P1	1.14E-05	1.94E-04	1.64E-04	7.74E-05	6.03E-06	-7.04E-05	-1.66E-05	-4.81E-05	-5.09E-06	-2.37E-05	-1.02E-05
S26P2	-6.60E-05	8.36E-05	-2.45E-05	-6.94E-05	5.23E-05	-1.14E-04	1.43E-05	4.38E-05	-7.05E-06	-4.54E-06	-1.03E-05
S26P3	2.12E-05	1.05E-04	8.35E-05	3.91E-05	2.82E-05	-6.20E-05	-8.66E-05	-3.82E-05	3.00E-05	-1.81E-05	-7.96E-05
S26P4	-1.92E-04	1.44E-04	5.68E-05	-6.98E-05	5.38E-05	1.90E-05	-5.31E-05	1.00E-05	-2.39E-05	3.26E-05	3.54E-05
S26P5	5.84E-05	-4.25E-05	-5.52E-05	-3.89E-05	-1.00E-04	-3.45E-06	-2.45E-06	7.63E-05	-1.26E-06	-2.19E-05	-5.04E-05
S27P1	-1.24E-04	-5.94E-05	-1.57E-05	-3.18E-05	1.63E-05	1.47E-04	1.53E-05	-4.40E-05	-5.96E-05	1.83E-05	-2.42E-05
S27P2	2.91E-04	-3.20E-05	-1.27E-04	1.97E-05	1.40E-05	-6.69E-06	-7.21E-05	-3.83E-05	5.14E-05	3.15E-08	1.39E-05
S27P3	2.39E-05	-5.27E-05	-8.17E-06	-5.25E-05	-1.67E-05	1.47E-05	-8.60E-06	1.38E-05	9.26E-06	-3.22E-05	-3.86E-05
S27P4	1.19E-04	-1.31E-04	1.28E-04	-1.13E-05	-5.19E-05	-1.28E-06	-3.39E-05	5.80E-05	-3.32E-05	-2.61E-05	-4.13E-05

S27P5	-8.61E-05	-2.53E-04	-5.30E-05	-3.57E-05	-1.84E-05	2.64E-06	-4.06E-05	4.31E-05	1.85E-05	4.50E-05	-1.10E-04
S28P1	9.02E-05	-1.55E-04	-1.87E-05	7.29E-05	4.16E-05	6.21E-06	-1.03E-06	-1.41E-05	-6.06E-06	5.48E-05	2.73E-07
S28P2	5.96E-05	1.19E-05	1.46E-04	-9.14E-05	4.39E-05	1.72E-05	1.12E-05	-2.57E-06	-2.51E-05	-1.67E-05	-4.18E-05
S28P3	4.32E-05	-3.50E-05	-1.29E-04	2.91E-05	1.84E-05	-5.47E-05	-3.28E-06	6.65E-05	-5.48E-05	-2.36E-05	9.10E-06
S28P4	2.10E-04	2.22E-05	6.19E-05	-6.00E-05	5.82E-05	7.83E-05	6.44E-06	-3.14E-06	3.66E-05	-1.69E-05	-1.23E-05
S28P5	9.53E-05	-1.56E-04	1.13E-04	5.72E-05	-7.07E-05	5.35E-05	-5.98E-06	3.16E-05	-1.98E-05	1.99E-07	3.81E-05
S29P1	-7.15E-07	-6.20E-05	-9.29E-05	-7.68E-05	4.52E-05	-3.73E-05	-1.00E-04	6.09E-06	-6.47E-06	3.76E-05	2.68E-05
S29P2	-2.07E-04	5.13E-06	-1.09E-05	-1.34E-04	8.54E-05	4.24E-06	6.69E-05	-2.02E-05	-7.32E-06	-8.38E-05	-6.80E-05
S29P3	3.07E-06	-4.30E-05	6.52E-05	-6.41E-06	1.19E-04	4.23E-06	5.94E-05	3.55E-05	-3.81E-05	-3.72E-05	8.60E-06
S29P4	-3.92E-06	-5.94E-07	4.03E-05	2.77E-06	-6.28E-05	-7.35E-05	1.97E-06	1.30E-05	3.98E-05	1.63E-06	-2.00E-05
S29P5	-2.20E-04	1.27E-04	-9.11E-05	7.59E-05	-2.20E-05	-9.57E-06	7.27E-05	-1.72E-05	-2.80E-05	1.89E-06	3.36E-05
S30P1	1.84E-04	-2.53E-04	6.61E-06	-3.27E-05	8.86E-05	-2.06E-06	-6.72E-05	3.81E-05	-4.01E-06	2.83E-05	1.81E-05
S30P2	-8.67E-05	-5.63E-05	5.59E-05	-8.06E-06	-2.05E-06	5.42E-05	-4.17E-05	-8.61E-06	-2.93E-05	-5.92E-07	2.85E-06
S30P3	-3.13E-04	1.35E-04	6.99E-05	-4.14E-05	-4.91E-05	9.04E-05	-3.87E-06	1.67E-06	-3.70E-05	-2.45E-05	-7.19E-05
S30P4	-9.56E-05	-9.13E-05	2.93E-05	7.06E-05	1.11E-05	-5.44E-05	3.29E-05	-2.71E-05	1.22E-05	3.48E-06	4.49E-05
S30P5	1.36E-04	5.01E-05	-1.46E-04	9.73E-05	-9.07E-05	-9.43E-05	-6.58E-05	8.55E-05	-2.96E-05	-1.77E-05	4.85E-05
S31P1	8.82E-05	-3.11E-05	3.11E-05	1.41E-04	-3.88E-05	-5.05E-06	-6.07E-05	1.64E-05	5.95E-05	-3.72E-05	3.27E-07
S31P2	4.84E-05	5.51E-05	-2.39E-04	-1.52E-04	-1.66E-06	1.30E-05	-2.49E-06	7.46E-05	4.42E-06	-7.28E-05	1.99E-05
S31P3	1.12E-04	4.04E-05	-8.66E-05	5.27E-05	1.80E-05	-5.18E-05	-1.38E-05	-4.08E-05	-1.81E-05	4.92E-05	-5.84E-06
S31P4	3.65E-05	5.53E-05	-5.73E-05	-5.77E-05	-1.84E-06	1.76E-05	-1.97E-05	-3.56E-05	1.94E-05	-4.43E-05	1.78E-05

S31P5	2.26E-04	5.66E-05	-3.31E-05	1.03E-04	2.04E-05	1.11E-05	-3.06E-06	-1.06E-05	1.25E-07	-2.55E-05	1.57E-05
S32P1	8.18E-06	-1.06E-04	2.56E-05	1.74E-05	8.09E-05	4.25E-05	-2.79E-06	-1.89E-05	1.68E-05	4.84E-06	1.32E-05
S32P2	-2.03E-04	1.09E-05	-7.42E-05	-8.60E-06	-2.73E-05	4.21E-05	-2.89E-05	-3.23E-05	6.75E-05	3.38E-05	-3.80E-05
S32P3	-3.55E-05	-5.85E-05	8.27E-05	3.86E-05	3.26E-05	-6.99E-05	-1.71E-05	-6.74E-06	1.28E-05	3.37E-05	-5.24E-05
S32P4	-1.67E-04	-4.64E-05	-1.32E-05	-1.43E-05	1.62E-05	-4.87E-05	3.04E-05	-5.07E-05	2.32E-05	-6.70E-05	-3.54E-05
S32P5	1.49E-04	1.15E-05	-7.99E-05	-5.54E-05	-4.84E-05	7.79E-05	-9.10E-06	8.48E-06	2.77E-06	1.84E-06	9.26E-05
S33P1	3.36E-05	-5.19E-05	4.29E-05	-1.77E-05	5.27E-05	-8.11E-05	3.57E-05	-2.84E-05	3.72E-05	2.01E-05	9.46E-06
S33P2	-6.60E-05	-1.39E-04	2.64E-05	6.56E-05	-3.77E-05	-3.57E-05	-6.84E-05	-3.23E-05	-3.46E-05	5.19E-06	-3.37E-05
S33P3	-1.27E-04	-6.06E-05	9.93E-05	-4.16E-05	6.39E-05	7.94E-05	-6.32E-06	-2.44E-05	-5.52E-05	4.24E-06	-2.79E-06
S33P4	-9.01E-05	6.57E-05	-1.98E-04	-1.43E-06	3.82E-05	3.75E-06	-2.28E-05	-8.77E-06	-4.35E-05	-4.13E-05	2.68E-05
S33P5	-3.76E-05	1.80E-04	-1.22E-04	5.17E-05	7.34E-05	7.70E-06	-1.93E-05	3.96E-05	-1.91E-05	4.16E-05	4.12E-05
S34P1	1.04E-05	-2.25E-05	-1.47E-05	-9.97E-06	-5.57E-06	-2.84E-05	1.01E-04	3.75E-05	2.71E-05	4.20E-06	5.95E-05
S34P2	1.69E-04	2.90E-05	9.69E-06	-9.95E-05	-8.70E-06	-2.08E-05	4.68E-05	-3.03E-05	2.20E-05	-1.43E-05	1.60E-05
S34P3	7.06E-05	-4.83E-05	-6.70E-05	4.31E-05	-6.71E-05	-5.22E-05	-1.08E-04	-3.18E-05	-1.38E-05	-7.53E-05	-2.74E-05
S34P4	-5.66E-05	1.03E-04	1.39E-04	-4.48E-05	-4.91E-05	-3.74E-05	5.86E-05	-3.59E-05	-8.46E-06	2.36E-05	-1.20E-05
S34P5	8.41E-05	-1.38E-04	3.09E-05	-1.33E-04	-2.49E-05	-1.32E-05	1.87E-05	1.13E-05	-1.08E-05	-7.21E-06	1.56E-07
S35P1	3.98E-05	-3.05E-05	8.90E-06	1.01E-04	4.28E-05	-1.07E-04	-1.06E-05	-4.28E-05	-3.04E-05	9.28E-06	-2.45E-05
S35P2	-1.64E-05	6.62E-05	9.00E-05	-6.78E-05	5.25E-06	3.63E-05	-7.24E-05	3.13E-05	-4.62E-05	1.84E-06	-1.68E-06
S35P3	-2.58E-04	2.49E-04	5.28E-05	-2.14E-05	-1.80E-04	1.84E-05	-7.32E-05	1.89E-05	-6.63E-05	-2.50E-05	-2.77E-05
S35P4	2.74E-05	1.25E-04	-4.91E-05	9.63E-06	-1.09E-04	-9.92E-06	3.34E-05	5.21E-05	7.44E-05	6.09E-05	-5.32E-06

S35P5	1.22E-04	2.99E-05	5.37E-05	8.68E-05	-1.49E-04	-2.47E-06	-6.97E-05	1.54E-05	9.32E-06	2.84E-05	5.41E-07
S36P1	-1.05E-04	4.57E-05	6.94E-05	3.26E-05	1.28E-04	4.53E-05	2.64E-05	4.93E-05	2.46E-05	-2.98E-05	-4.47E-06
S36P2	-2.13E-04	-1.61E-05	2.85E-05	-5.84E-06	8.53E-06	-9.72E-05	4.54E-06	1.34E-05	3.78E-05	-1.85E-05	1.02E-05
S36P3	-1.13E-04	-5.40E-05	-1.05E-04	-2.74E-06	3.93E-05	-5.20E-05	6.26E-06	6.74E-05	4.06E-05	2.40E-05	2.06E-06
S36P4	-1.09E-04	3.73E-05	-6.17E-05	5.27E-05	1.45E-05	-8.69E-06	9.01E-05	1.73E-05	2.18E-05	1.99E-05	-2.31E-05
S36P5	-7.92E-05	-1.32E-04	-7.84E-05	1.46E-05	9.16E-06	8.11E-05	-8.11E-05	-3.57E-05	1.07E-05	-1.02E-05	4.23E-06
S37P1	4.42E-05	3.56E-04	-4.81E-05	4.79E-04	4.11E-05	1.96E-04	4.11E-04	5.31E-04	2.69E-04	3.34E-04	4.74E-04
S37P2	3.71E-05	-7.22E-05	8.09E-05	-1.04E-05	-1.21E-05	-7.58E-05	2.19E-05	1.00E-06	-2.92E-06	-3.10E-05	2.37E-05
S37P3	2.15E-05	-1.78E-05	-5.40E-05	1.05E-05	-6.38E-05	1.40E-05	2.47E-05	-6.22E-05	2.83E-06	-4.93E-05	-3.93E-05
S37P4	2.38E-04	-5.14E-05	-4.19E-05	-6.21E-05	-2.72E-05	4.10E-05	4.84E-05	-1.09E-06	-1.70E-05	-7.09E-05	4.57E-05
S37P5	-6.80E-05	9.12E-05	9.81E-05	2.12E-05	7.90E-05	2.81E-05	-6.19E-05	-5.79E-05	-3.67E-05	-1.09E-05	2.59E-05
S38P1	-6.48E-05	6.30E-05	-6.65E-05	7.66E-06	6.15E-05	-4.07E-05	-4.59E-05	-3.15E-05	-1.98E-06	1.09E-05	5.61E-05
S38P2	-3.04E-04	-1.76E-05	1.41E-05	-5.36E-05	9.67E-06	5.80E-05	-4.27E-05	5.89E-06	1.91E-05	3.43E-05	-2.46E-05
S38P3	6.28E-05	-3.51E-05	8.19E-05	-7.87E-06	-1.08E-04	-2.91E-05	5.71E-05	-3.56E-05	-1.65E-05	-5.18E-05	-5.14E-05
S38P4	2.46E-04	7.66E-05	-3.97E-05	8.80E-05	-5.19E-06	-3.12E-05	-4.92E-05	-3.69E-05	-3.16E-05	8.13E-05	4.55E-05
S38P5	3.37E-05	-5.00E-05	1.45E-04	-3.63E-05	-7.64E-05	-4.62E-05	-2.52E-05	-6.67E-05	-4.81E-05	-1.02E-05	-3.47E-05
S39P1	-1.41E-04	5.10E-04	2.06E-04	6.64E-05	3.15E-04	3.80E-04	2.42E-04	3.13E-04	5.66E-04	5.79E-05	5.16E-04
S39P2	5.20E-05	-1.78E-06	2.20E-04	-1.06E-04	-1.75E-05	-7.28E-05	-2.43E-05	-4.34E-05	-3.54E-06	-6.68E-06	3.41E-06
S39P3	5.93E-05	-2.56E-06	-2.40E-04	-7.51E-05	1.35E-05	1.20E-04	-1.04E-05	1.73E-05	-2.00E-05	-3.57E-05	-1.15E-05
S39P4	-3.72E-05	1.77E-04	6.67E-05	-5.85E-05	2.65E-05	2.77E-05	8.56E-05	4.12E-06	4.68E-05	-1.12E-04	-2.65E-05

S39P5	-9.12E-05	-3.80E-05	-1.56E-05	-5.30E-05	-5.91E-05	-4.11E-05	-9.66E-06	3.99E-05	-5.90E-05	-7.89E-07	-3.64E-05
S40P1	-1.33E-04	6.16E-04	7.43E-04	1.05E-04	1.40E-04	3.15E-04	3.75E-04	4.37E-04	3.66E-04	2.99E-04	4.47E-04
S40P2	1.80E-04	7.94E-05	-3.15E-05	1.92E-05	-5.74E-05	9.29E-05	1.02E-05	-7.00E-05	-6.98E-05	4.57E-05	9.44E-06
S40P3	2.36E-05	9.22E-05	-1.13E-05	-7.84E-05	-3.27E-06	-4.38E-05	5.92E-05	5.98E-06	-3.69E-05	-6.56E-05	1.86E-05
S40P4	4.68E-05	1.51E-04	1.37E-06	4.24E-05	-1.20E-04	3.05E-05	1.56E-05	-1.70E-05	3.39E-05	4.18E-05	7.14E-06
S40P5	2.67E-05	-1.87E-04	4.09E-05	-5.21E-05	3.61E-06	-5.61E-06	-5.76E-05	-2.10E-05	-4.48E-05	3.05E-05	-5.10E-05
S41P1	6.75E-05	-8.94E-05	7.87E-05	5.26E-05	8.54E-05	-5.29E-05	-2.36E-05	-3.97E-05	1.55E-05	-3.29E-05	-2.77E-05
S41P2	-1.74E-05	-9.66E-06	6.07E-05	1.42E-05	2.72E-05	-2.54E-05	2.61E-05	1.21E-05	-2.92E-05	-1.65E-05	-1.25E-05
S41P3	1.42E-04	6.76E-05	6.73E-05	1.81E-05	-2.28E-05	1.51E-05	-1.98E-05	5.81E-06	-2.74E-05	5.76E-05	2.67E-05
S41P4	2.33E-04	1.44E-05	4.79E-05	-3.35E-05	-6.10E-05	5.81E-05	-1.08E-05	5.60E-05	-2.55E-05	1.37E-05	-3.31E-05
S41P5	2.15E-05	-1.20E-06	2.08E-06	-2.52E-05	7.12E-06	3.10E-05	1.60E-05	5.61E-05	-1.16E-05	-2.29E-05	1.06E-05
S42P1	8.31E-05	3.58E-04	2.50E-04	1.55E-04	3.65E-04	4.74E-04	1.23E-04	1.52E-04	4.61E-04	9.22E-05	7.64E-05
S42P2	-7.84E-05	7.22E-06	-5.21E-05	9.46E-06	-4.45E-05	8.67E-05	-2.59E-05	4.67E-05	-2.17E-06	-2.02E-05	3.04E-05
S42P3	6.90E-06	5.10E-05	6.07E-05	8.92E-05	1.37E-05	7.96E-05	-2.06E-05	-2.29E-05	2.20E-05	-2.81E-05	1.66E-05
S42P4	1.16E-04	-6.30E-05	1.09E-04	-8.92E-06	1.55E-05	-4.12E-05	5.71E-05	-4.46E-05	5.37E-05	1.19E-05	-3.73E-06
S42P5	-7.87E-05	-9.55E-06	-5.05E-05	4.35E-05	-2.89E-05	-1.03E-04	3.43E-05	-6.57E-05	-2.17E-05	7.06E-06	2.21E-05
S43P1	-1.57E-04	-3.36E-05	1.06E-05	-6.10E-05	7.09E-05	1.11E-04	-8.08E-06	-9.86E-06	6.99E-06	-3.41E-05	2.93E-05
S43P2	1.71E-04	1.33E-04	-7.91E-05	-9.71E-05	9.10E-05	-2.98E-05	1.10E-05	5.33E-05	1.51E-05	9.09E-06	-4.33E-05
S43P3	2.90E-04	5.76E-06	1.10E-04	7.92E-05	4.24E-05	1.21E-05	-1.13E-04	-3.19E-06	-3.22E-05	-2.21E-05	1.56E-05
S43P4	9.67E-05	1.16E-04	1.77E-05	1.25E-05	-6.58E-05	6.34E-05	-1.80E-05	-5.58E-05	-1.20E-05	1.01E-05	5.89E-05

S43P5	-3.76E-05	7.94E-05	-1.96E-05	-4.32E-05	2.94E-05	2.04E-05	-8.80E-05	-3.72E-05	-2.82E-05	4.42E-06	-2.59E-05
S44P1	1.89E-04	1.76E-04	-1.10E-04	7.14E-05	1.75E-06	-7.20E-05	6.83E-06	-2.70E-05	-9.38E-06	5.85E-05	-2.85E-05
S44P2	-1.07E-04	2.03E-04	1.92E-05	1.25E-05	-3.18E-05	5.23E-05	8.84E-06	4.20E-05	2.35E-05	-8.25E-06	-5.72E-05
S44P3	1.99E-04	-1.04E-04	-1.43E-05	5.31E-05	-5.85E-05	-8.15E-05	-4.25E-05	6.90E-05	-2.11E-05	-1.50E-05	4.02E-05
S44P4	2.77E-04	-1.35E-04	-1.76E-04	-2.18E-05	3.92E-05	2.30E-05	3.44E-05	-4.68E-05	2.31E-05	1.02E-05	-3.72E-06
S44P5	6.92E-05	1.09E-04	-9.73E-05	-1.02E-04	1.95E-05	5.04E-05	-3.23E-05	1.18E-05	-7.23E-05	2.85E-05	-1.77E-06
S45P1	-7.51E-05	1.47E-04	1.31E-04	-4.68E-05	6.05E-05	-6.54E-05	1.51E-05	-5.59E-05	3.34E-05	-4.69E-05	4.04E-06
S45P2	1.06E-04	-1.60E-06	8.23E-05	1.08E-04	6.75E-05	4.06E-06	-4.43E-05	2.16E-05	3.59E-06	4.36E-05	7.89E-05
S45P3	-1.36E-05	-1.25E-04	-4.16E-05	-4.06E-05	-1.36E-04	-5.40E-05	-6.47E-05	-4.19E-05	-2.84E-05	5.86E-05	6.47E-05
S45P4	2.11E-05	-1.21E-04	-8.60E-05	-2.47E-05	8.50E-05	5.04E-05	2.45E-05	-4.36E-05	2.39E-05	-9.42E-05	-5.57E-05
S45P5	-1.32E-04	-7.47E-06	-2.20E-05	3.94E-05	-4.21E-05	-8.72E-05	3.15E-05	-1.08E-05	3.42E-05	2.53E-05	4.29E-05
S46P1	-9.00E-05	3.97E-05	8.30E-05	6.82E-05	2.00E-06	4.96E-06	-7.36E-05	2.32E-05	-9.68E-05	2.37E-05	1.66E-05
S46P2	2.51E-04	-1.89E-04	-3.52E-06	-6.08E-05	-5.15E-05	-6.57E-05	-4.02E-06	1.45E-05	-2.06E-05	3.26E-05	-1.59E-05
S46P3	-2.31E-05	3.90E-05	-2.13E-05	-1.59E-05	4.37E-06	-4.58E-05	1.63E-05	-2.60E-05	-2.43E-05	5.36E-05	1.30E-05
S46P4	2.09E-04	-1.73E-04	4.02E-05	3.73E-05	1.27E-05	-9.94E-06	-1.50E-06	9.58E-05	-3.73E-05	4.75E-06	6.19E-05
S46P5	1.33E-04	2.30E-05	-6.44E-05	2.00E-05	2.49E-05	8.59E-05	4.20E-05	3.07E-05	-1.75E-05	2.21E-05	2.32E-05
S47P1	7.34E-05	3.99E-05	2.38E-05	-5.73E-05	-9.05E-05	4.72E-05	-1.01E-04	-1.47E-06	1.95E-05	1.40E-05	2.70E-05
S47P2	-2.00E-04	-7.24E-05	-1.15E-04	2.87E-05	5.06E-06	1.74E-05	-1.12E-04	-1.45E-05	6.55E-05	1.37E-05	5.02E-05
S47P3	1.45E-04	-1.69E-04	2.79E-05	2.66E-05	-2.17E-05	1.10E-05	4.41E-05	-2.74E-05	6.31E-05	-4.55E-05	-5.40E-05
S47P4	1.09E-04	-5.08E-05	8.00E-05	1.51E-05	2.77E-05	2.83E-05	-8.43E-05	-1.56E-05	-2.49E-06	1.50E-05	6.74E-05

S47P5	1.72E-04	3.55E-05	5.47E-05	4.33E-05	-6.67E-06	-5.42E-06	-5.01E-05	9.01E-06	-1.88E-06	-2.93E-05	1.98E-05
S48P1	3.48E-05	-2.24E-06	6.94E-05	-2.88E-05	-1.72E-05	-3.67E-05	-4.78E-05	-3.00E-05	1.89E-05	7.78E-06	-1.93E-05
S48P2	8.61E-05	-1.38E-04	1.38E-06	4.91E-05	-8.92E-05	1.08E-05	8.88E-06	-2.26E-05	-6.09E-05	2.41E-05	-4.80E-05
S48P3	-1.84E-05	-2.12E-04	-6.19E-05	1.27E-04	-6.31E-05	9.57E-05	-2.59E-05	-3.96E-05	3.87E-05	2.33E-05	-4.10E-05
S48P4	-1.57E-05	2.12E-04	5.53E-05	-3.87E-05	-6.90E-05	4.65E-05	-1.06E-04	1.64E-05	-7.25E-05	1.94E-05	2.79E-05
S48P5	-7.15E-05	8.95E-05	-6.52E-05	-1.31E-05	7.00E-05	-5.53E-05	-1.01E-05	-1.53E-05	-2.06E-05	2.33E-05	-5.05E-06
S49P1	1.39E-04	5.35E-05	-2.16E-06	1.81E-05	-1.23E-05	3.62E-05	4.79E-05	4.55E-05	-3.50E-06	7.28E-05	2.33E-05
S49P2	1.07E-04	8.11E-05	6.57E-05	-2.70E-05	3.30E-05	7.37E-05	6.47E-05	2.09E-05	7.07E-05	-4.83E-05	-8.50E-05
S49P3	6.46E-05	3.91E-05	-2.93E-05	-7.63E-05	9.75E-05	3.49E-06	3.29E-05	7.45E-05	1.01E-05	1.74E-05	-2.71E-05
S49P4	4.05E-05	1.61E-05	-6.42E-05	-2.41E-05	1.34E-05	4.24E-05	-5.31E-06	2.25E-05	-3.30E-05	1.52E-05	1.20E-05
S49P5	-1.27E-04	-1.79E-05	8.03E-05	-1.35E-04	-3.42E-05	-5.76E-06	-1.65E-05	-6.26E-06	3.27E-06	-1.15E-05	4.84E-05
S50P1	-8.04E-05	6.39E-05	-8.31E-05	1.21E-04	5.01E-05	-9.90E-06	1.10E-05	-1.95E-05	-4.27E-05	5.42E-06	-1.78E-05
S50P2	4.88E-05	-5.35E-05	-1.23E-05	-4.67E-05	5.24E-05	-5.11E-05	6.64E-06	1.87E-05	9.45E-06	-2.51E-05	1.95E-05
S50P3	9.56E-05	-8.07E-05	2.33E-06	-1.62E-05	-2.10E-05	1.32E-05	-1.28E-06	-3.09E-05	-3.01E-05	3.56E-05	2.47E-05
S50P4	7.03E-06	5.15E-05	1.07E-04	5.77E-05	1.41E-05	3.91E-05	-3.43E-07	4.99E-05	2.42E-05	-8.38E-06	2.71E-05
S50P5	-2.68E-04	-1.62E-05	-1.25E-04	-5.49E-05	4.12E-05	-5.26E-05	5.54E-05	-3.93E-05	2.72E-05	-1.55E-05	3.96E-06
S51P1	-6.46E-05	6.64E-05	9.22E-05	4.32E-05	-7.30E-05	-7.86E-06	4.69E-05	4.22E-05	-1.33E-05	-5.40E-05	-3.11E-05
S51P2	-2.45E-04	1.52E-04	-1.38E-04	1.14E-06	-1.04E-04	9.00E-05	-3.51E-05	2.04E-05	6.04E-05	4.19E-05	-2.24E-06
S51P3	-7.29E-05	4.68E-05	1.15E-04	-9.27E-05	-2.53E-05	6.77E-06	-2.24E-05	-1.87E-05	2.05E-05	1.87E-05	5.27E-05
S51P4	2.38E-04	1.41E-04	3.56E-04	5.07E-04	6.00E-05	2.13E-04	3.17E-04	1.47E-04	9.56E-05	9.82E-06	1.73E-04

S51P5	-1.75E-04	7.81E-06	-1.20E-04	2.11E-05	-6.14E-06	-5.10E-05	6.14E-06	-6.83E-06	-5.08E-06	-4.08E-05	-2.33E-05

† **S***k***P***m* notation that refers process metric *m* (i.e., m = 1, …, 5) of supply chain step *k* (i.e., k = 1, …, 51)

‡ Higher loadings signify the importance of metric (S*P*) for a given data set. These values can be sorted to determine which metrics are more important than others.

Appendix A5 – Sorted Component Loading Values

The component loadings in each data set (refer to *Appendix A4*) can be sorted based on their absolute values (from the highest to the lowest). The loadings of different supply chain steps (within each data set) can be compared with each other since they are generated from a scaled data. Higher component loadings indicate that those process metrics are more crucial than the ones having lower component values. Appendices A5/A and A5/B show the ranked component loading values for simulated clusters one and two, respectively. These values represent the top 20 component loadings from the set of 255 measurements.

A5/A – Sorted Component Loading Values (Cluster 1 –only shown the top 20)

Sorted component loading values (top 20) of each simulated data set in the first cluster are provided below:

Table 21 - Sorted Component Latent Values (Cluster 1)

	Dataset 0		Dataset 1		Dataset 2		Dataset 3		Dataset 4		Dataset 5		Dataset 6		Dataset 7		Dataset 8		Dataset 9		Dataset 10	
Rank	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading	Step #	Loading
1	S7P2	3.41E-04	S29P4	9.95E-04	S29P4	1.04E-03	S29P4	9.91E-04	S29P4	1.00E-03	S29P4	1.02E-03	S29P4	1.01E-03	S29P4	9.77E-04	S29P4	9.85E-04	S29P4	9.90E-04	S29P4	9.57E-04
2	S10P3	2.83E-04	S51P2	1.19E-04	S45P1	1.31E-04	S3P4	1.04E-04	S20P3	1.16E-04	S45P2	1.02E-04	S16P5	9.07E-05	S51P1	1.07E-04	S20P5	1.02E-04	S23P4	8.24E-05	S27P5	1.11E-04
3	S21P1	2.74E-04	S9P1	1.10E-04	S21P3	1.13E-04	S34P4	1.00E-04	S8P5	1.05E-04	S43P3	7.59E-05	S13P5	8.40E-05	S43P3	1.02E-04	S26P3	9.95E-05	S49P3	7.91E-05	S50P4	1.06E-04
4	S30P5	2.59E-04	S16P5	1.08E-04	S3P3	1.09E-04	S2P1	9.23E-05	S24P4	1.00E-04	S20P5	7.41E-05	S48P2	8.37E-05	S7P3	8.91E-05	S25P4	9.08E-05	S34P5	7.88E-05	S16P1	1.03E-04
5	S28P1	2.55E-04	S17P5	8.79E-05	S8P5	1.02E-04	S32P1	8.90E-05	S23P2	7.99E-05	S27P2	7.33E-05	S31P5	8.03E-05	S24P3	8.42E-05	S40P4	8.62E-05	S17P5	7.68E-05	S2P2	9.39E-05
6	S9P5	2.46E-04	S13P2	8.48E-05	S47P1	9.43E-05	S17P2	8.83E-05	S26P2	7.91E-05	S49P1	7.33E-05	S44P4	7.77E-05	S50P1	8.01E-05	S39P3	8.38E-05	S15P3	7.12E-05	S44P2	8.12E-05
7	S29P4	2.38E-04	S36P1	8.29E-05	S18P3	9.28E-05	S19P2	8.43E-05	S24P5	7.65E-05	S3P2	6.84E-05	S19P1	7.75E-05	S47P3	7.97E-05	S33P1	7.94E-05	S47P1	6.88E-05	S29P2	8.10E-05
8	S35P2	2.29E-04	S49P1	8.18E-05	S29P3	8.52E-05	S24P1	8.34E-05	S24P2	7.52E-05	S4P1	6.82E-05	S37P3	7.68E-05	S26P5	7.60E-05	S22P5	7.68E-05	S14P4	6.80E-05	S15P4	7.96E-05
9	S8P1	2.18E-04	S40P4	8.12E-05	S10P5	8.16E-05	S37P4	8.34E-05	S3P1	7.17E-05	S16P5	6.53E-05	S50P4	7.66E-05	S6P2	7.20E-05	S38P5	7.59E-05	S9P4	6.69E-05	S11P5	7.33E-05
10	S10P4	2.13E-04	S47P3	8.02E-05	S11P5	8.15E-05	S36P4	8.17E-05	S46P3	6.94E-05	S32P1	6.49E-05	S16P2	7.28E-05	S13P1	7.04E-05	S3P1	7.24E-05	S37P2	6.33E-05	S11P2	6.68E-05
11	S20P4	2.01E-04	S48P1	7.26E-05	S18P1	7.48E-05	S7P1	8.15E-05	S37P5	6.73E-05	S1P5	6.10E-05	S25P3	7.17E-05	S49P1	5.49E-05	S11P5	6.97E-05	S8P5	6.28E-05	S15P2	6.63E-05
12	S13P2	1.97E-04	S46P4	7.23E-05	S39P2	7.26E-05	S9P1	7.79E-05	S15P5	6.54E-05	S33P2	5.98E-05	S8P3	7.07E-05	S7P4	5.35E-05	S44P2	6.88E-05	S50P3	6.11E-05	S36P1	6.16E-05
13	S22P1	1.90E-04	S38P1	7.15E-05	S39P5	7.21E-05	S11P2	7.61E-05	S51P1	6.50E-05	S4P5	5.71E-05	S37P2	6.85E-05	S41P1	5.34E-05	S20P1	6.78E-05	S48P5	5.77E-05	S3P4	5.97E-05
14	S22P4	1.81E-04	S39P1	7.10E-05	S11P3	7.20E-05	S45P2	7.51E-05	S12P3	6.16E-05	S47P4	5.70E-05	S47P4	6.77E-05	S32P2	5.18E-05	S35P2	6.13E-05	S14P3	5.59E-05	S16P3	5.82E-05
15	S33P5	1.78E-04	S25P2	6.96E-05	S7P5	6.98E-05	S30P2	7.21E-05	S34P1	6.14E-05	S1P4	5.56E-05	S2P4	6.70E-05	S29P2	5.05E-05	S49P5	5.93E-05	S16P3	5.54E-05	S13P5	5.60E-05
16	S51P4	1.78E-04	S40P3	6.45E-05	S34P4	6.65E-05	S18P5	6.68E-05	S38P2	6.13E-05	S14P1	5.32E-05	S27P5	6.68E-05	S28P5	4.99E-05	S47P4	5.92E-05	S3P1	5.45E-05	S12P5	5.46E-05
17	S38P5	1.77E-04	S38P4	6.35E-05	S37P4	6.33E-05	S49P4	6.67E-05	S20P1	6.04E-05	S14P5	5.31E-05	S13P4	6.52E-05	S37P4	4.99E-05	S27P5	5.86E-05	S6P4	5.45E-05	S21P5	5.37E-05
18	S23P2	1.72E-04	S21P1	6.14E-05	S23P2	6.05E-05	S49P5	6.59E-05	S3P3	6.00E-05	S43P4	5.29E-05	S51P2	5.94E-05	S47P4	4.95E-05	S23P2	5.85E-05	S25P3	5.08E-05	S30P1	5.24E-05
19	S8P2	1.69E-04	S2P2	6.10E-05	S38P2	5.95E-05	S48P2	6.43E-05	S13P2	5.91E-05	S40P1	5.17E-05	S48P4	5.78E-05	S5P1	4.73E-05	S21P1	5.47E-05	S35P2	4.97E-05	S6P5	5.14E-05
20	S47P3	1.67E-04	S42P3	5.96E-05	S5P2	5.89E-05	S5P3	6.34E-05	S5P5	5.89E-05	S25P1	5.16E-05	S38P3	5.69E-05	S32P3	4.71E-05	S27P4	5.44E-05	S46P2	4.80E-05	S48P1	4.93E-05

† The component loadings from A4/A are sorted from the highest value to the lowest to determine which metrics are crucial for a given data set. Out of 255 measurements, only twenty loadings having the highest loadings are shown in the table above.

A5/B – Sorted Component Loading Values (Cluster 2 –only shown the top 20)

Sorted component loading values (top 20) of each simulated data set in the second cluster are provided below:

Table 22 - Sorted Component Latent Values (Cluster 2)

	Dataset 0		Dataset 1		Dataset 2		Dataset 3		Dataset 4		Dataset 5		Dataset 6		Dataset 7		Dataset 8		Dataset 9		Dataset 10	
Rank	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**	**Step #**	**Loading**
1	**S2P4**	3.14E-04	**S40P1**	6.16E-04	**S40P1**	7.43E-04	**S18P4**	5.31E-04	**S17P1**	7.58E-04	**S18P4**	7.59E-04	**S18P4**	5.98E-04	**S18P4**	5.43E-04	**S39P1**	5.66E-04	**S18P4**	5.47E-04	**S39P1**	5.16E-04
2	**S30P3**	3.13E-04	**S39P1**	5.10E-04	**S1P5**	4.80E-04	**S17P1**	5.24E-04	**S11P4**	4.50E-04	**S42P1**	4.74E-04	**S17P1**	4.31E-04	**S37P1**	5.31E-04	**S42P1**	4.61E-04	**S17P1**	4.64E-04	**S37P1**	4.74E-04
3	**S11P5**	3.06E-04	**S42P1**	3.58E-04	**S51P4**	3.56E-04	**S51P4**	5.07E-04	**S42P1**	3.65E-04	**S39P1**	3.80E-04	**S37P1**	4.11E-04	**S40P1**	4.37E-04	**S40P1**	3.66E-04	**S11P4**	4.62E-04	**S40P1**	4.47E-04
4	**S38P2**	3.04E-04	**S37P1**	3.56E-04	**S11P1**	3.37E-04	**S37P1**	4.79E-04	**S39P1**	3.15E-04	**S17P1**	3.61E-04	**S40P1**	3.75E-04	**S39P1**	3.13E-04	**S37P1**	2.69E-04	**S37P1**	3.34E-04	**S17P1**	3.20E-04
5	**S4P4**	2.98E-04	**S11P4**	3.36E-04	**S18P4**	3.25E-04	**S1P5**	3.39E-04	**S1P5**	2.69E-04	**S40P1**	3.15E-04	**S11P4**	3.26E-04	**S11P4**	1.55E-04	**S11P4**	2.29E-04	**S40P1**	2.99E-04	**S1P5**	2.09E-04
6	**S27P2**	2.91E-04	**S18P4**	3.06E-04	**S42P1**	2.50E-04	**S19P4**	1.56E-04	**S18P4**	2.63E-04	**S11P4**	2.39E-04	**S51P4**	3.17E-04	**S42P1**	1.52E-04	**S18P4**	2.15E-04	**S1P5**	1.76E-04	**S11P4**	2.00E-04
7	**S43P3**	2.90E-04	**S17P2**	2.64E-04	**S39P3**	2.40E-04	**S42P1**	1.55E-04	**S35P3**	1.80E-04	**S51P4**	2.13E-04	**S1P5**	2.43E-04	**S51P4**	1.47E-04	**S17P1**	1.12E-04	**S39P4**	1.12E-04	**S18P4**	1.89E-04
8	**S6P3**	2.80E-04	**S27P5**	2.53E-04	**S31P2**	2.39E-04	**S31P2**	1.52E-04	**S20P4**	1.50E-04	**S37P1**	1.96E-04	**S39P1**	2.42E-04	**S1P5**	1.11E-04	**S1P5**	1.07E-04	**S45P4**	9.42E-05	**S51P4**	1.73E-04
9	**S44P4**	2.77E-04	**S30P1**	2.53E-04	**S11P4**	2.22E-04	**S23P5**	1.52E-04	**S35P5**	1.49E-04	**S27P1**	1.47E-04	**S42P1**	1.23E-04	**S17P1**	1.11E-04	**S46P1**	9.68E-05	**S42P1**	9.22E-05	**S27P5**	1.10E-04
10	**S50P5**	2.68E-04	**S35P3**	2.49E-04	**S39P2**	2.20E-04	**S8P3**	1.50E-04	**S7P3**	1.43E-04	**S10P2**	1.43E-04	**S4P5**	1.18E-04	**S17P3**	1.05E-04	**S51P4**	9.56E-05	**S29P2**	8.38E-05	**S32P5**	9.26E-05
11	**S3P2**	2.61E-04	**S48P3**	2.12E-04	**S17P1**	2.16E-04	**S2P4**	1.47E-04	**S40P1**	1.40E-04	**S9P2**	1.26E-04	**S8P4**	1.18E-04	**S46P4**	9.58E-05	**S17P5**	7.57E-05	**S23P3**	8.33E-05	**S9P1**	9.24E-05
12	**S35P3**	2.58E-04	**S48P4**	2.12E-04	**S39P1**	2.06E-04	**S31P1**	1.41E-04	**S45P3**	1.36E-04	**S23P4**	1.25E-04	**S43P3**	1.13E-04	**S8P3**	9.40E-05	**S13P3**	7.56E-05	**S38P4**	8.13E-05	**S49P2**	8.50E-05
13	**S46P2**	2.51E-04	**S44P2**	2.03E-04	**S33P4**	1.98E-04	**S10P5**	1.36E-04	**S22P4**	1.31E-04	**S39P3**	1.20E-04	**S4P3**	1.13E-04	**S24P3**	9.12E-05	**S35P4**	7.44E-05	**S16P2**	7.68E-05	**S26P3**	7.96E-05
14	**S11P3**	2.51E-04	**S19P2**	1.95E-04	**S21P5**	1.79E-04	**S49P5**	1.35E-04	**S36P1**	1.28E-04	**S26P2**	1.14E-04	**S47P2**	1.12E-04	**S23P2**	8.99E-05	**S48P4**	7.25E-05	**S34P3**	7.53E-05	**S45P2**	7.89E-05
15	**S23P3**	2.50E-04	**S26P1**	1.94E-04	**S2P5**	1.77E-04	**S29P2**	1.34E-04	**S6P1**	1.28E-04	**S43P1**	1.11E-04	**S10P2**	1.11E-04	**S30P5**	8.55E-05	**S44P5**	7.23E-05	**S7P3**	7.51E-05	**S42P1**	7.64E-05
16	**S16P1**	2.50E-04	**S46P2**	1.89E-04	**S44P4**	1.76E-04	**S20P5**	1.34E-04	**S9P3**	1.28E-04	**S16P1**	1.11E-04	**S34P3**	1.08E-04	**S15P2**	8.24E-05	**S49P2**	7.07E-05	**S19P1**	7.38E-05	**S3P2**	7.59E-05
17	**S22P4**	2.48E-04	**S40P5**	1.87E-04	**S10P5**	1.66E-04	**S34P5**	1.33E-04	**S40P4**	1.20E-04	**S35P1**	1.07E-04	**S48P4**	1.06E-04	**S6P5**	8.21E-05	**S40P2**	6.98E-05	**S49P1**	7.28E-05	**S30P3**	7.19E-05
18	**S38P4**	2.46E-04	**S24P4**	1.83E-04	**S6P5**	1.64E-04	**S24P5**	1.29E-04	**S29P3**	1.19E-04	**S13P2**	1.06E-04	**S47P1**	1.01E-04	**S26P5**	7.63E-05	**S14P3**	6.96E-05	**S31P2**	7.28E-05	**S29P2**	6.80E-05
19	**S51P2**	2.45E-04	**S33P5**	1.80E-04	**S26P1**	1.64E-04	**S9P1**	1.28E-04	**S11P1**	1.14E-04	**S42P5**	1.03E-04	**S20P5**	1.01E-04	**S9P3**	7.62E-05	**S32P2**	6.75E-05	**S3P2**	7.22E-05	**S47P4**	6.74E-05
20	**S37P4**	2.38E-04	**S39P4**	1.77E-04	**S13P4**	1.54E-04	**S48P3**	1.27E-04	**S8P3**	1.14E-04	**S16P5**	9.99E-05	**S34P1**	1.01E-04	**S31P2**	7.46E-05	**S16P3**	6.74E-05	**S37P4**	7.09E-05	**S10P5**	6.61E-05

† The component loadings from A4/B are sorted from the highest value to the lowest to determine which metrics are crucial for a given data set. Out of 255 measurements, only twenty loadings having the highest loadings are shown in the table above.

Appendix A6 – R^2 Values Based on the Number of Retained Predictor Variables having the Highest Loadings

In this appendix, R^2 values of different number of retained components from the top 20 component loading list of the second data cluster (Appendix A4/B on p. 174) are compared with each using linear regression modeling in SPSS. Results reveal that even retaining five variables (having the highest loading) can provide enough explanatory power for the model by regressing process steps having highest loadings with the dependent variable (i.e., *Yield*). The table highlights that even when we retain four to five predictor variables (with highest loading from the PLS test), the explanatory power of the model remains substantial. For example, for data sets 7 to 10, retaining only three variables with highest PLS loading provide R^2 values greater than 0.60. R^2 values of data sets 0 to 2 remain relatively low even when we retain twenty predictor variables, but R^2 values remain relatively constant even when five predictor variables remain in the model. The decline of R^2 values of data sets 8 to 10 is more apparent especially after retaining six or fewer predictor variables in the model.

Table 23 - R^2 Values (Linear Regression SPSS Output)

	3 Variables		4 Variables		5 Variables		6 Variables		7 Variables		8 Variables		9 Variables		10 Variables		15 Variables		20 Variables	
Dataset	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**	**R2**	**Adjusted R**
0	0.018	0.015	0.023	0.019	0.031	0.026	0.033	0.027	0.035	0.028	0.038	0.030	0.040	0.032	0.045	0.035	0.070	0.056	0.084	0.065
1	0.101	0.098	0.117	0.113	0.144	0.139	0.156	0.151	0.159	0.153	0.162	0.156	0.170	0.163	0.172	0.163	0.190	0.178	0.199	0.183
2	0.182	0.179	0.192	0.189	0.205	0.201	0.217	0.212	0.221	0.216	0.224	0.218	0.239	0.232	0.245	0.237	0.271	0.260	0.281	0.267
3	0.251	0.249	0.325	0.322	0.361	0.357	0.361	0.357	0.373	0.369	0.374	0.369	0.375	0.369	0.380	0.373	0.385	0.376	0.395	0.383
4	0.354	0.352	0.390	0.388	0.422	0.419	0.436	0.433	0.440	0.436	0.444	0.439	0.445	0.440	0.445	0.440	0.460	0.451	0.465	0.454
5	0.368	0.366	0.409	0.406	0.467	0.464	0.500	0.497	0.515	0.512	0.516	0.512	0.518	0.514	0.519	0.514	0.521	0.515	0.532	0.523
6	0.386	0.384	0.450	0.447	0.510	0.507	0.561	0.559	0.590	0.587	0.641	0.638	0.655	0.652	0.655	0.652	0.658	0.653	0.662	0.655
7	0.657	0.656	0.730	0.729	0.758	0.756	0.783	0.782	0.791	0.790	0.804	0.802	0.828	0.827	0.828	0.827	0.829	0.826	0.830	0.827
8	0.703	0.702	0.756	0.755	0.818	0.817	0.878	0.878	0.898	0.898	0.913	0.913	0.913	0.913	0.920	0.919	0.920	0.919	0.921	0.919
9	0.711	0.710	0.856	0.856	0.948	0.948	0.979	0.979	0.979	0.979	0.979	0.979	0.981	0.981	0.981	0.981	0.981	0.981	0.981	0.981
10	0.678	0.677	0.798	0.797	0.863	0.863	0.906	0.906	0.964	0.964	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Appendix A7 – Latent Component Summary Statistics (Manufacturing Data set)

Summary statistics to test the predictive power of the *training* data (r^2 and R^2) and *test* data (q^2 and Q^2) for each latent component of the manufacturing data set are provided in this appendix. These measures signify whether a model is weak or strong as discussed in §4.3.1.2 (p. 45). The summary statistics are provided for different number of retained latent variables. As in the case of Appendix A3, as we retain more latent variables the predictive power of the training data (r^2 and R^2) increases. However, we limit the number of retained latent components to five, since studies show that a maximum of five retained components is enough for models (Geladi and Kowalski, 1986; Linton, 2004). The first block ("1 Latent Variable") gives the values for the first component for each data set. To calculate the impact of the second latent component individually, R^2 values from "1 Latent Variables" can be subtracted from the corresponding value in the "2 Latent Variable". For example, R^2 of 0.00774 from "2 Latent Variables" can be subtracted from 0.00436 of "1 Latent Variable" to obtain an R^2 value of 0.00338 for the second component. Similarly, the third latent component can be calculated by subtracting "2 Latent Variables" from "3 Latent Variables" block. Further discussion is provided in §5.2.1.1 (p. 58).

Table 24 - Summary Statistics about Individual Components (Manufacturing Data)

Component	r^2	R^2	q^2	Q^2
1	0.00436	0.00436	0.99872	1.00570
2	0.00774	0.00774	0.99943	1.00122
3	0.01055	0.01055	0.99846	1.00276
4	0.01164	0.01164	0.99814	1.00720
5	0.01213	0.01212	0.99783	1.01072