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An Economic Analysis of the Transition of a Contingency Military Installation to an Enduring Status Using Monte Carlo Simulations

Ryan M. Amedee

AN ECONOMIC ANALYSIS OF THE TRANSITION OF A CONTIGENCY MILITARY INSTALLATION TO AN ENDURING STATUS USING MONTE CARLO SIMULATIONS

THESIS

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Abstract

The rapid construction of expeditionary bases is associated with the forward deployment of Department of Defense (DoD) assets in response to contingency operations such as natural disasters, terrorist operations, or armed conflict. Usually expected to be transitory, expeditionary bases are constructed with temporary materials that can be erected quickly to provide an agile and flexible combat support. The Global War on Terrorism is entering its fifteenth year, and bases within Central Command that were expected to be temporary in duration have had an enduring presence. The decision to transition a base from temporary construction or semi-permanent construction to permanent construction is difficult, as it requires a substantial capital investment for facility construction. The decision is further complicated by unknown mission durations. The DoD has attempted to reduce the decision's complexity with a model that guides the development of a base with a set of construction standards with suggested time horizons.

This study evalulated the validity of the model through an economic analysis with the assumption a mission's duration is unknown. A life-cycle cost model is developed to evaluate investments in temporary and permanent construction design alternatives to determine when or if permanent construction is fiscally advantageous for a given contingency duration. Despite limitations in the availability in cost data from Air Force Civil Engineer databases, the results show that temporary construction is preferable for contingency operations lasting up to twelve years in duration, while permanent construction is preferable after twelve years. With respect to the DoD's construction standard model, this research's results provide a different time horizon for choosing construction standards, when cost is the primary objective.

Acknowledgments

It would be impossible for me to entirely explain how valuable and difficult this experience was to me, but I must send my thanks to everyone involved because they undoubtedly deserve recognition. First and foremost, I would like to thank my God for guiding my through one of the toughest experiences in my life. I would also like to thank my wife for encouraging and believing in me throughout this process, especially when I did not encourage or believe in myself. She’s been my guiding light throughout my time here at AFIT, and I cannot thank her enough for walking this path with me. My mother and father’s support throughout these 18 months also deserves recognition, as their support and guidance has helped me immensely as it always since I was young.

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I. Introduction

Background

Contingencies, or "…emergencies involving military forces caused by natural disasters, terrorists, or military operations," often require the rapid construction of expeditionary bases to mitigate the emergency or conflict (Gibbs, 2012). Usually expected to be transitory, expeditionary bases are created with temporary construction in order to provide an agile and flexible means of providing support. The recent U.S. contingency operations in Middle East have, however, lasted much longer than most historical contingency operations or overseas conflicts. The ongoing mission to stabilize the region, coupled with the emergence of new threats, has required some expeditionary bases to remain open for over a decade. The longevity of the conflicts and the advent of new threats have led senior leaders to decide if they want to give bases a long-term, or enduring, status and provide more permanent construction or continue operations in an expeditionary state. A reduction in war funding and geo-political sensitivities has, however, made the decision to shift a base to an enduring status difficult to justify. The emergence of Islamic State in Iraq and Levant (ISIL) and the continued Afghan conflict have lead one to question what is the most cost effective mission support construction standard under uncertainties of a contingency operation.

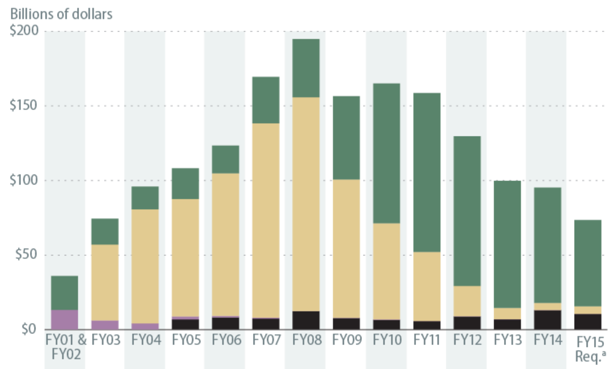
Post 9/11 In-Country Troop and Funding Growth

In an immediate response to Al Qaeda's attacks on September 11, 2001, the US rapidly expanded its capability and footprint in the Middle East and increased in the Department of Defense's (DoD) war-related spending. Within the first six months of Operation Enduring Freedom (OEF), the US established or significantly upgraded 12 bases within the Central Command (CENTCOM) area of responsibility to provide agile combat support of air and ground missions. During the first year of the conflict, the US expeditionary base construction rate was comparable to the World War II requirement (Marion, 2006). The invasion of Iraq in 2003, coined Operation Iraqi Freedom (OIF) further expanded the US's installation footprint within CENTCOM. By March of 2003, the number of deployed US troops had substantially grown from less than 20,000 to approximately 149,000 troops, supporting both OIF and OEF (Belasco, 2014). Consequently, the steady rise of deployed troops and the consistent expansion of the US's Middle Eastern footprint forced the DoD to consistently increase war funding to sustain its operational capability. From 2001 to 2008, US overseas contingency spending rose from $36 billion to $195 billion, as shown in Figure 1. In short, the rapid expansion of the U.S's footprint in the region contributed to the steady increase in the DoD's war funding.

Budget Control Act of 2011

The Budget Control Act of 2011 cut the DoD's funding levels within CENTCOM. In response to the BCA's passing, or sequestration as commonly known, the end of the Iraq mission, and the reduced mission in Afghanistan, the DoD reduced its war budget to $74 billion, cutting all war-related funding in half since 2011(Belasco, 2014).

The reduced war budget has made the large CENTCOM installation footprint difficult to sustain.



Operation	FY01 & FY02	FY03	FY04	FY05	FY06	FY07	FY08	FY09	FY10	FY11	FY12	FY13	FY14	FY15 Req.[a]	Cumulative Enacted*
Afghanistan/ OEF[b]	$23	$17	$15	$21	$19	$31	$39	$56	$94	$107	$101	$86	$77	$58	**$686**
Iraq/ OIF/OND[c]	$0	$51	$77	$79	$96	$131	$144	$93	$65	$47	$20	$8	$5	$5	**$815**
Enhanced Security[d]	$13	$6	$4	$2	$1	$1	$**	$**	$**	$**	$**	$**	$**	$**	**$27**
Other[e]	$0	$0	$0	$7	$8	$7	$12	$7	$6	$5	$9	$7	$13	$10	**$81**
Total	$36	$74	$96	$108	$124	$170	$195	$157	$165	$159	$130	$100	$95	$74	**$1,609**

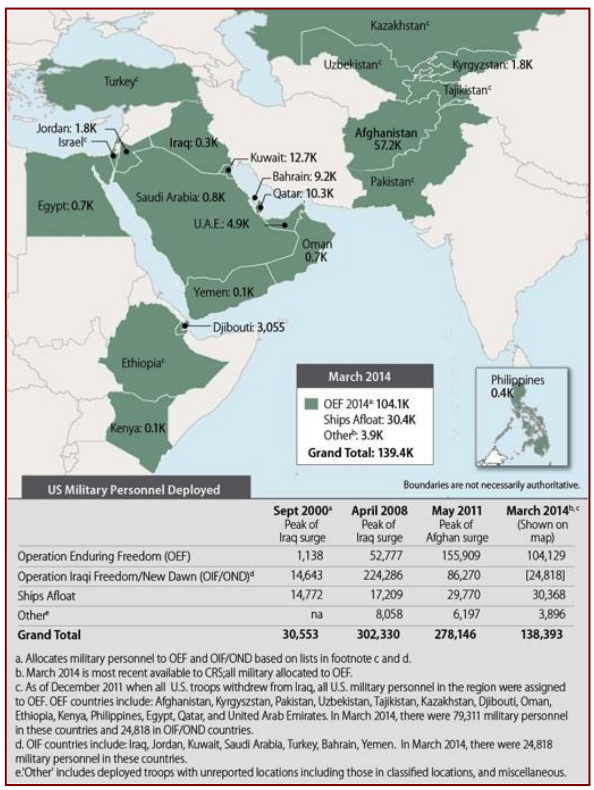
* Cumulative enacted (FY01-FY14). ** Amounts less than $200 million.

Figure 1: Estimated War Funding By Operation (Belasco, 2014)

Shift in Strategy

After taking office in 2009, the Obama administration reevaluated of the US's long term strategic plan in Iraq and Afghanistan to control the steady increase in war funding and footprint in the southwest Asia. The Obama administration's new goal for the DoD was to begin a transition to a "advisory and assistance" role in Iraq and a "train and assistance role" in Afghanistan to bring closure to OIF and OEF (Belasco, 2014). The change in strategy, in both Iraq and Afghanistan, required significant reductions in US forces to facilitate a full turnover of operations to the Iraqi and Afghani security forces.

By December 2014, the US's combat mission in Afghanistan had ended with conclusion of OEF and the shift to train, advise, and assist began with Operation Resolute Support (ORS) (NATO, 2015). By the commencement of ORS, the US had 30 remaining expeditionary bases in the Afghanistan, which was previously 300 during the height of OEF (Lopez, 2015). To offset the force reduction in Afghanistan, some US owned expeditionary bases in nearby countries, including those shown in Figure 2, remained open and shifted to enduring locations. President Obama administration's shift in strategy, thus, aligned the US's future in the theater with anticipated reductions of the DoD's budget.



	Sept 2000[a] Peak of Iraq surge	April 2008 Peak of Iraq surge	May 2011 Peak of Afghan surge	March 2014[b, c] (Shown on map)
Operation Enduring Freedom (OEF)	1,138	52,777	155,909	104,129
Operation Iraqi Freedom/New Dawn (OIF/OND)[d]	14,643	224,286	86,270	[24,818]
Ships Afloat	14,772	17,209	29,770	30,368
Other[e]	na	8,058	6,197	3,896
Grand Total	**30,553**	**302,330**	**278,146**	**138,393**

a. Allocates military personnel to OEF and OIF/OND based on lists in footnote c and d.
b. March 2014 is most recent available to CRS;all military allocated to OEF.
c. As of December 2011 when all U.S. troops withdrew from Iraq, all U.S. military personnel in the region were assigned to OEF. OEF countries include: Afghanistan, Kyrgyszstan, Pakistan, Uzbekistan, Tajikistan, Kazakhstan, Djibouti, Oman, Ethiopia, Kenya, Philippines, Egypt, Qatar, and United Arab Emirates. In March 2014, there were 79,311 military personnel in these countries and 24,818 in OIF/OND countries.
d. OIF countries include: Iraq, Jordan, Kuwait, Saudi Arabia, Turkey, Bahrain, Yemen. In March 2014, there were 24,818 military personnel in these countries.
e.'Other' includes deployed troops with unreported locations including those in classified locations, and miscellaneous.

Figure 2: OEF and OIF Deployed U.S. Troops (Belasco, 2014)

New Threats

The emergence of new threats has, however, made the US's shift in strategy difficult and perhaps made a long-term presence a requirement for stability in the region. Aside from Al Qaeda, one of the most prominent threats in the Middle East has been the Islamic State in Iraq and Levant (ISIL). Three years after the final pullout of all US forces in Iraq, ISIL began an invasion that would eventually lead to the control of large portions of both Iraq and Syria. As ISIL continued to cause instability in the theater, the US launched a long-term campaign to counter the threat of ISIL in both Iraq and Libya (The White House, 2015). Russia's actions in the Ukraine and expansion into Crimea have also become a key issue in the region. Since Crimea's annexation to Russia, relations with Russia have grown tense because of a sizable growth of their military forces on the eastern Ukrainian boarder (Webber, 2014). Russia's actions have encouraged the US to protect Ukraine and its neighbors from potential future aggression. Ultimately, new threats like ISIL and Russia make decisions in investing limited war funds difficult because the duration of potential operations that address these threats is difficult to predict.

Problem Statement/Research Objective

Overall, decisions that determine the allocation of funds for expeditionary bases have become more important now than ever in the history of the conflicts in the Middle East. The BCA of 2011 and strategy to reduce the US footprint in the Middle East have made investments in enduring locations with permanent construction more difficult to justify. Conversely, the need for success in ORS and the emergence of new threats has created a demand for a sustained presence in the region. As new threats materialize and the US's interests move away from the President's reduction strategy, the actual duration of the conflict becomes increasingly difficult to predict. Consequently, an investment decision in temporary or permanent construction for an expeditionary base transforms from a decision with some certainty to a decision with a great deal of uncertainty. Thus, the objective of this research is to conduct an economic analysis of investments in various forms of construction in order to determine the most economical choice, given mission duration is unknown. In order to meet these objectives, this study will attempt to answer the following investigative questions:

1) How does a decision maker determine if a transition to an enduring status is advantageous?

2) How does the duration of a contingency operation affect the decision to transition to an enduring status?

3) How does an uncertainty in duration of a contingency operation affect the dynamics of the decision to transition to an enduring status?

4) How does a decision maker's attitude towards risk affect the decision to transition to an enduring status when uncertain about the duration of the mission?

Scope

While the problem of interest is DoD contingency construction standards, the quantitative analysis was limited to Air Force lodging facilities. The results of the literature review provides a decision framework that can be used by decision makers to evaluate the utility of committing significant resources towards the development of contingency bases with permanent construction; this framework is applicable to all installations and all building types. However, the analysis to determine the effect of mission duration on life cycle costs for contingency installations was scoped to consider only Air Force lodging facilities at the contingency bases of Al Udeid, Qatar and Al-Dhafra, UAE. Consequently any inferences from the life cycle cost analysis should be appropriately caveated by the small scope.

Implications

Academic

This study interprets DoD policy and doctrine to build a framework for evaluating contingency construction alternatives in the transformation of a contingency base to an enduring base.

Practical

This study produces a useable model to assist decision makers seeking to improve the infrastructure of an expeditionary base. The model incorporates the facility life cycle costs, a decision maker's current state of information, and data describing the variance in mission duration in Afghanistan.

Preview

This study follows traditional five-chapter format. Chapter II provides an answer to the first investigative question through an examination of literature. Chapter II uses DoD doctrine on expeditionary base development and foundational concepts of decision analysis to break down the decision. Ultimately, Chapter II shall synthesize the DoD's expeditionary base model into measurable objectives. Chapter III provides methodologies to answer the next three investigative questions by focusing on only one of the objectives: minimizing cost. Chapter III focuses on the objective by providing a life cycle cost estimation model that evaluates and compares design alternatives used in contingency operations to provide recommendations. Chapter IV presents the results of the implementation the model with real data from contingency bases. Finally, Chapter V provides a discussion of the results with respect to each investigative question and provides recommendations for future research to enhance the research.

II. Literature Review

Chapter Overview

The purpose of the literature review is to provide a framework for decision makers that can be used evaluate if a contingency installation should use permanent construction standards of if the installation should continue to use temporary or semi-permanent construction. The DoD's doctrine on expeditionary base development is examined and discussed to offer an in-depth understanding the objectives within the DoD's model. Next, decision analysis techniques are used to synthesize the DoD's doctrine into measurable objectives to enhance the DoD's model. Each objective is examined and discussed to provide insight into how they may be measured. The chapter concludes by presenting a decision framework developed from the literature.

Expeditionary Base Development

Expeditionary base development is the process of planning, constructing, sustaining, expanding, and divesting the assets of a expeditionary base in order to support a strategic mission (Quasney, 2012). The DoD and AF have two to models to explain the expeditionary base development process. The first model is the Air and Space Expeditionary Task Force (AETF) force module (FM) construct, which guides engineers through the concepts and operations of the initial stages of an expeditionary base's construction. The other model, the Construction Standards framework, builds on the

AETF FM construct and provides details on the construction standards used in the phases of an expeditionary base's life cycle.

AETF Force Module Phased Deployment

Contingency operations often require the rapid beddown of forces in austere locations in order to support the expedient mitigation of an emergency or conflict. Engineers support the beddown of forces by constructing bare bases, which provide an initial platform to launch contingency operations (Quasney, 2012). Bare bases are expeditionary bases that have minimum capabilities to sustain or support a strategic mission (Quasney, 2012). Most expeditionary bases are initially constructed as bare bases under the AF's AETF FM construct.

The AETF FM construct is a concept that describes the systematic process of opening an airfield, establishing operational capability, and conducting subsequent air operations (Quasney, 2012). The construct groups Unit Type Codes (UTCs), or a group of personnel and equipment providing specific capabilities, to deliver combat and engineering support functions into force modules (FM). Each FM, therefore, plays a specific role in both the development of a bare base and the deployment of forces. The deployment of each UTC is planned around force modules to methodically construct a bare base. The modules are designed to build off of one another in a synergistic manner to provide seamless transitions and continuity in the bare base development process (Gorenc, 2006). The construct, as shown in Figure 3, consists of six element which include open the airbase, command and control (C2), establish the airbase, generate the mission, operate the airbase, and robust the airbase (Gorenc, 2006).

Figure 3: AETF Force Module Phased Deployment (Gibbs, 2012)

The first FM, Open the Airbase, initiates the bare base development process. The UTCs provided in the Open the Airbase FM arrive first to the designated location and must fulfill three critical tasks within 36 hours of arrival. The UTCs must secure the area, assess resources, and, most importantly, establish minimum operational capabilities (Gorenc, 2006). Establishing minimum operational capabilities involves the construction of initial infrastructure and facilities, while either establishing or rehabilitating an airfield to support the arrival of subsequent UTCs. Therefore, the first FM builds the foundation of the expeditionary base and its success is crucial to AETF FM construct.

The next FM is the Command and Control (C2) FM. The goal of the C2 FM is to establish an air expeditionary wing command and control structure at the location in 16 hours upon arrival. A typical air expeditionary wing C2 structure is comprised of aircraft maintenance, operations, mission support, and medical group staffs. The group staffs work together to further coordinate the development of the expeditionary base and provide a command structure for their respective squadrons. Once the UTCs of the C2 force module have organized a structured expeditionary air wing, the leadership personnel of the command structure assume command of the airbase, including all initial elements of the Open the Airbase FM. In short the C2 FM establishes an organizational structure to the expeditionary airbase.

Once all initial assets are built by the Open the Airbase UTCs, the Establish the Airbase FM UTCs arrive with the task to enhance the infrastructure of expeditionary base. Since opening the airbase has few infrastructure requirements, the civil engineer services and mission related capabilities of the airbase are limited upon arrive of these UTCs. Thus, the UTCs in the module either build new or adapt existing infrastructure to both establish mission related infrastructure and enhance other support infrastructure. For example, the UTCs construct liquid fuels infrastructure and munitions storage to provide the base's first mission related capabilities. Moreover, additional tents and support utilities, like water, electrical, and communications, are installed to improve the quality of life of the base (Gorenc, 2006). Overall, the Establish the Airbase UTCs take about 10 days to enhance the expeditionary base's infrastructure (Quasney, 2012).

Perhaps the force module with the most mission related importance is the Generate the Mission force module. The module is designed to provide mission and aviation packages to the expeditionary base in order to align its operational capabilities with the vision of the combatant commander (CCDRs) (Gorenc, 2006). UTCs in the FM sometimes arrive early in the bare base development process so that they can coordinate with UTCs tasked with opening the airbase, C2, and establishing the airbase. Some services provided by the follow-on UTCs may be needed to fully generate the mission; therefore, the UTCs are given 80 hours from the start of the arrival of the follow-on force module to complete their mission. At completion the base should be able to adequately achieve its intended mission.

The next two FMs are primarily transition the expeditionary base to a more robust and established location through UTCs providing mission support capabilities. The Operate the Airbase FM contains UTCs required to enhance most, if not all, mission support capabilities in order to make the airbase fully operational within seven days. The module provides equipment and mission support personnel to improve the installation's force protection systems and quality of life conditions. Perhaps the most important function of the module is that it initiates the transition from an austere or initial construction standards to temporary construction standard (Quasney, 2012). The next FM, Robust the Airbase, is ongoing until an airbase's closure. The UTCs in the module arrive 30 days after the Establish the Airbase UTCs complete their tasks. The UTCs deliver capabilities that support the sustainment and enhancement of the expeditionary base for the remainder of the base's life. Ultimately, the transition of an airbase from contingency to enduring occurs in these two-force modules.

Construction Standards

As shown in the AETF FM construct, an expeditionary base's infrastructure is progressively improved to some degree with the deployment of each FM. Joint publication (JP) 3-34, Joint Engineer Operations, supplements the AETF FM construct by establishing a framework for both selecting and improving construction standards in the last two FMs. Construction standards are, effectively, guidelines by which an airbase constructs or improves its infrastructure. JP 3-34 provides five classifications of construction standards which are intended "to ensure efficient application of limited engineering assets and to responsively support the commander's intent" for the contingency operation (Gortney, 2011). The timeline provided in Figure 4 summarizes JP 3-34's framework for the maturation of construction standards as a base develops in time. The five classifications of construction standards are subdivided into the two phases of an expeditionary airbase's development, which are the contingency phase and the enduring phase.

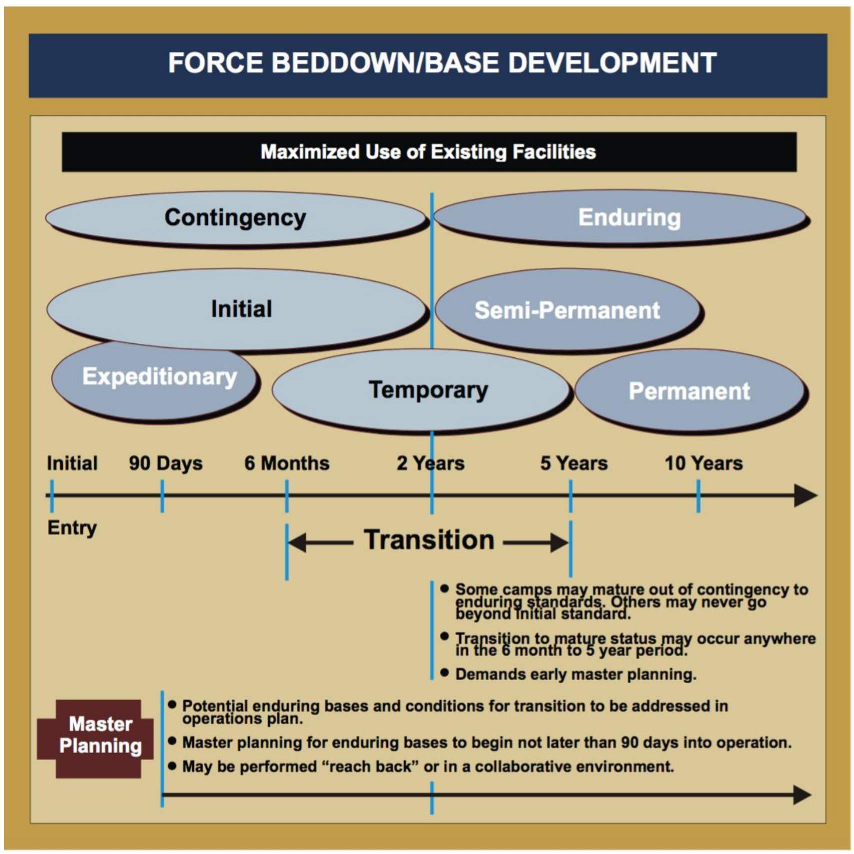


Figure 4: Force Beddown and Basing Continuum (Gortney, 2011)

The contingency phase of an expeditionary airbase begins when the first UTCs arrive to open the airbase and continue until the two-year mark. Standards typically used in the contingency phase include the organic, initial, and temporary construction standards. Organic, or expeditionary, construction is used in the initial establishment of an expeditionary airbase, as described in the AETF FM construct. Organic assets are assets that are necessary to move, receive and beddown forces in austere locations with no external engineering support (Quasney, 2012). Organic construction is used to support an interim solution until subsequent engineering support arrives. Organic construction is a subset of initial construction standards but is usually intended for use up to 90 days. Initial construction is, also, intended for ephemeral operations but the standards generally include any facility designs that can be used for up to six months. According to JP 3-34 initial construction is "…characterized austere facilities requiring minimal engineer effort…" and is intended to bypass the challenges of resource availability in harsh locations (Gortney, 2011). Finally, the most advanced form of construction used in the contingency phase is temporary construction standards. Temporary construction is a standard that include facilities that require additional engineer support, in comparison to initial standards. Temporary construction provides the infrastructure to extend an expeditionary base's capabilities beyond those provided by initial construction. Usually intended for use up to 24 months, temporary construction can be used to sustain non-transient operations for up to five years with additional engineering support and may replace initial construction. In general, installations in the contingency phase use construction that is mobile, flexible, and short-lived.

The enduring phase of an expeditionary airbase begins after two years of contingency operations. Semi-permanent and permanent construction standards are typical of the enduring phase of an expeditionary airbase because the mission is no longer expected to be transient. Semi-permanent construction include facilities that are designed for "…moderate energy, maintenance, and life cycle costs…" and are typically used to enhance or modernize an installation's current infrastructure, whether initial or temporary (Gortney, 2011). According to JP 3-34 any facility design that has a "…life expectancy…" of more than 2 but less than 10 years is considered semi-permanent construction (Gortney, 2011). In comparison permanent construction includes facilities that are designed for high-energy efficiency with low life cycle and maintenance costs. Permanent construction is best suited for missions lasting longer than 10 years because their qualities surpass those of semi-permanent construction. In general enduring standards are intended for longer missions than those of contingency operations because of the efficiencies provided by semi-permanent and permanent facility designs best suite long-term use.

Choosing Construction Standards

Although the framework presents a timeline for all construction standards, the actual development of an expeditionary base is not always linear as the framework suggests. For example, combatant commanders (CCDRs), the decision makers in expeditionary base development, may decide to either sustain initial standards, mature to the next standard, or skip a standard in the framework's timeline (Gortney, 2011). The future of the base is a result of their selection of an optimal standard that best suits the contingency operation. CCDRs select a standard that aligns with the strategic objectives of expeditionary base development, while considering the construction funding timelines, limitations of international policies, and the volatile environment.

According to JP 3-34, CCDRs have two strategic objectives when selecting the optimal construction standard. The first is selecting a construction standard that "…optimizes engineer effort on any given facility" (Gortney, 2011). For example, CCDRs may choose to avoid a construction standard with facility designs that need extensive maintenance to sustain their requirements for the expected duration of their use. Generally, selecting a standard that optimizes engineer effort entails evaluating the long-term investment of a facility design. The second objective is ensuring that the facility designs of the standard are "…adequate for health, safety, and mission accomplishment" (Gortney, 2011). Under the conditions and environment of the contingency, CCDRs must evaluate the facility design's quality of life amenities and resilience to attack to provide optimal conditions for the users of the facility. In short, CCDRs must select a construction standard that provides facilities that balance long-term costs and overall quality.

In addition to achieving strategic objectives, CCDRs must also consider the implications of using military construction (MILCON), operations and maintenance (O&M), and 3080 funds for construction projects in the selection of a standard. Most enduring construction projects are subject to the MILCON approval process because of their high cost. According to Title 10 of the United States Code (USC), a construction project amounting to more than $1,000,000 in cost, which is not solely intended to correct some deficiency in life, health, or safety, must be funded with MILCON funds (Hughes, 2005). The challenge in using MILCON funds is the requirement of congressional approval before use. Often times the wait for approval may delay projects for up to five years, making other construction standards with different funding venues more attractive. Most contingency construction standards can, however, be procured and constructed faster than enduring projects because of their use of cheap, temporary materials. For example, Title 10 says that any project cheaper than $1,000,000 can be funded Operations and Maintenance (O&M) funds, which are not subject to congressional review (Hughes, 2005). Although O&M funds are readily available, the amount of O&M funds is limited because many other mission requirements, other than construction, compete for their use. If a project is expensive, then it may be difficult to fund with O&M funds because the base may need a substantial amount of the funds to ensure continuity of its mission. Because most construction projects are expensive and have an immediate need, investment equipment funds, or 3080 funds, are used because the amount of funds are more robust than that of O&M funds and they are readily available. While 3080 funds are typically used for equipment purchases, they can also be used for construction purposes. For example, if the construction is not permanent and a complete building system is less than $250,000, then 3080 funds can be used because the project can be reclassified as a procurement of equipment (Bolton, 2015). Relocatable buildings (RLBs), a form of semi-permanent construction, are typically procured with 3080 funds because they can be assembled as building systems costing less than

$250,000. Overall, MILCON, O&M, and 3080 funds all have setbacks and advantages that a CCDR must consider in selecting a construction standard.

CCDRs must also consider DoD and host nation policies that limit permanency. In some cases, the selection of a standard is either mandatory or highly discouraged by the DoD. For example, if a RLB is being considered, then he/she must consult DoD policy. A relocatable building, as defined by Department of Defense Instruction (DODI) 4165.56, is "…a habitable prefabricated structure that is designed and constructed to be readily moved […], erected, disassembled, stored, and reused" (Esteves, 2013). DODI 4165.56 allows relocatable buildings to be used in one of two ways in contingency environments. First, relocatable buildings can be used when they are the most cost effective way to deliver short-term facility requirements (Esteves, 2013). For example, an installation may be awaiting congressional approval of a project that is intended to provide permanent construction but needs an interim facility. Second, the DoD prefers the use of relocatable buildings can be used when the length of the mission requirement is unknown (Esteves, 2013). Another example of a DoD policy that regulates the selection of a construction standard is AFI 32-1032's policy on permanent construction. AFI 32-1032 that emphasizes that permanent construction should only be used for anti-terrorism force protection or special mission operations (Green, 2014). As a substitute the AFI promotes the use of relocatable buildings, encouraging their use as much as possible in contingency operations. Aside from DoD policy, host nations (HNs) may have limitations on permanency. HNs are nations that have agreed to host US forces on their nation's soil. However, some HNs may either lack a bilateral agreement with the US clarifying the US's long-term presence in their country or have an agreement with limitations on permanency. If such circumstances exist, the US must resort to contingency standards for construction. Ultimately, DoD and HN policies on permanency can limit a CCDR in their decision of choosing an optimal standard.

Perhaps the most challenging constraint in the selection of a construction standard is the uncertainty of the duration's mission. Contingency operations are inherently volatile because they are responses to emergency situations. As the emergency either diminishes or intensifies, the mission requirements needed to mitigate the emergency fluctuate. Consequently, an expeditionary base's mission requirements change with the operation's requirements. Therefore, the expected life of an expeditionary base is difficult to predict in these conditions and the selection of each construction standard has risks. Decisions to maintain the initial standards, after beddown of initial forces, are indicative of a volatile contingency operation with much uncertainty in its longevity. Thus, decision makers seek to minimize risk by avoiding investments in new construction. Alternatively, stable conditions with minimal variance in mission requirements may bring clarity to the duration of an expeditionary base's mission. If the decision maker has some confidence that the mission's duration aligns with guidelines with or higher than the next standard, then they may seek to either mature to the next standard or skip the next standard to minimize the risk of a poor investment. Thus, combatant commanders (CCDRs) must evaluate the risks of each construction standard under the cloud of uncertainty.

Summary of Expeditionary Base Development

JP 3-34 has demonstrated that the transition from contingency to enduring is a decision to improve an expeditionary base to a non-transient construction standard. The AETF FM construct has illustrated that most, if not all, expeditionary bases are born with organic or initial standards. The JP 3-34's construction standard framework becomes relevant to CCDRs after the initial beddown of forces. The framework serves merely as a guide for CCDRs to select an optimal standard for an expeditionary base in a contingency operation. Although the framework suggests timeframes for each construction standard, JP 3-34 argues that CCDR's must consider the four strategic objectives of expeditionary base development, constraints of funding, international policy, and expected length of the contingency operation. The length of contingency operations, however, is difficult to predict. Thus, the decision to transition to an enduring status is a decision with multiple objectives with uncertainty.

Decision Analysis

Decision analysis is "…a philosophy and a social-technical process to create value for decision makers and stakeholders facing difficult decisions" (Parnell et al., 2013). Decision analysis is particularly useful for breaking down for decisions like the decision problem of transitioning to an enduring status. Clemens and Reilly (2013) argue that decision analysis is advantageous when a decision maker is faced with a complex decision that has uncertainty, multiple and competing objectives, and more than one stakeholder. Moreover, decision analysis methods and techniques have been previously applied to infrastructure improvement situations.

Karvetski et al. (2009) experienced many of the same problems of expeditionary base development when they used decision analysis methods to priortize infrastructure construction projects in Nangarhar, a border province of Afghanistan. The study was conducted in, 2008, in the midst of OEF, when conditions were extremely volatile in the region. At the time, the DoD and US Department of State were funding infrastructure projects to stimulate growth. Both agencies worked closely working with the Afghanistan military and Nangarhar civil authorities to rebuild the province. The goal of the authors was to develop a multi-criteria decision model that incorporated the values of all stakeholders to score and prioritize infrastructure improvement projects. To account for the volatile conditions of the region, Karvetski et al. included scenarios into their model that reflected emergent, or possible, conditions in the province. Some scenarios accounted for the safety of the population with security upturn or downturn scenarios. Others accounted for natural, normal, and abnormal disaster situations to understand the value of a infrastructure project during these events (Javed et al., 2009; Karvetski et al., 2009). The resulting multi-criteria model proved to meet the requirements of each stakeholder. In general, Karvetski et al.'s model demonstrates that decision analysis is applicable to the decision to transition to an enduring status because the decision involves improving infrastructure.

Zhoa et al. (2004) used a real options approach, a branch of decision analysis, for a decision-making under uncertainty. The authors developed a multi-stage stochastic model to select an optimal highway design, incorporating several uncertainties to account for political, social, and environmental changes. As opposed to Karvetski et al. (2009)'s model, Zhoa et al. (2004)'s model only included an objective to maximize expected payoff. Some of these uncertainties were traffic demand, land price, and highway service quality. Traffic demand was used in the model to account for changes in the use of the potential highway design, as populations fluctuate over time due to external factors. Land price was included to account for changes in land use and market value. Highway service quality was used to account for the natural deterioration of the pavement material of the highway. The model also included a cost function to model the life cycle cost changes in time. Ultimately, a solution algorithm was developed from a Monte Carlo simulation was and a least squares regression. The result of the model provided a suggested a number of lanes, width of lanes, and expected payback of the recommended design (Zhao et al., 2004). Zho et al.'s model is similar to the decision to transition to an enduring status in that the selection of an optimal construction standards, or design, is of interest in an uncertain situation.

As illustrated in Karvetski et al. (2009)'s and Zhao et al. (2004)'s models, the practice of decision analysis can be broken down into two general categories: single objectives decision analysis and multiple objective decision analysis. Single objective decision analysis is the simpler form. In some cases decisions makers have one objective in selecting optimal alternatives. Often these lone objectives are monetary in nature because cost, profit, or revenue is of interest to the decision maker. Typically seen in business organizations, one common example of an objective in single objective decision analysis is maximizing shareholder value using some monetary scale (Parnell et al., 2013). Zhao et al's model was similar in that their model's objective was to maximize expected payoff. The second form of decision analysis is multiple objective decision analysis (MODA). MODA offers a methodical process, of evaluating alternatives with multiple objectives. Often executive positions of large organizations have several objectives because other parties, who have a stake in the decision, have different goals. Some of these goals may be non-monetary objectives; therefore, MODA applications typically use a philosophy called Value Focused Thinking (VFT) to objectively quantify non-monetary objectives. According to Keeney (1994), VFT is a process that is "…designed to focus the decision maker on the essential activities that must occur prior to solving a decision problem". VFT starts with the values, generates better alternatives than those that already exist, creates better decision opportunities, and uses the values to generate better alternatives. Because MODA evaluates several objectives in one decision, it is especially useful in investigating tradeoffss in other values of an alternative. For example, in a decision to select an apartment to rent, one might pay more money for more livable space. Thus, there is a monetary trade of with more or less livable space. In Karvetski's et al's model, monetary tradeoffss between stakeholder values was investigated in their infrastructure prioritization model. Of the two branches of decision analysis, MODA is more commonly used, as complex decisions often have multiple objectives.

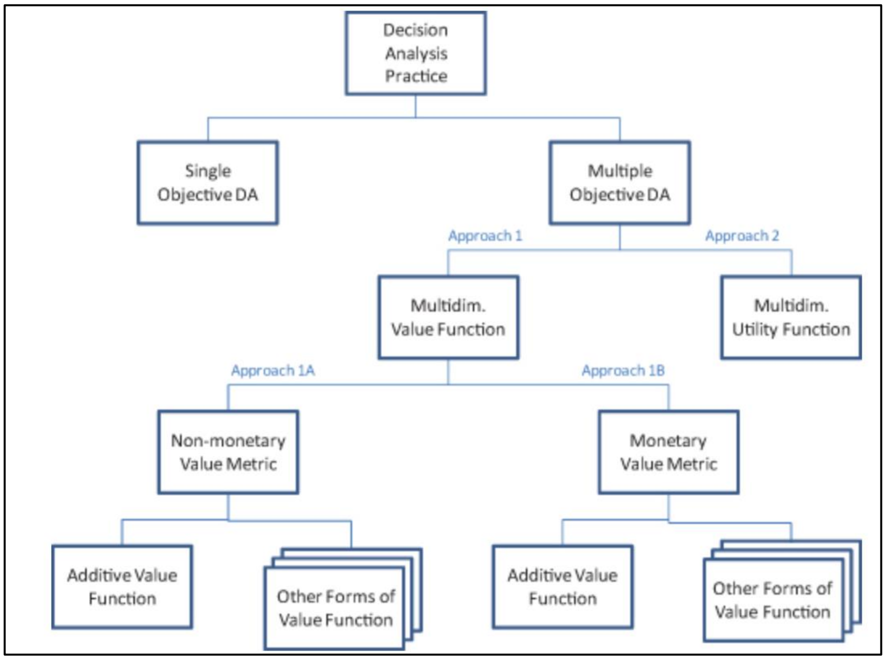


Figure 5: Organization of Decision Analysis Practice (Parnell et al., 2013)

Application of Decision Analysis

Parnell et al. (2013) suggest that the most important step in the decision analysis process is framing the decision. Framing the decision helps the decision maker clearly define the decision and the implications of the decision. A well-defined decision frame specifies the purpose of the decision, gives perspective on the decision situation, and properly scopes the decision to what needs to be considered (Parnell et al., 2013). Thus, in order to accurately define the decision to transition to an enduring status, the decision classification must be identified and the decision's vision statement must be developed.

According to Parnell et al. a decision is an irrevocable allocation of resources that has three classifications, or levels of hierarchy, as shown in Figure 6, that shed light on the perspective of the decision (Parnell et al., 2013). The first type of decision is a strategic decision. Strategic decisions are high-level, foundational decisions that are typically made at the executive level of an organization. Strategic decisions are focused on the long range goals of an organization and address the future desired states of the organization (Parnell et al., 2013). In contingency environments strategic decisions are made at the general officer level and establish the overall vision and mission to mitigate the threat or emergency. For example, a strategic decision in a contingency operation may be the selection of a location of an expeditionary base. Next, operational decisions are decisions that are generated from the outcome of strategic decisions. Operational decisions use the vision and missions of an organization to determine how resources are to be mobilized in order to meet those long-range objectives. The selection of a construction standard is prime example of an operational decision because the decision effects the allocation of funds and resources. Finally, the last classification of decisions is tactical decisions. Tactical decisions are routine, daily decisions and are generated from tactical decisions in the organization. In expeditionary base development, some example of tactical decisions may be decisions on where to construction facilities or maintenance strategies for the facilities. In general, the selection of a construction standard is an operational decision, as it is the focus of the process.

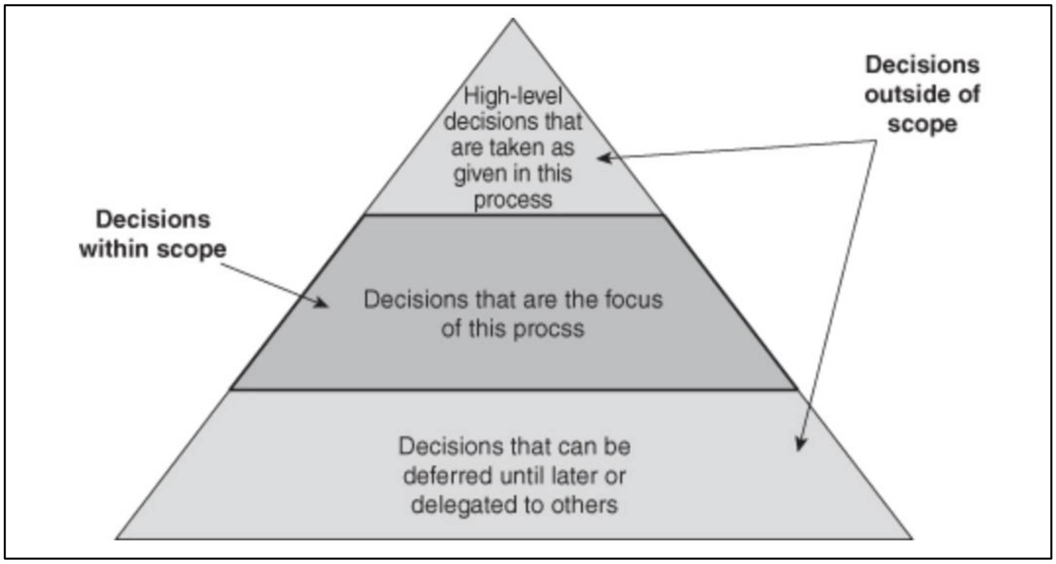


Figure 6: Decision Hierarchy (Parnell et al., 2013)

A decision vision statement aids in defining the purpose and scope of the decision. A decision's vision statement succinctly clarifies: 1) the definition of the decision, 2) the purpose of the decision, and 3) a precedent for success in the decision (Parnell et al., 2013). JP 3-34's construction standards framework has defined most of the decision. JP 3-34 illustrated that the transition of contingency to enduring is a decision to improve to a higher construction standard. A decision in selection of a construction standard, however, is not an irrevocable allocation of resources as no tangible resources are tied to construction standard. A decision maker does not allocate resources if they were to select a specific construction standard. Conversely, selecting a design for construction at an expeditionary base is an irrevocable allocation of resources, as it requires funds, materials, and manpower. JP 3-34 did allude to the fact the construction standards are classifications of facility designs. For example, facility designs may be classified as initial, temporary, semi-permanent, or permanent facility designs. Furthermore, semi-permanent and permanent design may be classified as enduring designs while initial or temporary design may be classified as contingency designs. In short, the decision to transition to an enduring status is made through evaluating design alternatives with respect to the demands and environment of the contingency operation.

Next, the purpose of the decision was communicated through JP 3-34's strategic objectives of selecting construction standards. The purpose of the decision is to optimize engineer effort and meet user requirements such as health, safety, and mission accomplishment.

Finally, JP 3-34 established that there are multiple stakeholders in the decision. Some examples of stakeholders include host nations, users of the facilities, and the funding source of the construction of the facility. Thus, the precedent of success is when all stakeholders are satisfied with the selected facility design. Using JP 3-34 literature on the decision, a possible vision statement for selecting a construction standard is shown below in Figure 7.

Vision Statement:
We will decide which design alternative to construct at a given expeditionary base. We are building this facility to meet optimize engineer effort and to provide conditions that are adequate for health, safety and mission accomplishment. When all stakeholders are satisfied in the selected design alternative, we will know that we have succeeded.

Figure 7: Vision Statement

Objectives and Value Measures

The next step in evaluating the decision is the identification of objectives. According the Clemen and Reilly (2013), an objective is something specific that a decision maker wishes to achieve in the context of the decision's frame. In decision analysis objectives are used to measure the value of an alternative with respect to the direction of preference of each objective. For example, in order to determine which bases should be closed in the 2005 BRAC, decision makers sought to measure the maneuver space that each base provided (Ewing Jr. et al., 2006). If a base had a relatively large amount of maneuver space, then the base scored well in the objective because the direction of preference was to maximize maneuver space. Similarly, in a decision model for evaluating the US Marine Corps' mobile protected weapons system, decision makers valued weapons systems that were accurate in non-stationary, long-range attacks (Buede & Bresnick, 1992). The Marine Corps' objective was to maximize the accuracy of non-stationary, long-range attacks. Thus, decision makers must identify all objectives that holistically conceptualize the desired qualities of an alternative, in order to build a reliable model that aids in decision-making.

Each objective is quantified with a metric, or value measures, that properly communicates and measures how the alternatives score. Because there are multiple frameworks for measuring the achievement of objectives, value measures have four classifications: natural, constructed, direct, and proxy measures. A natural scale is a scale that is commonly used to measure an objective of interest. Dollars is a typical natural scale used in acquisition decision models. Conversely, constructed scales, or scales that are developed to suite particular objectives, are used when natural scales cannot accurately or precisely quantify the achievement of an objective. In Ewing Jr. et al's article on 2005 BRAC, the decision model included a constructed scale that measured the quality of available space at a particular base because no existing scale could effectively measure the objective (Ewing Jr et al., 2006). A direct scale directly measures the degree of attainment of an objective. Profit is a common direct scale metric that is used in objectives that seek to maximize income to an organization. On the other hand, proxy scales are indirect measurements through reflecting the degree of attainment of its associated objective (Kirkwood, 1996). In general, a value measure can either have a natural or constructed and direct or proxy scale, as shown in Figure 8.

	Natural	**Constructed**
Direct	Net Present Value Time to Accomplish Cost to Accomplish	Olympic Diving Scoring Weather Prediction Categories R&D Project Categories
Proxy	Gross National Product (Economic Growth) Number of Subsystems (System Reliability)	Performance Evaluation Categories (Promotion Potential) Student Grades (Student Learning)

Figure 8: Example of Value Measures (Tryon, 2005)

Since the frame has defined the decision as a selection of an optimal facility design, the objectives of the decision must measure a facility's characteristics in relation to other facility designs. System lifecycle properties, or desired characteristics of systems that surface after the system has been put to use, can provide a means for measuring the characteristics facilities (de Weck, 2012). According to McManus et al (2007), system lifecycle properties provide a way to change in response to the changes in the requirements and context of the system. Thus, engineers consider system lifecycle properties in the development of their facility designs. Among all others quality, safety, and reliability are some system lifecycle properties that JP 3-34 alludes, as it requires a facility that is adequate for "…health, safety, and mission requirements" and that "…optimizes engineer effort" (Gortney, 2011)

Quality: Maximize Quality of Life of Personnel

One of the most basic system lifecycle properties in expeditionary base development is a facility's quality. According to DeWeck et al. (2011), quality is the ability of a system to achieve its intended function. In JP 3-34 the four real estate requirements are used to communicate four basic intended purposes of facility designs at expeditionary bases. The four real estate requirements are operational facilities, logistics facilities, common-use facilities, and force beddown facilities (Gortney, 2011). Operational facilities are designed to execute the mission by providing a platform for weapons systems or command and control capabilities. For example, some common AF expeditionary operational facilities are aircraft hangers, airfields, and command post buildings. Logistical facilities are purposed for directly supporting mission requirements. Maintenance facilities, ammunitions supply points, and warehouses are examples of logistical facilities. Common use facilities are primarily dedicated for the transportation of goods and services, like roads or railroads. Finally, force beddown facilities are provide quality of life amenities and services to base personnel. Force beddown facilities include billeting, dining halls, medical clinics, and religious support facilities, along with many other facilities. Thus, one objective in selecting a facility design may be measuring the degree to which it fulfills its mission requirements.

Among all other facility on expeditionary bases, force beddown facilities are central in expeditionary base development. Not only do force beddown facilities represent the largest portion of an expeditionary base's asset portfolio, but they also contribute directly to the health and readiness of personnel on the base. Because force beddown facilities are key in an expeditionary base's development, the quality of life amenities and services provided by these facilities are of high importance to decision makers. For example, during the opening ceremony of the second Blatchford-Preston Complex dormitory at Al Udeid Airbase, Colonel Caroline Miller asserted that the dorms were built to improve the quality of life for deployed service members (Babcock, 2015). Additionally, force beddown facilities may contribute to the health, morale, and welfare of the deployed service members. Since no measure has been suggested other to measure quality of life, a direct constructed scale should be considered to measure the degree of the quality of life of a particular facility design. Because they are central to the transition, billeting facilities designs are the focus of this study.

Safety: Maximize Antiterrorism Protection

Another critical system lifecycle property in expeditionary base development, according to JP 3-34, is safety. For the purposes of this research, safety is the ability of a system to protect its users and others from the harm of some other circumstance. Since expeditionary bases are constructed in austere environments, local threats in the environments pose the biggest safety risk to personnel. Some risks include vehicle born improvised explosive devises, mortars, and small arms fire. To mitigate such risk and protect base personnel from a local threat, Antiterrorism (AT) standards of UFC 4-010-01 are incorporated into base master planning and the selection of facility designs. According to Hudson et al. (2005), antiterrorism is the practice of "fostering awareness of potential threats, deterring aggressors, developing security measures, planning for future events, interdicting an event in process, and ultimately mitigating and managing the consequences of an event." AT standards typically drive site planning because some policy requires standoff distances from roads for different types of facilities. In addition JP 3-34 suggests selection of construction standards and facility designs (Gortney, 2011). A comprehensive and transitory antiterrorism scale that measures a facility design's ability to account for adverse threats, however, does not exist because all contingency environment have different threats. Thus, another objective in the selection of a facility design is maximizing antiterrorism protection; furthermore, a direct constructed scale should be developed to account for the contingency's surrounding environment.

Reliability: Minimize Life Cycle Costs

Reliability is the ability of a system to consistently sustain a specified functional requirement or condition. While describing each construction standard and objective in the selection process, JP 3-34 makes several allusions to the need for reliable facility designs. For example, one of the strategic objectives in selecting construction standards is optimizing the "…engineer effort…" of any given facility (Gortney, 2011). Effectively, JP 3-34's first strategic objective references the need to minimize maintenance efforts because externalities, including those shown in Figure 9, adversely affect a system's reliability (Grussing, 2006). As each component of the facility degrades over time, the need for maintenance increases because either the facility is no longer in an acceptable condition or the facility is not meeting some functional performance requirement (Labi, 2014). Thus, based on JP 3-34's strategic objective, a system that requires extensive or continuous maintenance to extend its useful life is not preferred.

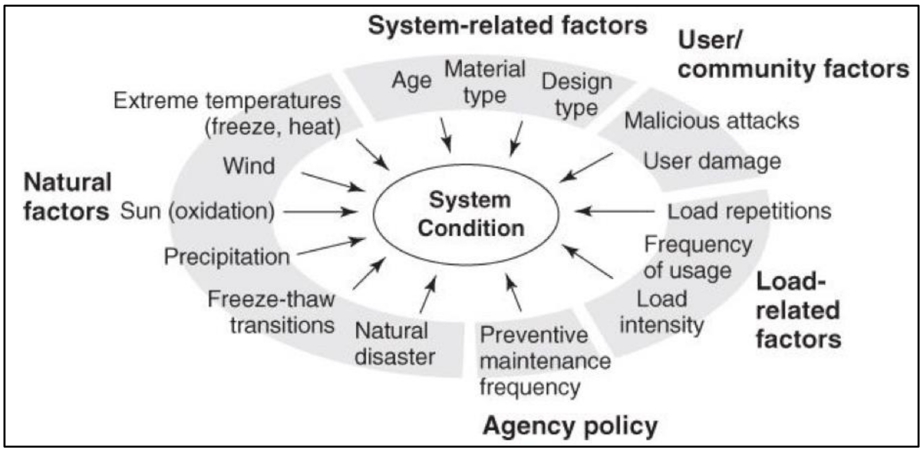


Figure 9: Factors Contributing to a Systems Condition (De Weck et al., 2011)

While there are many tools for measuring a facility's reliability, the purpose of measuring reliability is to plan maintenance strategies in order to minimize the total life cycle cost of a facility, or the total of all costs incurred over the facility's life. According to De Weck et al. (2011), there are two types of maintenance strategies: preventative maintenance and corrective maintenance. Preventative maintenance is maintenance that is purposed for ensure that a facility does not fail to meet some preferred condition or functional requirement. Preventative maintenance actions are relatively low in cost take place periodically throughout the facility's useful. Conversely, corrective maintenance involves any repair or rehabilitation action to bring a facility back to either a suitable condition or functional state. Corrective maintenance actions are relatively higher in cost than preventative maintenance, and they typically occur after some deficiency has occurred in the facility (Hicks et al., 1999). Hicks et al demonstrates the difference in cost per maintenance strategy in pavement sustainment. As shown in the figure, preventative maintenance occurs during the time that a system is reliable so that the requirement is sustained for a longer period of time. On the other hand, correct maintenance occurs when the reliability of the system is relatively low because corrective maintenance is purposed for repairing or rehabilitating the facility. Thus, because cost is an integral part of selecting a maintenance strategy, minimizing life cycle cost is another objective in selecting a construction standard.

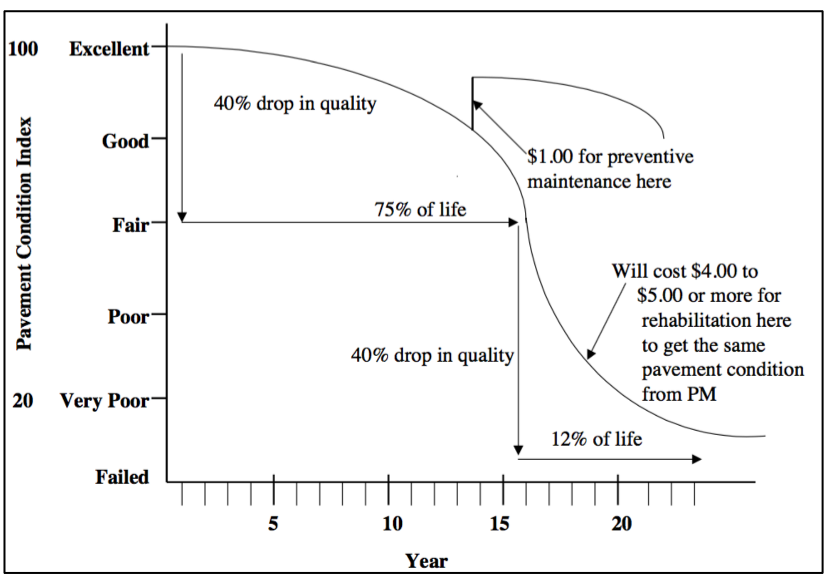


Figure 10: The Costs of Different Maintenance Strategies (Hicks et al., 1999)

In short, this study has observed three objectives in the selection of a design alternative. The first objective is to maximize quality. Literature suggested that quality is the ability of a system to fulfill its intend purpose. Since the focus of this research is billeting facilities, the objective in the selection of a design alternative is to maximize the quality of life. Direct constructed scales are perhaps the most suitable scale for measuring quality. The second objective is maximize safety. Safety is the ability of a system to protect its users from harm or some other adverse consequence. With respect to this research, decision makers are interested in design alternatives that may protect against some adverse local threat of the contingency environment. Direct constructed scales are perhaps best suited for measuring the degree of safety of a design alternative. Finally, the last objective is related to reliability. Reliability is the ability of a system to consistently perform its intended function. Since reliability of a system is closely tied to its preventative maintenance strategy, a life cycle cost is a more accurate measure of its reliability since they incorporate maintenance and operation costs. Therefore, life cycle cost will be a natural proxy measure for reliability. Overall, these three objectives align in two classifications of value measures, as shown in Table 1:

Table 1: Decision Objective Value Measures

	Direct	**Proxy**
Natural	N/A	Reliability (Life Cycle Costs)
Constructed	Quality (Quality of Life); Safety (Degree of Safety)	N/A

Potential Alternatives

The third step in the decision process is identifying potential alternatives for evaluation. Tryon previously identified several construction alternatives that the Rapid Engineer Deployable Heavy Operational Repair Squadron Engineers (RED HORSE) uses in contingency locations. In particular, he identified four examples of billeting facility designs, including Basic Expeditionary Airfield Resource (BEAR) Small Shelter Systems (SSS), K-Spans, relocatabale buildings (RLBs), and pre-engineered buildings (PEBs).

BEAR assets are war readiness assets that are configured, stored, and always ready to deploy as they are a quick means of constructing an expeditionary base. BEAR assets typically classified as initial construction standards because they are used during beddowns. BEAR SSSs are tent shelters used for billeting, work areas, latrines and showers, and storage during the initial stages of a beddown. When fully erected, BEAR SSSs measures 32.5 feet long by 20 feet. The external shell is made of a weaved plastic and the internal girders are made of high grade aluminum.

Figure 11: BEAR Assets (Col Darren P. Gibbs, 2012b)

K-Spans, as shown in Figure 12 are a facility design that is typically considered a semi-permanent or permeate form of construction, depending on their materials. K-Spans are constructed with fastened galvanized steel plates that are arched to form the shape of the building (Gibbs, 2012). Designs for K-Spans may vary because designs can be customized onsite via a device that forms the arch of the galvanized steel plates. K-spans are also considered semi-permanent because of their concrete foundation. The advantages of construction K-pans lie in the speed of construction and the cost per square foot for a facility (Tryon, 2005). While K-Spans are typically used as storage buildings and maintenance shops, they can also be used for troop housing during contingency operations.

Figure 12: K-Span Structures (Gibbs, 2012b)

Relocatable buildings (RLBs) are perhaps the most flexible form of temporary or semi-permanent construction in contingency operations. Similar to that of intermodal shipping containers, relocatable buildings are constructed with steel or aluminum walls and can be modified to provide air conditioning, electricity, water, and wastewater systems. While some relocatable building designs only allow for the assembly of as stand alone facilities, others permit the assembly of multiple modular buildings they can be assembled as a building. RLBs are particularly cheap and, as stated previously, can be advantageous when there is an immediate demand for semi-permanent billeting.

Figure 13: Relocatable Buildings (RLBs)(Quasney, 2012)

Depending on the design pre-engineered buildings (PEBs) can be considered semi-permanent or permanent facilities. According to Tryon (2005), a PEB is defined as a “metal building system that consists of a fully integrated, computer-designed, factory fabricated structural, roof, and exterior wall system.” PEBs are commonly used for offices, small aircraft hangars, large warehouses, or billeting depending of the amount of space provided by the design. PEBs are particularly advantageous in situations where a requirements is needed soon because they can be quickly constructed compared to traditional steel building designs

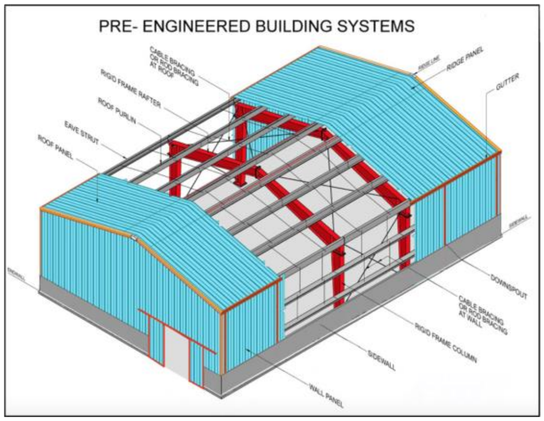


Figure 14: Pre-Engineered Building

In short, this study has identified four different types of billeting facilities design used in contingency locations. BEAR assets, specifically small shelter systems, are used as organic or initial standards to satisfy requirements for the initial beddown of forces. RLBs, K-Spans, and PEBs, however, are used in the latter stages of expeditionary base development to robust the airbase. RLBs can typically considered to be classified under either temporary or semi-permanent standards, depending on the materials they are typically constructed with. Similarly, K-Spans and PEBs are either Semi-permanent or permanent construction depending on their materials. It should be noted that there are many more types of designs used in contingency environments; however, these four designs, summarized in Table 2, are commonly used.

Table 2: Summary of Identified Designs

Design	Construction Standard
BEAR assets	Organic/ Initial
RLBs	Temporary/Semi-Permanent
K-Span	Semi-Permanent/Permanent
PEBs	Semi-Permanent/Permanent

Chapter Summary

In summary, a synthesis of DoD doctrine with decision analysis methods has provided insight into how decision maker determines if a transition to an enduring status is advantageous. The AETF FM construct and the construction standard framework have illustrated that the transition from contingency to enduring is a decision to enhance a base's infrastructure to a higher construction standard. An investigation into DoD doctrine also revealed that the decision has many objectives, constraints, and uncertain conditions. Decision analysis, however, offers a framework that aids in breaking down the elements of the decision through a five-step process. The construction of the decision frame precisely defined the decision as the selection of an optimal force beddown facility designs, as opposed to the selection of a construction standard. The objectives of the decision were discovered to be a facility's system lifecycle properties, including but not limited to quality, safety, and reliability. Finally, some commonly used billeting facility designs were discussed to provide an understanding of what available alternatives decision makers have in facing the decision to transition. These designs include, BEAR assets, RLBs, K-Spans, and PEBs. Ultimately, the decision to transition to an enduring status requires evaluating the system lifecycle properties of force beddown facilities, like those identified in the decision hierarchy below in Figure 15.

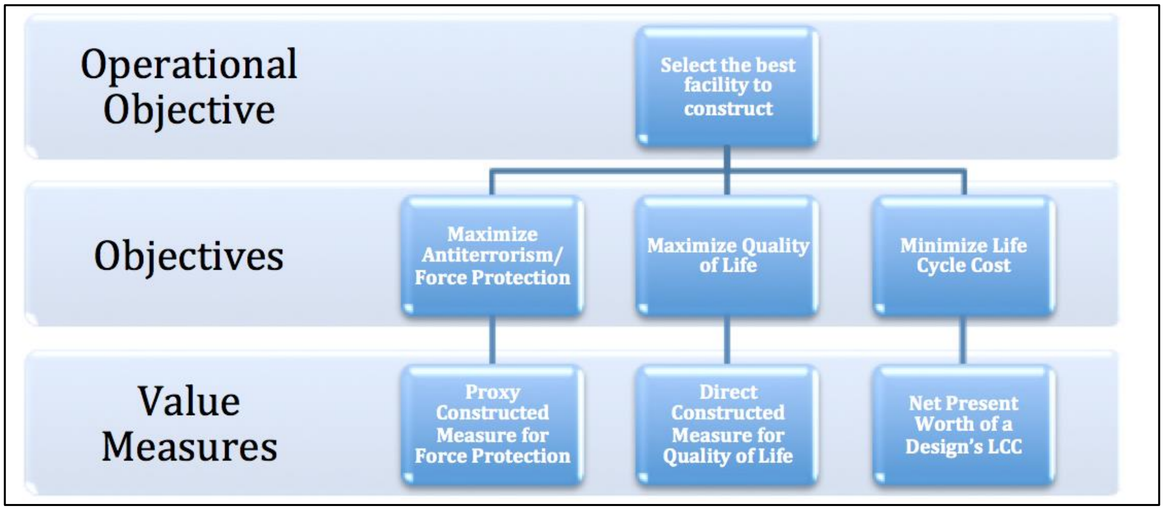


Figure 15: Decision Hierarchy

III. Methodology

Chapter Overview

Literature review has suggested an answer to the first investigative question in that decisions to transition to an enduring status are made on the basis of several objectives. These decisions involve selecting optimal lodging facility designs to best suit the environment of the contingency operation with respect to each objective in the decision. Decision makers must select designs that maximize quality of life and safety and minimize cost to the government. Chapter Three focuses strictly on providing a methodology in evaluating alternatives with the cost objective.

Furthermore, the methodology provided in this chapter specifically focuses on answering the second, third, and fourth investigative questions with respect to the cost objective. The second investigative question asks how the duration of a contingency operation affects the transition to an enduring status. In order to answer this question, a sensitivity analysis on the duration of a contingency operation is suggested to investigate changes in the cheapest alternative. The third investigate question asks how uncertainty in duration affects the decision. A methodology is, therefore, proposed that relaxes the assumption of a certainty, using two probabilistic distributions to describe the duration of a contingency. Finally, the fourth investigative question asks how a decision maker's risk attitude affects the decision. Utility theory is, thus, proposed to incorporate into the model to account potential differences in risk attitudes among decision makers. In short, all three of these proposed methodologies are to be executed in chapter four using real data from Air Force Civil Engineer databases.

Analysis of Selection Under Certain Conditions

The second investigative question of this research inquires into how the duration of a contingency operation affects the decision to transition to an enduring status. JP 3-34 has shown that organic, initial, and temporary standards are indicative of a contingency status, while semi-permanent or permanent construction standards are typically for an enduring status. Moreover, JP 3-34 suggests that these semi-permanent and permanent construction standards are suitable for non-transient contingencies because they are energy efficient, require minimal maintenance, and have relatively low life cycle costs. The goal of this portion of the research is to validate JP 3-34's assumptions by comparing the life cycle costs of design alternatives to investigate how the duration of a contingency affects preferred alternatives. This portion of the analysis assumed a contingency operation's expected duration is a certainty and was treated as the independent variable, while a design alternative's life cycle cost was treated as the dependent variable.

Life Cycle Cost Analysis (LCCA)

One technique used to investigate the costs of a design alternative is a life cycle cost analysis (LCCA). LCCA compares the cost-effectiveness of an investment of an design alternative for decision makers interested in the economic trade-offs (Norris, 2001). LCCA quantifies the total cost of an investment of a design alternative by summing all known costs that a design experiences during the time of its use. Other than initial cost, some of the costs incurred during a facility's life include the cost of repair, maintenance, operations, and demolition (Uddin et al., 2013). A design's life cycle cost is typically used as a decision metric, as its resulting value cannot be used for budgeting purposes. When comparing two or more designs, the design that has the lowest life cycle cost is considered the cheapest alternative. Thus, quantifying each facility design's life cycle cost enables a decision maker to determine the cheapest facility design in order to minimize the cost of the transition to enduring.

Another useful tool in evaluating facility design costs is the net present worth method. The present worth method consolidates the costs of an alternatives into a single value by assuming that money spent today is not equal to money spent in the future (Ross, 1995). Including the effects of inflation and interest rates, the method allows a decision maker to conceptualize an investment in a design alternative with a single value that currently reflects a dollar's value. Uddin et al. (2013) expresses the model for the present worth of a facility design's life cycle cost as:

$$TPWC_{x1,n} = (ICC)_{x1} + \sum_{t=0}^{n} \left\{ pwf_{i,t} \left[(CC)_{x1,t} + (OM)_{x1,t} + (UC)_{x1,t} \right] \right\} - pwf_{i,n}(SV)_{x1,n}$$

Where,

$TPWC_{x1,n}$ = total present worth of costs for alternative x1, for analysis period of n years

$(ICC)_{x1}$ = initial capital costs of construction, etc., for alternative x1

$(CC)_{x1,t}$ = capital cost of construction, etc., for alternative x1, in year t, where t <n

$pwf_{i,t}$ = present worth factor for discount rate, i, for t years = $\frac{1}{(1+i)^t}$

$(OM)_{x1,t}$ = maintenance plus operation costs for alternative x1 in year t

$(UC)_{x1,t}$ = user costs, if applicable for alternative 1 in year t

$(SV)_{x1,n}$ = salvage value for alternative x1, at the end of the analysis period, n yearss

The variables in Uddin et al.'s model have three categories: acquisition costs, service life costs, and divestment costs. Acquisitions costs are any costs required for purchasing the facility and take place prior to the use of the facility. Two types of acquisition costs are initial capital construction costs (ICC) and capital construction costs (CC). ICCs are any initial costs needed to begin the construction of the facility. An example of an ICC is a down payment to a construction contractor so the contractor can begin work on the facility. Capital costs of construction (CC) are subject to interest rates because they are subsequent to the ICC. Because some construction contracts require payment by progress, Uddin et al includes CCs to account for the interest gained by payments made after the initial cost. The second dimension, service life costs, includes any costs incurred during the facility's use. Operations and maintenance costs (OM) and user costs (UC) are two types of service life costs. OM costs are costs gained through operating, repairing, or maintaining the facility. Some examples of OM costs are energy costs, corrective repair costs, and reoccurring maintenance cost. User costs are costs incurred by the user. Each of these costs is calculated for a given payment period. For buildings payment periods are typically assumed to be years; therefore, each year of a service life cost is summed to represent that variables contribution to the LCC (Asiedu & Gu, 1998). Finally, divestment costs are costs incurred after the facility's use. One of the most common examples of a divestment cost is the cost to dispose of the facility;

however, Uddin et al includes salvage value into the model to account for any benefit gained from selling the facility. Generally, acquisition costs, service life costs, and divestment costs are common in a facility's life cycle.

Model Modifications

Some adjustments to the model were made to scope Uddin et al's model to align with the intent of this research effort. While a complete LCCA includes all potential incurred costs of a design, the scope of this research is limited to an LCCA that only includes construction, maintenance, and disposal costs. Therefore, the model was adjusted to include one acquisition cost, one service life cost, and one divestment cost. Initial costs of construction were used as an acquisition cost, maintenance costs were used as a service life cost, and disposal costs were used as a divestment cost of the model. Although salvage value is typically in an LCCA, facilities in contingency operations are typically demolished and disposed of at the end of a contingency operation.

The model was also adjusted to account for variance in costs. This research treated design alternative's initial construction, maintenance, and disposal costs as a random variable to account for the variance within a design alternative, unless the data suggests that these values are constant. Touran, Wiser, and Chau suggested that cost data can typically be described by the lognormal distribution; therefore, the model was adjusted to represent each cost as a random variable from the lognormal distribution (Touran & Wiser, 1992; Wing Chau, 1995). With respect to the present worth factor, the model's discount rate was assumed to be uniform distribution with minimum and maximum values of 2 to 3%. The modified model for this research is as follows:

$$NPW(t)_{x1} = AC(ln(\mu,\sigma))_{x1} + \sum_{t=0}^{n}\left\{\left(\frac{1}{(1+i)^t}\right)[MC((ln(\mu,\sigma)))]_{x1,t}\right\} + \left[\left(\frac{1}{(1+i)^t}\right)(DC(ln(\mu,\sigma)))_{x1}\right]$$

Where,

NPW_{x1} = net present worth of costs for facility design x1, for analysis period of t years

$(AC)_{x1}$ = acquisition cost for alternative x1

$[MC]_{x1,t}$ = maintenance costs for alternative x1 in year t

$(DC)_{x1}$ = disposal cost for alternative x1, at the end of the analysis period, t years

i = discount rate for t years

Monte Carlo Simulation

Since the model deals with random variables from particular distributions, Monte Carlo Simulations (MCS) were used to simulate design alternative's distribution of life cycle costs. A MCS is a method that approximates random variables through the generation of a large sample of random numbers to repeatedly calculate a mathematical or empirical operation (Ang & Tang, 2007). For this research a MCS generated random numbers from the lognormal distribution of acquisition, annual maintenance, and disposal costs to simulate a distribution of life cycle costs for a potential design alternative. Using R statistical software, each MCS generated 10,000 random numbers for each random variable in the model, and the result showed the variance in life cycle costs for each design alternative for a particular length of a contingency.

In order to simulate multiple scenarios of different durations of contingency operations, a sensitivity analysis was performed on the number of years a contingency operation is expected to last. Assuming a year for construction and a year for disposal of a facility, the results sensitivity analysis showed how the distributions of life cycle costs change when a used for longer or shorter periods of time. Because JP 3-34's proposed timeline spans for contingencies lasting up to 10 years, the sensitivity analysis includes scenarios of three to ten year contingencies. Additionally, a design alternative that represents each construction standard was included to see if JP 3-34' construct aligns with the results of the analysis. An individual investigation of each scenario shows which construction standard is preferable for that particular scenario.

Within each scenario, the resulting distributions for each design alternative was tested for independence to determine if there is an actual difference in the life cycle costs of each design alternative. Depending on the resulting data, either a two sample Student's t-Test or the Wilcoxon Ranked Sum Test was used to test independence. The t-test is a test for independence when comparing two independently sampled populations that are normally distributed. Flexible for any population size, the Student's t-test assumes that each population under comparison have the same variance (Ruxton, 2006). The central tendency, or mean, of the distributions are of interest in the Student's T Test and test the following hypotheses:

H_o: The means of the two populations are equal

H_a: The means of the populations are not equal

If the test suggests that the null hypothesis should be rejected, then it can be inferred that the populations are not equal. If the test suggests that the null hypothesis has failed to be rejected, then the populations are, effectively, equal. Alternatively, the Mann-Whitney Ranked Sum test is a nonparametric form of the student's t-test. The Man-Whitney, or

Wilcoxon, Ranked Sum test compares the differences in central tendencies between two populations, of equal or unequal variance (Mann & Whitney, 1947). The test operates under three basic assumptions. The first assumption is that the data that it is comparing is not of the normal distribution. The second assumption is that all observations have independence. Finally, the third assumption is that the response variable is continuous or ordinal. Although the Mann-Whitey ranked sum test assumes that the data is non-normal, the test is similar to the two-sample t-test in that it tests the following hypotheses:

H_o: The distributions from both populations are equal

H_a: The distributions from both populations are not equal

For both tests the overall significance level, α_e , was 0.05. Since there is a danger of a type one error with multiple tests for each scenario, the Boneferroni Correction Method was used to adjust the significance level of each test. The overall significance level was divided by the number of comparisons executed in each sensitivity analysis scenario. Therefore, each tests significance level, $\alpha_{c,}$ was 0.0167. Each test will be conducted using R statistical software. Ultimately, the two sample Student's T test will be used if the resulting data is normal with equal variance, and the Mann Whitney Ranked Sum test will be used if the resulting data is not normal with unequal variance.

Analysis of Selection Under Uncertain Conditions

Since the third investigative question inquires into how uncertainty in duration may change the dynamics of the decision, this portion of the research sought to answer this question by treating the duration of a contingency operation as an uncertainty. Using the methodology proposed for selection under certain conditions, the duration of a contingency operation was treated as a random variable. Treating a contingency operation's duration as a random variable more accurately reflects the realities of the decision, as duration is rarely known with an absolute certainty. Like the previously mentioned methodology, the independent variable is duration and the dependent variable is the life cycle costs of particular design alternative. However, the independent variable was represented in two different ways in this research.

Operation Enduring Freedom Simulation

First, the duration of a contingency operation was assumed to follow the distributions of duration of OEF forward operating bases (FOB) in Afghanistan. The purpose of incorporating such data was to investigate if historical data in the life of a FOB Afghanistan may shed light on the decision to transition to enduring, if a contingency operation is expected to evolve as OEF did. Data that reflects the year of each base's opening establishment and decommissioning was gathered Wikipedia and verified via Wikipedia's sources. If a base's opening or closure year cannot be verified, then the data was not used in the research. Since the data will be the number of years in the form of integers, the data was tested for goodness of fit to the Poisson distribution. If the distribution of durations passes the goodness of fit test, then the parameter of the Poisson distribution was used in the MCS to generate random durations.

Similar to the methodology proposed for decisions under certain conditions, each design alternative's distribution of life cycle costs was tested for independence. If the simulated data is normal with equal variance, the paired Student's T test was used. Using the same assumptions and hypotheses as the two sample Student's t-test, the paired student's t-test compares distributions of equal sizes that have matched observations in each distribution. If the simulated data is not normal with unequal variance, then the Wilcoxon Signed Rank test was used to make comparisons. The Wilcoxon Signed Rank test is a nonparametric form of the paired student's t-test. The test is conducted under three assumptions. First, the data is assumed to be paired and from the same population. The next assumption is that the pair of each population is generated randomly. The final assumption is that the data is ordinal and can be ranked(Wilcoxon, 1945). In contrast to the Wilcoxon summed rank test, the Wilcoxon Signed Rank test uses the median to make a determination on the following hypotheses:

H_o*: The difference between the pairs follows a symmetric distribution around zero*

H_a*: The difference between the pairs follows a symmetric distribution around zero*

For both tests the overall significance level, $\alpha_{e,}$ was 0.05. Since there is a danger of a type one error with multiple tests for each scenario, the overall significance level was divided by the number of tests that were completed in each scenario. Therefore, each tests significance level, $\alpha_{c,}$ was 0.0167. Each test was conducted using R statistical software. Ultimately, the two sample Student's T test was used if the resulting data is normal with equal variance, and the Mann Whitney Ranked Sum test was used if the resulting data is not normal with unequal variance.

Lack of Knowledge Simulations

The second representation of the duration of a contingency was the through the triangular distribution. As literature revealed contingency operations are inherently volatile, and decision makers have difficulty predicting their duration. Therefore, selections of construction standards, or design alternatives, are dependent on a decision maker's uncertain feeling of the duration of the mission due to a lack of knowledge. Many applications of qualitative risk analysis have used a triangular distribution to describe the uncertainty of a decision maker due to their lack of knowledge (Hoffman & Hammonds, 1994). For this research, the triangular distribution's range of possible values, along with its mode, can be used to represent the worst case, best case, and most likely scenario for the duration of a contingency. To have a full understanding in how uncertainty may affect the decision, a sensitivity analysis was conducted on the mode of the triangular distribution to represent all possible scenarios of uncertainty within JP 3-34' ten year framework. Furthermore, the resulting distributions of life cycle costs was tested for independence using the previously calculated significances levels and compared to JP 3-34's framework to find similarities and differences between the models with respect to cost.

Risk Analysis in Selection Under Uncertain Conditions

The final investigative question of this research inquires into how a decision maker's risk attitude may change the decision to transition to enduring. In economics, an alternative's utility is often measured to compare competing investments with potential costs or benefits. Expected utility theory is a concept that concerns the preference of a decision maker with regard to an uncertain outcome. The theory suggests that decision makers have risk attitudes that reflect a decision maker's feelings on avoiding or seeking risky deals.

Expected utility theory is based on five basic assumptions or rules. The first rule of expected utility theory states that alternatives must be described as uncertain events. Since this research in grounded in the assumption that durations of contingencies are uncertain, the life cycle costs of alternatives are, therefore, uncertain. The second rule states that a decision maker can order alternatives based on some preference, and the ordering is transitive. This research assumes that decision makers are seeking investments that minimize life cycle costs; therefore, alternatives are to be order with respect to cost and prefer alternatives with lower costs. The third rule states that certain equivalence between deals can be created. For example, consider a situation in which a decision maker prefers alternative A to alternative B to alternative C. Expected utility theory suggests that a probability, p, can be specified such that the decision maker would be indifferent between receiving alternative B with certainty or a uncertain deal with the probability, p, of receiving alternative A and probability ($1-p$) of receiving alternative C. The fourth rule builds off the third rule in that the rule suggests that uncertain deals can be substituted with their respective certain equivalent deal because the decision maker would be indifferent to them. Finally, the fifth rule of expected utility theory assumes that decision makers prefer to take deals that have high probabilities of attaining some preferred outcome (Clemen & Reilly, 2013; Rabin, 2000; Schoemaker, 1982).

Utility theory incorporates the delta property to describe a decision maker's attitude towards risk. The delta property suggests that decision makers are inherently risk averse, as they are restricted by budgets or a current state of wealth. The delta property's concept, effectively, states that if some cost is added to each possible outcome of an uncertain investment or deal, then the certain equivalent must also increase by that amount. The delta property also suggests that a monetary unit of measure, or a dollar's, utility can be expressed through an exponential function, and the function incorporates a parameter, R, that reflects a decision maker's risk attitude. The risk aversion parameter can be obtained by asking a decision maker a series of questions that compares uncertain deals of winning or losing money (Rabin, 2000). Ultimately, repeatedly asking a decision maker this question with different amounts for wins or losses forces a decision maker to settle on a value of wins or losses. This value is then used to produces the risk aversion parameter for that particular decision maker. For the purposes of this study, the utility function, with the risk aversion parameter, was adapted to incorporate life cycle costs, as shown below:

$$u(NPW_{x1}) = 1 - e^{-\left(\frac{NPW_{x1}}{R}\right)}$$

Where,

u = the expected utility

NPW = Net Present Worth of Design alternative, x1

R = a decision maker's risk aversion parameter

The expected utility function was incorporated into the OEF simulation and the lack of knowledge simulations. Because this study is limited on time, two risk tolerances was tried to understand the changes in preferred alternatives. One risk attitude was significantly risk averse, while the other was moderately risk averse. The Wilcoxon Signed Rank test was used to test the independence of the distributions of utility. Ultimately, time was treated at the independent variable and expected utility will be treated as the dependent variable.

Chapter Summary

This research has proposed a model to answer the second, third, and fourth investigative questions of this research. The second investigative question will be answered through the analysis of selection in certain conditions. This analysis will use the model with durations of conditions ranging from three to nine years. The third investigative question will be answered through the analysis of selection in uncertain conditions. The analysis will be split into two parts. The first part will assume that there is a decision maker has some knowledge of uncertainty in duration. For example, the model will be incorporated with a distribution of durations of FOBs in Afghanistan, meaning that the decision maker feels that a contingency will be similar to OEF. The second part assumes that there is a lack of knowledge in uncertainty. Thus, the triangular distribution will be used to describe an uncertainty in the duration of a contingency operation. Finally, the fourth investigative question will be answered through the risk analysis of selection in uncertain conditions, using the two parts of the selection in uncertain conditions. The methodology is summarized in Figure 16.

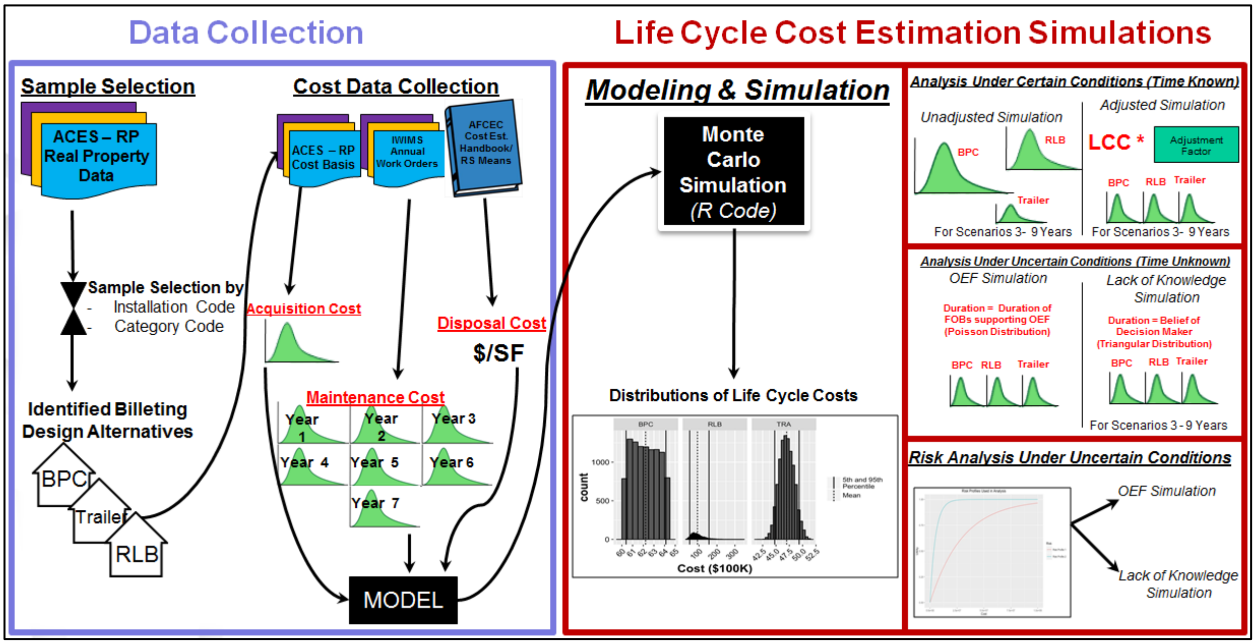


Figure 16: Methodology Summary Chart

IV. Analysis and Results

Chapter Overview

The purpose of chapter is to analyze the developed life-cycle cost model and to provide results. First, data was obtained from Air Force civil engineer databases and analyzed to describe its stochastic properties. The data's properties were then used in the life cycle cost model development. Next, the life cycle cost model was evaluated with the assumption of a certainty in duration of a contingency operation. Seven scenarios of different durations were simulated to understand changes in life cycle cost.

The life cycle model was then evaluated with the assumption of an uncertainty in the duration of a contingency operation, using two different distributions to represent it. First, the distribution of durations of FOBs in Afghanistan during OEF was used to evaluate the model. The model assumed that the decision maker believes that a contingency operation will be similar to OEF. Next, the triangular distribution was used to evaluate the model to simulate a decision maker's lack of knowledge in duration, using the mode representing the most likely duration. A sensitivity analysis was conducted that changed the mode, simulation seven different most likely scenarios.

Finally, risk attitude was incorporated into the model using expected utility theory to investigate how a decision maker's risk attitude changes the preferred alternative. Two risk averse attitudes were tried to investigate changes in the preferred alternative, with both previously identified distributions of duration.

Data Collection

The data collection process consisted of three parts. First, samples of design alternatives were selected for analysis from the AF's real property data in the Automated Civil Engineer System Real Property database (ACES-RP). Next, cost data from the identified design alternatives was collected from three sources, including ACES-RP, IWIMS, and the AFCEC historical AF cost estimation handbook. Finally, goodness-of-fit test were conducted on the data to provide model inputs.

Sample Selection

Of the AF's civil engineer databases, ACES-RP provided the best means of identifying and selecting samples for analysis. ACES-RP is a comprehensive inventory database that contains detailed information about the AF's real property assets. In particular the database annotates the location and purpose of each asset through the database's Installation Code field and Category Code field, respectively. An Installation Code is a four-digit alphanumeric identification code that represents the asset's owning installation, while Category Codes identify a facility's purpose though six digit alphanumeric code. Since the goal of this research is to provide an analysis of the life cycle costs of billeting facility designs in expeditionary environments, real property assets with installation and category codes, like those shown in Table 3 and Table 4, were considered for analysis. Thus, the installation and category codes were used for a query within the ACES-RP database. The result of the query provided data of billeting facilities located at Al Udeid Air Base (AUAB), Al Dhafra Air Base (ADAB), and Ali Al Salem Air Base (ASAB).

Table 3: Installation Codes Used for Sample Identification

Installation Code	Installation Name
ADAB	Al Dhafra Air Base
AUAB	Al Udeid Air Base
ASAB	Ali Al Salem Air Base

Table 4: Lodging Facility Category Codes Used for Sample Identification

Category Code	Description
721312	Enlisted Unaccompanied Personnel Housing
721314	Enlisted Unaccompanied Personnel Housing
721315	Enlisted Unaccompanied Personnel Housing, Transient
724417	Officer Unaccompanied Personnel Housing
725513	Officer Housing, Transient

Since ACES-RP does not provide information on the design of each asset, the similarities in the design between assets and their construction standards classification could not be determined without additional information or assumptions. The data from ACES-RP did indicate, however, that many of the billeting facilities at expeditionary locations had similar dates of construction and sizes. For example, many of the identified facilities showed similar values in ACES-RP's Year Completed field and Area field. The Year Completed field reflects the year in which construction of the facility was completed and handed over to the government for use. The Area field reports the gross area of the facility in square feet. Therefore, billeting facilities at the same location with approximately the same size and year of construction were assumed to share the same design, which consolidated the facilities into three groups, or designs alternatives. Moreover, the facility numbers of the facilities within each group were provided to the sponsor in order to determine each design alternative's construction standard. Ultimately, the three design alternatives entered into the analysis portion of the research were categorized as a temporary, semi-permanent, or permanent construction standard. These designs will be referred to as Relocatable Buildings (RLBs), Trailers, and Blatchford-Preston Complexes (BPCs). The details of each design alternative are provided in Table 5.

Table 5: Design Alternatives Used in Analysis

Design Alternative	Location	Construction Standard	Category Code	Year Completed	Size (SF)	Number of Facilities
BPC	AUAB	Permanent	721314	2008	77016	9
Trailer	AUAB	Semi-Permanent	721314	2008	4100	134
RLB	ADAB	Temporary	721312	2013	1320	35

Although the database query and assumptions produced three design alternatives, ACES-RP's limitations significantly reduced the potential validity and reliability of the analysis. For example, the three design alternatives are not representative of all construction standards, particularly those in the beginning stages of a force beddown. According to AFI 32-9007, real property is capitalized DoD assets that are not movable; therefore, initial force beddown facility designs, like small shelter systems, are not included in ACES-RP's inventory. Because data was not available for initial design alternatives, this research cannot determine if initial standards are the cheapest alternative in each scenario under analysis. Another limitation of ACES-RP is that it does not retain historical data of facilities that have been divested. Therefore, the analysis was limited to facilities that are currently in use, preventing a holistic life cycle cost analysis on designs that have been divested. In short, availability of data limited the scope of the research.

Life Cycle Cost Data Collection

Life Cycle Cost data of the facilities of each design alternatives was collected from three sources. The acquisition cost of each facility was collected from ACES-RP's Cost Basis Field. The Cost Basis Field reports any asset's construction cost amounting to more than $100,000. Since ACES-RP does not provide data of any other initial capital costs of construction, each facility's construction cost in reported ACES-RP was assumed to be its acquisition cost. Data collection of service life costs was limited to the AF's Interim Work Information Management System (IWIMS) database. The purpose of IWIMS is to manage maintenance work orders for AF real property assets. For example, IWIMS annually stores information of every maintenance action, including the cost and labor hours of a work order, in order to track the resources spent on a particular asset. Annual work order reports for each facility were used to determine the annual maintenance cost for each design alternative. Because government facilities are not typically salvaged in contingencies operations, data was collected on cost to dispose of a facility. The Automated Civil Engineer System – Program Management (ACES-PM) database was initially surveyed for historical demolition project costs. However, no projects were found that represent the demolition of designs that were comparable to those of interest to the analysis. Thus, disposal costs were estimated with demolition estimates in the Historical Air Force Cost Estimation Handbook and the RS Means cost estimation handbook. The handbook uses historical data from ACES, programming forms (DD 1391), the Parametric Cost Engineering System (PACES), and detailed quantity takeoff estimates from typical designs to calculate reliable demolition costs per square foot of a particular design. The handbook provided four estimates for the demolition of a wood, steel, and concrete structure. Similarly, the RS Means cost estimation handbook provided one estimate for a wood, steel, and concrete structure. For the purposes of this research, the BPC design was assumed to be a concrete design, the trailer design was considered to be a wood design, and the RLB was considered to be a steel design. Since each disposal cost is equally likely to be selected for demolition, the estimates were averaged and multiplied by the size of each facility. The disposal estimates per square foot for each design are provided in Table 6.

Table 6: Estimated Disposal Costs

Disposal Estimate	BPC (Concrete - Multi Story)	Trailer (Wood - One Story)	RLB (Steel - Multi Story)
AFCEC: No Dump Fee	$5.34/SF	$4.08/SF	$4.68/SF
AFCEC: $10/CY Dump Fee	$10.50/SF	$11.10/SF	$11.10/SF
AFCEC: $20/CY Dump Fee	$15.60/SF	$17.40/SF	$17.40/SF
AFCEC: $30/CY Dump Fee	$21.00/SF	$23.40/SF	$24.00/SF
RS Means: No Dump Fee	$6.36/SF	$4.92/SF	$4.44/SF
Average	**$11.76/SF**	**$12.18/SF**	**$12.32/SF**

Of the three sources used for life cycle cost data collection, IWIMS introduced additional limitations to the study. IWIMS's availability of historical work order data was perhaps the most significant limitation of the study. IWIMS only provided six years of work orders for the BPC and trailer design, while only three years of work order was available for the RLB design. As the RLB design only has three years of data, an analysis of comparisons of each alternative could only be performed for up to three years of use. However, an older RLB design, which is used at ADAB, was found to be comparable to the one of interest to this study; therefore, the three years of work order data of the older RLB design were used as the fifth, sixth, and seventh year of maintenance costs for the RLB design. In addition the limited amount of historical work order data, material costs of work orders for the RLB facilities was not available in ADAB's IWIMS database. In order to normalize the comparison between the three designs, material costs of work orders for BPC and trailer facilities were excluded from the analysis. Although this limitation excludes a portion of a maintenance cost of a facility, material costs are often not substantial portion of a work order because IWIMS work orders are typically minor maintenance and repair projects. Thus, the analysis continued under the assumption that material costs are not substantially consequential to the overall life-cycle costs of a facility. The last limitation discovered in the IWIMS data was missing of faulty years of maintenance data. The BPC and trailer maintenance data showed that 2011's work order data was unreliable, as many of the work orders were programmed against facilities that did not exist. Thus, the BPC's and trailer's work order data for 2011 was not used in the analysis. Additionally, a fourth year of maintenance was not available for the RLB design alternative. Although maintenance cost data for two RLB designs was combined to provide more information on an RLB's annual maintenance, the two designs only provided the first three years and the fifth, sixth, and seven year of annual maintenance. Adjustments to compensate faulty or missing data will be discussed in the distribution fitting section.

Distribution Fitting

JMP®'s statistical software was used to conduct distribution fitting and goodness-of-fit tests. All acquisitions and annual maintenance cost data was fit to the lognormal distribution, as suggested by Touran et al. (1992) and Chau (1995). JMP® uses the Komologorov-Smirnov (KS) test to test the data's goodness of fit to the lognormal distribution. The KS test calculates a test statistic, Kolmogorov's D, that is used to determine if the variance in a continuous set of data can be described by a specified distribution (Massey Jr, 1951). Since goodness of fit to the lognormal distribution is of interest, the KS test's null and alternative hypotheses were:

> H_o: *The sample comes from the population of a lognormal distribution*
>
> H_a: *The sample does not come from the population of a lognormal distribution*

Distribution fitting was largely successful, but two adjustments had to be made to the model. The first adjustment to the model was made for the BPC's acquisition costs. The BPC acquisition costs in ACES-RP were discovered to be constant across each observed facility; thus, the design's acquisition costs were considered deterministic and were not tested. The trailer and RLB designs' acquisition costs, on the other hand, were considered random variables and tested for goodness of fit because they were found to be continuous. The second adjustment was made because of abnormalities in labor rates for each year's maintenance costs. Initially, many data sets failed the goodness of fit tests, so the IWIMS annual work order reports for each design alternative were consulted to investigate any data entry errors. No data entry errors were found, but hourly labor rates were found to vary per work order for each design alternative. As a result, each year's maintenance hours were tested for goodness of fit to the lognormal distribution, instead of each year's maintenance costs. With the exception of the trailer's fourth year of maintenance hours, the lognormal distribution proved to generally describe the variance in annual maintenance hours of each design alternative. The results of each data set's KS tests for fitting to the lognormal distribution are provided in Table 8 and Table 9. The mean and standard deviation of the resulting distribution were noted for use in simulation portion of the analysis. In order to solve the problem of missing years of maintenance data in each design, an average location and scale parameters were calculated using the parameters prior to and after the missing year of data.

Table 7: BPC KS Test Results for the Lognormal Distribution

Distribution	Source	Location Parameter	Median	Scale Parameter	Kolmogorov's D	Prob>D
MX Hrs Year 1 (2009)	IWIMS	1945.51	1874.07	237.45	0.166	0.15
MX Hrs Year 2 (2010)	IWIMS	1514.84	1530.48	428.53	0.207	0.15
MX Hrs Year 4 (2012)	IWIMS	712.24	733.91	111.39	0.213	0.15
MX Hrs Year 5 (2013)	IWIMS	3495.18	3657.66	743.86	0.182	0.15
MX Hrs Year 6 (2014)	IWIMS	2585.56	2499.9	223.73	0.201	0.15
MX Hrs Year 7 (2015)	IWIMS	2450.57	2466.3	411.25	0.184	0.15

Table 8: Trailer KS Test Results for the Lognormal Distribution

Distribution	Source	Location Parameter	Median	Scale Parameter	Kolmogorov's D	Prob>D
Acquisition ($)	ACES - RP	1135101.1	1139381	23936.44	0.119	0.01*
MX Hrs Year 1 (2009)	IWIMS	119.47	111	40.27	0.048	0.15
MX Hrs Year 2 (2010)	IWIMS	99.98	96.83	43.19	0.068	0.118
MX Hrs Year 4 (2012)	IWIMS	44.47	41.62	15.18	0.079	0.042*
MX Hrs Year 5 (2013)	IWIMS	191.99	284.24	61.03	0.043	0.15
MX Hrs Year 6 (2014)	IWIMS	185.57	177.65	125.88	0.073	0.079
MX Hrs Year 7 (2015)	IWIMS	168.35	162.5	52.04	0.053	0.15

Table 9: RLB KS Test Results for the Lognormal Distribution

Distribution	Source	Location Parameter	Median	Scale Parameter	Kolmogorov's D	Prob>D
Acquisition ($)	ACES - RP	118787.61	87000	48563.73	0.33	0.01*
MX Hrs Year 1 (2013)	IWIMS	52.43	47	30.39	0.097	0.15
MX Hrs Year 2 (2104)	IWIMS	203.71	186.2	82.99	0.096	0.15
MX Hrs Year 3 (2015)	IWIMS	141.47	123	56.62	0.133	0.141
MX Hrs Year 5 (2013) (Comparable Design)	IWIMS	175.43	159.5	82.85	0.084	0.15
MX Hrs Year 6 (2014) (Comparable Design)	IWIMS	163.323	165.75	89.81	0.139	0.0947
MX Hrs Year 7 (2015) (Comparable Design)	IWIMS	252.88	233.75	171.66	0.105	0.15

Analysis of Selection in Certain Conditions

The purpose of the analysis of selection in certain conditions was to understand how the life cycle costs of each design alternative changes as the duration of the mission changes. Since changes in cost were of interest, the analysis took on the form of a sensitivity analysis with a key underlying assumption of a certainty in the longevity of the mission. The sensitivity analysis was done for durations of contingency operations ranging from three to nine years because the data could only describe seven maintenance years with one year for construction and one year for disposal. The analysis of selection in certain conditions was broken down into two Monte Carlo simulations. The first strictly simulated and summed costs for each design alternative to understand their life cycle costs. The second Monte Carlo Simulation simulated and summed costs with a capacity adjustment factor, which enabled a proportionately equivalent comparison for billeting a fixed number of personnel for each respective design alternative. Each simulation investigated contingency durations of three to nine years using the following model:

$$NPW(t)_{x1} = AC(ln(\mu,\sigma))_{x1} + \sum_{t=0}^{n}\left\{\left(\frac{1}{(1+i)^t}\right)[MC((ln(\mu,\sigma)))]_{x1,t}\right\} + \left[\left(\frac{1}{(1+i)^t}\right)(DC(ln(\mu,\sigma)))_{x1}\right]$$

Where,

NPW_{x1} = net present worth of costs for facility design x1, for analysis period of t years

$(AC)_{x1}$ = acquisition cost for alternative x1

$[MC]_{x1,t}$ = maintenance costs for alternative x1 in year t

$(DC)_{x1}$ = disposal cost for alternative x1, at the end of the analysis period, t years

i = discount rate for t years

Unadjusted Simulation Results

The Monte Carlo Simulation with the unadjusted costs was executed under three key assumptions. The first assumption addressed the interest rates for present worth calculations. Interest rates of two to three percent are typically used for independent government estimates at AFCEC. Thus, interest rates were assumed to be of the uniform distribution with a rage of two to three percent. Using these interest rate random variables, acquisition and maintenance costs for each design were brought to the present from the year in which they were spent. Disposal costs, however, were assumed to be present worth dollars. The second assumption was a fixed shop labor rate per the location of a design alternative. The sponsor provided current shop rates for AUAB and ADAB, which were reported to be $44.06 and $38.00 respectively. These shop rates are different because local national labor in incorporated into the calculation of a base's respective shop rate. Each year's maintenance hour distribution was multiplied by the shop labor rates to simulate a randomly generated maintenance labor cost for the respective year. The maintenance hour distributions for the RLB design alternative used ADAB's shop labor rate, while the BPC and trailer design alternatives used AUAB's labor rate. Finally, the analysis assumed that the maintenance years are independent within a design alternative. This assumption was made in light of the results from correlation matrices. Each design's correlation matrix showed little to no correlation. Therefore, randomly generated maintenance hours were not adjusted for covariance between years. In general, the assumptions of a fixed interest rate, fixed shop labors rate, and independency between the maintenance hours for each year of a design were consistent in subsequent simulations of the research.

The results of the unadjusted analysis showed that acquisitions costs are the largest contributor to total life cycle cost for each design alternative. As shown in Figure 17, Figure 18, and Figure 19, each design alternative’s acquisition cost was substantially larger than cumulative maintenance costs and disposal costs for each scenario. Additionally, the labor costs for maintenance actions do not contribute significantly to changes in the life cycle cost for each design alternative.

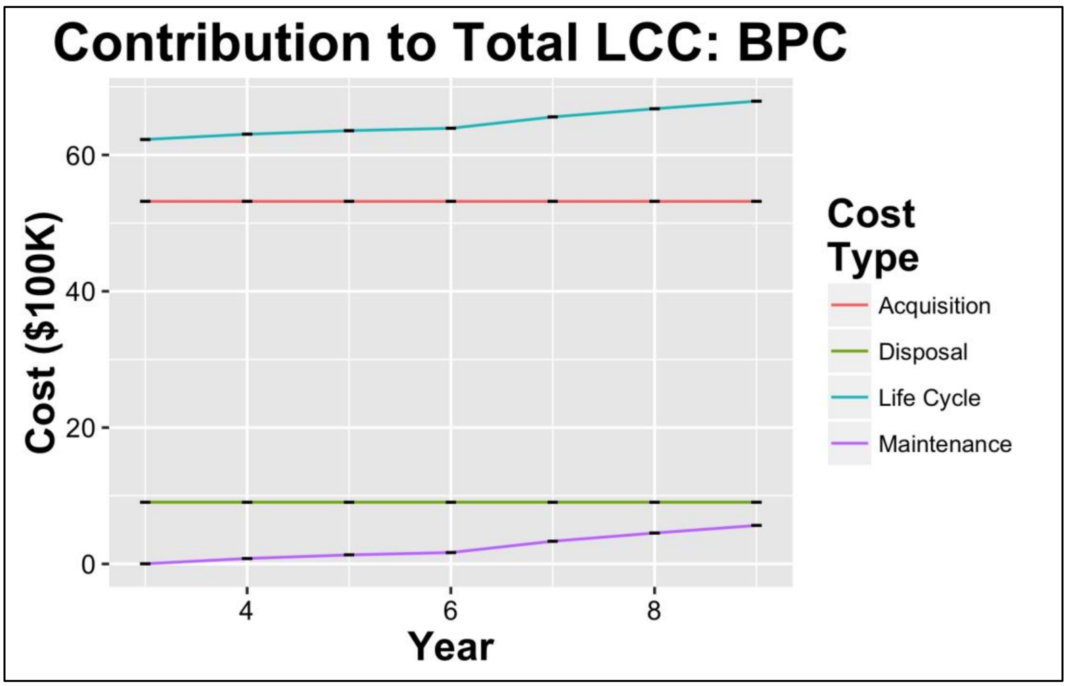


Figure 17: BPC Costs Per Years of Use

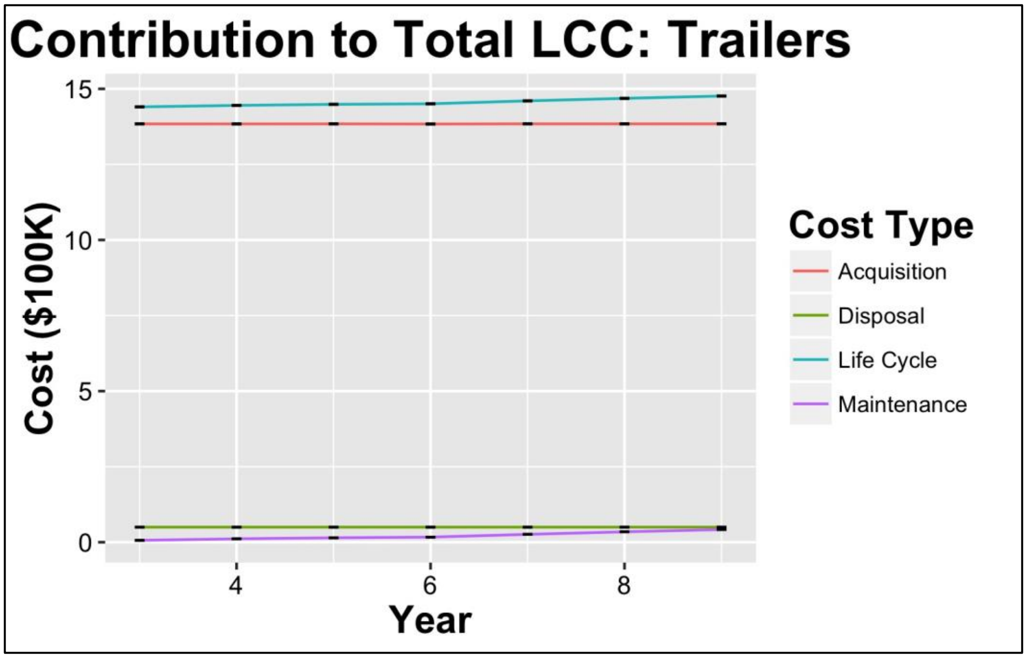


Figure 18: Trailer Costs Per Years of Use

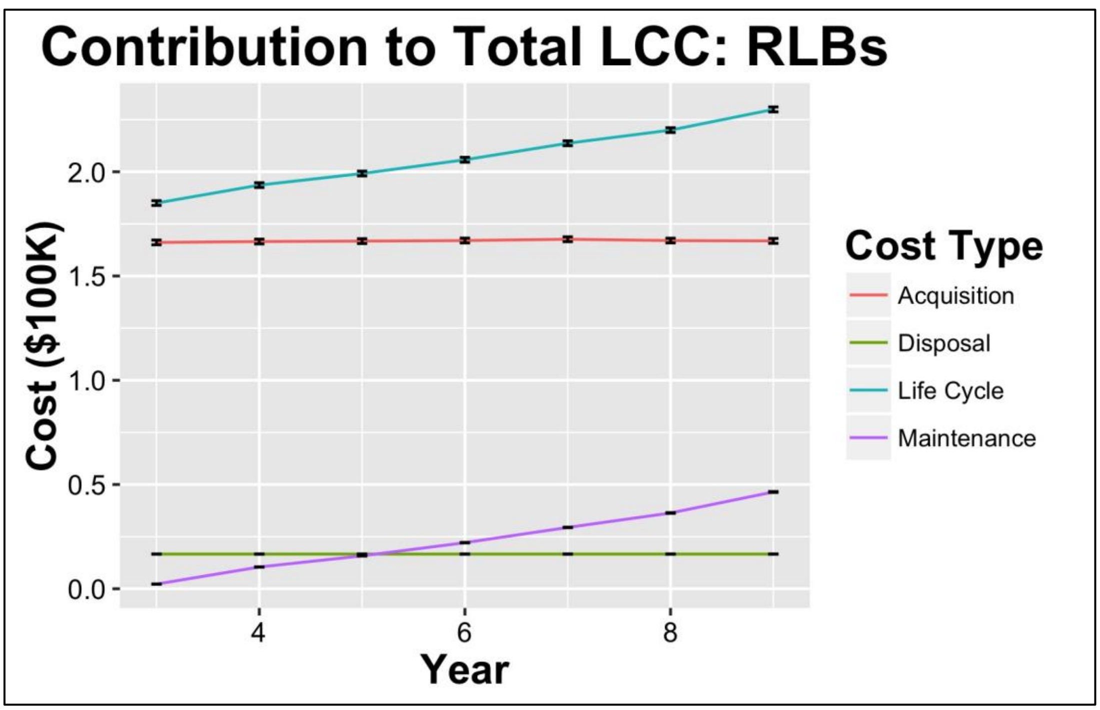


Figure 19: RLB Costs Per Years of Use

Each scenario showed that the BPC's large size makes it the most expensive of the design alternatives. Although it is semi-permanent, the RLB design is the cheapest among the alternatives for each scenario. The RLB design's stochastic dominance over the trailer design can be attributed to the trailer's large upfront cost. The mean of the trailer's acquisition cost is approximately $1.4 million while the RLB's acquisition costs is $170 thousand. In general, the results of the unadjusted analysis further motivated the requirement of an adjustment to the costs to compensate for the number of personnel they are designed to house. Descriptive statistics of the costs of each contingency scenario can be found in Appendix B.

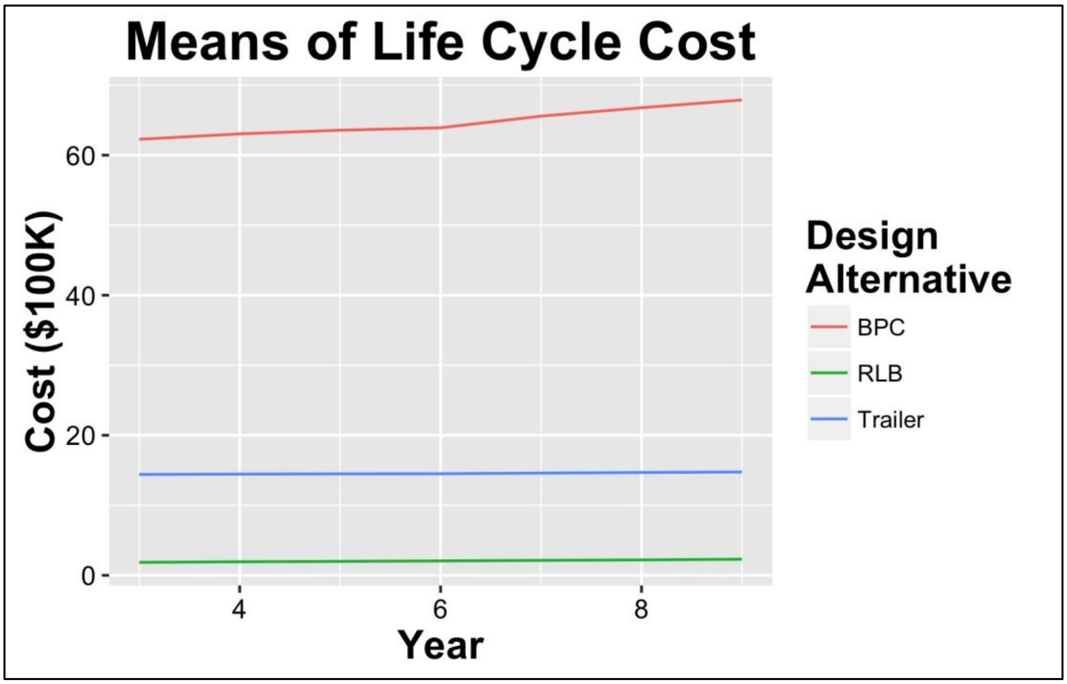


Figure 20: Life Cycle Cost Per Years of Use

Adjusted Simulation Results

While the unadjusted simulation only communicated the cheapest design regardless of its housing capacity, the adjusted simulation incorporated housing capacity to illustrate the total cost of billeting a fixed number of personnel. The adjusted simulation integrated a capacity adjustment factor that reflected the number facilities needed to meet a requirement for a fixed number of personnel. To calculate the adjustment factors for each design, the sponsor provided surge capacity data, shown in Table 10, of each design alternative. Surge capacity is the absolute maximum amount of personnel the facility can house in the event of a surge, or the introduction of a new mission to the base. Since the BPC has the largest capacity, its capacity was used as a baseline the adjustments. The BPC's capacity was divided by trailer's and RLB's capacity to calculate an adjustment factors for their designs, resulting in the values shown in Table 10.

Table 10: Capacity Adjustment Factors for Design Alternatives

Design	Capacity at Surge (Number of Personnel)	Adjustment Factor
BPC	392	N/A
Trailer	120	3.26
RLB	8	49

In contrast to the unadjusted analysis, the Wilcoxon ranked sum test was used to compare the life cycle cost of each design alternative. The results of the Wilcoxon ranked sum test were used to determine: 1) if the simulated distributions of life cycle cost are statically different, and 2) which design alternative is stochastically cheaper. The p-values were used to determine if the independence of the distributions of life cycle costs. Since the overall significance level for a scenario, α_e, was 0.05, the p-value must be less than the individual test significance level, $\alpha_{c,}$ which is 0.0167. The signs of the differences in location were used to which design alternative was stochastically cheaper of the two in comparison. For example, if *sample x* and *sample y* is being compared and the sign in the difference in location is negative, then *sample x* is stochastically cheaper. The results of Wilcoxon ranked sum tests showed that the RLB design alternative was stochastically the most expensive and the trailer design alternative was stochastically the cheapest in each scenario, as shown in Figure 21. Since the trailers are the stochastically cheapest, the results suggest that a semi-permanent construction standard is optimal for contingencies ranging from three to nine years in length. The results of each Wilcoxon text are reported in

Table 11.

Table 11: Adjusted Simulation Wilcoxon Ranked Sum Test Results

Years of Use	Comparison	W	p-value	90% Confidence Interval	Difference in Location
3 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[15.19, 15.25]	15.23
	BPC to RLB	19065000	<0.0001*	[-23.33, -22.22]	-22.77
	Trailer to RLB	4185300	<0.0001*	[-38.54, -37.45]	-38.00
4 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[15.80, 15.86]	15.84
	BPC to RLB	14668000	<0.0001*	[-27.00, -26.03]	-26.52
	Trailer to RLB	2540900	<0.0001*	[-42.83, -41.85]	-42.35
5 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[16.20, 16.26]	16.23
	BPC to RLB	12842000	<0.0001*	[-27.32, -26.24]	-26.78
	Trailer to RLB	1435500	<0.0001*	[-43.55, -42.48]	-43.02
6 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[16.47, 16.54]	16.51
	BPC to RLB	10206000	<0.0001*	[-31.53, -30.51]	-31.02
	Trailer to RLB	952370	<0.0001*	[-48.03, -47.02]	-47.53
7 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[17.84, 17.91]	17.88
	BPC to RLB	8012200	<0.0001*	[-33.47, -32.47]	-32.97
	Trailer to RLB	379010	<0.0001*	[-51.35, -50.35]	-50.85
8 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[18.77, 18.84]	18.81
	BPC to RLB	6650600	<0.0001*	[-35.40, -34.41]	-34.91
	Trailer to RLB	182850	<0.0001*	[-54.21, -53.22]	-53.72
9 Years	BPC to Trailer	$1.00*10^8$	<0.0001*	[19.63, 19.70]	19.67
	BPC to RLB	4697900	<0.0001*	[-39.50, -38.51]	-39.01
	Trailer to RLB	54163	<0.0001*	[-59.17, -58.18]	-58.68

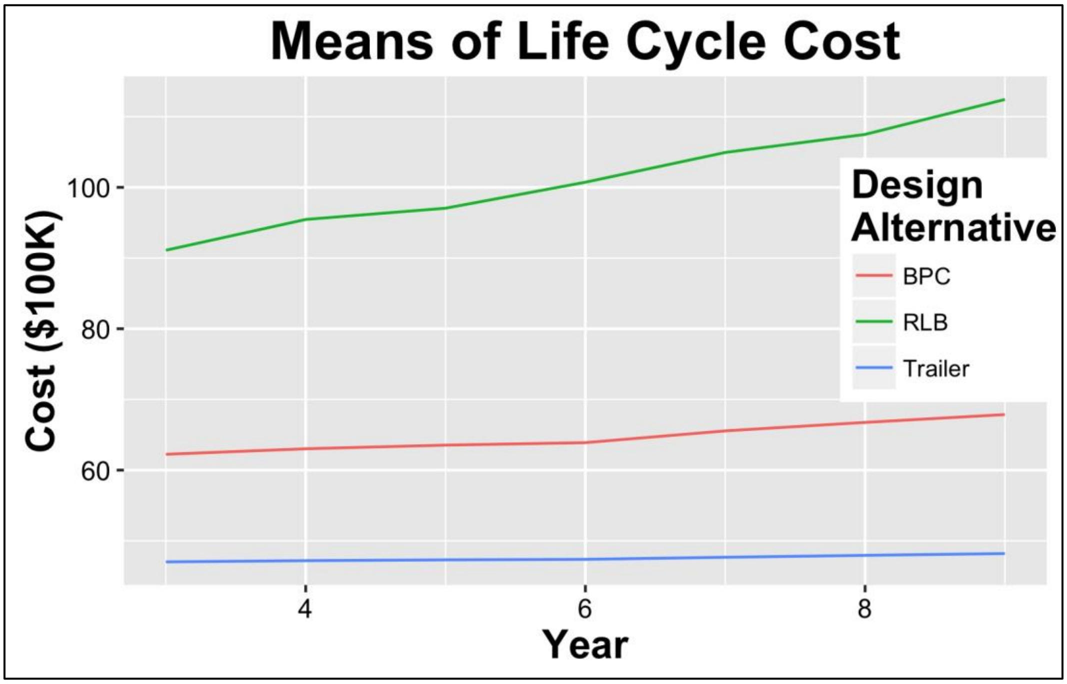


Figure 21: Adjusted Simulated Life Cycle Cost

Since the MCS produced distributions of life cycle costs, a deeper investigation in each scenario was conducted to investigate the probability that one design is cheaper or more expensive than the other. In each scenario, the BPC and trailer design's had very little variance in life cycle cost, while the RLB had a substantial amount of variance. The RLB's large range of variance, as shown in Figure 22, introduces some uncertainty into a decision, as some of the observations of the BPC's and trailer's life cycle costs are more expensive than that of the simulated observations of the RLB's. For scenarios with durations of three years, most all trailer life cycle cost observations were found to be cheaper than the observations of the BPC, as shown in Figure 22. Approximately 80.2%

life cycle cost observations for the RLB were larger than the BPC's, and approximately 85.9% of the RLB's observations were larger than that of the trailer's.

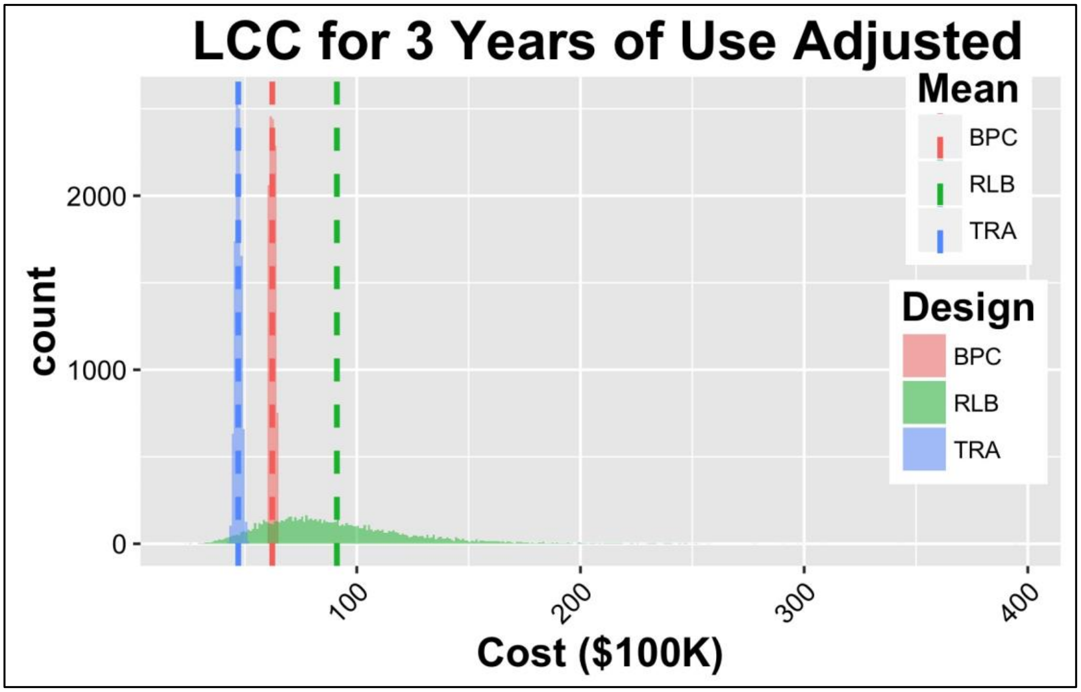


Figure 22: Year 3 LCC Histograms

Each scenario was, subsequently, investigated for changes in stochastic dominance. No significant changes, however, were discovered leading up to the nine-year scenario. The nine-year scenario showed a shift in costs to the right and showed less of a probability that the life cycle costs of either the BPC or trailer is less expensive that the RLB. These results indicated that there is more of a certainty that the RLB design is the most expensive. The result of all scenarios, shown in Table 12, indicates that the probability that the RLB is the most expensive alternative increases as duration increases. For example, the nine year scenario, shown in Figure 23, depicts a shift to the right in the

RLB's life cycle costs. Descriptive statistics of each scenario can be found in Appendix B.

Table 12: Adjusted Simulation Stochastic Dominance Chart

Scenario	P(BPC < TRA)	P(BPC < RLB)	P(TRA < RLB)
3 Years	0	0.8089	0.9579
4 Years	0	0.8537	0.975
5 Years	0	0.8725	0.9857
6 Years	0	0.8987	0.9912
7 Years	0	0.9218	0.9961
8 Years	0	0.9333	0.998
9 Years	0	0.9528	0.9994

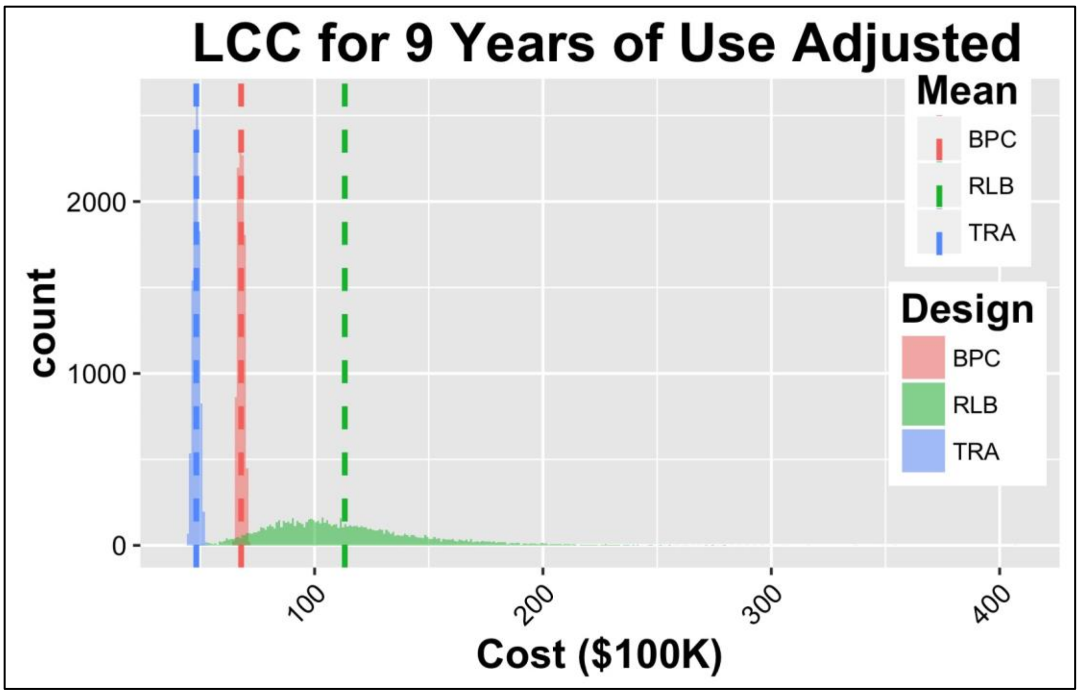


Figure 23: Year 9 LCC Histograms

In addition to comparisons of their life cycle costs, the distribution of the difference of the observations of each design's life cycle costs was investigated to see if the means of the differences are approaching zero. Since the difference is being taken of positive costs, then the sign indicates which design alternative is stochastically cheaper. For example, if *sample x* and *sample y* is being compared and the difference is negative, then *sample x* is stochastically cheaper. Otherwise, *sample y* is stochastically cheaper. The difference in observations of the BPC and trailer showed that the mean almost crosses zero for contingencies lasting nine years. Additionally, the upper tail of the 90 percent confidence interval crosses zero after 8 years of use, as shown in Figure 24. This indicates that the trailer is preferred for contingencies up to 9 years in length.

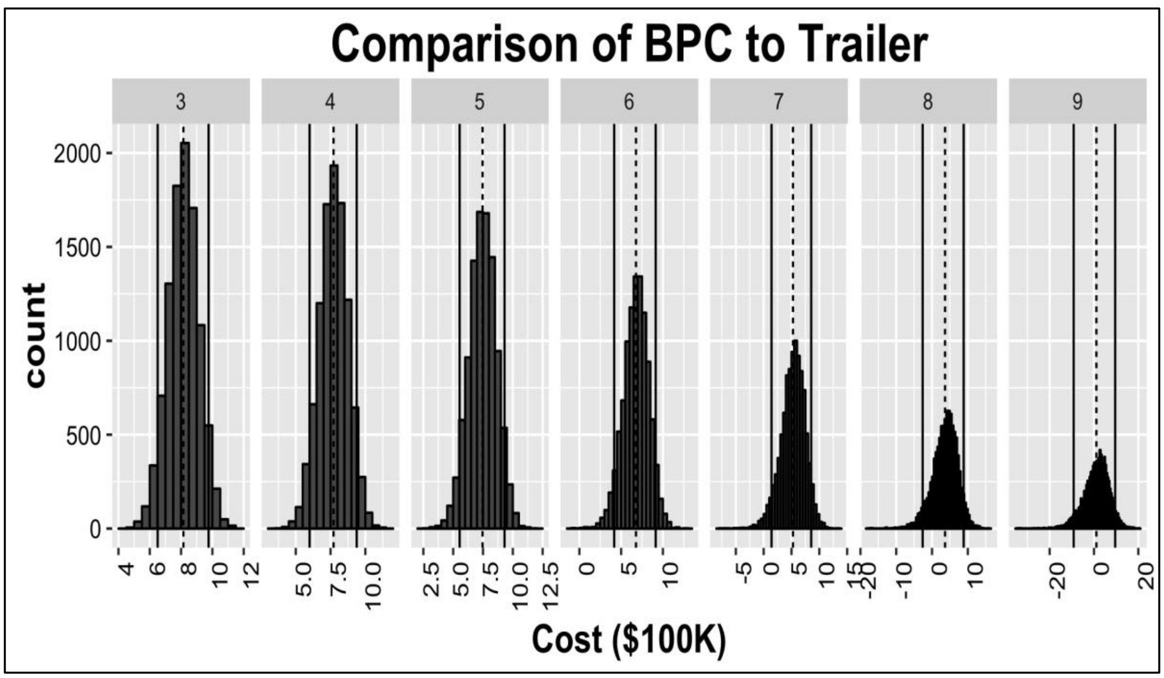


Figure 24: Difference in Observations for BPC and Trailer

The distribution of differences between the BPC and RLB showed that zero was always included within the 90 percent confidence interval. Additionally, the mean was found to be positive after seven years of use, indicating that with the trailers there is a greater probability that the RLB design will be cheaper than the BPC design. The comparison between the trailer and RLBs showed similar results. The mean was found to be positive after seven years of, and the zero was always included within the 90 percent confidence interval. Effectively, RLBs are the cheaper option in scenarios that are less than seven years, with respect to the other two designs. The visual illustrations of these investigations are shown in Figure 25 and Figure 26. Descriptive statistics of the difference calculations can be found in Appendix B.

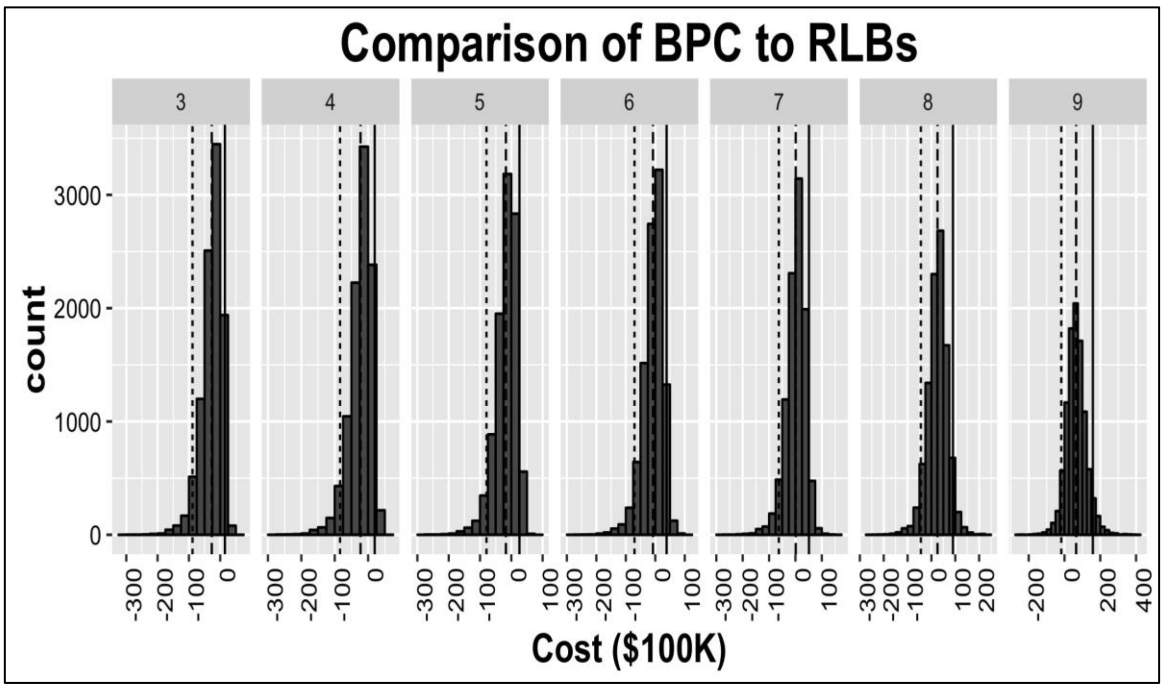


Figure 25: Difference in Observations for BPC and RLB

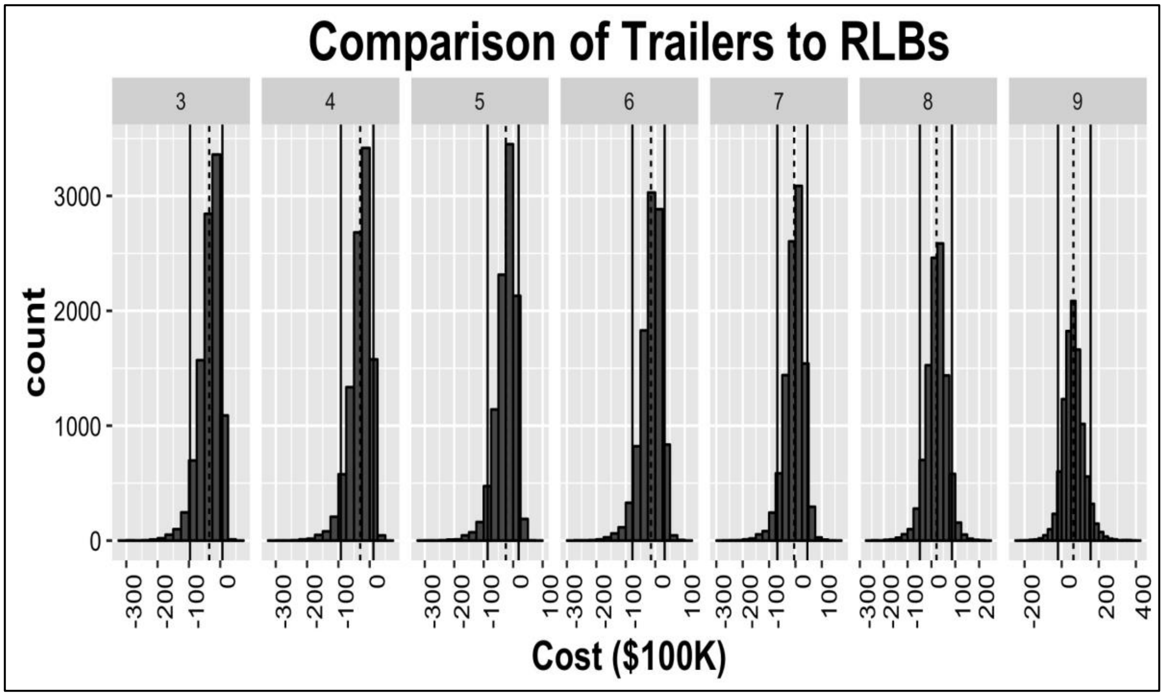


Figure 26: Difference in Observations for Trailer and RLB

Table 13: Difference Analysis Stochastic Dominance Chart

	P(Diff > 0)		
Scenario	**BPC - Trailer**	**BPC - RLB**	**Trailer - RLB**
3 Years	1	0.1973	0.1035
4 Years	1	0.2549	0.1585
5 Years	1	0.3302	0.2291
6 Years	0.9997	0.4586	0.3679
7 Years	0.9844	0.5621	0.4907
8 Years	0.8591	0.7569	0.7247
9 Years	0.6089	0.8973	0.8936

50 Year Life Cycle Comparison

Since the BPC has a fifty-year life cycle, its life cycle cost will be conceptually cheap because its design is more resilient and reliable. The purpose of the fifty-year life cycle comparison was to investigate if the BPC's reliability will make it the most economic alternative in scenarios for which the duration of the contingency is long. As in the previous analysis, changes in stochastic dominance are of interest. In order to investigate changes in stochastic dominance, the cost to house personnel with the trailer and RLB designs must be calculated for a period of fifty year, matching the BPC's life cycle. Thus, the BPC was assumed to have a fifty-year service life, while the RLB and trailer designs were assumed to have a ten-year service life.

Major assumptions were made to simulate fifty-year service lives with limited data. For example, maintenance year's one through seven were repeated for the BPC design in order to simulation a fifty-year life cycle. Alternatively, maintenance years one through seven were used to simulate the first seven years of the trailer's and RLB's service lives. Moreover, the last three years were assumed to be similar to years five, six, and seven. Acquisitions and disposal costs were, also, added five times to simulate the disposal of a dilapidated facility and a construction of a new facility in its place.

The simulation demonstrated that permanent construction is preferred for periods greater than or equal to 12 years, while semi-permanent construction is preferred for periods less than 11 years. The RLB design was consistently the most expensive design; however, the first five years of the design's service life seem to overlap with the other two design's distribution of life cycle costs. Ultimately, these results suggest that semi-permanent designs are preferable for contingencies less than 12 years, while permanent standards for preferable for contingencies of 12 years or more. Descriptive statistics of each contingency scenario can be found in Appendix B.

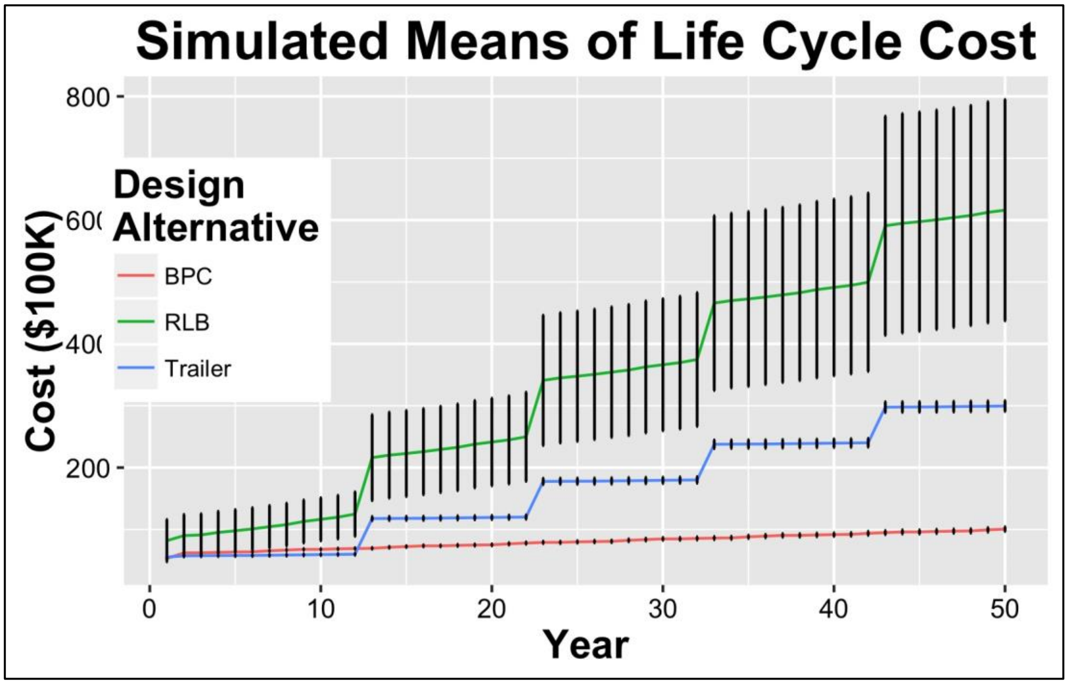


Figure 27: 50 Year Comparison Means Plot

Analysis of Selection in Uncertain Conditions

The purpose of the analysis of selection in uncertain conditions was to understand how the life cycle costs of each design alternative changes as the certainty of a mission duration changes. In contrast to analysis under certain conditions, the probabilistic analysis introduced uncertainty in the selection of a design alternative. The probabilistic analysis was broken down into two Monte Carlo simulations. The first simulation assumed the duration of a mission that followed the distribution of durations of forward operation bases used during Operation Enduring Freedom (OEF). The second simulation's purpose was to provide bring some utility to the model, as it sought to resemble a decision maker's feeling of certainty of mission duration. With time as a random variable, each simulation used the adjustment factors with the following model:

$$NPW(t)_{x1} = AC(ln(\mu,\sigma))_{x1} + \sum_{t=0}^{n}\left\{\left(\frac{1}{(1+i)^t}\right)[MC((ln(\mu,\sigma)))]_{x1,t}\right\} + \left[\left(\frac{1}{(1+i)^t}\right)(DC(ln(\mu,\sigma)))_{x1}\right]$$

Where,

NPW_{x1} = net present worth of costs for facility design x1, for analysis period of t years

$(AC)_{x1}$ = acquisition cost for alternative x1

$[MC]_{x1,t}$ = maintenance costs for alternative x1 in year t

$(DC)_{x1}$ = disposal cost for alternative x1, at the end of the analysis period, t years

i = discount rate for t years

Operation Enduring Freedom Simulation

The OEF simulation's key assumption was that a base's life cycle could be modeled via the distribution of OEF forward operating base durations of Operation Enduring Freedom. Data on the open and closure dates of several FOBs were collected from various sources and subtracted to calculate a net duration for each observation. Since the result was integer, time based data, the Poisson distribution was tried for goodness-of-fit. Similar to the cost data distribution fitting, JMP® was used to test durations with the KS The results of the goodness of fit test from JMP® are shown in Figure 28.

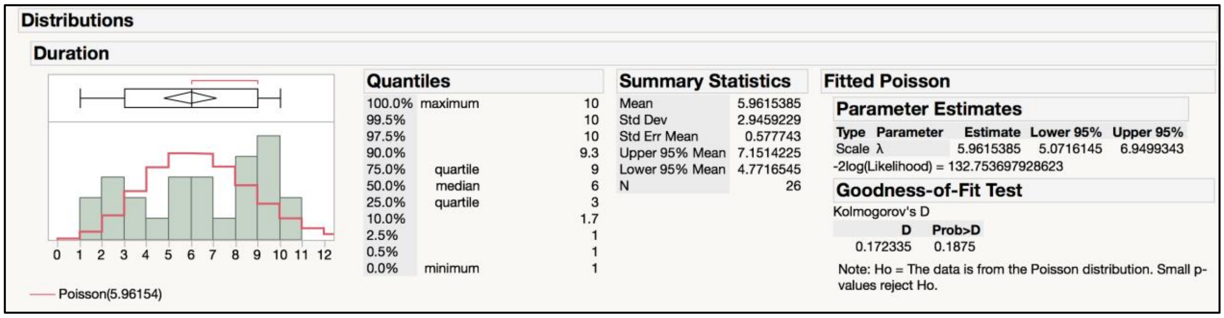


Figure 28: Duration Goodness of Fit Test

Unlike the analysis of selection in certain conditions, the variance in distribution of time forced the Monte Carlo simulation to generate random scenarios of contingency duration. Therefore, the simulation calculated 10,000 life cycle costs that were calculated for each generated scenario of a contingency. In contrast to the analysis under certain conditions, the Wilcoxon signed rank test was executed to compare the differences of the observations of each design. The results of the tests, shown in Table 14, indicated that each distributions of life cycle costs are independent. Moreover, the trailer was found to be stochastically cheaper than the other designs. This simulation's histograms are shown in Figure 29 and the comparisons are shown in

Table 15. Descriptive statistics of the simulation can be found in Appendix C.

Table 14: OEF Simulation Wilcoxon Signed Rank Test Results

Comparison	V	p-value	90% Confidence Interval	Pseudo median
BPC to. Trailer	50005000	<0.0001*	[19.64, 19.67]	19.65
BPC To RLB	291620	<0.0001*	[-42.75, -41.67]	-42.21
Trailer to RLB	95	<0.0001*	[-62.42, -61.34]	-61.88

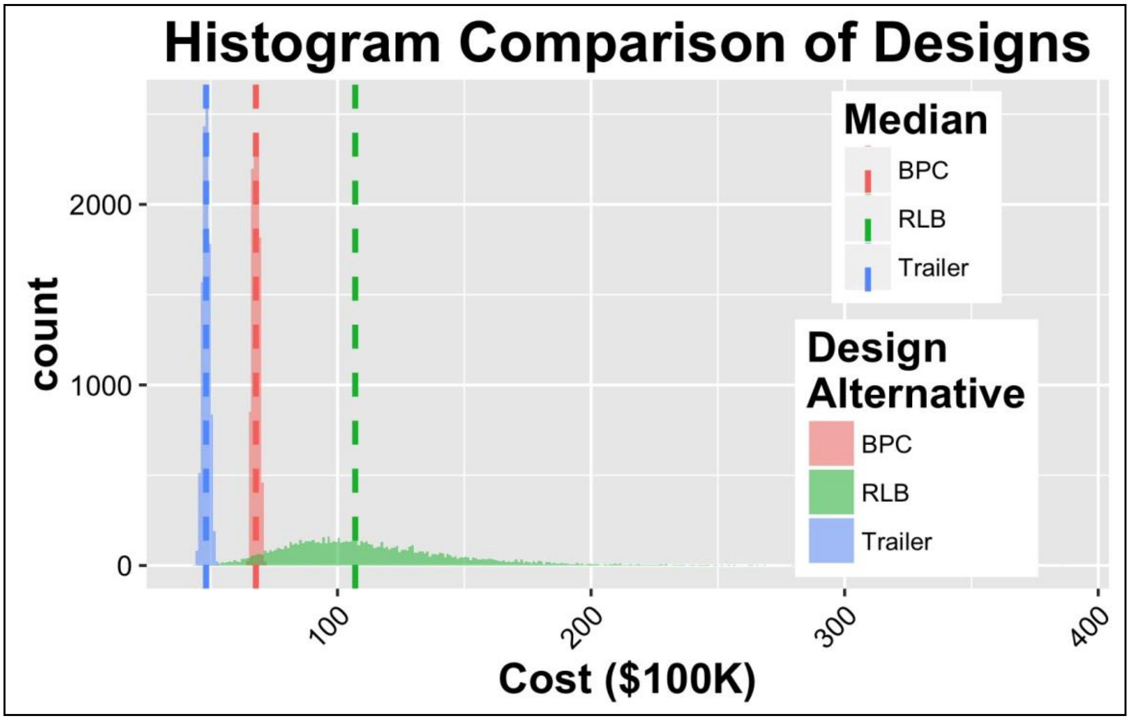


Figure 29: OEF Simulation LCC Histograms

Table 15: OEF Simulation Stochastic Dominance Chart

Comparison	Probability
BPC < TRA	0
BPC < RLB	0.9571
TRA < RLB	0.9997

Lack of Knowledge Simulations

The lack of knowledge simulations' purpose was to model a decision maker's uncertainty on a potential duration of a contingency. As literature suggested, a triangular distribution was assumed to describe a decision maker's uncertainty on the duration of a mission. The minimum and maximum values for the distribution were assumed to be three and nine, respectively. The mode, on the other hand, was changed from 3 years to 9 years to simulate a decision maker's estimate on a likely scenario. Thus, this portion of the analysis was similar to the adjusted analysis under certainty.

Like the OEF simulation, the expected value, or mean, of the distribution of a design's life cycle cost can shed light on which design alternative is statically cheapest. The Wilcoxon Signed Rank test tested the paired differences of each scenario and determined if the distributions are statistically independent. The results, shown in Table 16, indicated that each distribution was statistically independent. Additionally, the RLB was found to be the most expensive design, while the trailer was found to be the least expensive design, as shown in Figure 30. Descriptive statistics of each scenario are provided in Appendix C.

Table 16: Lack of Knowledge Simulations Wilcoxon Signed Rank Test Results

Years of Use	Comparison	V	p-value	90% Confidence Interval	Pseudomedian
3 Years	BPC to Trailer	50005000	<0.0001*	[19.65, 19.69]	19.67
	BPC To RLB	295870	<0.0001*	[-42.13, -41.03]	-41.58
	Trailer to RLB	57	<0.0001*	[-61.80, -60.70]	-61.25
4 Years	BPC to Trailer	50005000	<0.0001*	[19.67, 19.70]	19.69
	BPC To RLB	298100	<0.0001*	[-42.58, -41.49]	-42.04
	Trailer to RLB	71	<0.0001*	[-62.27, -61.18]	-61.73
5 Years	BPC to Trailer	50005000	<0.0001*	[19.64, 19.68]	19.66
	BPC To RLB	340270	<0.0001*	[-41.92, -40.80]	-41.36
	Trailer to RLB	248	<0.0001*	[-61.59, -60.48]	-61.03
6 Years	BPC to Trailer	50005000	<0.0001*	[19.63, 19.67]	19.66
	BPC To RLB	345900	<0.0001*	[-42.31, -41.19]	-41.76
	Trailer to RLB	282	<0.0001*	[-61.97, -60.85]	-61.41
7 Years	BPC to Trailer	50005000	<0.0001*	[19.65 19.69]	19.68
	BPC To RLB	335000	<0.0001*	[-41.75, -40.64]	-41.20
	Trailer to RLB	2	<0.0001*	[-61.43, -60.33]	-60.88
8 Years	BPC to Trailer	50005000	<0.0001*	[19.66, 19.69]	19.68
	BPC To RLB	316700	<0.0001*	[-42.28, -41.18]	-41.74
	Trailer to RLB	92	<0.0001*	[-61.96, -60.86]	-61.42
9 Years	BPC to Trailer	50005000	<0.0001*	[19.63, 19.67]	19.66
	BPC To RLB	320130	<0.0001*	[-42.44, -41.34]	-41.90
	Trailer to RLB	184	<0.0001*	[-62.11, -61.01]	-61.56

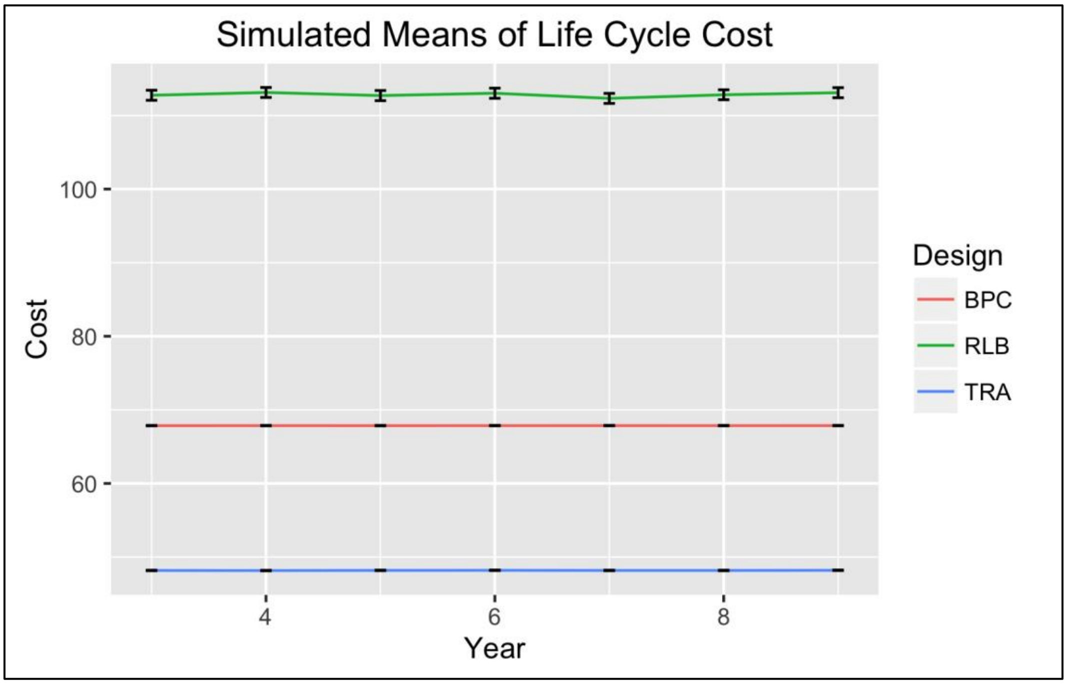


Figure 30: Expected Value of LCC for each Design in Each Scenario

In addition, each scenario was individually investigated to further understand stochastic dominance. The results found that the trailer was consistently the cheapest design, while the RLB was the most expensive design. The variance of each design, however, introduces uncertainty in a clear answer of the cheapest design; therefore, the probability that one design is cheaper than another is a more accurate measurement. The histograms of the three and nine year scenarios, in Figure 31 and Figure 32, do not show significant changes in stochastic dominance. Moreover, Table 17 reflects this observation of minimal changes in the results of each comparison of each design alternatives. Descriptive statistics of each scenario can be found in Appendix C.

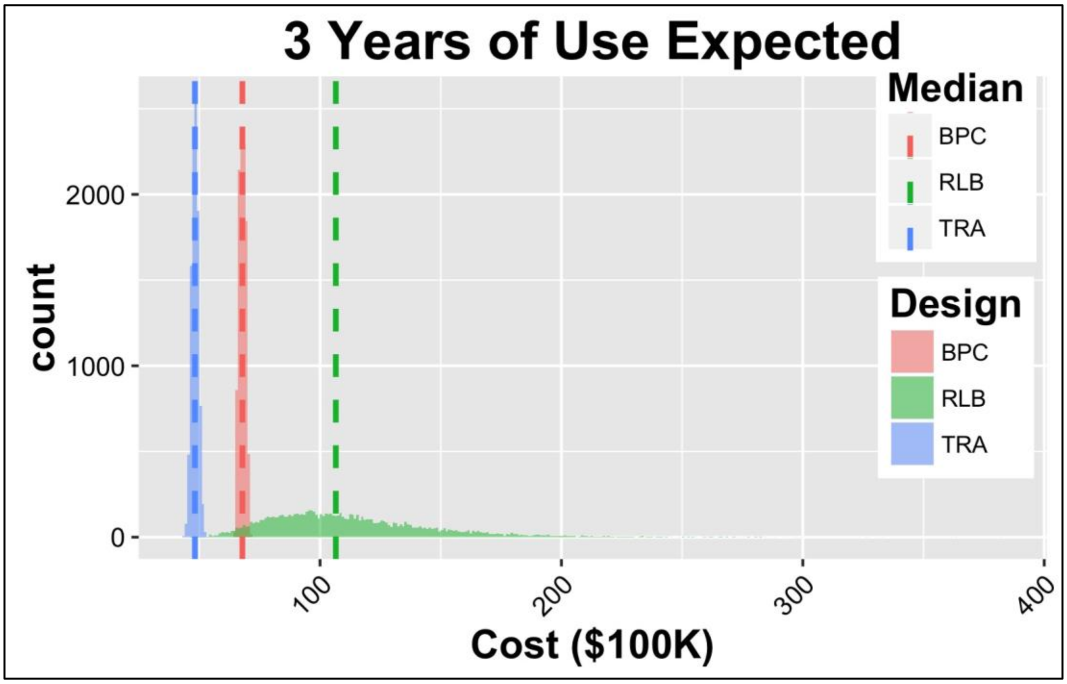


Figure 31: Simulated LCC for 3 Years of Use Most Probable

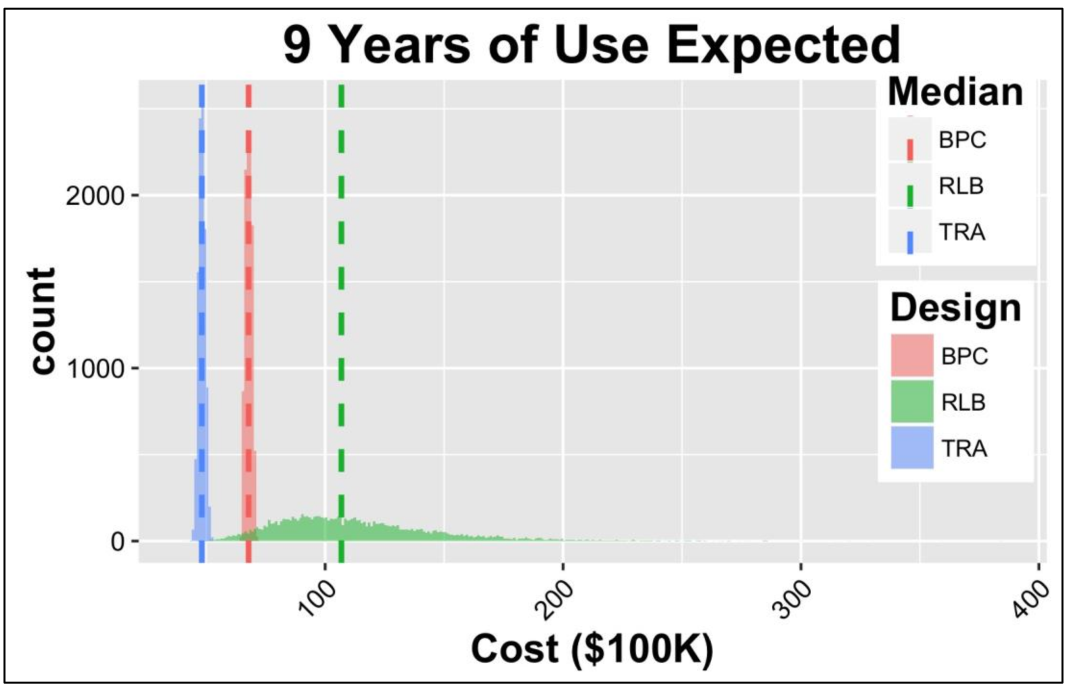


Figure 32: Simulated LCC for 9 Years of Use Most Probable

Table 17: Lack of Knowledge Simulation Stochastic Dominance Chart

Scenario	P(BPC < TRA)	P(BPC < RLB)	P(TRA < RLB)
3	0	0.9564	0.9994
4	0	0.9577	0.9995
5	0	0.955	0.9992
6	0	0.9525	0.9989
7	0	0.9557	0.9999
8	0	0.9555	0.9995
9	0	0.9544	0.9993

Risk Analysis Under Uncertain Conditions

The purpose of the risk analysis was to understand how a decision makers risk profile might affect the outcome of a decision. Whereas all aforementioned analysis reported results of risk neutral risk profiles, the risk analysis under uncertain conditions assumes that decision makers are inherently risk averse and prefer alternatives that have the least expected utility. The two risk averse profiles shown in Figure 33, were tried in the simulation, describing a two different tolerances of risk with respect to a decision maker's current budget or state of wealth. The risk aversion profiles are described though the expected utility function and its risk aversion parameter, ρ. For the purposes of this research, risk profile #1 and #2 assumes that a decision maker has a risk aversion factor of 30,000,000 and 5,000,000, respectively. Risk profile #1 is considered as a highly risk averse profile while risk profile #2 is moderately risk averse. Since this research deals with costs, small utility values indicate preferred alternatives for the OEF simulation and lack of knowledge simulation. The two simulations conducted in the analysis under uncertain conditions were performed with the life cycle cost model and then transformed to an expected utility, using the function shown below.

$$u(NPW_{x1}) = 1 - e^{-\left(\frac{NPW_{x1}}{R}\right)}$$

Where,

u = the expected utility

NPW = Net Present Worth of Design alternative, x1

R = a decision maker's risk aversion parameter

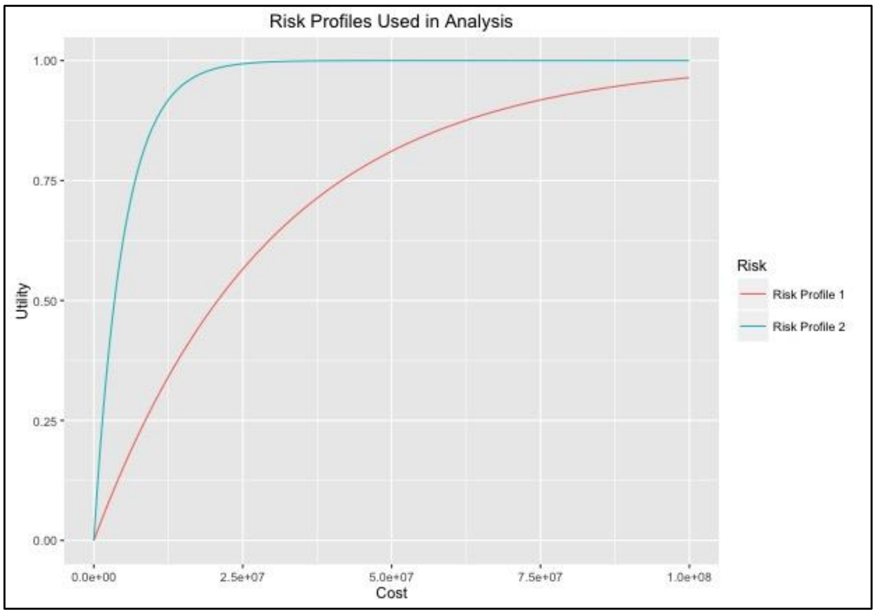


Figure 33: Risk Profiles Used In Analysis

Operation Enduring Freedom Simulation

The introduction of the two decision maker risk profiles did not change the preferred alternatives. As in the analysis for selection in uncertain conditions, the OEF simulation resulted in the trailer as being the preferred alternative for both risk profiles. Risk profile #1's distributions of utility for each design alternative scored lower than that of risk profile #2, as shown in Figure 34. Since smaller scores are better when considering costs, this indicates that all design alternatives are less risky with risk profile 1. Alternatively, the alternatives are more risky with risk profile #2 because of the decision maker's budget or current state of wealth. The results of the simulation were tested for independence with the Wilcoxon Signed Ranked test, and the three designs were found to be statistically independent, as indicated in Table 18. The comparisons for each risk profile are shown in

Table 19. Descriptive statistics of the simulations can be found in Appendix D.

Table 18: OEF Simulation Risk Analysis Wilcoxon Signed Rank Test Results

Risk Profile	Comparison	V	p-value	90% Confidence Interval	Pseudomedian
1	BPC to Trailer	50005000	<0.0001*	[0.054, 0.054]	0.054
	BPC To RLB	362500	<0.0001*	[-0.102, -0.099]	-0.101
	Trailer to RLB	154	<0.0001*	[-0.156, -0.153]	-0.222
2	BPC to Trailer	50005000	<0.0001*	[0.124, 0.124]	0.124
	BPC To RLB	458550	<0.0001*	[-0.135, -0.132]	-0.134
	Trailer to RLB	173	<0.0001*	[-0.259, -0.257]	-0.258

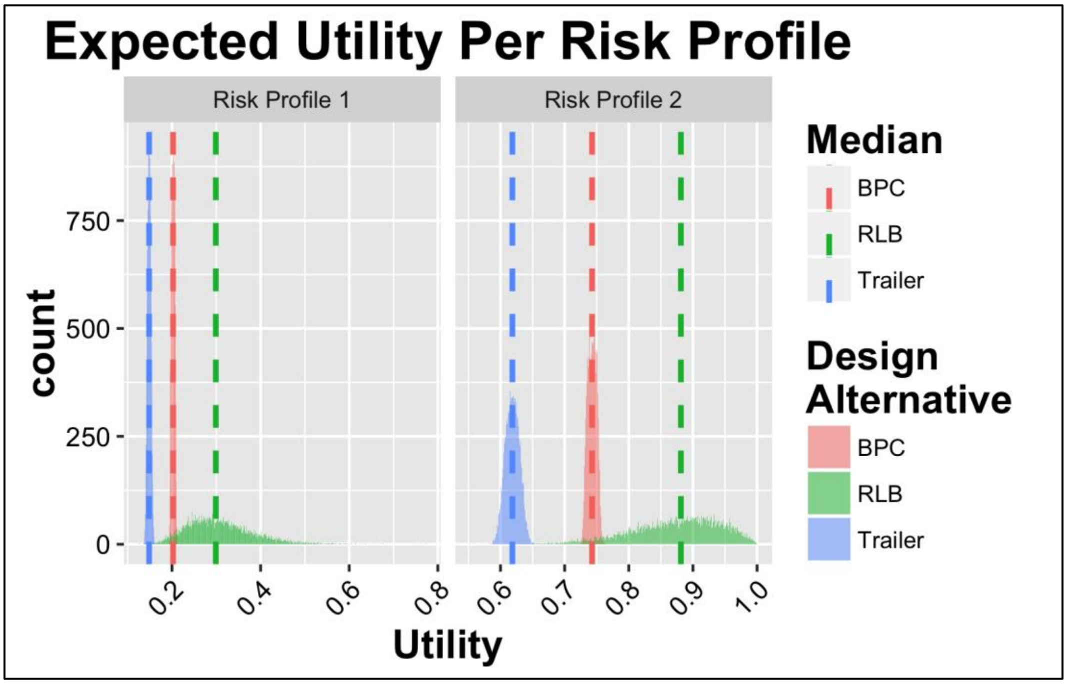


Figure 34: OEF Risk Analysis Histograms

Table 19: OEF Simulation Risk Analysis Comparisons

Comparison	Risk Profile 1	Risk Profile 2
P(BPC < Trailer)	0	0
P(BPC < RLB)	0.9531	0.9531
P(Trailer < RLB)	0.9991	0.9991

Lack of Knowledge Simulations

Like the OEF Risk analysis, the incorporation of the two risk profiles did not change the preferred alternatives for all scenarios. The trailer was consistently found to be the desired design alternative as it had the lowest expected utility of the three designs. The results of each scenario were tested for independence through the Wilcoxon Signed Rank test, and the results are reported in

Table 21. The three designs' distribution of utility for each risk profile was found to be statistically independent for all scenarios.

To provide some depth of understand for the results, each scenario was investigated to understand the stochastic dominance of each design. There were no significant changes in expected utility in the scenarios for three years of use to nine years of use, as shown in their respective histograms in Figure 35 and Figure 36. Table 20 shows this observation in detail. Descriptive statistics of the results are provided in Appendix D.

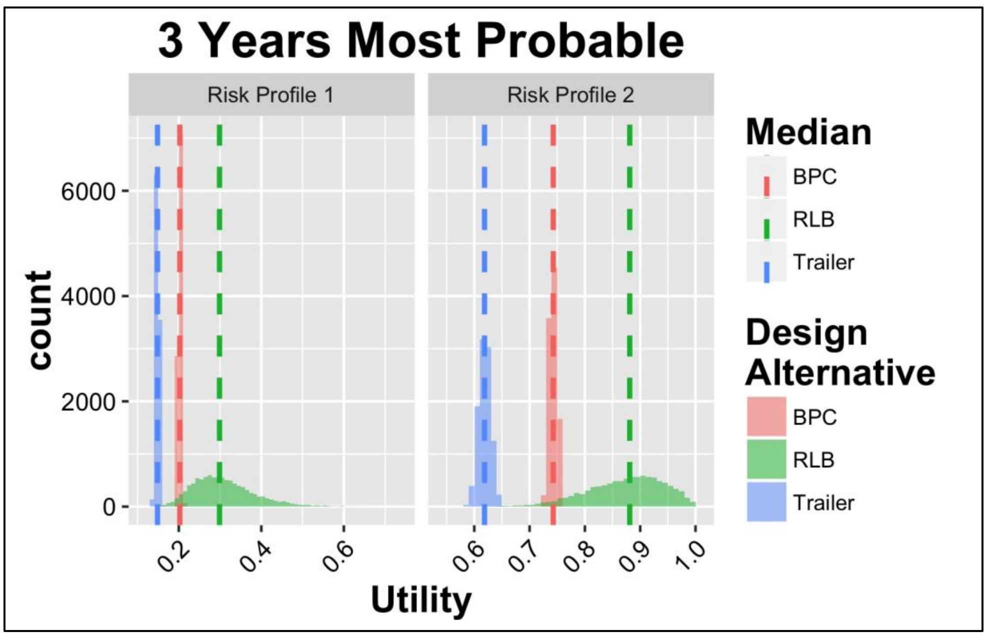


Figure 35: Risk Analysis Results for 3-Year Scenario

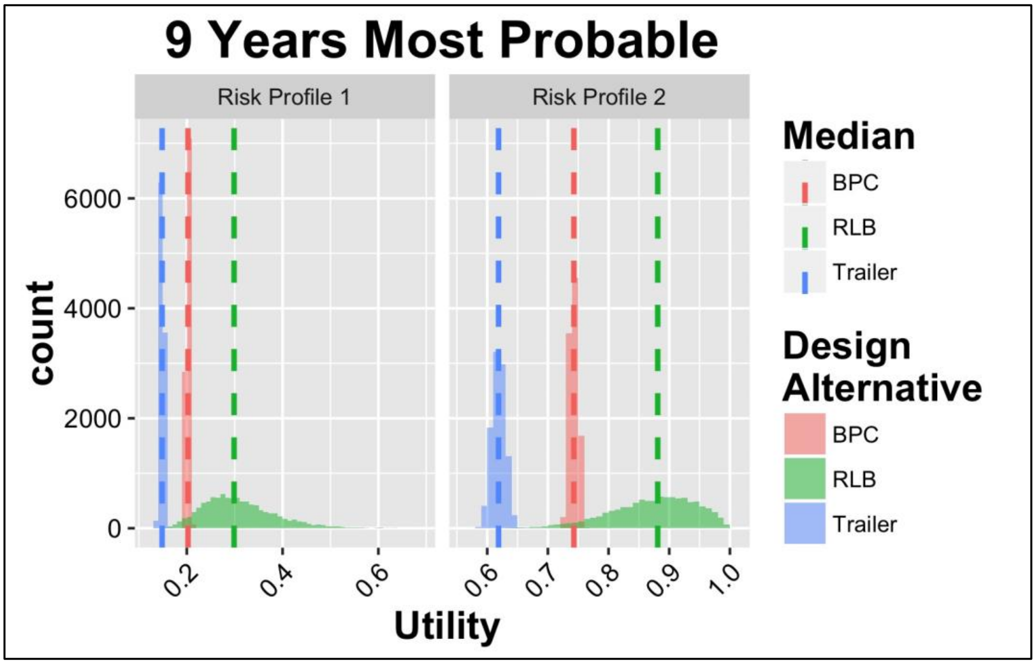


Figure 36: Risk Analysis Results for 9-Year Scenario

Table 20: Lack of Knowledge Risk Analysis Comparisons

Risk Profile	Year	BPC < TRA	BPC < RLB	TRA < RLB
1	3	0	0.9524	0.9991
	4	0	0.952	0.9995
	5	0	0.9541	0.9993
	6	0	0.9583	0.9997
	7	0	0.9572	0.9995
	8	0	0.9559	0.9994
	9	0	0.9555	0.999
2	3	0	0.9524	0.9991
	4	0	0.952	0.9995
	5	0	0.9541	0.9993
	6	0	0.9583	0.9997
	7	0	0.9572	0.9995
	8	0	0.9559	0.9994
	9	0	0.9555	0.999

Table 21: Wilcoxon Signed Rank Test Results

Risk Profile	Years of Use	Comparison	V	p-value	90% Confidence Interval	Pseudomedian
1	3 Years	BPC to Trailer	50005000	<0.0001*	[0.054, 0.054]	0.054
		BPC To RLB	365230	<0.0001*	[-0.102, -0.099]	-0.101
		Trailer to RLB	187	<0.0001*	[-0.156, -0.153]	-0.155
	4 Years	BPC to Trailer	50005000	<0.0001*	[0.053, 0.054]	0.054
		BPC To RLB	326800	<0.0001*	[-0.102, -0.099]	-0.101
		Trailer to RLB	35	<0.0001*	[-0.156, -0.153]	-0.155
	5 Years	BPC to Trailer	50005000	<0.0001*	[0.053, 0.054]	0.054
		BPC To RLB	331460	<0.0001*	[-0.102, -0.100]	-0.102
		Trailer to RLB	55	<0.0001*	[-0.156, -0.154]	-0.156
	6 Years	BPC to Trailer	50005000	<0.0001*	[0.054, 0.054]	0.054
		BPC To RLB	302170	<0.0001*	[-0.102, -0.100]	-0.101
		Trailer to RLB	29	<0.0001*	[-0.156, -0.154]	-0.155
	7 Years	BPC to Trailer	50005000	<0.0001*	[0.059, 0.054]	0.054
		BPC To RLB	295860	<0.0001*	[-0.102, -0.100]	-0.102
		Trailer to RLB	45	<0.0001*	[-0.156, -0.154]	-0.156
	8 Years	BPC to Trailer	50005000	<0.0001*	[0.053, 0.054]	0.054
		BPC To RLB	329420	<0.0001*	[-0.103, -0.100]	-0.102
		Trailer to RLB	135	<0.0001*	[-0.157, -0.154]	-0.156
	9 Years	BPC to Trailer	50005000	<0.0001*	[0.053, 0.054]	0.054
		BPC To RLB	341310	<0.0001*	[-0.101, -0.099]	-0.101
		Trailer to RLB	153	<0.0001*	[-0.155, -0.153]	-0.155
2	3 Years	BPC to Trailer	50005000	<0.0001*	[0.124, 0.124]	0.124
		BPC To RLB	451160	<0.0001*	[-0.134, -0.132]	-0.133
		Trailer to RLB	214	<0.0001*	[-0.258, -0.256]	-0.258
	4 Years	BPC to Trailer	50005000	<0.0001*	[0.123, 0.124]	0.124
		BPC To RLB	389350	<0.0001*	[-0.134, -0.132]	-0.134
		Trailer to RLB	39	<0.0001*	[-0.259, -0.256]	-0.258
	5 Years	BPC to Trailer	50005000	<0.0001*	[0.123, 0.124]	0.124
		BPC To RLB	407570	<0.0001*	[-0.135, -0.133]	-0.134
		Trailer to RLB	55	<0.0001*	[-0.259, -0.257]	-0.258
	6 Years	BPC to Trailer	50005000	<0.0001*	[0.124, 0.124]	0.124
		BPC To RLB	371430	<0.0001*	[-0.135, -0.132]	-0.134
		Trailer to RLB	29	<0.0001*	[-0.259, -0.256]	-0.258
	7 Years	BPC to Trailer	50005000	<0.0001*	[0.123, 0.124]	0.124
		BPC To RLB	368220	<0.0001*	[-0.135, -0.133]	-0.135
		Trailer to RLB	49	<0.0001*	[-0.259, -0.257]	-0.259
	8 Years	BPC to Trailer	50005000	<0.0001*	[0.123, 0.124]	0.124
		BPC To RLB	405960	<0.0001*	[-0.135, -0.133]	-0.135
		Trailer to RLB	156	<0.0001*	[-0.259, -0.257]	-0.259
	9 Years	BPC to Trailer	50005000	<0.0001*	[0.123, 0.123]	0.124
		BPC To RLB	436670	<0.0001*	[-0.134, -0.132]	-0.134
		Trailer to RLB	159	<0.0001*	[-0.258, -0.256]	-0.258

Chapter Summary

In short, the model development and simulations discussed in chapter three were successfully executed with historical ACES-RP and IWIMS data. The results of the simulations, however, are limited in making significant conclusions because many problems presented themselves in the data collection process. Several assumptions were made to address limitations. Nevertheless, the results consistently suggested that the trailer design alternative is the cheapest design if a contingency is to last anywhere between three and nine years. Additionally, the fifty-year analysis suggested that the BPC may be the cheapest alternative for contingencies greater than 12 years, while the trailer was shown to be the cheapest alternative for contingencies less than 12 years.

V. Conclusions and Recommendations

Chapter Overview

The purpose of chapter five is to synthesize the results reported in chapter four in order to answer the investigative questions. In this chapter, answers that reflect the results of the study are provided for all investigative questions. In addition, areas for future research are suggested to enhance the model to provide more reliable information for decision makers considering the transition to enduring.

Investigative Questions Answered

This study was motivated by five investigative questions to provide insight into the decision to transition a contingency base to an enduring status.

Investigative Question 1

How does a decision maker determine if a transition to an enduring status is advantageous?

JP 3-34's guidelines presented the argument that a transition to an enduring status is, effectively, a decision to enhance a contingency base's infrastructure to a higher construction standard. Construction standards are guidelines by which a base constructs or maintains its infrastructure and have five classifications. According to JP 3-34 framework, organic, initial, and temporary standards are suggested for use in contingencies less than two years, while semi-permanent and permanent standards are for those longer than two years. Moreover, JP 3-34 suggests that decision makers should consider the host nation's interests, the COCOM's strategy, and cost efficiency to when considering improving a base's infrastructure. The decision, however, is often made under a substantial amount of uncertainty with several stakeholders having an in interest in the outcome.

Literature strongly supported the idea that uncertain decision situations, similar to that of considering a transition to enduring status, can be simplified into measurable objectives using Multi Objective Decision Analysis (MODA). MODA offers a method of quantifying the monetary and intrinsic value of several alternatives when faced with more than one objective. With respect to a decision to transition to an enduring status, literature suggested that some objectives might include minimizing life cycle cost, maximizing the quality of life, and maximizing force protection of billeting facilities. In order to holistically assess if a transition to an enduring status is advantageous, the economic and intrinsic value of all design alternatives must quantified and evaluated. If an enduring design alternative scores the highest with respect to each objective, then the decision maker can say with some certainty that a transition is advantageous.

Investigative Question 2

How does the duration of a contingency operation affect the decision to transition to an enduring status?

Literature revealed that external and internal factors affect be the reliability over the time the facility is used because materials deteriorate. A decrease in an assets reliability lead to an increase in its maintenance cost over time; therefore, the duration of use of a facility affects its life cycle cost. The results of the analysis under certain conditions aligned with literature, as it suggested that cost does increase with time.

Moreover, the results suggested that a semi-permanent design, the trailer, might be the cheapest for contingencies lasting from 3 to 9 years. The results were also in alignment in what is expected of a temporary design because it was found to be the most expensive for all scenarios. Additionally, the 50-year horizon aligned with literature, as it suggested that permanent designs are optimal for contingencies greater than 12 years. Ultimately, the results showed that duration does seem to affect a design's life cycle.

It should be noted, however, that the results of the analysis under certain conditions are not conclusive because of significant limitations in the model. Acquisitions, maintenance, and disposal costs were only able to be included in the model, as user and operational cost data was not available for each design. In addition, the maintenance data did not include material costs, which explains why maintenance is not a significant contributor to life cycle costs. Additionaly, it appears that if material costs were also included, the preferred time horizon for permanent construction would be less than 12 years. Based on these limitations, one might expect the true optimal transition period to be less than 12 years.

Aside from limitations in data, more research is needed to bring more clarity to the answer of this question because other important objectives of this decision were not included in this scope of this research. It may be the case that temporary designs are valuable to decision makers in certain contingency operations because they provide certain capababilities that fit certain situations. If future research determines this, this may change the time horizons for perfered alternatives.

Investigative Question 3

> *Can an uncertainty in duration of a contingency operation be quantified and incorporated into the decision to transition to an enduring status?*

While literature suggested that uncertainty might change the preferred alternative, the analysis under uncertain conditions suggested otherwise. Despite the introduction of an uncertainty in duration, the analysis's results were consistent with that of the analysis under certain conditions, in that trailer was still found to be the cheapest design alternative. The OEF simulation suggested that if a contingency is expected to be similar to that of OEF, then a trailer might be the cheapest design alternative. Similarly, the lack of knowledge simulation suggested, modeling a decision maker's uncertainty with the triangular distribution, suggested the same. Since there is a high amount of variance in the cost of an RLB, this does present the possibility that there may be events where the RLB is the cheapest design alternative. If additional maintenance cost data was incorporated into the model, it may shrink the variance in the RLB costs or change the preferred alternative. Overall, uncertainty in the duration of the mission did produced different results from that of the analysis under certain conditions.

Investigative Question 4

> *Since risk in inherent in any uncertain decision, how does a decision maker's risk attitude affect the decision to transition to an enduring status?*

Literature suggested that a decision maker's risk attitude could affect the expected utility of alternatives in uncertain decisions. In addition, literature suggested that decision makers typically follow the delta property; therefore, they tend to be risk averse. Because the analysis under certain conditions' results showed that the BPC design alternative is stochastically cheaper in all scenarios, the two risk averse profiles did not produce any change in the preferred alternative. The analysis did show, however, that expected utility did change as a risk attitude approaches risk neutrality. This suggests that a risk-seeking profile might show that the trailer or RLB is desired over the BPC design because the decision maker seeks risk in decisions. Nonetheless, the results showed that risk profiles do change the results but the analysis showed no change in the preferred alternative.

Recommendations for Future Research

In light of an analysis of the result of this study, more research should be done to enhance the model and better inform decision makers facing this decision. With respect to an economical analysis, a few more practical and easily executable studies could include additional information into Uddin et al's model. Future research should include the material cost for maintenance in a comparison of the designs. During the data collection process of this study, it was discovered that material costs at AUAB were being collected and stored in IWIMS. If a study were to include this data, it could at least shed more light on the comparison of the BPC to the trailer designs. Additionally, it is recommended that any subsequent studies to this research investigate sources of information for user and operational costs. Including these costs to the model will provide a stronger analysis of the comparison of the design alternatives as it includes all variables in Uddin et al's life cycle cost model. Finally, future research should be conducted that include historical costs for all variables in Uddin et al's model. This research could provide substantial reliability in its results because all costs have been spent and no prediction or extrapolation is needed.

Outside of an economic analysis, a MODA application that includes all objectives in the decision should be done to determine which alternative is optimal for all involved stakeholders. Since a MODA application incorporates all objectives in a decision, it can include the results from an economic analysis, similar to this study, in its model. This would provide a better understanding of preferred alternatives, when considering all objectives. Furthermore, better alternatives may be developed as a result of such a model. Perhaps the most interesting academic contribution a MODA application would accomplish would be the process of measuring quality of life. The quality of life of a design is a difficult and abstract objective; however, it must be included in a decision to enduring is of interest because it is central to the decision. It is highly recommended that MODA be used in future research as it provides a holistic understanding of the decision to transition to enduring and it may provide better insight into the time horizons of preferred alternatives.

Summary

In conclusion, the goal of this research was to understand the decision of transitioning a contingency base to an enduring status. The study provided a review of literature to investigate how the decision is currently solved and find some additional tools that could be used to make the decision easier. As results of the literature review, a methodology was developed that focused solely on providing an analysis of the life cycle costs of potential design alternatives. The methodology was executed on three design alternatives; however, data availability significantly limited the results of the analysis. Nevertheless, the results showed that the semi-permanent design alternative was stochastically the cheapest design for scenarios where contingencies last anywhere from three to twelve year. For scenarios greater than 12 years, permanent construction standards are stochastically cheapest.

Ultimately, the decision to transition a contingency base to an enduring status is an evaluation of facility designs with respect to a senior decision maker's objectives in a contingency operation. Although this research identified some objectives and quantified some life cycle costs, the decision has not yet been completely been conceptualized. Indeed, this research has shown that cost is an integral piece of the decision; however, multi-objective frameworks quantify both cost and value of designs alternatives. These frameworks are powerful as they allow decision makers to evaluate tradeoffs of designs. Thus, such frameworks should be used to evaluate which bases remain open as Operation Resolute Support continues closing its bases. Moreover, such a framework could be leveraged for future contingency operations to empower decision makers to make informed construction decisions for FOBs in the contingency. Nevertheless, future research in this field is imperative if the DoD is to continue to sustain a presence in the Middle East with limited funds and personnel.

Appendix A: Data Collection

Distribution	Mean	Standard Deviation
MX Hrs Year 1 (2009)	7.56	0.117
MX Hrs Year 2 (2010)	7.28	0.31
MX Hrs Year 3 (2011)	6.91	0.241
MX Hrs Year 4 (2012)	6.56	0.171
MX Hrs Year 5 (2013)	8.14	0.216
MX Hrs Year 6 (2014)	7.85	0.086
MX Hrs Year 7 (2015)	7.79	0.171

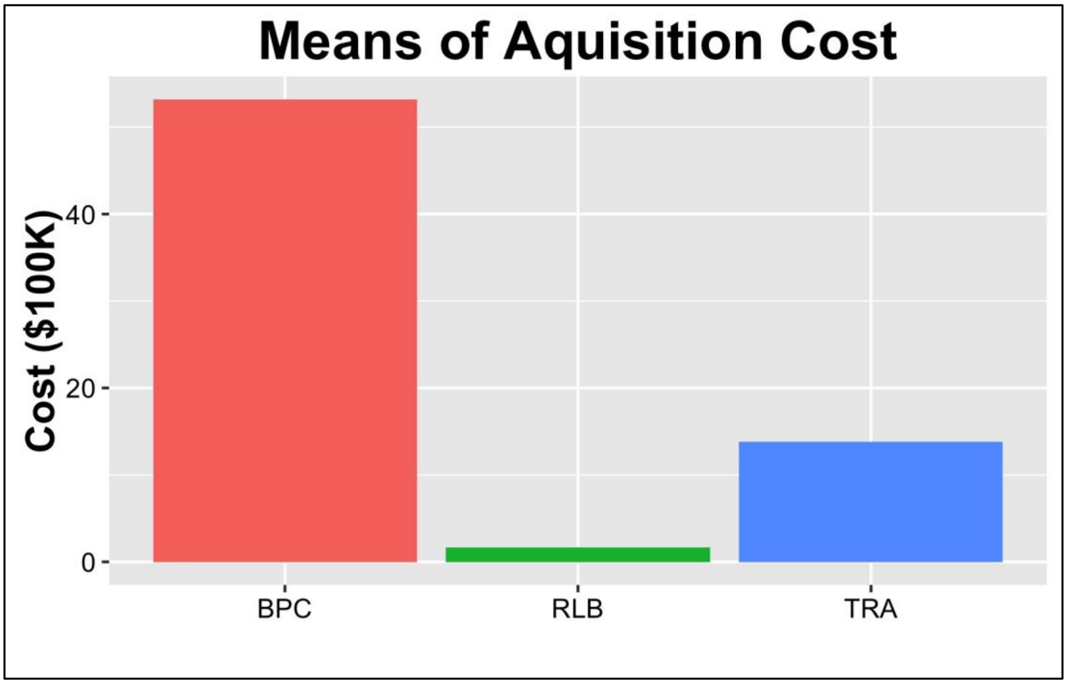
Distribution	Mean	Standard Deviation
Acquisition ($)	13.94	0.021
MX Hrs Year 1 (2009)	4.73	0.338
MX Hrs Year 2 (2010)	4.51	0.468
MX Hrs Year 3 (AVG)	4.13	0.378
MX Hrs Year 4 (2012)	3.75	0.288
MX Hrs Year 5 (2013)	5.21	0.329
MX Hrs Year 6 (2014)	5.12	0.412
MX Hrs Year 7 (2015)	5.07	0.324

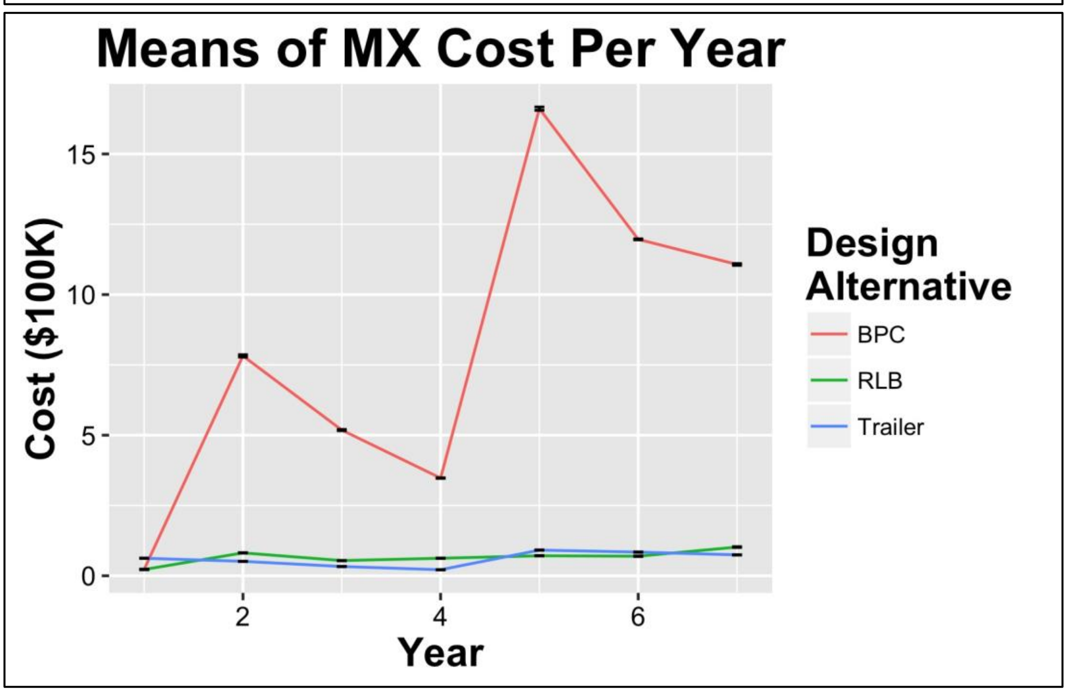
Distribution	Mean	Standard Deviation
Acquisition ($)	11.61	0.372
MX Hrs Year 1 (2013)	3.77	0.661
MX Hrs Year 2 (2014)	5.22	0.444
MX Hrs Year 3 (2015)	4.85	0.422
MX Hrs Year 4 (AVG)	4.95	0.451
MX Hrs Year 5 (2013)	5.06	0.479
MX Hrs Year 6 (2014)	4.89	0.739
MX Hrs Year 7 (2015)	5.33	0.689

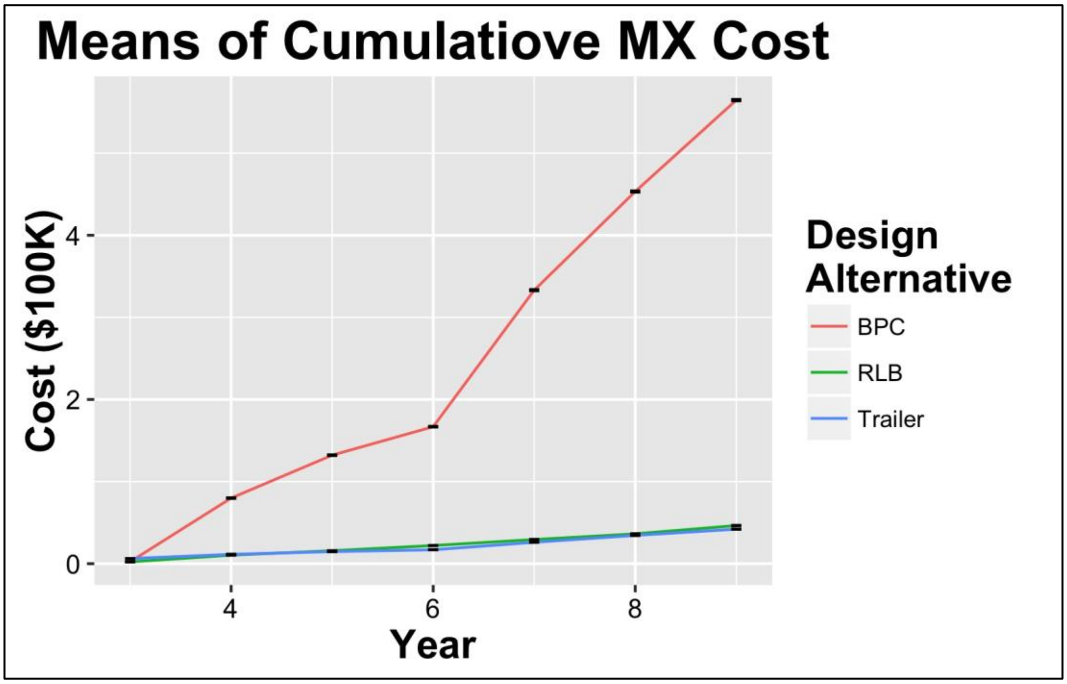
Appendix B: Analysis for Selection Under Certain Conditions

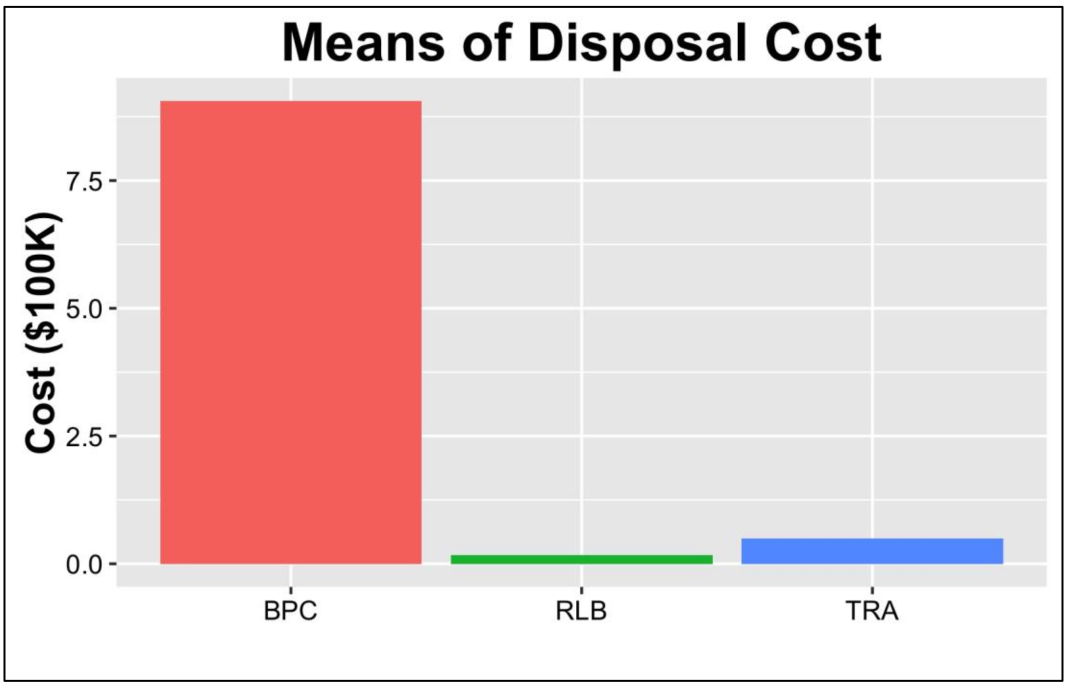
Design Alternative Cost Descriptive Statistics ($100K)						
Design	**Year**	**Cost Type**	**Mean**	**Standard Deviation**	**Standard Error**	**Confidence Interval**
BPC	3	Acquisition	53.186	1.196	0.012	0.020
BPC	3	Disposal	9.057	0.000	0.000	0.000
BPC	3	Life Cycle	62.266	1.196	0.012	0.020
BPC	3	Maintenance	0.023	0.003	0.000	0.000
BPC	4	Acquisition	53.186	1.196	0.012	0.020
BPC	4	Disposal	9.057	0.000	0.000	0.000
BPC	4	Life Cycle	63.042	1.230	0.012	0.020
BPC	4	Maintenance	0.799	0.241	0.002	0.004
BPC	5	Acquisition	53.186	1.196	0.012	0.020
BPC	5	Disposal	9.057	0.000	0.000	0.000
BPC	5	Life Cycle	63.565	1.246	0.012	0.020
BPC	5	Maintenance	1.322	0.278	0.003	0.005
BPC	6	Acquisition	53.186	1.196	0.012	0.020
BPC	6	Disposal	9.057	0.000	0.000	0.000
BPC	6	Life Cycle	63.912	1.255	0.013	0.021
BPC	6	Maintenance	1.669	0.289	0.003	0.005
BPC	7	Acquisition	53.186	1.196	0.012	0.020
BPC	7	Disposal	9.057	0.000	0.000	0.000
BPC	7	Life Cycle	65.575	1.311	0.013	0.022
BPC	7	Maintenance	3.331	0.459	0.005	0.008
BPC	8	Acquisition	53.186	1.196	0.012	0.020
BPC	8	Disposal	9.057	0.000	0.000	0.000
BPC	8	Life Cycle	66.776	1.333	0.013	0.022
BPC	8	Maintenance	4.533	0.476	0.005	0.008
BPC	9	Acquisition	53.186	1.196	0.012	0.020
BPC	9	Disposal	9.057	0.000	0.000	0.000
BPC	9	Life Cycle	67.889	1.341	0.013	0.022
BPC	9	Maintenance	5.646	0.516	0.005	0.008
RLB	3	Acquisition	1.661	0.689	0.007	0.011
RLB	3	Disposal	0.166	0.000	0.000	0.000
RLB	3	Life Cycle	1.850	0.690	0.007	0.011
RLB	3	Maintenance	0.022	0.017	0.000	0.000
RLB	4	Acquisition	1.665	0.690	0.007	0.011
RLB	4	Disposal	0.166	0.000	0.000	0.000
RLB	4	Life Cycle	1.936	0.691	0.007	0.011
RLB	4	Maintenance	0.104	0.042	0.000	0.001
RLB	5	Acquisition	1.667	0.695	0.007	0.011
RLB	5	Disposal	0.166	0.000	0.000	0.000
RLB	5	Life Cycle	1.992	0.696	0.007	0.011
RLB	5	Maintenance	0.158	0.047	0.000	0.001
RLB	6	Acquisition	1.670	0.702	0.007	0.012
RLB	6	Disposal	0.166	0.000	0.000	0.000
RLB	6	Life Cycle	2.058	0.704	0.007	0.012

RLB	6	Maintenance	0.221	0.057	0.001	0.001
RLB	7	Acquisition	1.676	0.700	0.007	0.012
RLB	7	Disposal	0.166	0.000	0.000	0.000
RLB	7	Life Cycle	2.137	0.705	0.007	0.012
RLB	7	Maintenance	0.294	0.069	0.001	0.001
RLB	8	Acquisition	1.670	0.678	0.007	0.011
RLB	8	Disposal	0.166	0.000	0.000	0.000
RLB	8	Life Cycle	2.200	0.684	0.007	0.011
RLB	8	Maintenance	0.363	0.091	0.001	0.001
RLB	9	Acquisition	1.669	0.708	0.007	0.012
RLB	9	Disposal	0.166	0.000	0.000	0.000
RLB	9	Life Cycle	2.299	0.717	0.007	0.012
RLB	9	Maintenance	0.464	0.121	0.001	0.002
TRA	3	Acquisition	13.841	0.427	0.004	0.007
TRA	3	Disposal	0.499	0.000	0.000	0.000
TRA	3	Life Cycle	14.403	0.428	0.004	0.007
TRA	3	Maintenance	0.062	0.022	0.000	0.000
TRA	4	Acquisition	13.839	0.435	0.004	0.007
TRA	4	Disposal	0.499	0.000	0.000	0.000
TRA	4	Life Cycle	14.452	0.437	0.004	0.007
TRA	4	Maintenance	0.114	0.034	0.000	0.001
TRA	5	Acquisition	13.841	0.425	0.004	0.007
TRA	5	Disposal	0.499	0.000	0.000	0.000
TRA	5	Life Cycle	14.487	0.429	0.004	0.007
TRA	5	Maintenance	0.147	0.036	0.000	0.001
TRA	6	Acquisition	13.836	0.422	0.004	0.007
TRA	6	Disposal	0.499	0.000	0.000	0.000
TRA	6	Life Cycle	14.505	0.426	0.004	0.007
TRA	6	Maintenance	0.169	0.037	0.000	0.001
TRA	7	Acquisition	13.842	0.431	0.004	0.007
TRA	7	Disposal	0.499	0.000	0.000	0.000
TRA	7	Life Cycle	14.602	0.436	0.004	0.007
TRA	7	Maintenance	0.261	0.048	0.000	0.001
TRA	8	Acquisition	13.841	0.426	0.004	0.007
TRA	8	Disposal	0.499	0.000	0.000	0.000
TRA	8	Life Cycle	14.685	0.433	0.004	0.007
TRA	8	Maintenance	0.345	0.061	0.001	0.001
TRA	9	Acquisition	13.842	0.428	0.004	0.007
TRA	9	Disposal	0.499	0.000	0.000	0.000
TRA	9	Life Cycle	14.762	0.436	0.004	0.007
TRA	9	Maintenance	0.420	0.064	0.001	0.001

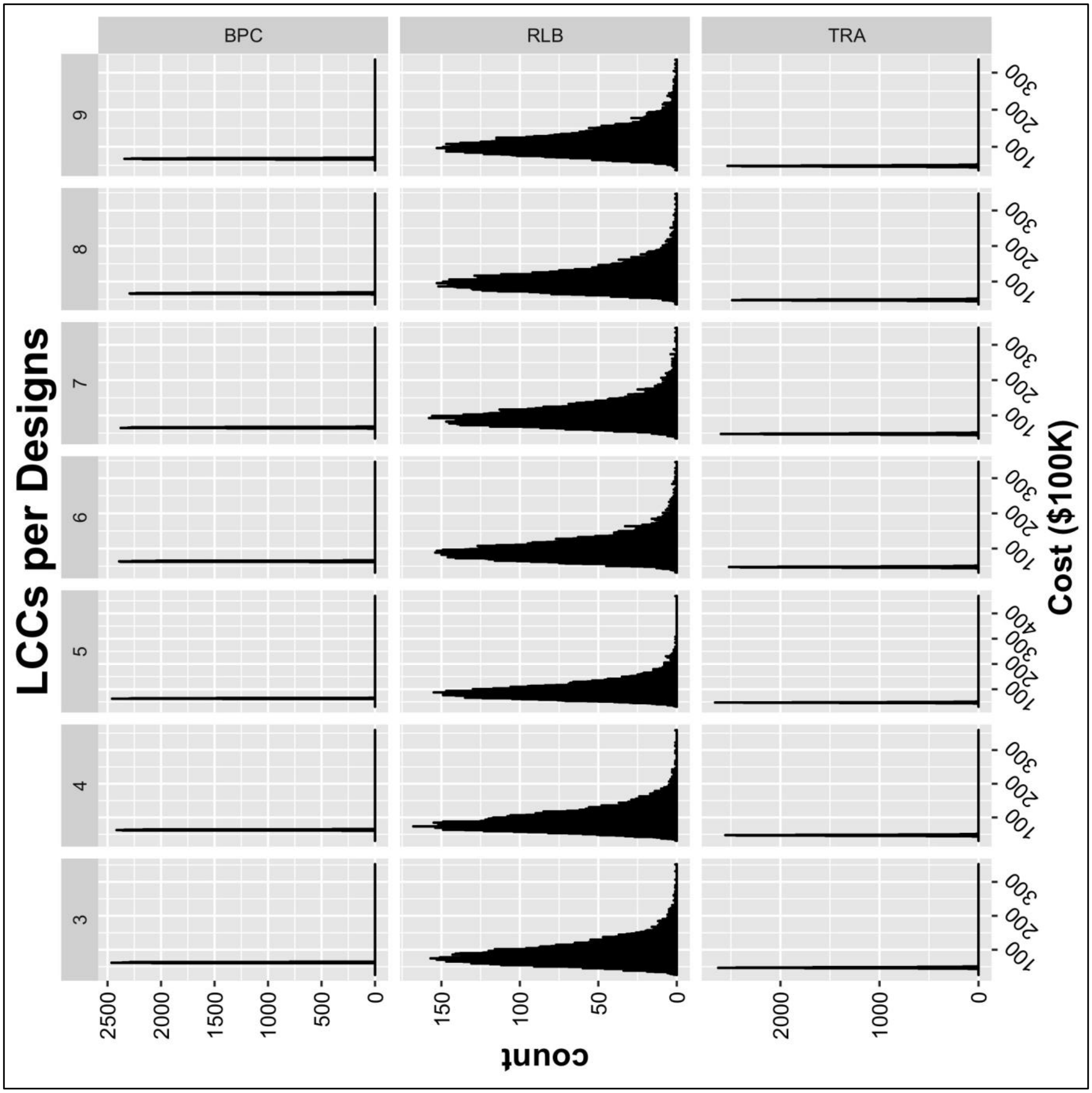

Means of Aquisition Cost
Cost ($100K)
0
20
40
BPC
RLB
TRA


Means of MX Cost Per Year
Cost ($100K)
0
5
10
15
2
4
6
Year
Design Alternative
BPC
RLB
Trailer

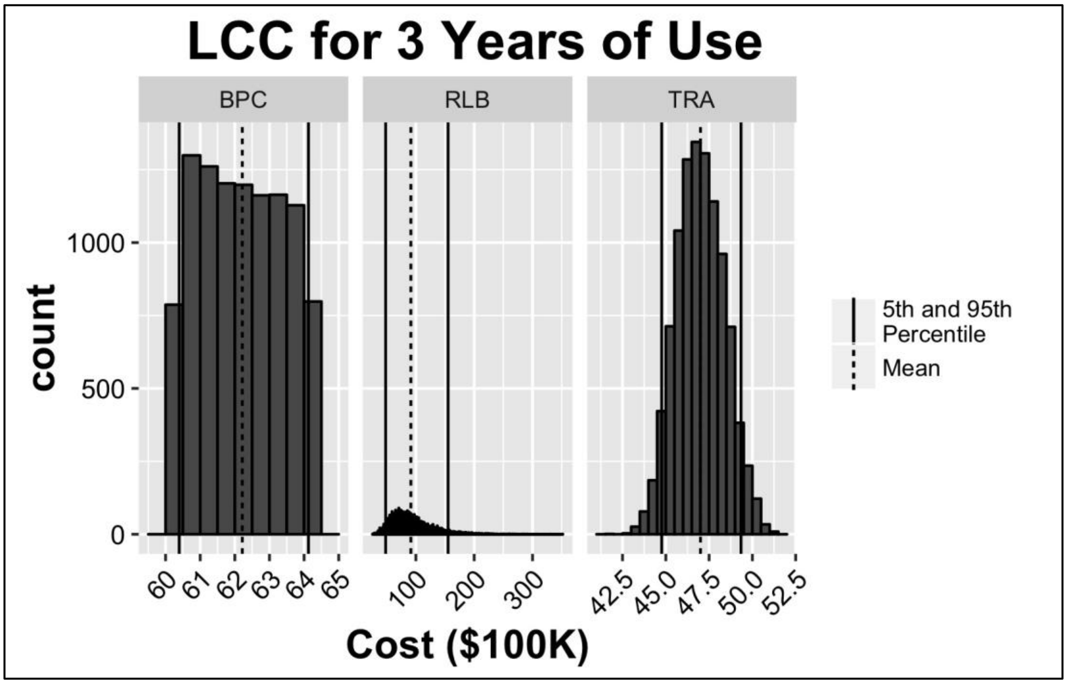

Means of Cumulatiove MX Cost
Cost ($100K)
0
2
4
4
6
8
Year
Design Alternative
BPC
RLB
Trailer

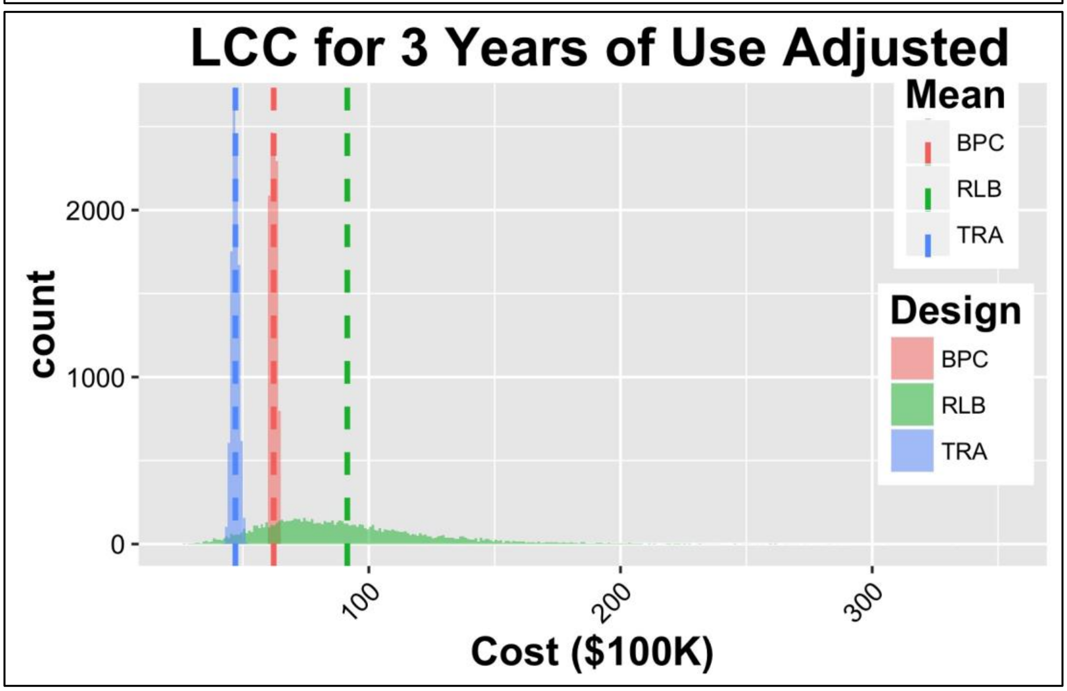

Means of Disposal Cost
Cost ($100K)
0.0
2.5
5.0
7.5
BPC
RLB
TRA

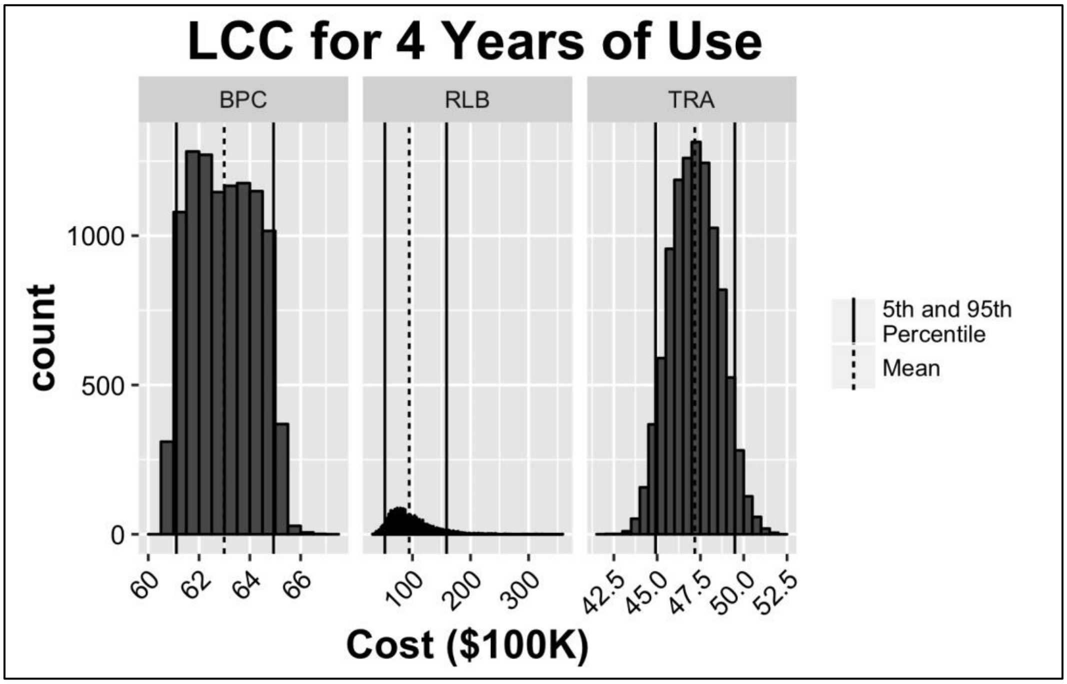
Adjusted Life Cycle Cost Descriptive Statistics ($100K)						
Design	Year	Mean	Standard Deviation	Standard Error	5th Percentile	95th Percentile
BPC	3	62.215	1.192	0.012	60.376	64.111
BPC	4	62.993	1.233	0.012	61.093	64.945
BPC	5	63.512	1.241	0.012	61.584	65.465
BPC	6	63.862	1.246	0.012	61.939	65.817
BPC	7	65.522	1.321	0.013	63.440	67.636
BPC	8	66.715	1.321	0.013	64.631	68.821
BPC	9	67.824	1.336	0.013	65.750	69.959
RLB	3	91.101	33.985	0.340	48.626	153.976
RLB	4	95.192	34.312	0.343	52.554	158.745
RLB	5	98.164	34.210	0.342	55.525	162.740
RLB	6	101.259	34.927	0.349	57.643	165.795
RLB	7	103.914	34.333	0.343	61.020	167.821
RLB	8	108.134	34.726	0.347	64.511	173.107
RLB	9	113.221	34.480	0.345	69.131	177.930
TRA	3	47.000	1.396	0.014	44.753	49.325
TRA	4	47.175	1.386	0.014	44.941	49.463
TRA	5	47.283	1.376	0.014	45.091	49.565
TRA	6	47.339	1.402	0.014	45.081	49.685
TRA	7	47.668	1.418	0.014	45.406	50.012
TRA	8	47.909	1.408	0.014	45.676	50.233
TRA	9	48.174	1.412	0.014	45.880	50.540

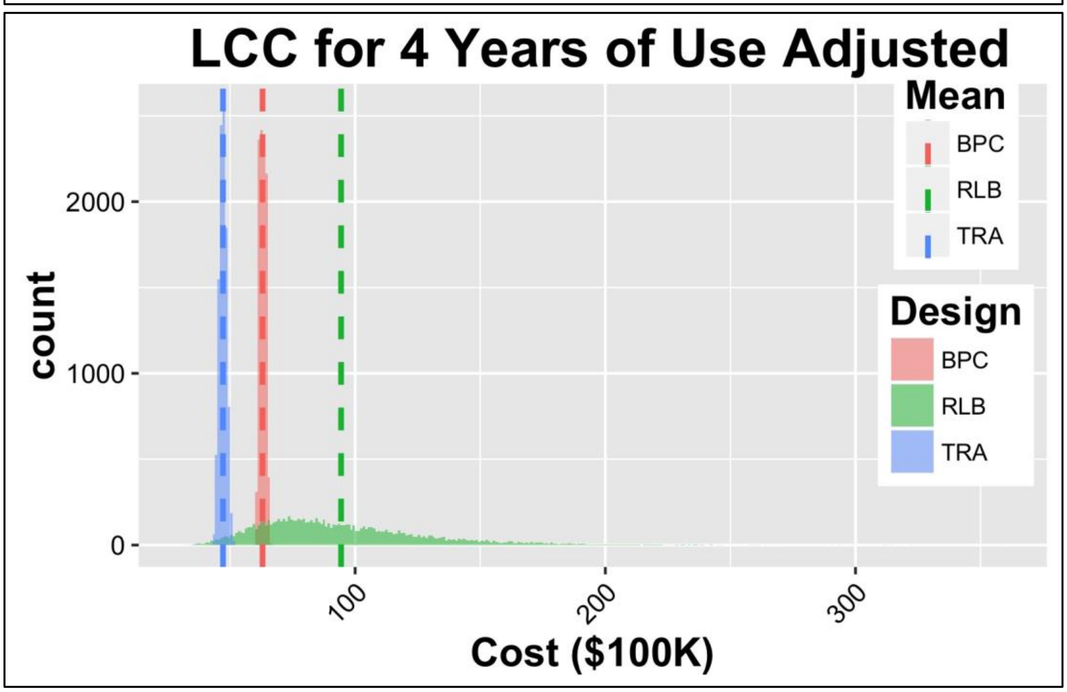


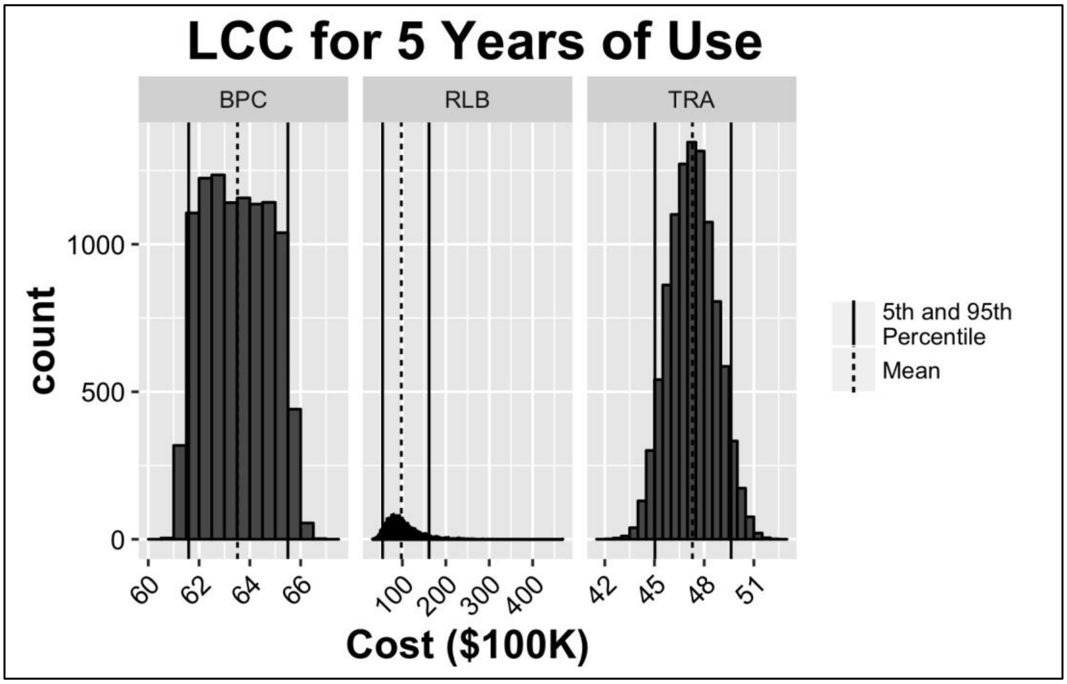
LCCs per Designs
BPC
RLB
TRA
3
4
5
6
7
8
9
count
Cost ($100K)

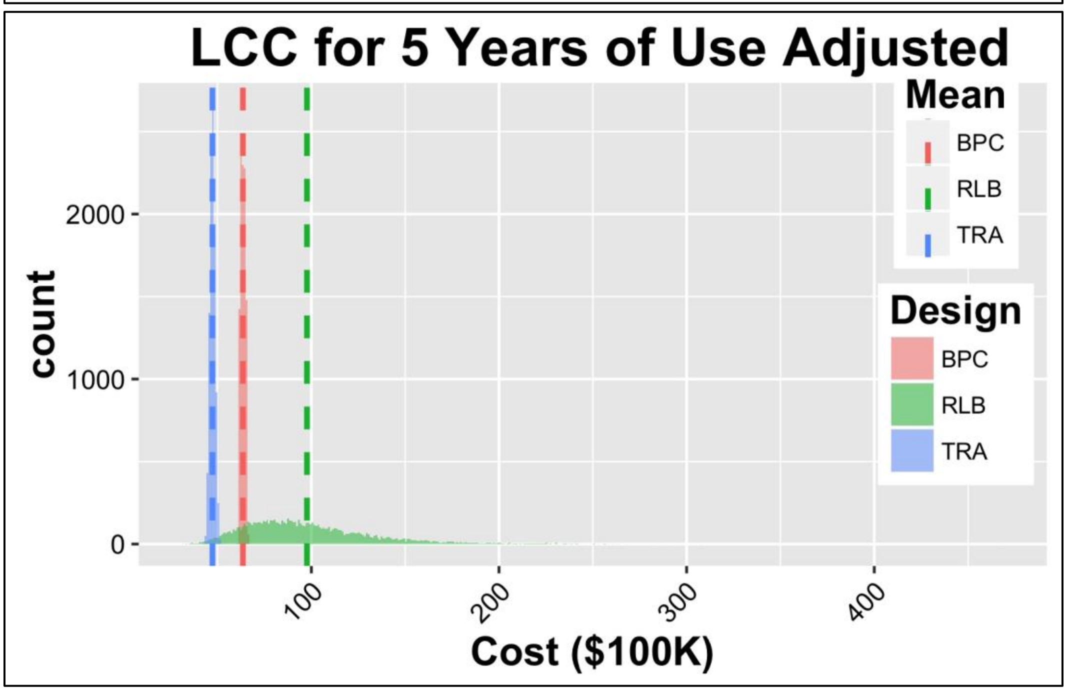

LCC for 3 Years of Use
BPC
RLB
TRA
count
Cost ($100K)
5th and 95th Percentile
Mean

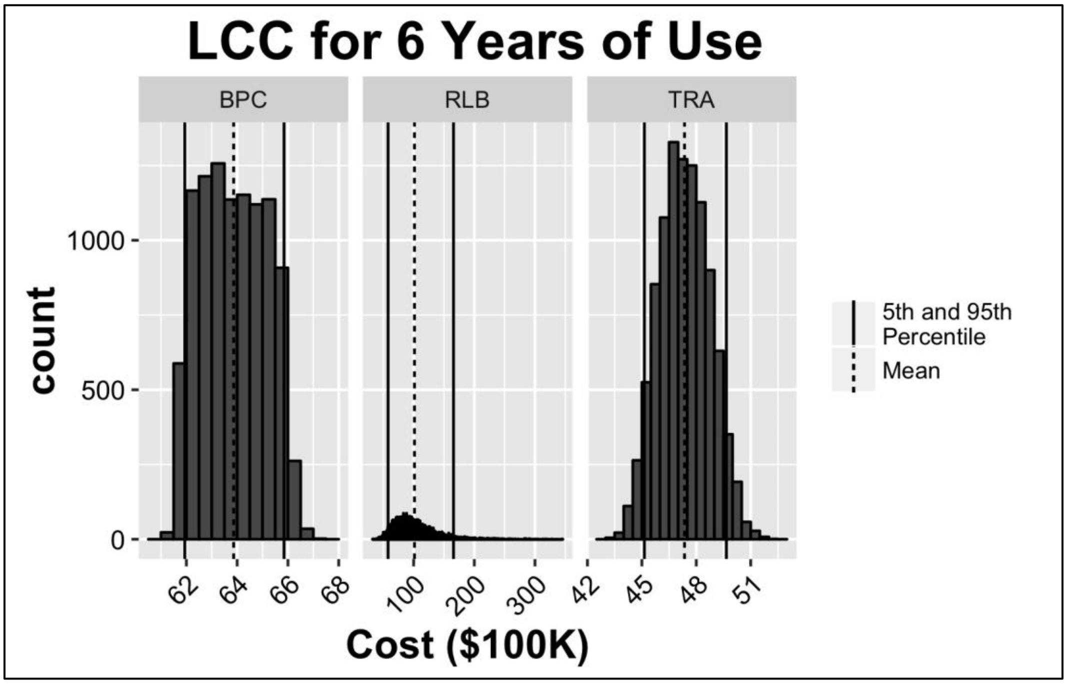

LCC for 3 Years of Use Adjusted
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
count
Cost ($100K)

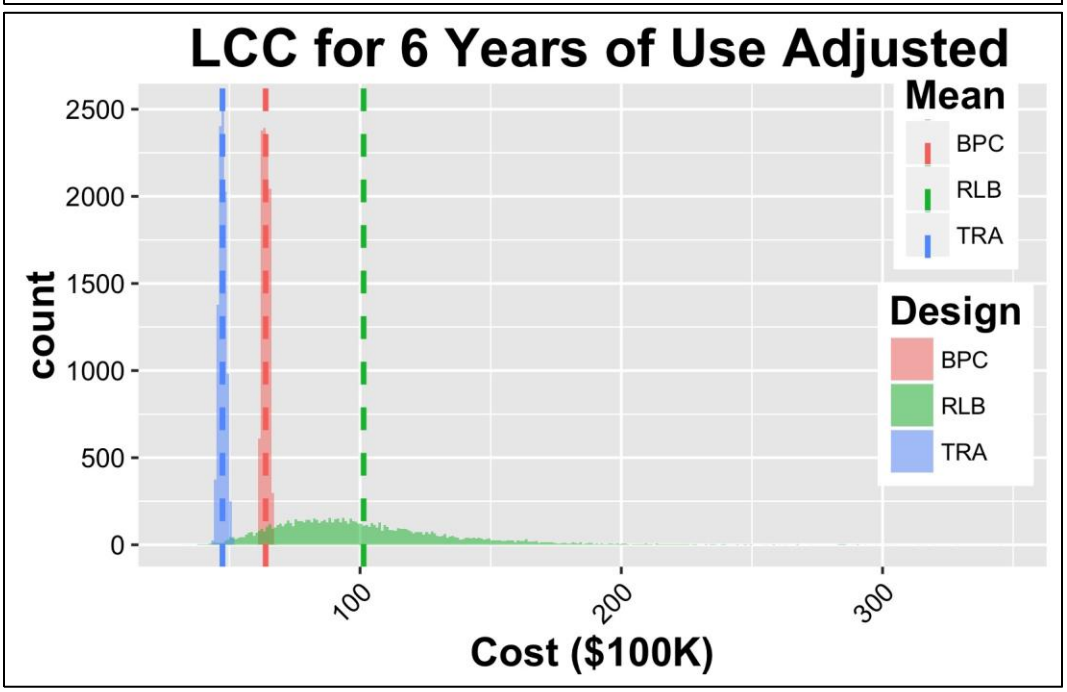

LCC for 4 Years of Use
BPC
RLB
TRA
count
1000
500
0
60
62
64
66
100
200
300
42.5
45.0
47.5
50.0
52.5
5th and 95th
Percentile
Mean
Cost ($100K)

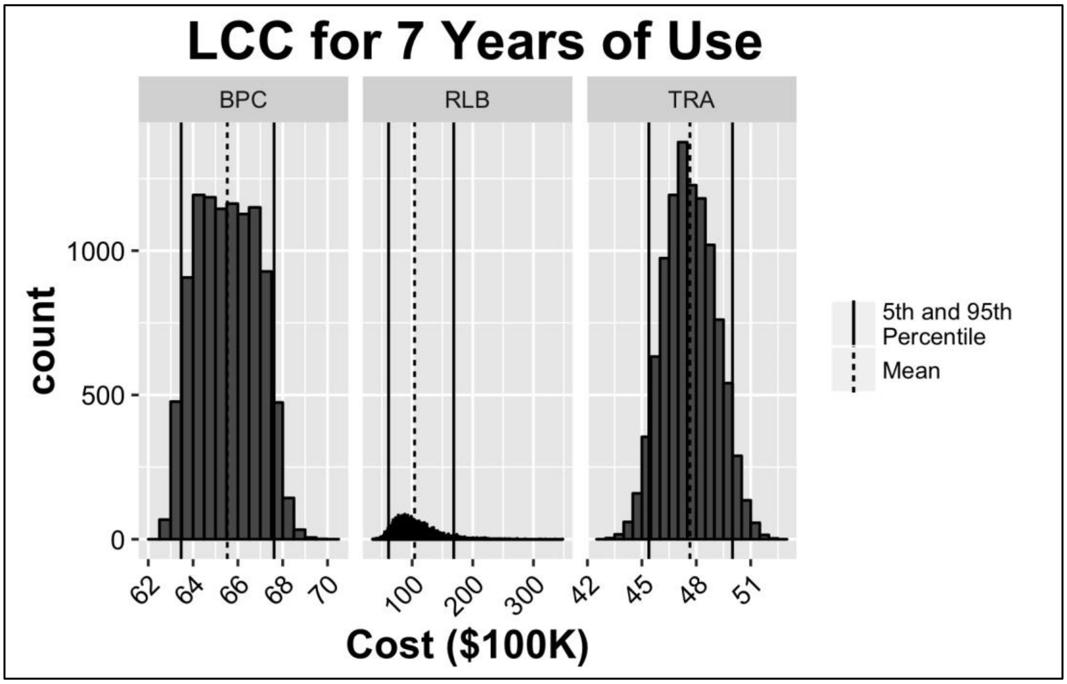

LCC for 4 Years of Use Adjusted
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
count
2000
1000
0
100
200
300
Cost ($100K)


LCC for 5 Years of Use
BPC
RLB
TRA
count
1000
500
0
60
62
64
66
100
200
300
400
42
45
48
51
Cost ($100K)
5th and 95th Percentile
Mean

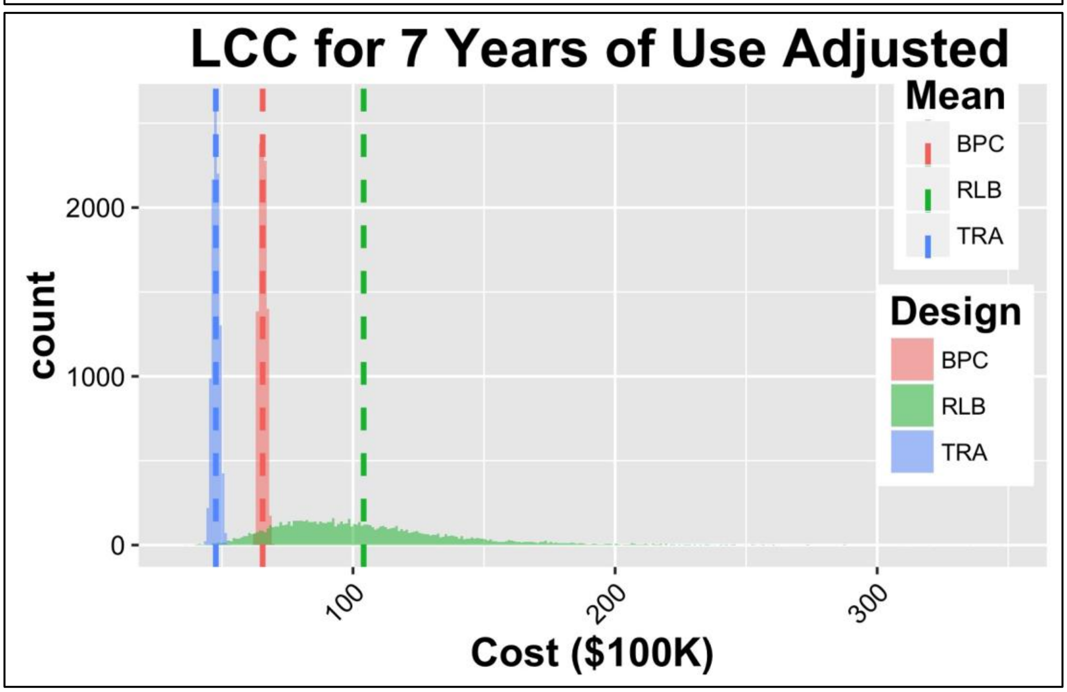

LCC for 5 Years of Use Adjusted
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
count
2000
1000
0
100
200
300
400
Cost ($100K)


LCC for 6 Years of Use
BPC
RLB
TRA
count
1000
500
0
62
64
66
68
100
200
300
42
45
48
51
Cost ($100K)
5th and 95th Percentile
Mean

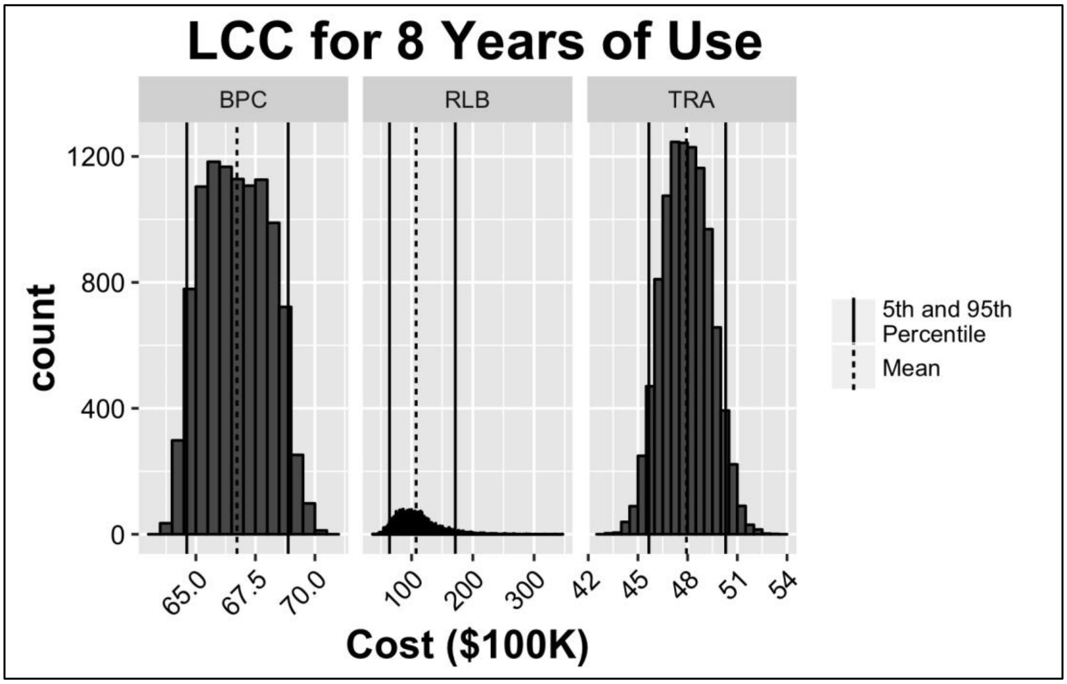

LCC for 6 Years of Use Adjusted
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
count
2500
2000
1500
1000
500
0
100
200
300
Cost ($100K)

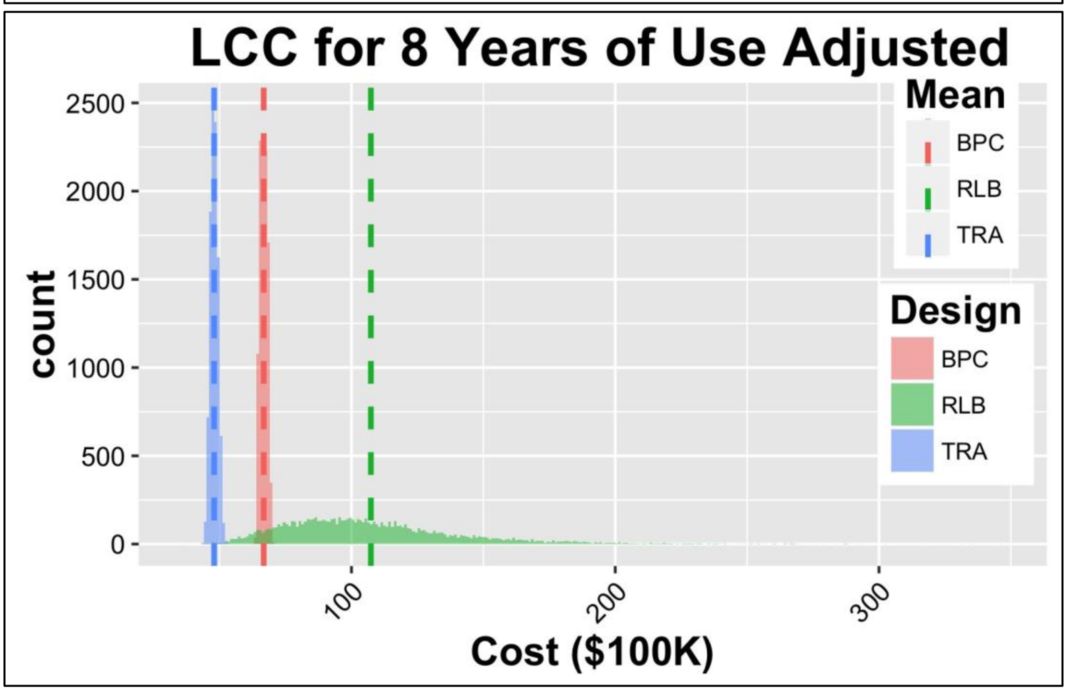


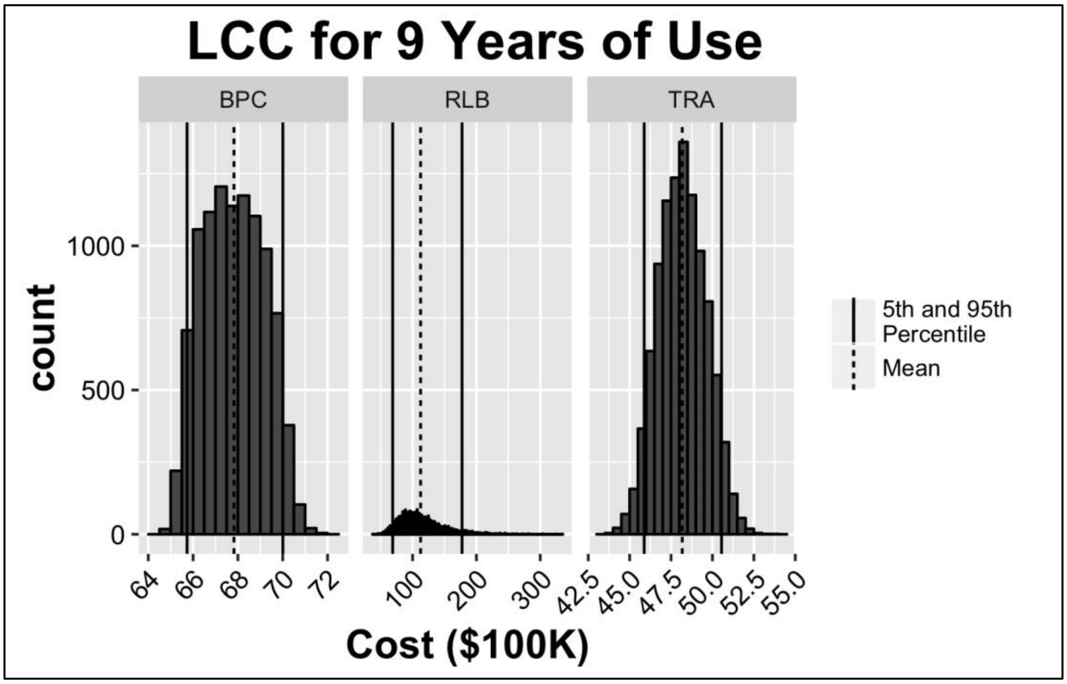
LCC for 7 Years of Use
BPC
RLB
TRA
count
1000
500
0
62
64
66
68
70
100
200
300
42
45
48
51
Cost ($100K)
5th and 95th Percentile
Mean

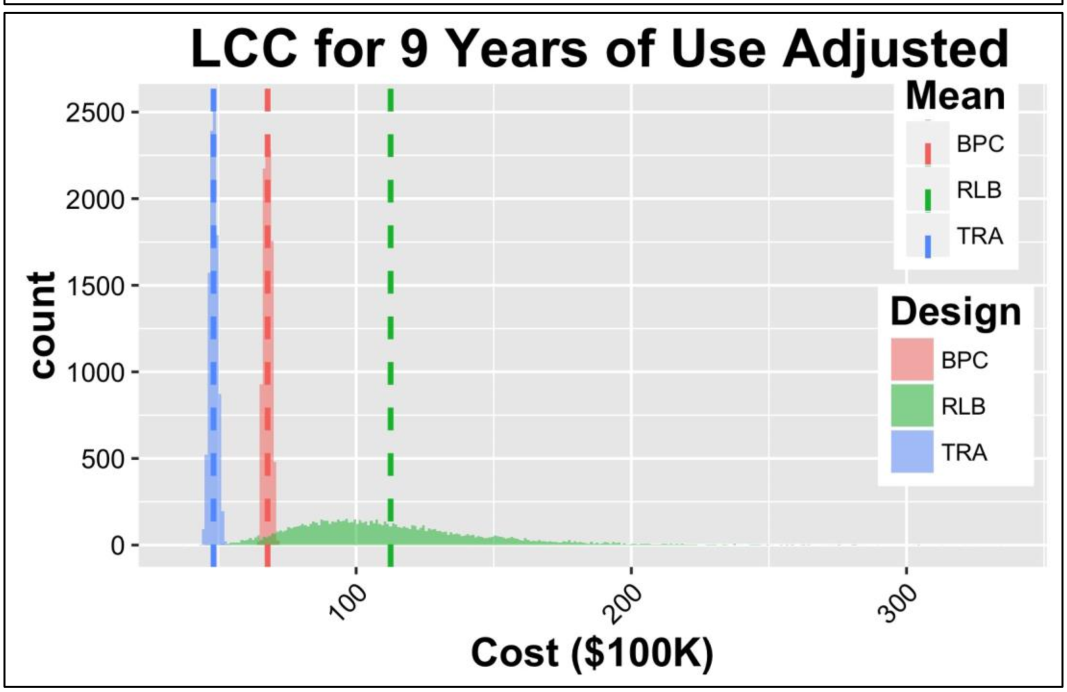


LCC for 7 Years of Use Adjusted
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
count
2000
1000
0
100
200
300
Cost ($100K)


LCC for 8 Years of Use
BPC
RLB
TRA
1200
800
400
0
count
5th and 95th Percentile
Mean
65.0
67.5
70.0
100
200
300
42
45
48
51
54
Cost ($100K)


LCC for 8 Years of Use Adjusted
2500
2000
1500
1000
500
0
count
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
100
200
300
Cost ($100K)


LCC for 9 Years of Use
BPC
RLB
TRA
count
1000
500
0
5th and 95th Percentile
Mean
64
66
68
70
72
100
200
300
42.5
45.0
47.5
50.0
52.5
55.0
Cost ($100K)


LCC for 9 Years of Use Adjusted
Mean
BPC
RLB
TRA
Design
BPC
RLB
TRA
count
2500
2000
1500
1000
500
0
100
200
300
Cost ($100K)

Difference Comparisons Descriptive Statistics							
Comparison	**Year**	**Mean**	**Standard Deviation**	**Standard Error**	**Confidence Interval**	**5th Percentile**	**95th Percentile**
BPC vs RLB	3	-2744689	3394358	33944	55837	-387553	-7880
BPC vs RLB	4	-2317256	3400501	34005	55938	-428999	-36369
BPC vs RLB	5	-1784969	3425263	34253	56346	-461312	2530051
BPC vs RLB	6	-825248	3514688	35147	57817	-569833	3737708
BPC vs RLB	7	51485	3659270	36593	60195	-814404	5027657
BPC vs RLB	8	2503213	4228001	42280	69551	-1160212	8862678
BPC vs RLB	9	6446948	5537517	55375	91092	-1726582	15585589
BPC vs Trailer	3	-193900	115877	1159	1906	-9140372	1494111
BPC vs Trailer	4	-228816	119884	1199	1972	-8720123	1943267
BPC vs Trailer	5	-240921	131880	1319	2169	-8202693	2530051
BPC vs Trailer	6	-287942	168618	1686	2774	-7302008	3737708
BPC vs Trailer	7	-417951	233550	2336	3842	-6533869	5027657
BPC vs Trailer	8	-524098	371768	3718	6116	-4569353	8862678
BPC vs Trailer	9	-689373	606056	6061	9970	-2033447	15585589
Trailer vs RLB	3	-2550789	3397544	33975	55890	-8926510	1702897
Trailer vs RLB	4	-2088440	3403704	34037	55991	-8488873	2191181
Trailer vs RLB	5	-1544048	3428639	34286	56401	-7950506	2764364
Trailer vs RLB	6	-537306	3518133	35181	57874	-7008792	4017127
Trailer vs RLB	7	398554	3662653	36627	60251	-6137730	5331141
Trailer vs RLB	8	2956429	4231100	42311	69602	-4153474	9385371
Trailer vs RLB	9	7065439	5540130	55401	91135	-1354812	16204052

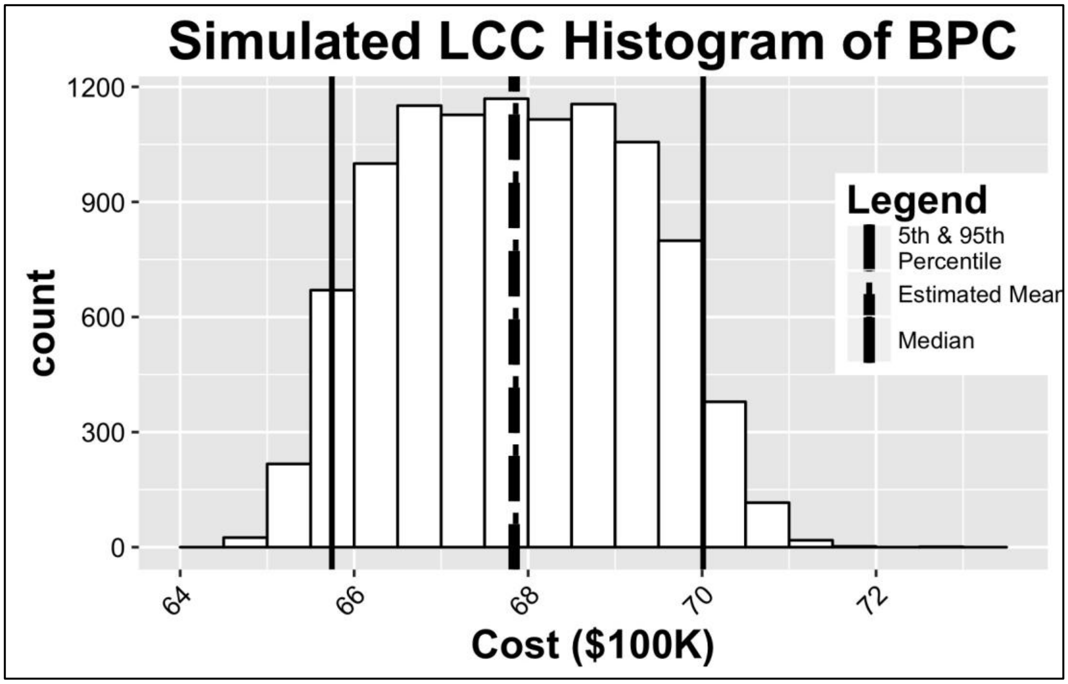
50 Year Horizon Descriptive Statistics						
Design	Year	Mean	Standard Deviation	Standard Error	5th Percentile	95th Percentile
BPC	1	53.176	1.202	0.012	51.307	55.050
BPC	2	62.233	1.202	0.012	60.364	64.107
BPC	3	62.256	1.202	0.012	60.386	64.132
BPC	4	63.035	1.243	0.012	61.106	64.955
BPC	5	63.554	1.256	0.013	61.610	65.497
BPC	6	63.902	1.261	0.013	61.942	65.854
BPC	7	65.566	1.323	0.013	63.484	67.642
BPC	8	66.763	1.336	0.013	64.659	68.868
BPC	9	67.867	1.352	0.014	65.729	70.011
BPC	10	67.890	1.352	0.014	65.750	70.034
BPC	11	68.669	1.433	0.014	66.390	70.984
BPC	12	69.188	1.456	0.015	66.873	71.519
BPC	13	69.536	1.463	0.015	67.214	71.891
BPC	14	71.200	1.602	0.016	68.649	73.842
BPC	15	72.397	1.619	0.016	69.809	75.043
BPC	16	73.501	1.655	0.017	70.858	76.227
BPC	17	73.524	1.655	0.017	70.881	76.250
BPC	18	74.303	1.758	0.018	71.503	77.236
BPC	19	74.822	1.786	0.018	71.976	77.774
BPC	20	75.170	1.793	0.018	72.305	78.146
BPC	21	76.834	1.977	0.020	73.672	80.177
BPC	22	78.031	1.997	0.020	74.830	81.399
BPC	23	79.135	2.044	0.020	75.884	82.562
BPC	24	79.158	2.045	0.020	75.908	82.586
BPC	25	79.937	2.157	0.022	76.517	83.576
BPC	26	80.456	2.188	0.022	76.982	84.155
BPC	27	80.804	2.196	0.022	77.309	84.509
BPC	28	82.468	2.404	0.024	78.695	86.541
BPC	29	83.665	2.425	0.024	79.861	87.768
BPC	30	84.769	2.479	0.025	80.868	88.931
BPC	31	84.792	2.480	0.025	80.892	88.960
BPC	32	85.571	2.598	0.026	81.533	89.954
BPC	33	86.090	2.629	0.026	81.981	90.537
BPC	34	86.438	2.637	0.026	82.318	90.918
BPC	35	88.102	2.860	0.029	83.654	92.958
BPC	36	89.299	2.882	0.029	84.829	94.185
BPC	37	90.403	2.940	0.029	85.813	95.386
BPC	38	90.426	2.940	0.029	85.835	95.409
BPC	39	91.205	3.061	0.031	86.443	96.399
BPC	40	91.724	3.093	0.031	86.921	97.001
BPC	41	92.072	3.101	0.031	87.266	97.383
BPC	42	93.736	3.333	0.033	88.596	99.414
BPC	43	94.933	3.355	0.034	89.739	100.638
BPC	44	96.037	3.416	0.034	90.730	101.808
BPC	45	96.060	3.416	0.034	90.752	101.830
BPC	46	96.839	3.538	0.035	91.370	102.868
BPC	47	97.358	3.571	0.036	91.839	103.444
BPC	48	97.706	3.579	0.036	92.188	103.806
BPC	49	99.370	3.816	0.038	93.492	105.874
BPC	50	100.567	3.839	0.038	94.640	107.100
RLB	1	81.945	34.293	0.343	39.566	145.432
RLB	2	90.097	34.293	0.343	47.718	153.585
RLB	3	91.189	34.298	0.343	48.872	154.784
RLB	4	95.215	34.335	0.343	52.600	158.449
RLB	5	97.875	34.353	0.344	55.274	161.538
RLB	6	100.939	34.408	0.344	58.198	164.845
RLB	7	104.452	34.437	0.344	61.509	168.481
RLB	8	107.898	34.593	0.346	64.934	172.120

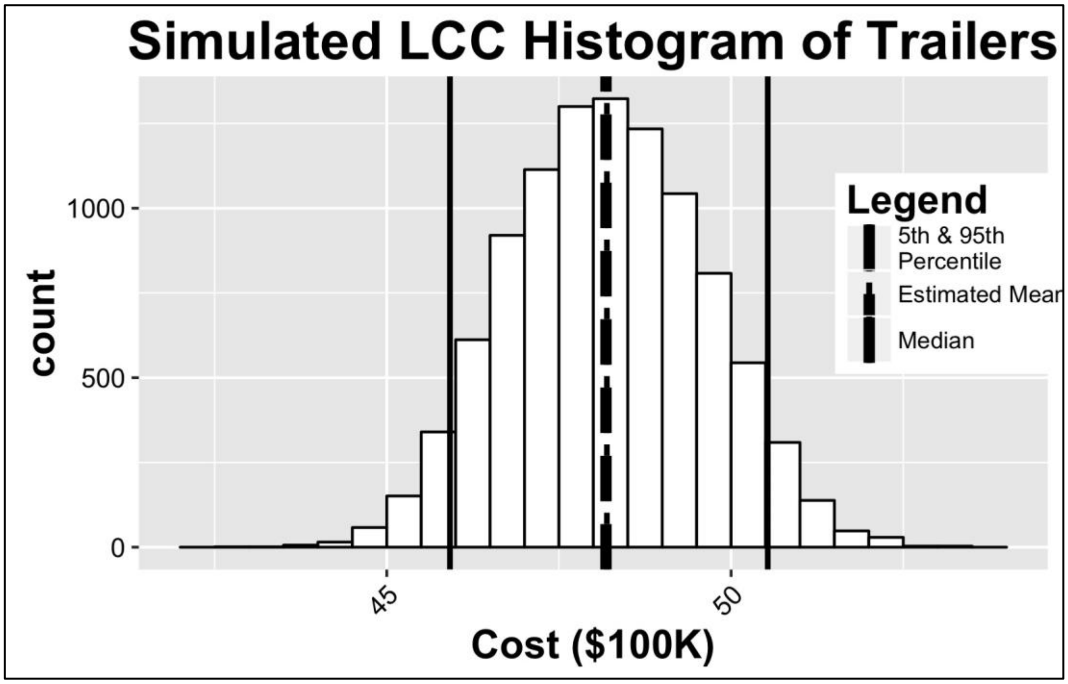
RLB	9	112.925	34.859	0.349	69.256	177.824
RLB	10	116.439	34.984	0.350	72.445	181.293
RLB	11	119.885	35.383	0.354	75.153	185.854
RLB	12	124.912	36.059	0.361	78.563	191.542
RLB	13	216.100	69.550	0.696	129.472	345.511
RLB	14	220.127	69.614	0.696	133.105	349.525
RLB	15	222.786	69.645	0.696	135.683	351.964
RLB	16	225.850	69.717	0.697	138.512	355.648
RLB	17	229.364	69.819	0.698	141.686	359.321
RLB	18	232.810	70.158	0.702	144.536	363.253
RLB	19	237.837	70.737	0.707	148.067	369.206
RLB	20	241.350	70.885	0.709	151.191	373.287
RLB	21	244.796	71.341	0.713	153.644	377.052
RLB	22	249.823	72.118	0.721	157.125	383.083
RLB	23	341.012	105.350	1.053	208.224	536.731
RLB	24	345.038	105.422	1.054	212.255	540.804
RLB	25	347.698	105.457	1.055	214.539	543.341
RLB	26	350.762	105.535	1.055	217.319	547.351
RLB	27	354.275	105.660	1.057	220.755	550.634
RLB	28	357.721	106.058	1.061	223.217	555.067
RLB	29	362.748	106.738	1.067	226.546	560.688
RLB	30	366.262	106.893	1.069	229.806	564.343
RLB	31	369.708	107.367	1.074	232.130	568.418
RLB	32	374.735	108.177	1.082	235.688	574.625
RLB	33	465.923	141.281	1.413	287.144	727.814
RLB	34	469.950	141.357	1.414	290.677	732.191
RLB	35	472.609	141.395	1.414	293.218	734.954
RLB	36	475.673	141.475	1.415	296.134	738.413
RLB	37	479.187	141.611	1.416	299.137	741.887
RLB	38	482.633	142.038	1.420	301.723	746.318
RLB	39	487.660	142.768	1.428	305.074	752.286
RLB	40	491.174	142.926	1.429	308.382	755.702
RLB	41	494.619	143.409	1.434	310.547	760.336
RLB	42	499.646	144.236	1.442	314.250	766.167
RLB	43	590.835	177.264	1.773	365.240	920.213
RLB	44	594.861	177.343	1.773	369.329	924.212
RLB	45	597.521	177.382	1.774	371.786	926.458
RLB	46	600.585	177.463	1.775	374.661	930.002
RLB	47	604.099	177.606	1.776	377.597	933.907
RLB	48	607.545	178.050	1.780	380.616	937.599
RLB	49	612.571	178.809	1.788	383.603	944.385
RLB	50	616.085	178.970	1.790	386.936	947.343
TRA	1	55.356	1.699	0.017	52.635	58.185
TRA	2	57.354	1.699	0.017	54.632	60.182
TRA	3	57.604	1.705	0.017	54.868	60.437
TRA	4	57.809	1.712	0.017	55.069	60.654
TRA	5	57.942	1.714	0.017	55.195	60.794
TRA	6	58.028	1.715	0.017	55.284	60.886
TRA	7	58.392	1.721	0.017	55.650	61.262
TRA	8	58.730	1.729	0.017	55.958	61.598
TRA	9	59.029	1.733	0.017	56.247	61.901
TRA	10	59.394	1.747	0.017	56.606	62.273
TRA	11	59.731	1.768	0.018	56.884	62.660
TRA	12	60.031	1.777	0.018	57.182	62.984
TRA	13	117.636	3.453	0.035	112.081	123.352
TRA	14	117.840	3.462	0.035	112.278	123.554
TRA	15	117.973	3.464	0.035	112.411	123.722
TRA	16	118.059	3.466	0.035	112.495	123.803
TRA	17	118.423	3.478	0.035	112.853	124.172
TRA	18	118.761	3.495	0.035	113.170	124.527
TRA	19	119.061	3.503	0.035	113.444	124.872

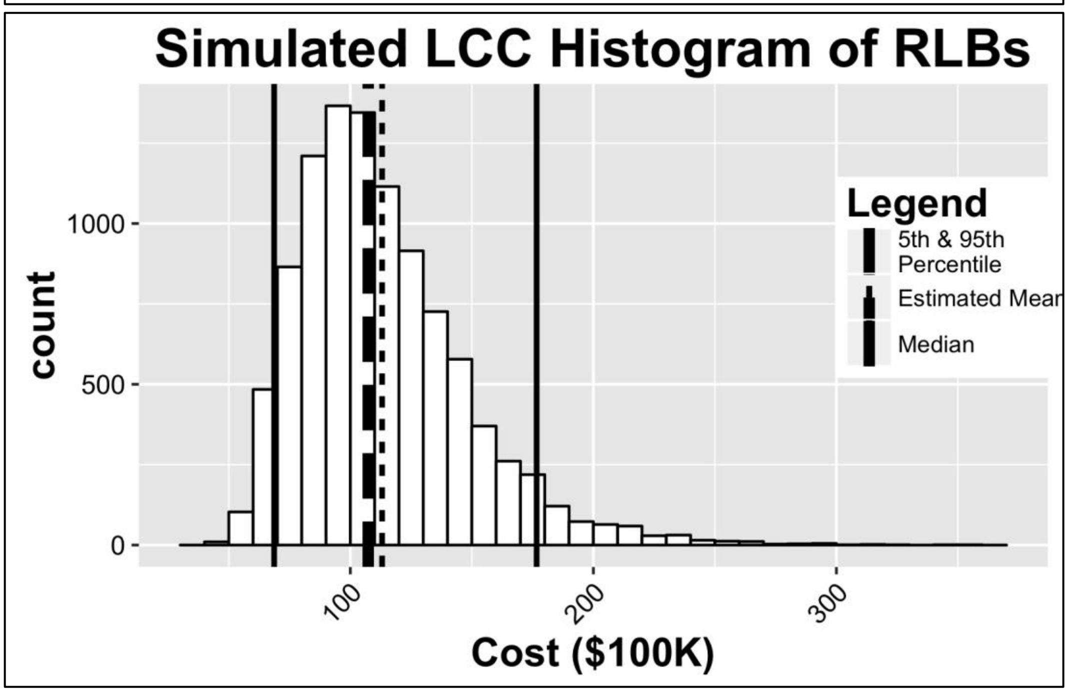
TRA	20	119.425	3.519	0.035	113.782	125.255
TRA	21	119.763	3.543	0.035	114.058	125.628
TRA	22	120.062	3.554	0.036	114.365	125.967
TRA	23	177.667	5.221	0.052	169.293	186.327
TRA	24	177.871	5.230	0.052	169.487	186.523
TRA	25	178.004	5.233	0.052	169.623	186.652
TRA	26	178.090	5.234	0.052	169.698	186.753
TRA	27	178.454	5.248	0.052	170.049	187.130
TRA	28	178.792	5.269	0.053	170.328	187.518
TRA	29	179.092	5.278	0.053	170.596	187.863
TRA	30	179.456	5.295	0.053	170.942	188.247
TRA	31	179.794	5.320	0.053	171.246	188.631
TRA	32	180.094	5.331	0.053	171.547	188.951
TRA	33	237.698	6.993	0.070	226.476	249.305
TRA	34	237.902	7.002	0.070	226.646	249.501
TRA	35	238.036	7.005	0.070	226.796	249.662
TRA	36	238.121	7.006	0.070	226.888	249.745
TRA	37	238.486	7.022	0.070	227.230	250.124
TRA	38	238.823	7.044	0.070	227.497	250.487
TRA	39	239.123	7.054	0.071	227.767	250.852
TRA	40	239.488	7.071	0.071	228.115	251.232
TRA	41	239.825	7.096	0.071	228.419	251.621
TRA	42	240.125	7.108	0.071	228.729	251.934
TRA	43	297.729	8.768	0.088	283.629	312.295
TRA	44	297.934	8.777	0.088	283.825	312.511
TRA	45	298.067	8.780	0.088	283.970	312.649
TRA	46	298.153	8.781	0.088	284.055	312.727
TRA	47	298.517	8.797	0.088	284.378	313.121
TRA	48	298.854	8.820	0.088	284.680	313.462
TRA	49	299.154	8.830	0.088	284.940	313.838
TRA	50	299.519	8.848	0.088	285.301	314.224

Appendix C: Analysis for Selection Under Uncertain Conditions

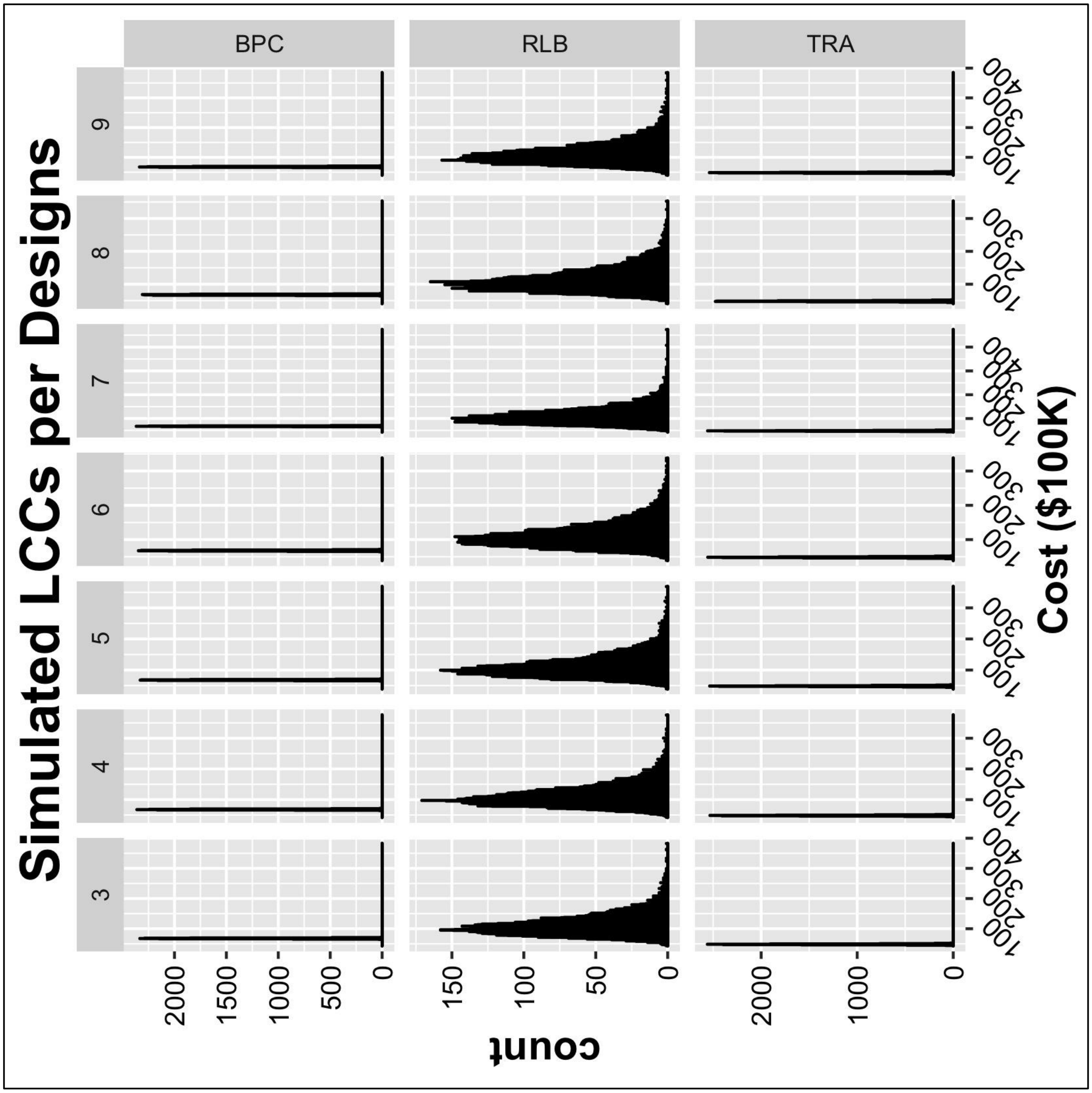
Design	Mean	Standard Deviation	Standard Error	Median	5th Percentile	95th Percentile
BPC	67.853	1.349	0.013	67.820	65.775	70.000
Trailer	48.175	1.407	0.014	48.149	45.902	50.497
RLB	113.071	34.512	0.345	107.363	68.658	176.658



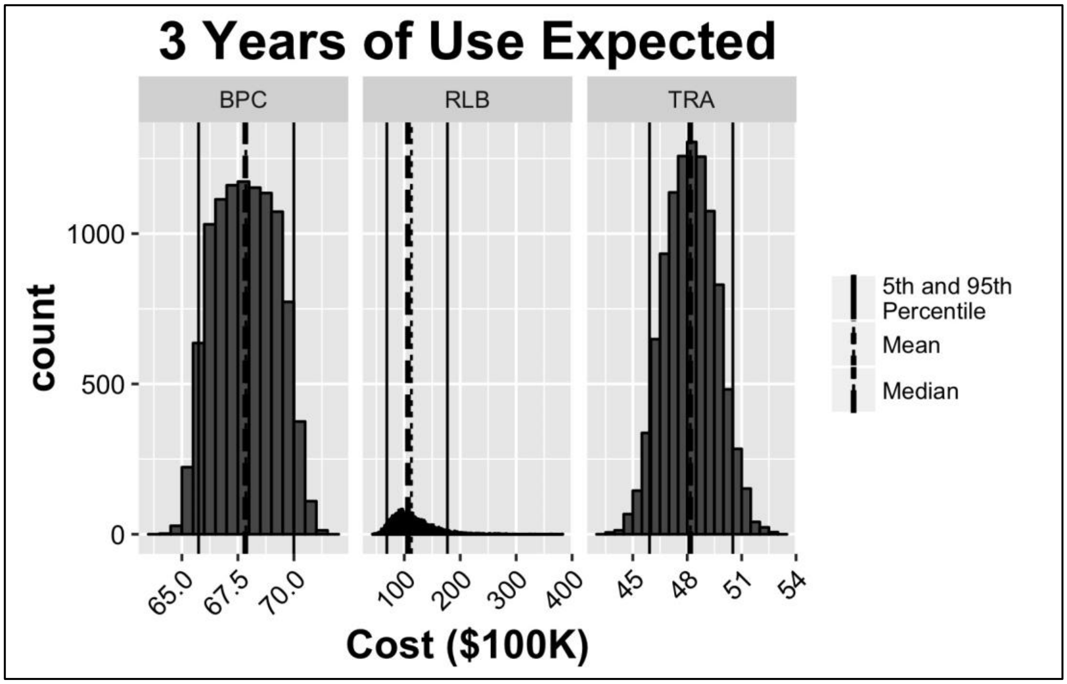

Simulated LCC Histogram of Trailers
count
1000
500
0
45
50
Cost ($100K)
Legend
5th & 95th Percentile
Estimated Mean
Median

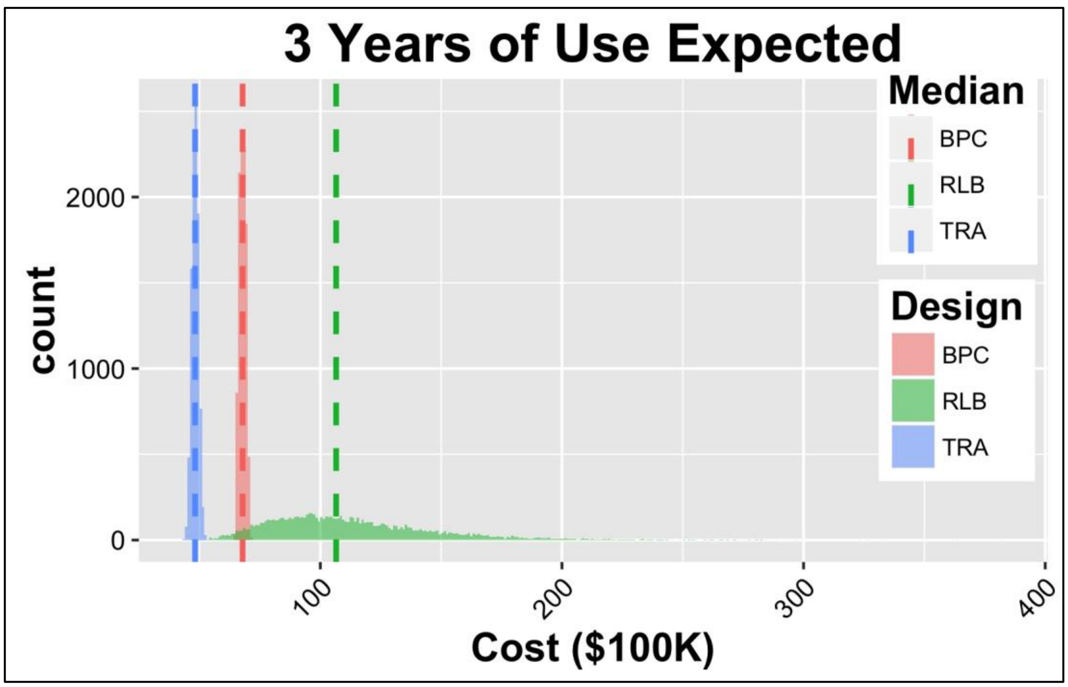

Simulated LCC Histogram of RLBs
count
1000
500
0
100
200
300
Cost ($100K)
Legend
5th & 95th Percentile
Estimated Mean
Median

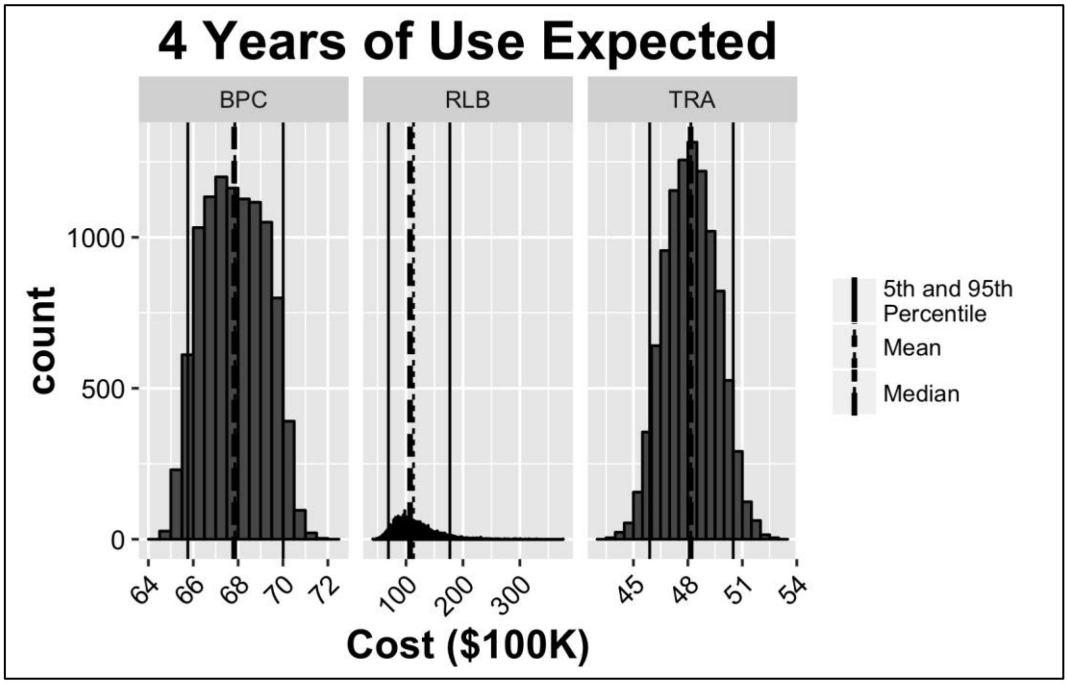
Design	Year	Mean	Standard Deviation	Standard Error	5th Percentile	95th Percentile	Median
BPC	3	67.854	1.341	0.013	65.745	69.996	67.830
BPC	4	67.855	1.345	0.013	65.758	70.009	67.825
BPC	5	67.853	1.335	0.013	65.757	69.979	67.825
BPC	6	67.857	1.347	0.013	65.739	70.014	67.848
BPC	7	67.859	1.345	0.013	65.744	70.007	67.837
BPC	8	67.857	1.341	0.013	65.758	69.992	67.831
BPC	9	67.859	1.351	0.014	65.739	70.039	67.824
RLB	3	112.746	34.777	0.348	68.858	177.117	106.533
RLB	4	113.124	34.505	0.345	69.063	176.989	107.058
RLB	5	112.702	35.159	0.352	68.903	178.550	106.076
RLB	6	113.022	35.088	0.351	68.197	180.368	106.859
RLB	7	112.321	34.686	0.347	68.749	177.811	106.113
RLB	8	112.814	34.415	0.344	68.848	178.455	107.046
RLB	9	113.094	34.952	0.350	68.742	178.706	106.823
TRA	3	48.177	1.405	0.014	45.921	50.515	48.164
TRA	4	48.166	1.413	0.014	45.897	50.496	48.152
TRA	5	48.186	1.421	0.014	45.897	50.510	48.165
TRA	6	48.197	1.420	0.014	45.935	50.533	48.171
TRA	7	48.180	1.421	0.014	45.853	50.545	48.170
TRA	8	48.179	1.430	0.014	45.871	50.587	48.141
TRA	9	48.201	1.414	0.014	45.955	50.594	48.167

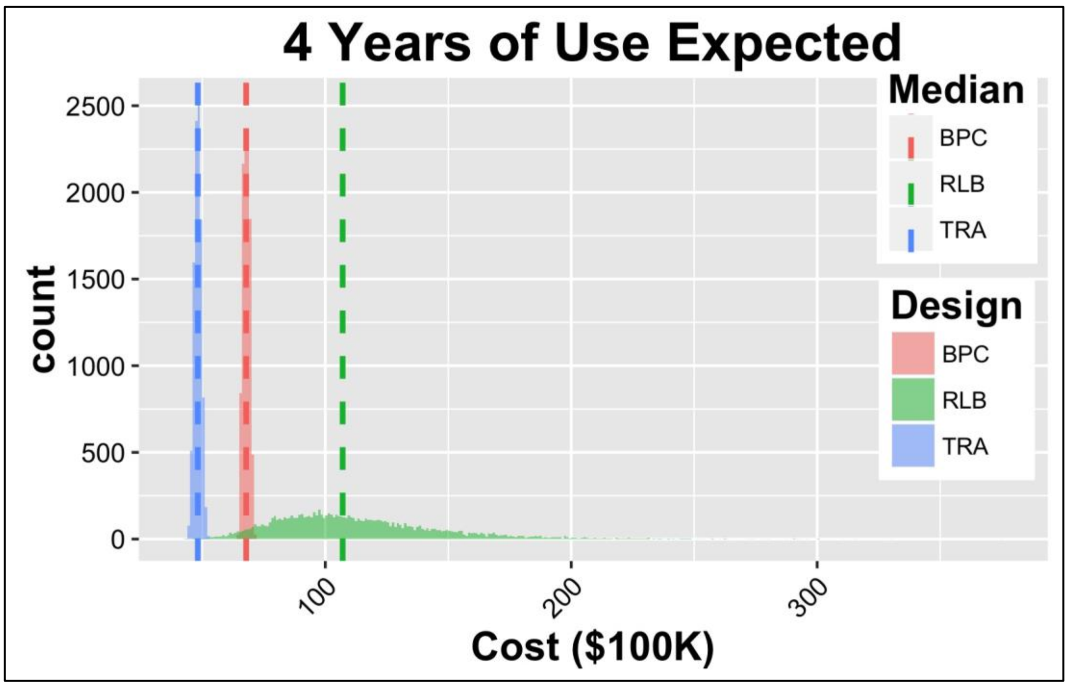


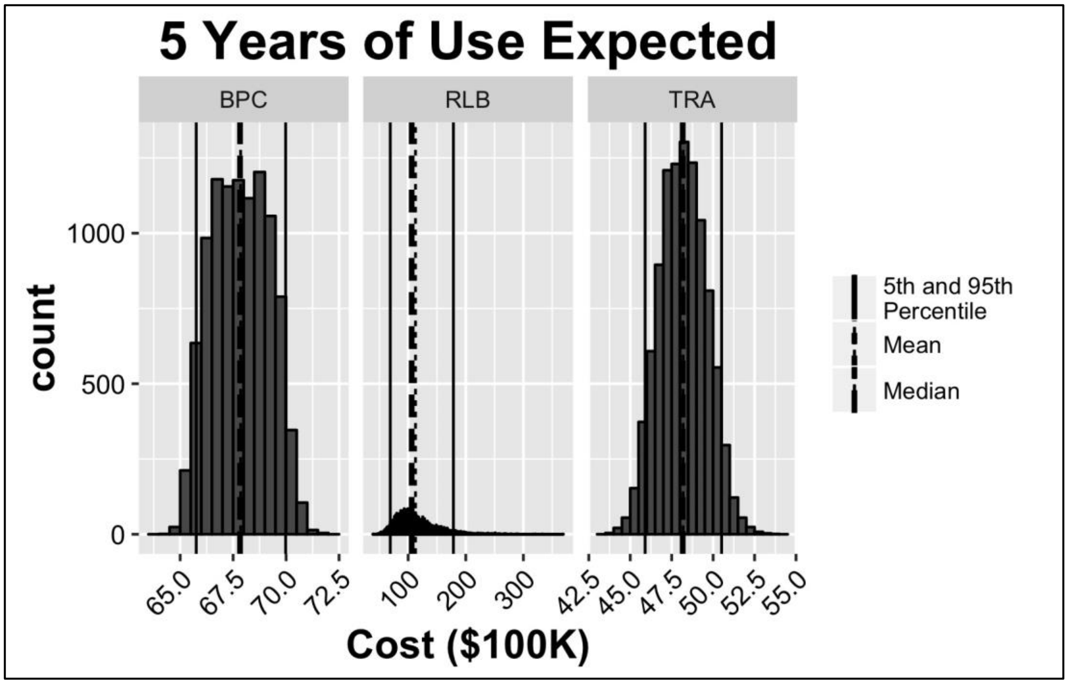
Simulated LCCs per Designs
BPC
RLB
TRA
3
4
5
6
7
8
9
count
Cost ($100K)

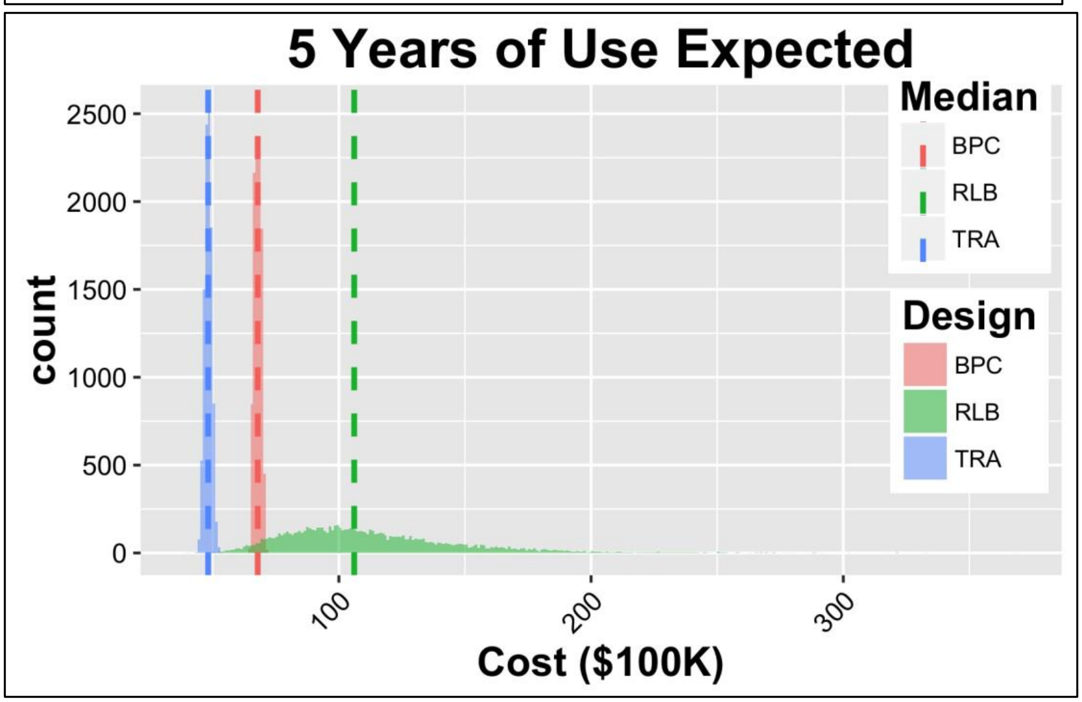

3 Years of Use Expected
BPC
RLB
TRA
count
1000
500
0
65.0
67.5
70.0
100
200
300
400
45
48
51
54
Cost ($100K)
5th and 95th Percentile
Mean
Median

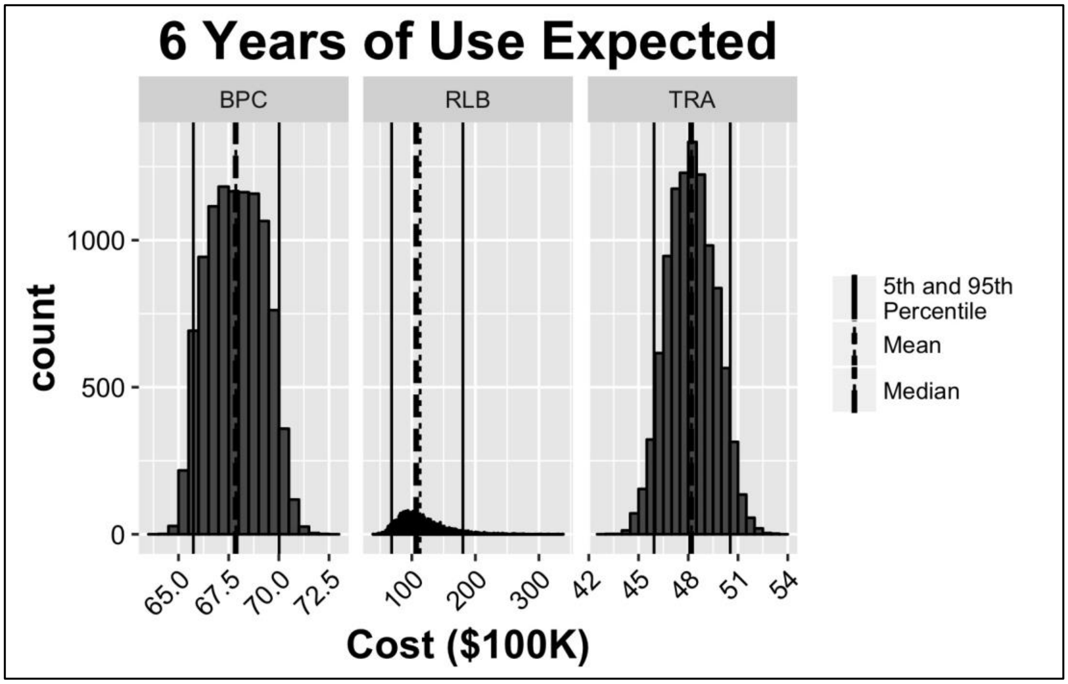

3 Years of Use Expected
count
2000
1000
0
100
200
300
400
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA


4 Years of Use Expected
BPC
RLB
TRA
count
1000
500
0
64
66
68
70
72
100
200
300
45
48
51
54
Cost ($100K)
5th and 95th Percentile
Mean
Median

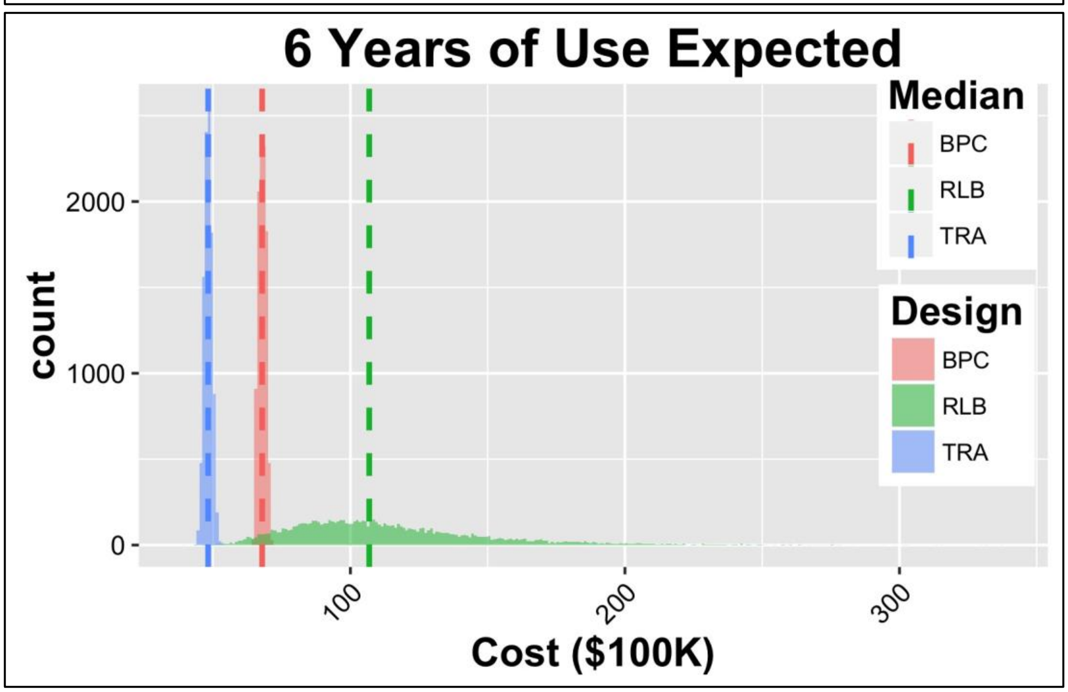

4 Years of Use Expected
count
2500
2000
1500
1000
500
0
100
200
300
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA


5 Years of Use Expected
BPC
RLB
TRA
count
1000
500
0
65.0
67.5
70.0
72.5
100
200
300
42.5
45.0
47.5
50.0
52.5
55.0
Cost ($100K)
5th and 95th Percentile
Mean
Median

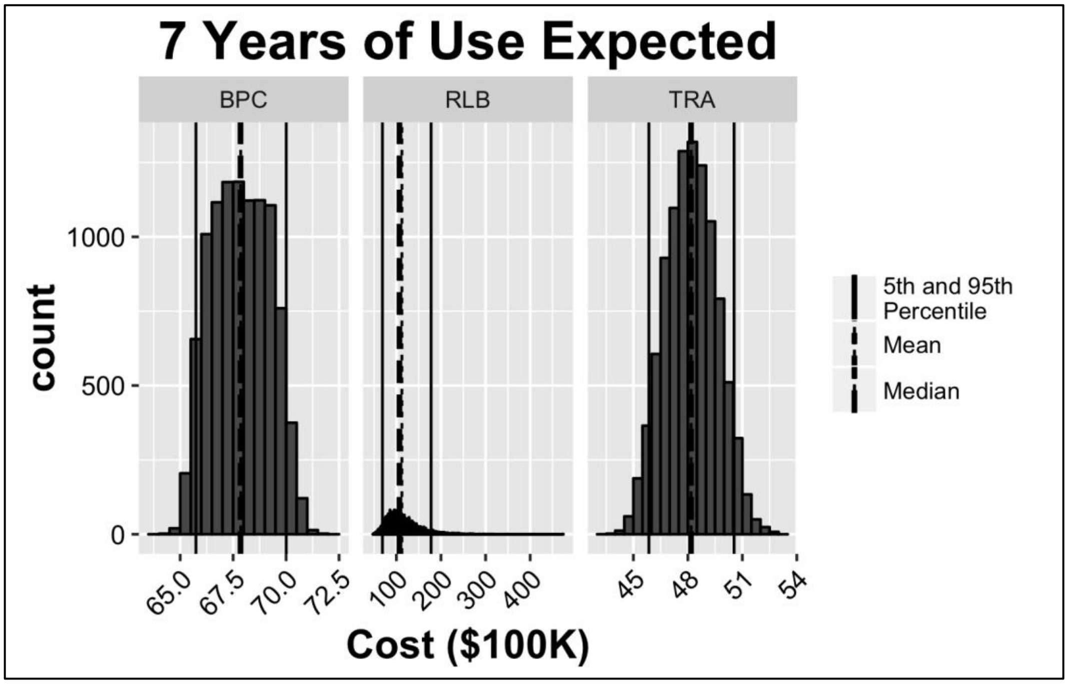

5 Years of Use Expected
count
2500
2000
1500
1000
500
0
100
200
300
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA

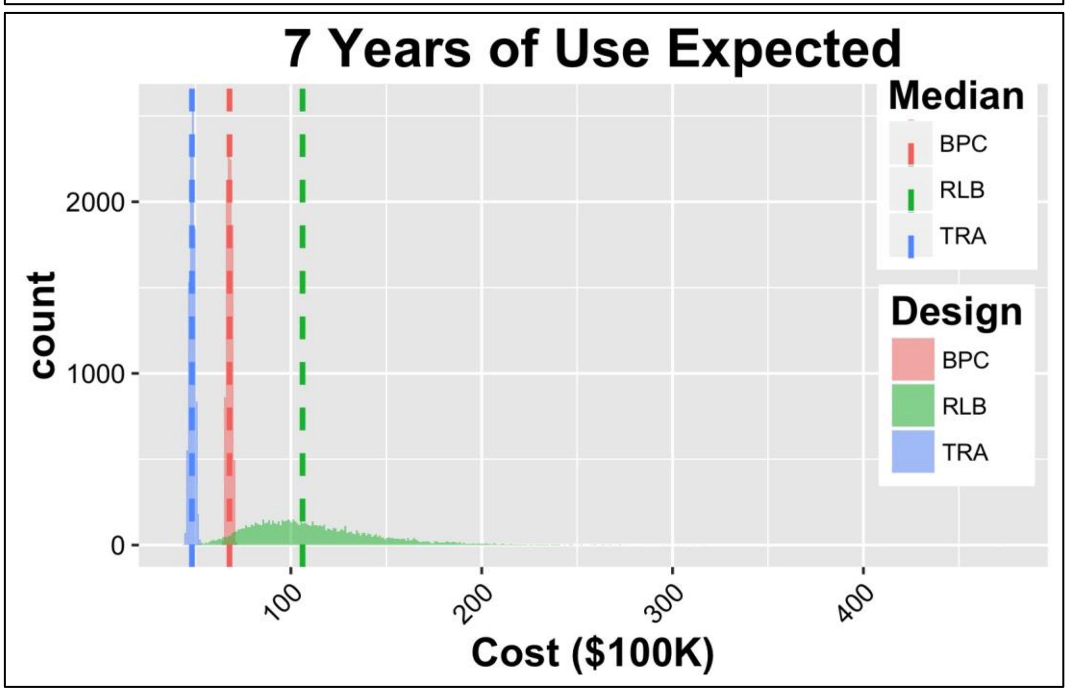


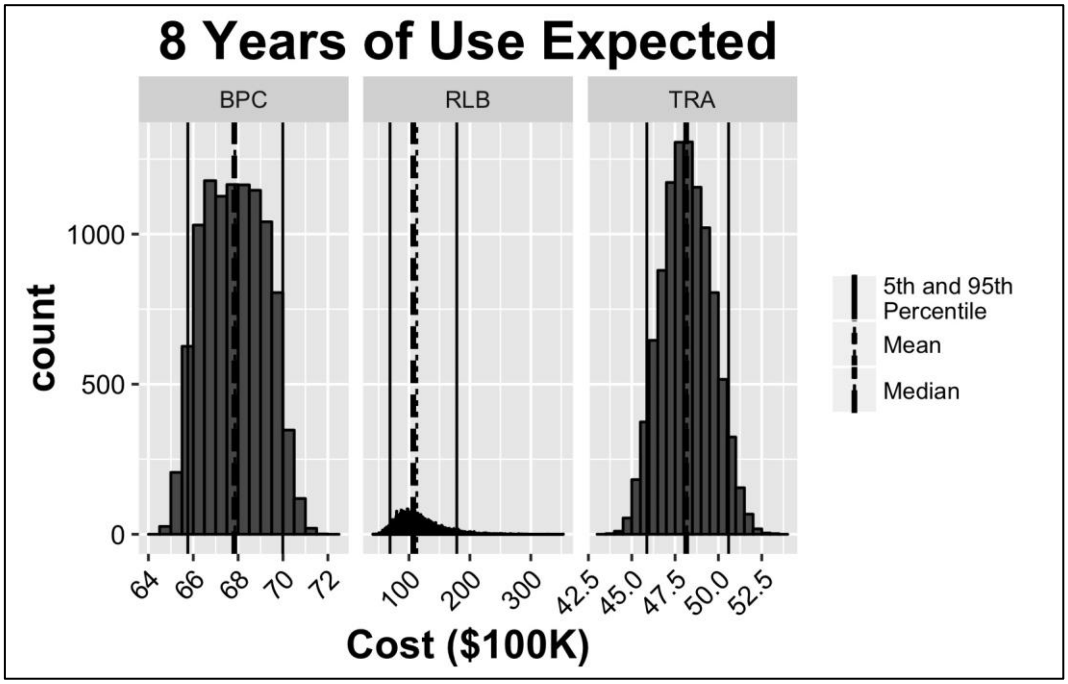
6 Years of Use Expected
BPC
RLB
TRA
count
1000
500
0
65.0
67.5
70.0
72.5
100
200
300
42
45
48
51
54
Cost ($100K)
5th and 95th Percentile
Mean
Median

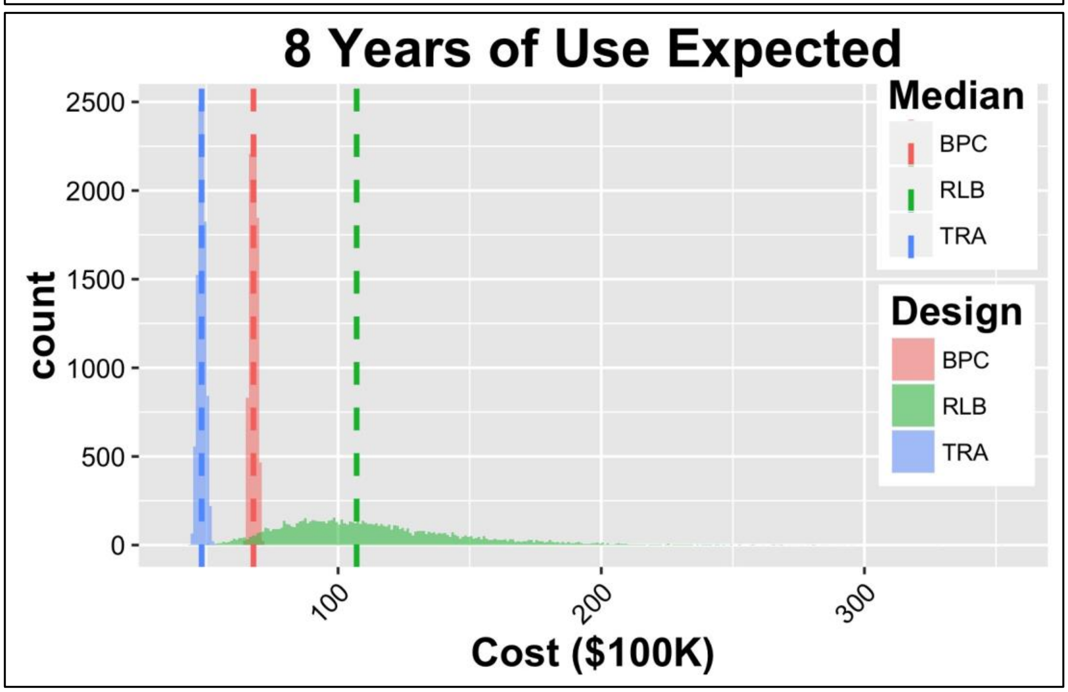


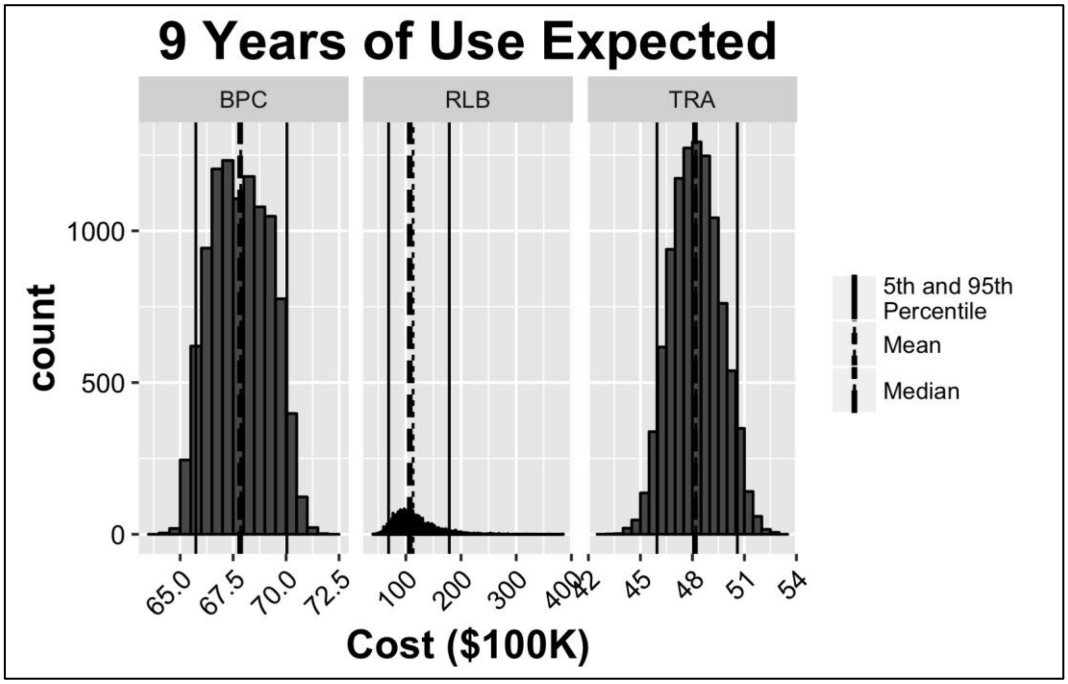
6 Years of Use Expected
count
2000
1000
0
100
200
300
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA

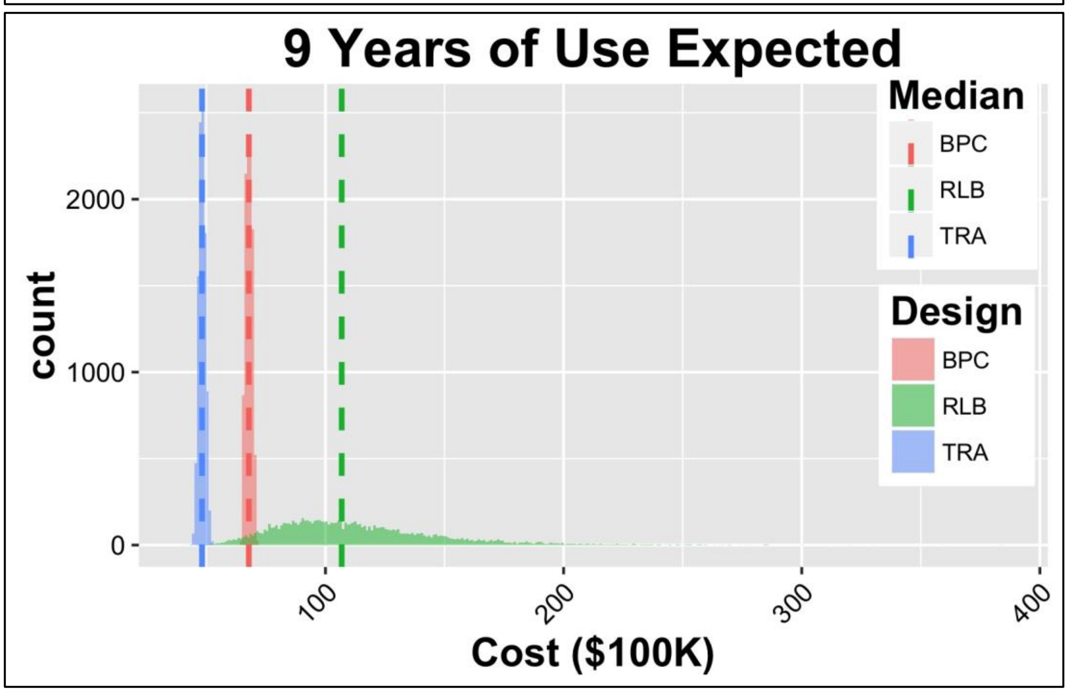

7 Years of Use Expected
BPC
RLB
TRA
count
1000
500
0
65.0
67.5
70.0
72.5
100
200
300
400
45
48
51
54
5th and 95th Percentile
Mean
Median
Cost ($100K)


7 Years of Use Expected
count
2000
1000
0
100
200
300
400
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA


8 Years of Use Expected
BPC
RLB
TRA
count
0
500
1000
64
66
68
70
72
100
200
300
42.5
45.0
47.5
50.0
52.5
Cost ($100K)
5th and 95th Percentile
Mean
Median

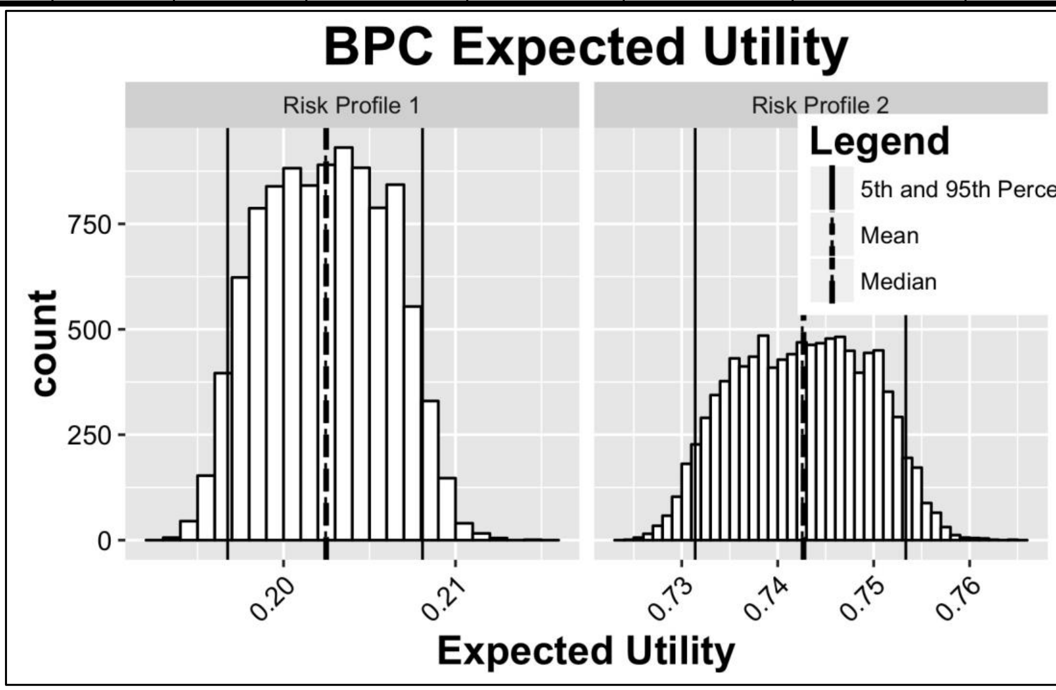

8 Years of Use Expected
count
0
500
1000
1500
2000
2500
100
200
300
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA

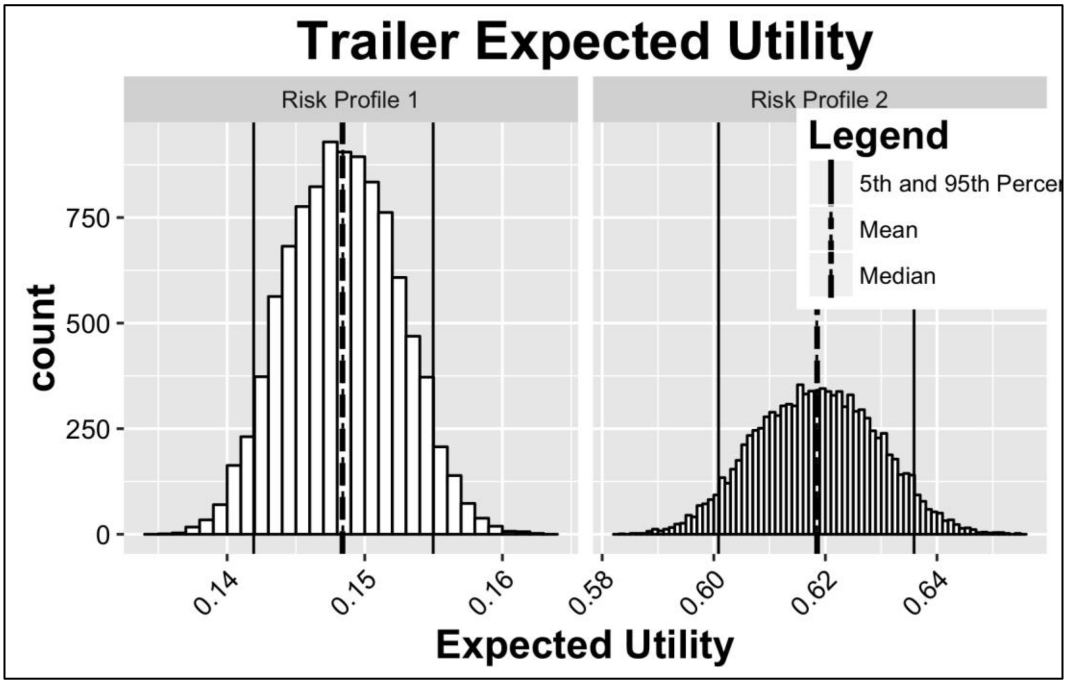

9 Years of Use Expected
BPC
RLB
TRA
count
1000
500
0
65.0
67.5
70.0
72.5
100
200
300
400
42
45
48
51
54
5th and 95th Percentile
Mean
Median
Cost ($100K)

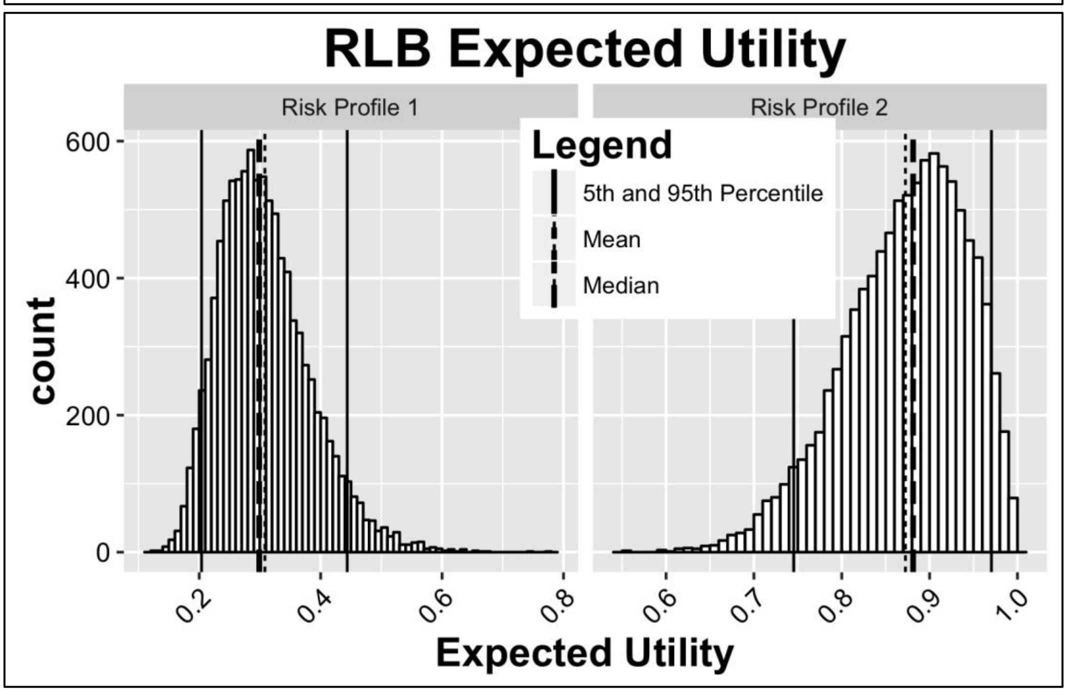

9 Years of Use Expected
count
2000
1000
0
100
200
300
400
Cost ($100K)
Median
BPC
RLB
TRA
Design
BPC
RLB
TRA

Appendix D: Risk Analysis Under Uncertain Conditions

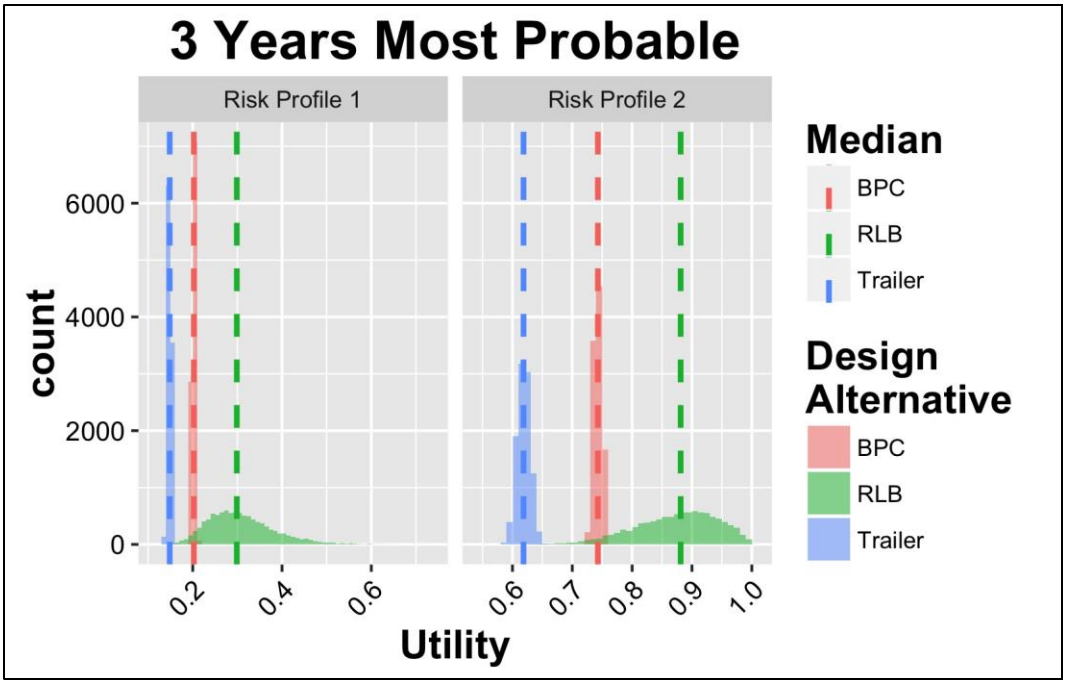
Profile	Design	Mean	Standard Deviation	Standard Error	5th Percentile	95th Percentile	Median
1	BPC	0.20245	0.00356	0.00004	0.19675	0.20808	0.20248
1	RLB	0.30818	0.07483	0.00075	0.20383	0.44376	0.14838
1	TRA	0.14841	0.00402	0.00004	0.14193	0.15497	0.29888
2	BPC	0.74255	0.00690	0.00007	0.73140	0.75335	0.74269
2	RLB	0.87249	0.06956	0.00070	0.74530	0.97038	0.61852
2	TRA	0.61846	0.01080	0.00011	0.60085	0.63589	0.88122

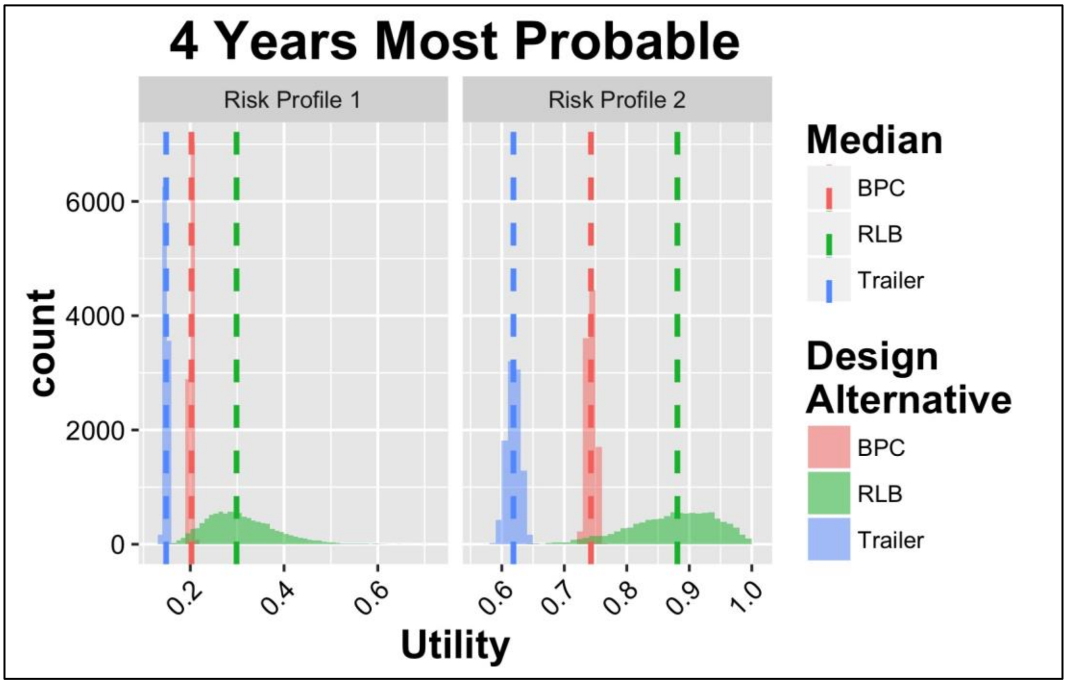


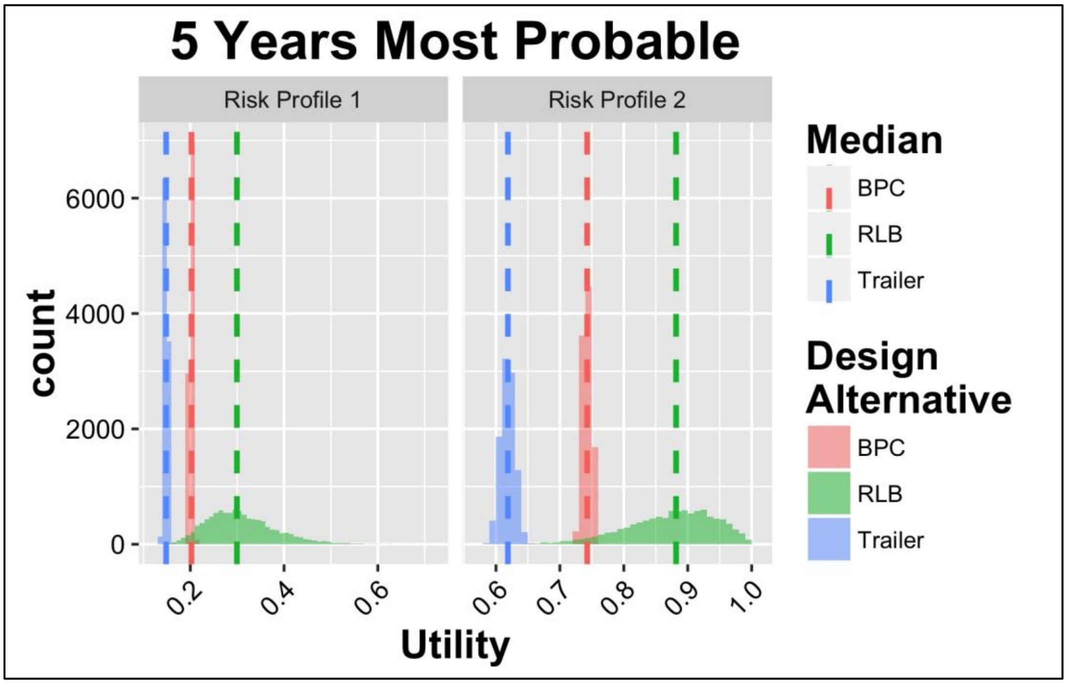

Trailer Expected Utility
Risk Profile 1
Risk Profile 2
Legend
5th and 95th Percer
Mean
Median
count
0
250
500
750
0.14
0.15
0.16
0.58
0.60
0.62
0.64
Expected Utility


RLB Expected Utility
Risk Profile 1
Risk Profile 2
Legend
5th and 95th Percentile
Mean
Median
count
0
200
400
600
0.2
0.4
0.6
0.8
0.6
0.7
0.8
0.9
1.0
Expected Utility

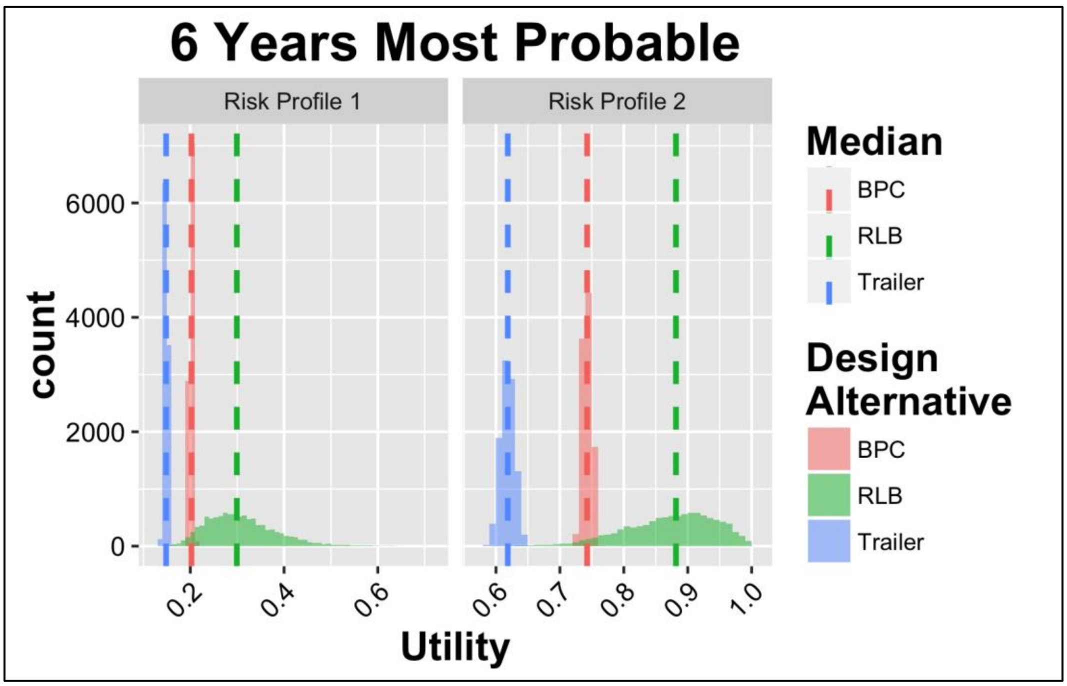
Profile	Year	Design	Mean	Median	Standard Deviation	Standard Error	5th Percentile	95 Percentile
1	3	BPC	0.2025	0.2025	0.0036	0.0000	0.1968	0.2082
	3	RLB	0.3082	0.1483	0.0753	0.0008	0.1418	0.1551
	3	TRA	0.1484	0.2984	0.0041	0.0000	0.2034	0.4458
	4	BPC	0.2025	0.2025	0.0036	0.0000	0.1968	0.2082
	4	RLB	0.3088	0.1484	0.0755	0.0008	0.1418	0.1550
	4	TRA	0.1484	0.2986	0.0040	0.0000	0.2034	0.4484
	5	BPC	0.2024	0.2025	0.0036	0.0000	0.1968	0.2082
	5	RLB	0.3087	0.1484	0.0742	0.0007	0.1418	0.1551
	5	TRA	0.1484	0.2994	0.0041	0.0000	0.2046	0.4450
	6	BPC	0.2025	0.2024	0.0036	0.0000	0.1968	0.2081
	6	RLB	0.3088	0.1484	0.0747	0.0007	0.1419	0.1551
	6	TRA	0.1484	0.2993	0.0040	0.0000	0.2060	0.4447
	7	BPC	0.2024	0.2024	0.0036	0.0000	0.1968	0.2081
	7	RLB	0.3091	0.1484	0.0745	0.0007	0.1419	0.1551
	7	TRA	0.1484	0.2999	0.0041	0.0000	0.2065	0.4438
	8	BPC	0.2025	0.2024	0.0036	0.0000	0.1968	0.2081
	8	RLB	0.3092	0.1484	0.0751	0.0008	0.1420	0.1550
	8	TRA	0.1484	0.3002	0.0040	0.0000	0.2052	0.4482
	9	BPC	0.2024	0.2024	0.0036	0.0000	0.1968	0.2081
	9	RLB	0.3079	0.1485	0.0737	0.0007	0.1420	0.1551
	9	TRA	0.1485	0.2980	0.0040	0.0000	0.2053	0.4426
2	3	BPC	0.7426	0.7427	0.0070	0.0001	0.1968	0.2082
	3	RLB	0.8723	0.6183	0.0698	0.0007	0.1418	0.1551
	3	TRA	0.6184	0.8808	0.0109	0.0001	0.2034	0.4458
	4	BPC	0.7426	0.7426	0.0070	0.0001	0.1968	0.2082
	4	RLB	0.8729	0.6186	0.0692	0.0007	0.1418	0.1550
	4	TRA	0.6185	0.8810	0.0108	0.0001	0.2034	0.4484
	5	BPC	0.7426	0.7426	0.0070	0.0001	0.1968	0.2082
	5	RLB	0.8733	0.6186	0.0688	0.0007	0.1418	0.1551
	5	TRA	0.6185	0.8818	0.0109	0.0001	0.2046	0.4450
	6	BPC	0.7426	0.7426	0.0070	0.0001	0.1968	0.2081
	6	RLB	0.8732	0.6185	0.0687	0.0007	0.1419	0.1551
	6	TRA	0.6185	0.8816	0.0108	0.0001	0.2060	0.4447
	7	BPC	0.7425	0.7426	0.0069	0.0001	0.1968	0.2081
	7	RLB	0.8737	0.6185	0.0684	0.0007	0.1419	0.1551
	7	TRA	0.6185	0.8822	0.0109	0.0001	0.2065	0.4438
	8	BPC	0.7426	0.7426	0.0070	0.0001	0.1968	0.2081
	8	RLB	0.8735	0.6185	0.0692	0.0007	0.1420	0.1550
	8	TRA	0.6184	0.8825	0.0107	0.0001	0.2052	0.4482
	9	BPC	0.7425	0.7426	0.0070	0.0001	0.1968	0.2081
	9	RLB	0.8726	0.6188	0.0689	0.0007	0.1420	0.1551
	9	TRA	0.6187	0.8804	0.0108	0.0001	0.2053	0.4426


3 Years Most Probable
Risk Profile 1
Risk Profile 2
count
0
2000
4000
6000
0.2
0.4
0.6
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer

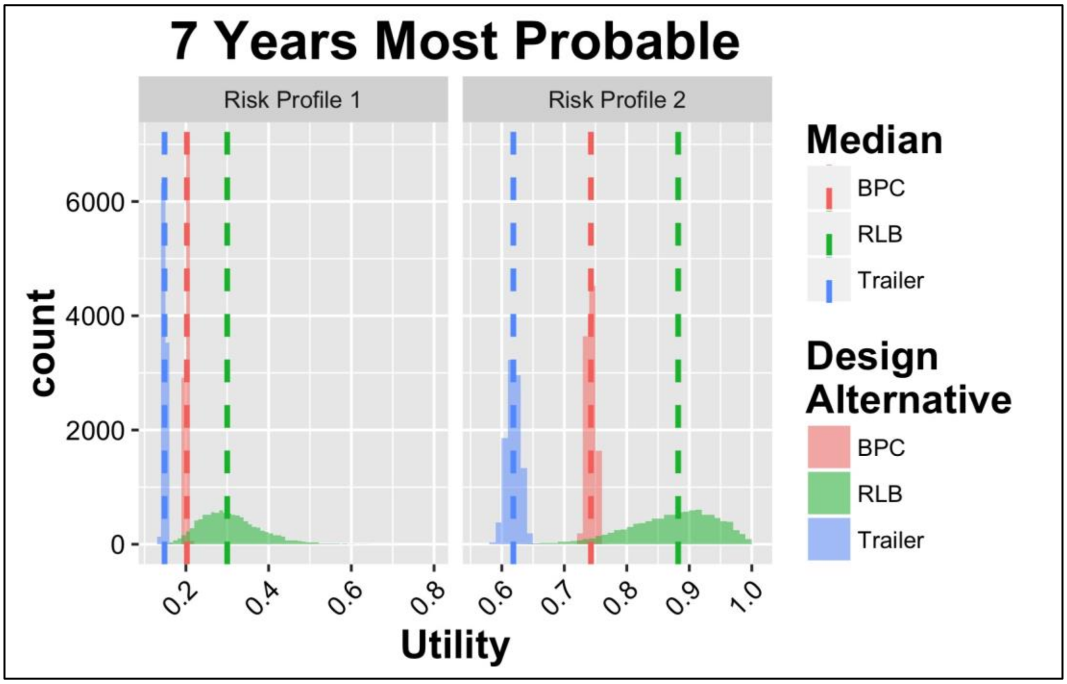

4 Years Most Probable
Risk Profile 1
Risk Profile 2
count
0
2000
4000
6000
0.2
0.4
0.6
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer

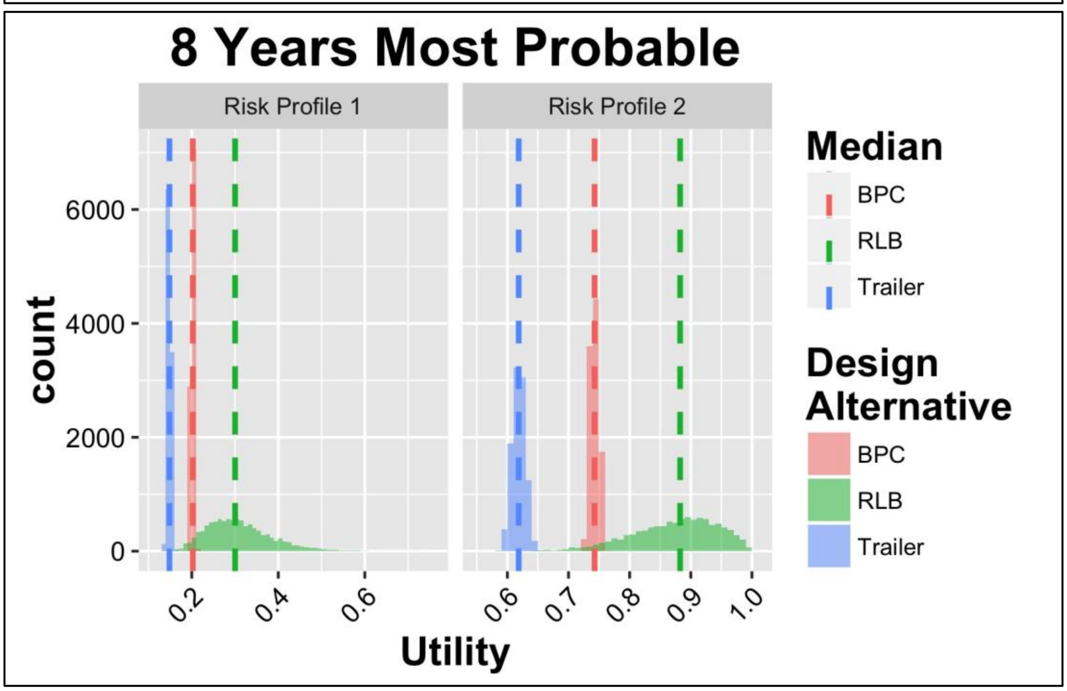


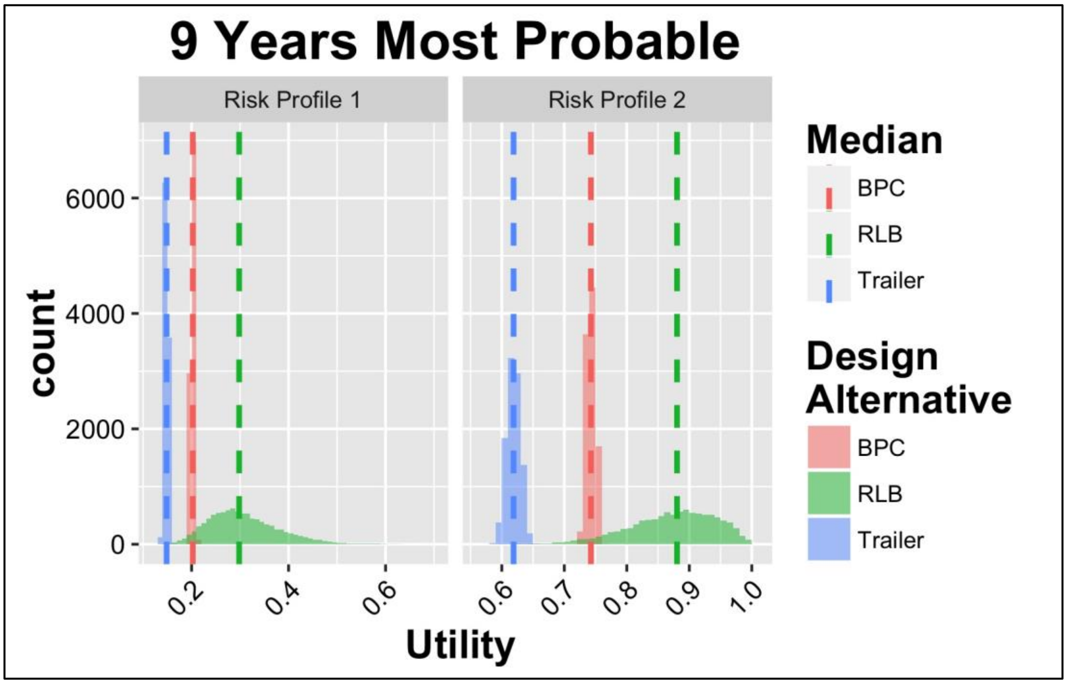
5 Years Most Probable
Risk Profile 1
Risk Profile 2
count
6000
4000
2000
0
0.2
0.4
0.6
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer



6 Years Most Probable
Risk Profile 1
Risk Profile 2
count
6000
4000
2000
0
0.2
0.4
0.6
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer


7 Years Most Probable
Risk Profile 1
Risk Profile 2
count
6000
4000
2000
0
0.2
0.4
0.6
0.8
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer


8 Years Most Probable
Risk Profile 1
Risk Profile 2
count
6000
4000
2000
0
0.2
0.4
0.6
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer



9 Years Most Probable
Risk Profile 1
Risk Profile 2
count
6000
4000
2000
0
0.2
0.4
0.6
0.6
0.7
0.8
0.9
1.0
Utility
Median
BPC
RLB
Trailer
Design Alternative
BPC
RLB
Trailer

Appendix E: R Code

Unadjusted Analysis.R

Ryan

Thu Feb 11 05:19:09 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/Question 3a"
)

# Assumptions
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06

# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
```

```
BPC.DCPSF3 <- 15.60
BPC.DCPSF4 <- 21.00
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
```

```
RLB2.MX2015.mean <- 5.333
RLB2.MX2015.stdev <- 0.690
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Present Worth of Life Cycle Cost Function
LCC <- function (t, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  if(t == 3){
    LCC <- AC + MX1 + DC
  }
  if(t == 4){
    LCC <- AC + MX1 + MX2 + DC
  }
  if(t == 5){
    LCC <- AC + MX1 + MX2 + MX3 + DC
  }
  if(t == 6){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC
  }
  if(t == 7){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC
  }
  if(t == 8){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC
  }
  if(t == 9){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7 + DC
  }
  return(LCC)
}

# 3 Year Duration Simulation
t <- 3
```

```
BPC.AC.3 <- BPC.AC * FGP(8,i)
BPC.MX1.3 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.3 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.3 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.3 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.3 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.3 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.3 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.3 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
TRA.MX1.3 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.3 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
TRA.MX4.3 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
TRA.MX5.3 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.3 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.3 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.DC.3 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.3 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
RLB.MX1.3 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.3 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.3 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
RLB.MX5.3 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.3 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
```

```
shop.rate * FGP(2,i)
RLB.MX7.3 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.DC.3 <- array(RLB.DC.AVG, n) * RLB.size

BPC.MX.3 <- BPC.MX1.3
TRA.MX.3 <- TRA.MX1.3
RLB.MX.3 <- RLB.MX1.3

BPC.LCC.3 <- LCC(t, BPC.AC.3, BPC.MX1.3, BPC.MX2.3, BPC.MX3.3, BPC.MX4.
3, BPC.MX5.3, BPC.MX6.3, BPC.MX7.3, BPC.DC.3)
TRA.LCC.3 <- LCC(t, TRA.AC.3, TRA.MX1.3, TRA.MX2.3, TRA.MX3.3, TRA.MX4.
3, TRA.MX5.3, TRA.MX6.3, TRA.MX7.3, TRA.DC.3)
RLB.LCC.3 <- LCC(t, RLB.AC.3, RLB.MX1.3, RLB.MX2.3, RLB.MX3.3, RLB.MX4.
3, RLB.MX5.3, RLB.MX6.3, RLB.MX7.3, RLB.DC.3)

# 4 Year Duration Simulation
t <- 4

BPC.AC.4 <- BPC.AC * FGP(8,i)
BPC.MX1.4 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.4 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.4 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.4 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.4 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.4 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.4 <- BPC.MX1.4 + BPC.MX2.4
BPC.DC.4 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.4 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
TRA.MX1.4 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.4 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.4 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
TRA.MX4.4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
```

```
TRA.MX5.4 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.4 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.4 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.MX.4 <- TRA.MX1.4 + TRA.MX2.4
TRA.DC.4 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.4 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
RLB.MX1.4 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.4 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.4 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
RLB.MX5.4 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.4 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX7.4 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX.4 <- RLB.MX1.4 + RLB.MX2.4
RLB.DC.4 <- array(RLB.DC.AVG, n) * RLB.size

BPC.LCC.4 <- LCC(t, BPC.AC.4, BPC.MX1.4, BPC.MX2.4, BPC.MX3.4, BPC.MX4.
4, BPC.MX5.4, BPC.MX6.4, BPC.MX7.4, BPC.DC.4)
TRA.LCC.4 <- LCC(t, TRA.AC.4, TRA.MX1.4, TRA.MX2.4, TRA.MX3.4, TRA.MX4.
4, TRA.MX5.4, TRA.MX6.4, TRA.MX7.4, TRA.DC.4)
RLB.LCC.4 <- LCC(t, RLB.AC.4, RLB.MX1.4, RLB.MX2.4, RLB.MX3.4, RLB.MX4.
4, RLB.MX5.4, RLB.MX6.4, RLB.MX7.4, RLB.DC.4)

# 5 Year Duration Simulation
t <- 5

BPC.AC.5 <- BPC.AC * FGP(8,i)
BPC.MX1.5 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.5 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.5 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.5 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
```

```
BPC.MX5.5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.5 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.5 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.5 <- BPC.MX1.5 + BPC.MX2.5 + BPC.MX3.5
BPC.DC.5 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.5 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
TRA.MX1.5 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.5 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.5 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
TRA.MX4.5 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
TRA.MX5.5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.5 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.5 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.MX.5 <- TRA.MX1.5 + TRA.MX2.5 + TRA.MX3.5
TRA.DC.5 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.5 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
RLB.MX1.5 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.5 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.5 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.5 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
RLB.MX5.5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.5 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX7.5 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX.5 <- RLB.MX1.5 + RLB.MX2.5 + RLB.MX3.5
RLB.DC.5 <- array(RLB.DC.AVG, n) * RLB.size

BPC.LCC.5 <- LCC(t, BPC.AC.5, BPC.MX1.5, BPC.MX2.5, BPC.MX3.5, BPC.MX4.
```

```
5, BPC.MX5.5, BPC.MX6.5, BPC.MX7.5, BPC.DC.5)
TRA.LCC.5 <- LCC(t, TRA.AC.5, TRA.MX1.5, TRA.MX2.5, TRA.MX3.5, TRA.MX4.
5, TRA.MX5.5, TRA.MX6.5, TRA.MX7.5, TRA.DC.5)
RLB.LCC.5 <- LCC(t, RLB.AC.5, RLB.MX1.5, RLB.MX2.5, RLB.MX3.5, RLB.MX4.
5, RLB.MX5.5, RLB.MX6.5, RLB.MX7.5, RLB.DC.5)

# 6 Year Duration Simulation
t <- 6

BPC.AC.6 <- BPC.AC * FGP(8,i)
BPC.MX1.6 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.6 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.6 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.6 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.6 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.6 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.6 <- BPC.MX1.6 + BPC.MX2.6 + BPC.MX3.6 + BPC.MX4.6
BPC.DC.6 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.6 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
TRA.MX1.6 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.6 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.6 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
TRA.MX4.6 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
TRA.MX5.6 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.6 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.MX.6 <- TRA.MX1.6 + TRA.MX2.6 + TRA.MX3.6 + TRA.MX4.6
TRA.DC.6 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.6 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
```

```
RLB.MX1.6 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.6 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.6 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.6 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
RLB.MX5.6 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX7.6 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX.6 <- RLB.MX1.6 + RLB.MX2.6 + RLB.MX3.6 + RLB.MX4.6
RLB.DC.6 <- array(RLB.DC.AVG, n) * RLB.size

BPC.LCC.6 <- LCC(t, BPC.AC.6, BPC.MX1.6, BPC.MX2.6, BPC.MX3.6, BPC.MX4.
6, BPC.MX5.6, BPC.MX6.6, BPC.MX7.6, BPC.DC.6)
TRA.LCC.6 <- LCC(t, TRA.AC.6, TRA.MX1.6, TRA.MX2.6, TRA.MX3.6, TRA.MX4.
6, TRA.MX5.6, TRA.MX6.6, TRA.MX7.6, TRA.DC.6)
RLB.LCC.6 <- LCC(t, RLB.AC.6, RLB.MX1.6, RLB.MX2.6, RLB.MX3.6, RLB.MX4.
6, RLB.MX5.6, RLB.MX6.6, RLB.MX7.6, RLB.DC.6)

# 7 Year Duration Simulation
t <- 7

BPC.AC.7 <- BPC.AC * FGP(8,i)
BPC.MX1.7 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.7 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.7 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.7 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.7 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.7 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.7 <- BPC.MX1.7 + BPC.MX2.7 + BPC.MX3.7 + BPC.MX4.7 + BPC.MX5.7
BPC.DC.7 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.7 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
```

```
TRA.MX1.7 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.7 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.7 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
TRA.MX4.7 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
TRA.MX5.7 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.7 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.MX.7 <- TRA.MX1.7 + TRA.MX2.7 + TRA.MX3.7 + TRA.MX4.7 + TRA.MX5.7
TRA.DC.7 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.7 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
RLB.MX1.7 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.7 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.7 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.7 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
RLB.MX5.7 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.7 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX7.7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX.7 <- RLB.MX1.7 + RLB.MX2.7 + RLB.MX3.7 + RLB.MX4.7 + RLB.MX5.7
RLB.DC.7 <- array(RLB.DC.AVG, n) * RLB.size

BPC.LCC.7 <- LCC(t, BPC.AC.7, BPC.MX1.7, BPC.MX2.7, BPC.MX3.7, BPC.MX4.
7, BPC.MX5.7, BPC.MX6.7, BPC.MX7.7, BPC.DC.7)
TRA.LCC.7 <- LCC(t, TRA.AC.7, TRA.MX1.7, TRA.MX2.7, TRA.MX3.7, TRA.MX4.
7, TRA.MX5.7, TRA.MX6.7, TRA.MX7.7, TRA.DC.7)
RLB.LCC.7 <- LCC(t, RLB.AC.7, RLB.MX1.7, RLB.MX2.7, RLB.MX3.7, RLB.MX4.
7, RLB.MX5.7, RLB.MX6.7, RLB.MX7.7, RLB.DC.7)

# 8 Year Duration Simulation
t <- 8

BPC.AC.8 <- BPC.AC * FGP(8,i)
```

```
BPC.MX1.8 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.8 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.8 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.8 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.8 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.8 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.8 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.8 <- BPC.MX1.8 + BPC.MX2.8 + BPC.MX3.8 + BPC.MX4.8 + BPC.MX5.8 +
BPC.MX6.8
BPC.DC.8 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.8 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
TRA.MX1.8 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.8 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.8 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
TRA.MX4.8 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
TRA.MX5.8 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.8 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.8 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.MX.8 <- TRA.MX1.8 + TRA.MX2.8 + TRA.MX3.8 + TRA.MX4.8 + TRA.MX5.8 +
TRA.MX6.8
TRA.DC.8 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.8 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
RLB.MX1.8 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.8 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.8 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.8 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
```

```
RLB.MX5.8 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.8 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX7.8 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX.8 <- RLB.MX1.8 + RLB.MX2.8 + RLB.MX3.8 + RLB.MX4.8 + RLB.MX5.8 +
RLB.MX6.8
RLB.DC.8 <- array(RLB.DC.AVG, n) * RLB.size

BPC.LCC.8 <- LCC(t, BPC.AC.8, BPC.MX1.8, BPC.MX2.8, BPC.MX3.8, BPC.MX4.
8, BPC.MX5.8, BPC.MX6.8, BPC.MX7.8, BPC.DC.8)
TRA.LCC.8 <- LCC(t, TRA.AC.8, TRA.MX1.8, TRA.MX2.8, TRA.MX3.8, TRA.MX4.
8, TRA.MX5.8, TRA.MX6.8, TRA.MX7.8, TRA.DC.8)
RLB.LCC.8 <- LCC(t, RLB.AC.8, RLB.MX1.8, RLB.MX2.8, RLB.MX3.8, RLB.MX4.
8, RLB.MX5.8, RLB.MX6.8, RLB.MX7.8, RLB.DC.8)

# 9 Year Duration Simulation
t <- 9

BPC.AC.9 <- BPC.AC * FGP(8,i)
BPC.MX1.9 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.9 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.9 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.9 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.9 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.9 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.9 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.9 <- BPC.MX1.9 + BPC.MX2.9 + BPC.MX3.9 + BPC.MX4.9 + BPC.MX5.9 +
BPC.MX6.9 + BPC.MX7.9
BPC.DC.9 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.9 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i)
TRA.MX1.9 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
TRA.MX2.9 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
TRA.MX3.9 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
```

```
TRA.MX4.9 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
TRA.MX5.9 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
TRA.MX6.9 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
TRA.MX7.9 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
TRA.MX.9 <- TRA.MX1.9 + TRA.MX2.9 + TRA.MX3.9 + TRA.MX4.9 + TRA.MX5.9 +
TRA.MX6.9 + TRA.MX7.9
TRA.DC.9 <- array(TRA.DC.AVG, n) * TRA.size

RLB.AC.9 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i)
RLB.MX1.9 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX2.9 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX3.9 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX4.9 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i))
RLB.MX5.9 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i)
RLB.MX6.9 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i)
RLB.MX7.9 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i)
RLB.MX.9 <- RLB.MX1.9 + RLB.MX2.9 + RLB.MX3.9 + RLB.MX4.9 + RLB.MX5.9 +
RLB.MX6.9 + RLB.MX7.9
RLB.DC.9 <- array(RLB.DC.AVG, n) * RLB.size

BPC.LCC.9 <- LCC(t, BPC.AC.9, BPC.MX1.9, BPC.MX2.9, BPC.MX3.9, BPC.MX4.
9, BPC.MX5.9, BPC.MX6.9, BPC.MX7.9, BPC.DC.9)
TRA.LCC.9 <- LCC(t, TRA.AC.9, TRA.MX1.9, TRA.MX2.9, TRA.MX3.9, TRA.MX4.
9, TRA.MX5.9, TRA.MX6.9, TRA.MX7.9, TRA.DC.9)
RLB.LCC.9 <- LCC(t, RLB.AC.9, RLB.MX1.9, RLB.MX2.9, RLB.MX3.9, RLB.MX4.
9, RLB.MX5.9, RLB.MX6.9, RLB.MX7.9, RLB.DC.9)

# Data Frame Construction
# Simulation Histograms and Means Plots Data Frames
design.array <- c(array("BPC",28*n),array("TRA",28*n),array("RLB",28*n)
)
year.array <- rep(c(array(3,n), array(4,n), array(5,n), array(6,n), arr
ay(7,n), array(8,n), array(9,n)),12)
cost.type.array <- rep(c(array("Acquisition",7*n), array("Maintenance",
7*n), array("Disposal",7*n), array("Life Cycle",7*n)),3)
```

```
BPC.AC <- (c(BPC.AC.3, BPC.AC.4, BPC.AC.5, BPC.AC.6, BPC.AC.7, BPC.AC.8
, BPC.AC.9))/10000
BPC.MX <- (c(BPC.MX.3, BPC.MX.4, BPC.MX.5, BPC.MX.6, BPC.MX.7, BPC.MX.8
, BPC.MX.9))/10000
BPC.DC <- (c(BPC.DC.3, BPC.DC.4, BPC.DC.5, BPC.DC.6, BPC.DC.7, BPC.DC.8
, BPC.DC.9))/10000
BPC.LCC <- (c(BPC.LCC.3, BPC.LCC.4, BPC.LCC.5, BPC.LCC.6, BPC.LCC.7, BP
C.LCC.8, BPC.LCC.9))/10000
BPC <- c(BPC.AC, BPC.MX, BPC.DC, BPC.LCC)

TRA.AC <- (c(TRA.AC.3, TRA.AC.4, TRA.AC.5, TRA.AC.6, TRA.AC.7, TRA.AC.8
, TRA.AC.9))/10000
TRA.MX <- (c(TRA.MX.3, TRA.MX.4, TRA.MX.5, TRA.MX.6, TRA.MX.7, TRA.MX.8
, TRA.MX.9))/10000
TRA.DC <- (c(TRA.DC.3, TRA.DC.4, TRA.DC.5, TRA.DC.6, TRA.DC.7, TRA.DC.8
, TRA.DC.9))/10000
TRA.LCC <- (c(TRA.LCC.3, TRA.LCC.4, TRA.LCC.5, TRA.LCC.6, TRA.LCC.7, TR
A.LCC.8, TRA.LCC.9))/10000
TRA <- c(TRA.AC, TRA.MX, TRA.DC, TRA.LCC)

RLB.AC <- (c(RLB.AC.3, RLB.AC.4, RLB.AC.5, RLB.AC.6, RLB.AC.7, RLB.AC.8
, RLB.AC.9))/10000
RLB.MX <- (c(RLB.MX.3, RLB.MX.4, RLB.MX.5, RLB.MX.6, RLB.MX.7, RLB.MX.8
, RLB.MX.9))/10000
RLB.DC <- (c(RLB.DC.3, RLB.DC.4, RLB.DC.5, RLB.DC.6, RLB.DC.7, RLB.DC.8
, RLB.DC.9))/10000
RLB.LCC <- (c(RLB.LCC.3, RLB.LCC.4, RLB.LCC.5, RLB.LCC.6, RLB.LCC.7, RL
B.LCC.8, RLB.LCC.9))/10000
RLB <- c(RLB.AC, RLB.MX, RLB.DC, RLB.LCC)

Designs.MX.Year <- data.frame(Design = c(array("BPC",7*n), array("TRA",
7*n), array("RLB",7*n)),Year = rep(c(array(1,n), array(2,n), array(3,n)
, array(4,n), array(5,n), array(6,n), array(7,n)),3), Cost = (c(BPC.MX1
.3,BPC.MX2.3,BPC.MX3.3,BPC.MX4.3,BPC.MX5.3,BPC.MX6.3,BPC.MX7.3,TRA.MX1.
3,TRA.MX2.3,TRA.MX3.3,TRA.MX4.3,TRA.MX5.3,TRA.MX6.3,TRA.MX7.3,RLB.MX1.3
,RLB.MX2.3,RLB.MX3.3,RLB.MX4.3,RLB.MX5.3,RLB.MX6.3,RLB.MX7.3))/10000)
cost.array <- c(BPC, TRA, RLB)
Cost.Data <- data.frame(Design = design.array, Year = year.array, Type
= cost.type.array, Cost = cost.array)
Cost.Data.Summary <- summarySE(Cost.Data, measurevar = "Cost", groupvar
s = c("Design", "Year", "Type"), conf.interval = .90)

# Plot Construction
# Simulation Means Plots
Designs.AC.Sum <- subset(Cost.Data.Summary, Type == "Acquisition" & Yea
```

```
r == 3 , select = c(Design, Year, Type, N, Cost, sd, se, ci))
Designs.MX.Year.Sum <- summarySE(Designs.MX.Year, measurevar = "Cost",
groupvars = c("Design","Year"), conf.interval = .90)
Designs.MX.Sum <- subset(Cost.Data.Summary, Type == "Maintenance", sele
ct = c(Design, Year, Type, N, Cost, sd, se, ci))
Designs.DC.Sum <- subset(Cost.Data.Summary, Type == "Disposal" & Year =
= 3, select = c(Design, Year, Type, N, Cost, sd, se, ci))
Designs.LCC.Sum <- subset(Cost.Data.Summary, Type == "Life Cycle" , sel
ect = c(Design, Year, Type, N, Cost, sd, se, ci))

AC.Means.Plot <- ggplot(data=Designs.AC.Sum, aes(x = Design ,y= Cost, f
ill = Design)) +
  geom_bar(stat = "identity") +
  labs(title = "Means of Aquisition Cost") +
  guides(fill=FALSE) +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_x_discrete(name="") +
  scale_y_continuous(name="Cost ($10K)")
MX.Means.Year.Plot <- ggplot(data=Designs.MX.Year.Sum) +
  geom_line(aes(x = Year,y = Cost,colour=Design)) +
  geom_errorbar(aes(x=Year,ymin = Cost-ci ,ymax= Cost+ci), width = 0.1)
+
  labs(title = "Means of MX Cost Per Year") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_y_continuous(name="Cost ($10K)")
MX.Means.Cum.Plot <- ggplot(data=Designs.MX.Sum) +
  geom_line(aes(x=Year,y=Cost,colour=Design)) +
  geom_errorbar(aes(x=Year,ymin = Cost-ci ,ymax= Cost+ci), width = 0.1)
+
  labs(title = "Means of Cumulatiove MX Cost") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
```

```
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_y_continuous(name="Cost ($10K)")
DC.Means.Plot <- ggplot(data=Designs.DC.Sum, aes(x = Design ,y= Cost, f
ill = Design)) +
  geom_bar(stat = "identity") +
  labs(title = "Simulated Means of Disposal Cost") +
  guides(fill=FALSE) +
  labs(title = "Means of Disposal Cost") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_x_discrete(name="") +
  scale_y_continuous(name="Cost ($10K)")
LCC.Means.Plot <- ggplot(data=Designs.LCC.Sum) +
  geom_line(aes(x=Year,y=Cost,colour=Design)) +
  labs(title = "Means of Life Cycle Cost") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_y_continuous(name="Cost ($10K)")

BPC.Cost.Sum <- subset(Cost.Data.Summary, Design == "BPC", select = c(T
ype, Year, Cost, sd, se, ci))
TRA.Cost.Sum <- subset(Cost.Data.Summary, Design == "TRA", select = c(T
ype, Year, Cost, sd, se, ci))
RLB.Cost.Sum <- subset(Cost.Data.Summary, Design == "RLB", select = c(T
ype, Year, Cost, sd, se, ci))

BPC.Means.Plot <- ggplot(BPC.Cost.Sum) +
  geom_line(aes(x = Year, y = Cost, colour = Type)) +
  geom_errorbar(aes(x=Year,ymin = Cost-ci ,ymax= Cost+ci), width = 0.1)
```

```
+
  labs(title = "Contribution to Total LCC: BPC") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Cost\nType") +
  scale_y_continuous(name="Cost ($10K)")
TRA.Means.Plot <- ggplot(TRA.Cost.Sum) +
  geom_line(aes(x = Year, y = Cost, colour = Type)) +
  geom_errorbar(aes(x=Year,ymin = Cost-ci ,ymax= Cost+ci), width = 0.1)
+
  labs(title = "Contribution to Total LCC: Trailers") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Cost Type") +
  scale_y_continuous(name="Cost ($10K)")
RLB.Means.Plot <- ggplot(RLB.Cost.Sum) +
  geom_line(aes(x = Year, y = Cost, colour = Type)) +
  geom_errorbar(aes(x=Year,ymin = Cost-ci ,ymax= Cost+ci), width = 0.1)
+
  labs(title = "Contribution to Total LCC: RLBs") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold")) +
  scale_colour_discrete(name  ="Cost Type") +
  scale_y_continuous(name="Cost ($10K)")

# Print All Plots
AC.Means.Plot
```

```
ggsave("AC_Means_Plot.jpg", width = 6, height = 5)
MX.Means.Year.Plot
```

```r
ggsave("MX_Means_Plot.jpg", width = 6, height = 5)
MX.Means.Cum.Plot
```

```r
ggsave("MX_Means_Cum_Plot.jpg", width = 6, height = 5)
DC.Means.Plot
```

```r
ggsave("DC_Means_Plot.jpg", width = 6, height = 5)
LCC.Means.Plot
```

```r
ggsave("LCC_Means_Plot.jpg", width = 6, height = 5)
BPC.Means.Plot
```

```r
ggsave("BPC_Means_Plot.jpg", width = 6, height = 5)
TRA.Means.Plot
```

```r
ggsave("TRA_Means_Plot.jpg", width = 6, height = 5)
RLB.Means.Plot
```

```r
ggsave("RLB_Means_Plot.jpg", width = 6, height = 5)

Cost.Data.Summary <- rename(Cost.Data.Summary, replace = c("Type"="Cost
Type", "Cost"= "Mean", "sd"="Standard Deviation", "se"="Standard Error"
, "ci"="Confidence Interval"))
write.csv(Cost.Data.Summary, "3a_Data.csv")
```

Adjusted Analysis.R

Ryan

Thu Feb 11 05:27:47 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/Question 3b"
)

# Assumptions
TRA.Adjustment.Factor <- 3.266667
RLB.Adjustment.Factor <- 49
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06

# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
BPC.DCPSF3 <- 15.60
BPC.DCPSF4 <- 21.00
```

```r
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
RLB2.MX2015.mean <- 5.333
RLB2.MX2015.stdev <- 0.690
```

```
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Present Worth of Life Cycle Cost Function
LCC <- function (t, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  if(t == 3){
    LCC <- AC + MX1 + DC
  }
  if(t == 4){
    LCC <- AC + MX1 + MX2 + DC
  }
  if(t == 5){
    LCC <- AC + MX1 + MX2 + MX3 + DC
  }
  if(t == 6){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC
  }
  if(t == 7){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC
  }
  if(t == 8){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC
  }
  if(t == 9){
    LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7 + DC
  }
  return(LCC)
}

# 3 Year Duration Simulation
t <- 3

BPC.AC.3 <- BPC.AC * FGP(8,i)
BPC.MX1.3 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
```

```
op.rate * FGP(7,i)
BPC.MX2.3 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.3 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.3 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.3 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.3 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.3 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.3 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.3 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.3 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.3 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.3 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.3 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.3 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.3 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.3 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.3 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.3 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.3 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.3 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.3 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
```

```
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.3 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.3 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.MX.3 <- BPC.MX1.3
TRA.MX.3 <- TRA.MX1.3
RLB.MX.3 <- RLB.MX1.3

BPC.LCC.3 <- LCC(t, BPC.AC.3, BPC.MX1.3, BPC.MX2.3, BPC.MX3.3, BPC.MX4.
3, BPC.MX5.3, BPC.MX6.3, BPC.MX7.3, BPC.DC.3)
TRA.LCC.3 <- LCC(t, TRA.AC.3, TRA.MX1.3, TRA.MX2.3, TRA.MX3.3, TRA.MX4.
3, TRA.MX5.3, TRA.MX6.3, TRA.MX7.3, TRA.DC.3)
RLB.LCC.3 <- LCC(t, RLB.AC.3, RLB.MX1.3, RLB.MX2.3, RLB.MX3.3, RLB.MX4.
3, RLB.MX5.3, RLB.MX6.3, RLB.MX7.3, RLB.DC.3)

# 4 Year Duration Simulation
t <- 4

BPC.AC.4 <- BPC.AC * FGP(8,i)
BPC.MX1.4 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.4 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.4 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.4 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.4 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.4 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.4 <- BPC.MX1.4 + BPC.MX2.4
BPC.DC.4 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.4 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.4 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.4 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.4 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
```

```
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.4 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.4 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.4 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.4 <- TRA.MX1.4 + TRA.MX2.4
TRA.DC.4 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.4 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.4 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.4 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.4 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.4 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.4 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.4 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.4 <- RLB.MX1.4 + RLB.MX2.4
RLB.DC.4 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.4 <- LCC(t, BPC.AC.4, BPC.MX1.4, BPC.MX2.4, BPC.MX3.4, BPC.MX4.
4, BPC.MX5.4, BPC.MX6.4, BPC.MX7.4, BPC.DC.4)
TRA.LCC.4 <- LCC(t, TRA.AC.4, TRA.MX1.4, TRA.MX2.4, TRA.MX3.4, TRA.MX4.
4, TRA.MX5.4, TRA.MX6.4, TRA.MX7.4, TRA.DC.4)
RLB.LCC.4 <- LCC(t, RLB.AC.4, RLB.MX1.4, RLB.MX2.4, RLB.MX3.4, RLB.MX4.
4, RLB.MX5.4, RLB.MX6.4, RLB.MX7.4, RLB.DC.4)

# 5 Year Duration Simulation
t <- 5

BPC.AC.5 <- BPC.AC * FGP(8,i)
BPC.MX1.5 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.5 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.5 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
```

```
BPC.MX4.5 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.5 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.5 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.5 <- BPC.MX1.5 + BPC.MX2.5 + BPC.MX3.5
BPC.DC.5 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.5 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.5 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.5 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.5 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.5 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.5 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.5 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.5 <- TRA.MX1.5 + TRA.MX2.5 + TRA.MX3.5
TRA.DC.5 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.5 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.5 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.5 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.5 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.5 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.5 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.5 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
```

```
RLB.MX.5 <- RLB.MX1.5 + RLB.MX2.5 + RLB.MX3.5
RLB.DC.5 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.5 <- LCC(t, BPC.AC.5, BPC.MX1.5, BPC.MX2.5, BPC.MX3.5, BPC.MX4.
5, BPC.MX5.5, BPC.MX6.5, BPC.MX7.5, BPC.DC.5)
TRA.LCC.5 <- LCC(t, TRA.AC.5, TRA.MX1.5, TRA.MX2.5, TRA.MX3.5, TRA.MX4.
5, TRA.MX5.5, TRA.MX6.5, TRA.MX7.5, TRA.DC.5)
RLB.LCC.5 <- LCC(t, RLB.AC.5, RLB.MX1.5, RLB.MX2.5, RLB.MX3.5, RLB.MX4.
5, RLB.MX5.5, RLB.MX6.5, RLB.MX7.5, RLB.DC.5)

# 6 Year Duration Simulation
t <- 6

BPC.AC.6 <- BPC.AC * FGP(8,i)
BPC.MX1.6 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.6 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.6 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.6 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.6 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.6 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.6 <- BPC.MX1.6 + BPC.MX2.6 + BPC.MX3.6 + BPC.MX4.6
BPC.DC.6 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.6 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.6 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.6 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.6 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.6 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.6 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.6 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
```

```
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.6 <- TRA.MX1.6 + TRA.MX2.6 + TRA.MX3.6 + TRA.MX4.6
TRA.DC.6 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.6 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.6 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.6 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.6 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.6 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.6 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.6 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.6 <- RLB.MX1.6 + RLB.MX2.6 + RLB.MX3.6 + RLB.MX4.6
RLB.DC.6 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.6 <- LCC(t, BPC.AC.6, BPC.MX1.6, BPC.MX2.6, BPC.MX3.6, BPC.MX4.
6, BPC.MX5.6, BPC.MX6.6, BPC.MX7.6, BPC.DC.6)
TRA.LCC.6 <- LCC(t, TRA.AC.6, TRA.MX1.6, TRA.MX2.6, TRA.MX3.6, TRA.MX4.
6, TRA.MX5.6, TRA.MX6.6, TRA.MX7.6, TRA.DC.6)
RLB.LCC.6 <- LCC(t, RLB.AC.6, RLB.MX1.6, RLB.MX2.6, RLB.MX3.6, RLB.MX4.
6, RLB.MX5.6, RLB.MX6.6, RLB.MX7.6, RLB.DC.6)

# 7 Year Duration Simulation
t <- 7

BPC.AC.7 <- BPC.AC * FGP(8,i)
BPC.MX1.7 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.7 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.7 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.7 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.7 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.7 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
```

```
BPC.MX7.7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.7 <- BPC.MX1.7 + BPC.MX2.7 + BPC.MX3.7 + BPC.MX4.7 + BPC.MX5.7
BPC.DC.7 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.7 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.7 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.7 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.7 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.7 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.7 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.7 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.7 <- TRA.MX1.7 + TRA.MX2.7 + TRA.MX3.7 + TRA.MX4.7 + TRA.MX5.7
TRA.DC.7 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.7 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.7 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.7 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.7 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.7 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.7 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.7 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.7 <- RLB.MX1.7 + RLB.MX2.7 + RLB.MX3.7 + RLB.MX4.7 + RLB.MX5.7
RLB.DC.7 <- array(RLB.DC.AVG, n) * RLB.size * RLB.Adjustment.Factor

BPC.LCC.7 <- LCC(t, BPC.AC.7, BPC.MX1.7, BPC.MX2.7, BPC.MX3.7, BPC.MX4.
7, BPC.MX5.7, BPC.MX6.7, BPC.MX7.7, BPC.DC.7)
TRA.LCC.7 <- LCC(t, TRA.AC.7, TRA.MX1.7, TRA.MX2.7, TRA.MX3.7, TRA.MX4.
```

```
7, TRA.MX5.7, TRA.MX6.7, TRA.MX7.7, TRA.DC.7)
RLB.LCC.7 <- LCC(t, RLB.AC.7, RLB.MX1.7, RLB.MX2.7, RLB.MX3.7, RLB.MX4.
7, RLB.MX5.7, RLB.MX6.7, RLB.MX7.7, RLB.DC.7)

# 8 Year Duration Simulation
t <- 8

BPC.AC.8 <- BPC.AC * FGP(8,i)
BPC.MX1.8 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.8 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.8 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.8 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.8 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.8 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.8 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.8 <- BPC.MX1.8 + BPC.MX2.8 + BPC.MX3.8 + BPC.MX4.8 + BPC.MX5.8 +
BPC.MX6.8
BPC.DC.8 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.8 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.8 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.8 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.8 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.8 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.8 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.8 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.8 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.8 <- TRA.MX1.8 + TRA.MX2.8 + TRA.MX3.8 + TRA.MX4.8 + TRA.MX5.8 +
TRA.MX6.8
TRA.DC.8 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor
```

```
RLB.AC.8 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.8 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.8 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.8 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.8 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.8 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.8 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.8 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.8 <- RLB.MX1.8 + RLB.MX2.8 + RLB.MX3.8 + RLB.MX4.8 + RLB.MX5.8 +
RLB.MX6.8
RLB.DC.8 <- array(RLB.DC.AVG, n) * RLB.size * RLB.Adjustment.Factor

BPC.LCC.8 <- LCC(t, BPC.AC.8, BPC.MX1.8, BPC.MX2.8, BPC.MX3.8, BPC.MX4.
8, BPC.MX5.8, BPC.MX6.8, BPC.MX7.8, BPC.DC.8)
TRA.LCC.8 <- LCC(t, TRA.AC.8, TRA.MX1.8, TRA.MX2.8, TRA.MX3.8, TRA.MX4.
8, TRA.MX5.8, TRA.MX6.8, TRA.MX7.8, TRA.DC.8)
RLB.LCC.8 <- LCC(t, RLB.AC.8, RLB.MX1.8, RLB.MX2.8, RLB.MX3.8, RLB.MX4.
8, RLB.MX5.8, RLB.MX6.8, RLB.MX7.8, RLB.DC.8)

# 9 Year Duration Simulation
t <- 9

BPC.AC.9 <- BPC.AC * FGP(8,i)
BPC.MX1.9 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.9 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.9 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.9 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.9 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.9 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.9 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.9 <- BPC.MX1.9 + BPC.MX2.9 + BPC.MX3.9 + BPC.MX4.9 + BPC.MX5.9 +
```

```
BPC.MX6.9 + BPC.MX7.9
BPC.DC.9 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.9 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.9 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.9 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.9 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.9 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.9 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.9 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.9 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.9 <- TRA.MX1.9 + TRA.MX2.9 + TRA.MX3.9 + TRA.MX4.9 + TRA.MX5.9 +
TRA.MX6.9 + TRA.MX7.9
TRA.DC.9 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.9 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.9 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.9 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.9 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.9 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.9 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.9 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.9 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.9 <- RLB.MX1.9 + RLB.MX2.9 + RLB.MX3.9 + RLB.MX4.9 + RLB.MX5.9 +
RLB.MX6.9 + RLB.MX7.9
RLB.DC.9 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.9 <- LCC(t, BPC.AC.9, BPC.MX1.9, BPC.MX2.9, BPC.MX3.9, BPC.MX4.
9, BPC.MX5.9, BPC.MX6.9, BPC.MX7.9, BPC.DC.9)
TRA.LCC.9 <- LCC(t, TRA.AC.9, TRA.MX1.9, TRA.MX2.9, TRA.MX3.9, TRA.MX4.
```

```
9, TRA.MX5.9, TRA.MX6.9, TRA.MX7.9, TRA.DC.9)
RLB.LCC.9 <- LCC(t, RLB.AC.9, RLB.MX1.9, RLB.MX2.9, RLB.MX3.9, RLB.MX4.
9, RLB.MX5.9, RLB.MX6.9, RLB.MX7.9, RLB.DC.9)

# Comparison Simulation
BPC.AC.CA <- BPC.AC * FGP(8,i)
BPC.MX1.CA <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.s
hop.rate * FGP(7,i)
BPC.MX2.CA <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.s
hop.rate * FGP(6,i)
BPC.MX3.CA <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB
.shop.rate * FGP(5,i)
BPC.MX4.CA <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.s
hop.rate * FGP(4,i)
BPC.MX5.CA <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.s
hop.rate * FGP(3,i)
BPC.MX6.CA <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.s
hop.rate * FGP(2,i)
BPC.MX7.CA <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.s
hop.rate * FGP(1,i)
BPC.MX.3YR.CA <- BPC.MX1.CA
BPC.MX.4YR.CA <- BPC.MX1.CA + BPC.MX2.CA
BPC.MX.5YR.CA <- BPC.MX1.CA + BPC.MX2.CA + BPC.MX.3YR.CA
BPC.MX.6YR.CA <- BPC.MX1.CA + BPC.MX2.CA + BPC.MX.3YR.CA + BPC.MX.4YR.C
A
BPC.MX.7YR.CA <- BPC.MX1.CA + BPC.MX2.CA + BPC.MX.3YR.CA + BPC.MX.4YR.C
A + BPC.MX.5YR.CA
BPC.MX.8YR.CA <- BPC.MX1.CA + BPC.MX2.CA + BPC.MX.3YR.CA + BPC.MX.4YR.C
A + BPC.MX.5YR.CA + BPC.MX.6YR.CA
BPC.MX.9YR.CA <- BPC.MX1.CA + BPC.MX2.CA + BPC.MX.3YR.CA + BPC.MX.4YR.C
A + BPC.MX.5YR.CA + BPC.MX.6YR.CA + BPC.MX.7YR.CA
BPC.DC.CA <- array(BPC.DC.AVG, n) * BPC.size


TRA.AC.CA <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.
Adjustment.Factor
TRA.MX1.CA <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.s
hop.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.CA <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.s
hop.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.CA <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB
.shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.CA <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.s
hop.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.CA <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.s
hop.rate * FGP(3,i) * TRA.Adjustment.Factor
```

```
TRA.MX6.CA <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.s
hop.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.CA <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.s
hop.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.3YR.CA <- TRA.MX1.CA
TRA.MX.4YR.CA <- TRA.MX1.CA + TRA.MX2.CA
TRA.MX.5YR.CA <- TRA.MX1.CA + TRA.MX2.CA + TRA.MX.3YR.CA
TRA.MX.6YR.CA <- TRA.MX1.CA + TRA.MX2.CA + TRA.MX.3YR.CA + TRA.MX.4YR.C
A
TRA.MX.7YR.CA <- TRA.MX1.CA + TRA.MX2.CA + TRA.MX.3YR.CA + TRA.MX.4YR.C
A + TRA.MX.5YR.CA
TRA.MX.8YR.CA <- TRA.MX1.CA + TRA.MX2.CA + TRA.MX.3YR.CA + TRA.MX.4YR.C
A + TRA.MX.5YR.CA + TRA.MX.6YR.CA
TRA.MX.9YR.CA <- TRA.MX1.CA + TRA.MX2.CA + TRA.MX.3YR.CA + TRA.MX.4YR.C
A + TRA.MX.5YR.CA + TRA.MX.6YR.CA + TRA.MX.7YR.CA
TRA.DC.CA <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.CA <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.
Adjustment.Factor
RLB.MX1.CA <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB
.shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.CA <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB
.shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.CA <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB
.shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.CA <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.ra
te * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.CA <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB
.shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.CA <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB
.shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.CA <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB
.shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.3YR.CA <- RLB.MX1.CA
RLB.MX.4YR.CA <- RLB.MX1.CA + RLB.MX2.CA
RLB.MX.5YR.CA <- RLB.MX1.CA + RLB.MX2.CA + RLB.MX.3YR.CA
RLB.MX.6YR.CA <- RLB.MX1.CA + RLB.MX2.CA + RLB.MX.3YR.CA + RLB.MX.4YR.C
A
RLB.MX.7YR.CA <- RLB.MX1.CA + RLB.MX2.CA + RLB.MX.3YR.CA + RLB.MX.4YR.C
A + RLB.MX.5YR.CA
RLB.MX.8YR.CA <- RLB.MX1.CA + RLB.MX2.CA + RLB.MX.3YR.CA + RLB.MX.4YR.C
A + RLB.MX.5YR.CA + RLB.MX.6YR.CA
RLB.MX.9YR.CA <- RLB.MX1.CA + RLB.MX2.CA + RLB.MX.3YR.CA + RLB.MX.4YR.C
A + RLB.MX.5YR.CA + RLB.MX.6YR.CA + RLB.MX.7YR.CA
RLB.DC.CA <- array(RLB.DC.AVG, n) * RLB.size * RLB.Adjustment.Factor
```

```
# Comparison Analysis
# BPC vs Trailer
BPC.TRA.SC <- BPC.AC.CA - TRA.AC.CA
BPC.TRA.MX.3YR <- BPC.MX.3YR.CA - TRA.MX.3YR.CA
BPC.TRA.MX.4YR <- BPC.MX.4YR.CA - TRA.MX.4YR.CA
BPC.TRA.MX.5YR <- BPC.MX.5YR.CA - TRA.MX.5YR.CA
BPC.TRA.MX.6YR <- BPC.MX.6YR.CA - TRA.MX.6YR.CA
BPC.TRA.MX.7YR <- BPC.MX.7YR.CA - TRA.MX.6YR.CA
BPC.TRA.MX.8YR <- BPC.MX.8YR.CA - TRA.MX.8YR.CA
BPC.TRA.MX.9YR <- BPC.MX.9YR.CA - TRA.MX.9YR.CA

BPC.TRA.3YR <- BPC.TRA.SC - BPC.TRA.MX.3YR
BPC.TRA.4YR <- BPC.TRA.SC - BPC.TRA.MX.3YR - BPC.TRA.MX.4YR
BPC.TRA.5YR <- BPC.TRA.SC - BPC.TRA.MX.3YR - BPC.TRA.MX.4YR - BPC.TRA.M
X.5YR
BPC.TRA.6YR <- BPC.TRA.SC - BPC.TRA.MX.3YR - BPC.TRA.MX.4YR - BPC.TRA.M
X.5YR - BPC.TRA.MX.6YR
BPC.TRA.7YR <- BPC.TRA.SC - BPC.TRA.MX.3YR - BPC.TRA.MX.4YR - BPC.TRA.M
X.5YR - BPC.TRA.MX.6YR - BPC.TRA.MX.7YR
BPC.TRA.8YR <- BPC.TRA.SC - BPC.TRA.MX.3YR - BPC.TRA.MX.4YR - BPC.TRA.M
X.5YR - BPC.TRA.MX.6YR - BPC.TRA.MX.7YR - BPC.TRA.MX.8YR
BPC.TRA.9YR <- BPC.TRA.SC - BPC.TRA.MX.3YR - BPC.TRA.MX.4YR - BPC.TRA.M
X.5YR - BPC.TRA.MX.6YR - BPC.TRA.MX.7YR - BPC.TRA.MX.8YR - BPC.TRA.MX.9
YR

# BPC vs Relocatable Building
BPC.RLB.SC <- BPC.AC.CA - RLB.AC.CA
BPC.RLB.MX.3YR <- BPC.MX.3YR.CA - RLB.MX.3YR.CA
BPC.RLB.MX.4YR <- BPC.MX.4YR.CA - RLB.MX.4YR.CA
BPC.RLB.MX.5YR <- BPC.MX.5YR.CA - RLB.MX.5YR.CA
BPC.RLB.MX.6YR <- BPC.MX.6YR.CA - RLB.MX.6YR.CA
BPC.RLB.MX.7YR <- BPC.MX.7YR.CA - RLB.MX.6YR.CA
BPC.RLB.MX.8YR <- BPC.MX.8YR.CA - RLB.MX.8YR.CA
BPC.RLB.MX.9YR <- BPC.MX.9YR.CA - RLB.MX.9YR.CA

BPC.RLB.3YR <- BPC.RLB.SC - BPC.RLB.MX.3YR
BPC.RLB.4YR <- BPC.RLB.SC - BPC.RLB.MX.3YR - BPC.RLB.MX.4YR
BPC.RLB.5YR <- BPC.RLB.SC - BPC.RLB.MX.3YR - BPC.RLB.MX.4YR - BPC.RLB.M
X.5YR
BPC.RLB.6YR <- BPC.RLB.SC - BPC.RLB.MX.3YR - BPC.RLB.MX.4YR - BPC.RLB.M
X.5YR - BPC.RLB.MX.6YR
BPC.RLB.7YR <- BPC.RLB.SC - BPC.RLB.MX.3YR - BPC.RLB.MX.4YR - BPC.RLB.M
X.5YR - BPC.RLB.MX.6YR - BPC.RLB.MX.7YR
BPC.RLB.8YR <- BPC.RLB.SC - BPC.RLB.MX.3YR - BPC.RLB.MX.4YR - BPC.RLB.M
X.5YR - BPC.RLB.MX.6YR - BPC.RLB.MX.7YR - BPC.RLB.MX.8YR
BPC.RLB.9YR <- BPC.RLB.SC - BPC.RLB.MX.3YR - BPC.RLB.MX.4YR - BPC.RLB.M
```

```
X.5YR - BPC.RLB.MX.6YR - BPC.RLB.MX.7YR - BPC.RLB.MX.8YR - BPC.RLB.MX.9
YR

#Trailer vs Relocatable Building
TRA.RLB.SC <- TRA.AC.CA - RLB.AC.CA
TRA.RLB.MX.3YR <- TRA.MX.3YR.CA - RLB.MX.3YR.CA
TRA.RLB.MX.4YR <- TRA.MX.4YR.CA - RLB.MX.4YR.CA
TRA.RLB.MX.5YR <- TRA.MX.5YR.CA - RLB.MX.5YR.CA
TRA.RLB.MX.6YR <- TRA.MX.6YR.CA - RLB.MX.6YR.CA
TRA.RLB.MX.7YR <- TRA.MX.7YR.CA - RLB.MX.6YR.CA
TRA.RLB.MX.8YR <- TRA.MX.8YR.CA - RLB.MX.8YR.CA
TRA.RLB.MX.9YR <- TRA.MX.9YR.CA - RLB.MX.9YR.CA

TRA.RLB.3YR <- TRA.RLB.SC - TRA.RLB.MX.3YR
TRA.RLB.4YR <- TRA.RLB.SC - TRA.RLB.MX.3YR - TRA.RLB.MX.4YR
TRA.RLB.5YR <- TRA.RLB.SC - TRA.RLB.MX.3YR - TRA.RLB.MX.4YR - TRA.RLB.M
X.5YR
TRA.RLB.6YR <- TRA.RLB.SC - TRA.RLB.MX.3YR - TRA.RLB.MX.4YR - TRA.RLB.M
X.5YR - TRA.RLB.MX.6YR
TRA.RLB.7YR <- TRA.RLB.SC - TRA.RLB.MX.3YR - TRA.RLB.MX.4YR - TRA.RLB.M
X.5YR - TRA.RLB.MX.6YR - TRA.RLB.MX.7YR
TRA.RLB.8YR <- TRA.RLB.SC - TRA.RLB.MX.3YR - TRA.RLB.MX.4YR - TRA.RLB.M
X.5YR - TRA.RLB.MX.6YR - TRA.RLB.MX.7YR - TRA.RLB.MX.8YR
TRA.RLB.9YR <- TRA.RLB.SC - TRA.RLB.MX.3YR - TRA.RLB.MX.4YR - TRA.RLB.M
X.5YR - TRA.RLB.MX.6YR - TRA.RLB.MX.7YR - TRA.RLB.MX.8YR - TRA.RLB.MX.9
YR

# Data Frame Construction
# Simulation Histograms and Means Plots Data Frames
design.array <- c(array("BPC",28*n),array("TRA",28*n),array("RLB",28*n)
)
year.array <- rep(c(array(3,n), array(4,n), array(5,n), array(6,n), arr
ay(7,n), array(8,n), array(9,n)),12)
cost.type.array <- rep(c(array("Acquisition",7*n), array("Maintenance",
7*n), array("Disposal",7*n), array("Life Cycle",7*n)),3)

BPC.AC <- (c(BPC.AC.3, BPC.AC.4, BPC.AC.5, BPC.AC.6, BPC.AC.7, BPC.AC.8
, BPC.AC.9))/100000
BPC.MX <- (c(BPC.MX.3, BPC.MX.4, BPC.MX.5, BPC.MX.6, BPC.MX.7, BPC.MX.8
, BPC.MX.9))/100000
BPC.DC <- (c(BPC.DC.3, BPC.DC.4, BPC.DC.5, BPC.DC.6, BPC.DC.7, BPC.DC.8
, BPC.DC.9))/100000
BPC.LCC <- (c(BPC.LCC.3, BPC.LCC.4, BPC.LCC.5, BPC.LCC.6, BPC.LCC.7, BP
C.LCC.8, BPC.LCC.9))/100000
BPC <- c(BPC.AC, BPC.MX, BPC.DC, BPC.LCC)
```

```
TRA.AC <- (c(TRA.AC.3, TRA.AC.4, TRA.AC.5, TRA.AC.6, TRA.AC.7, TRA.AC.8
, TRA.AC.9))/100000
TRA.MX <- (c(TRA.MX.3, TRA.MX.4, TRA.MX.5, TRA.MX.6, TRA.MX.7, TRA.MX.8
, TRA.MX.9))/100000
TRA.DC <- (c(TRA.DC.3, TRA.DC.4, TRA.DC.5, TRA.DC.6, TRA.DC.7, TRA.DC.8
, TRA.DC.9))/100000
TRA.LCC <- (c(TRA.LCC.3, TRA.LCC.4, TRA.LCC.5, TRA.LCC.6, TRA.LCC.7, TR
A.LCC.8, TRA.LCC.9))/100000
TRA <- c(TRA.AC, TRA.MX, TRA.DC, TRA.LCC)

RLB.AC <- (c(RLB.AC.3, RLB.AC.4, RLB.AC.5, RLB.AC.6, RLB.AC.7, RLB.AC.8
, RLB.AC.9))/100000
RLB.MX <- (c(RLB.MX.3, RLB.MX.4, RLB.MX.5, RLB.MX.6, RLB.MX.7, RLB.MX.8
, RLB.MX.9))/100000
RLB.DC <- (c(RLB.DC.3, RLB.DC.4, RLB.DC.5, RLB.DC.6, RLB.DC.7, RLB.DC.8
, RLB.DC.9))/100000
RLB.LCC <- (c(RLB.LCC.3, RLB.LCC.4, RLB.LCC.5, RLB.LCC.6, RLB.LCC.7, RL
B.LCC.8, RLB.LCC.9))/100000
RLB <- c(RLB.AC, RLB.MX, RLB.DC, RLB.LCC)

Designs.MX.Year <- data.frame(Design = c(array("BPC",7*n), array("TRA",
7*n), array("RLB",7*n)),Year = rep(c(array(1,n), array(2,n), array(3,n)
, array(4,n), array(5,n), array(6,n), array(7,n)),3), Cost = c(BPC.MX1.
3,BPC.MX2.3,BPC.MX3.3,BPC.MX4.3,BPC.MX5.3,BPC.MX6.3,BPC.MX7.3,TRA.MX1.3
,TRA.MX2.3,TRA.MX3.3,TRA.MX4.3,TRA.MX5.3,TRA.MX6.3,TRA.MX7.3,RLB.MX1.3,
RLB.MX2.3,RLB.MX3.3,RLB.MX4.3,RLB.MX5.3,RLB.MX6.3,RLB.MX7.3))
cost.array <- c(BPC, TRA, RLB)
Cost.Data <- data.frame(Design = design.array, Year = year.array, Type
= cost.type.array, Cost = cost.array)
Cost.Data.Summary <- summarySE(Cost.Data, measurevar = "Cost", groupvar
s = c("Design", "Year", "Type"), conf.interval = .90)

# Comparison Analysis Data Frames
comparison.array.CA <- c(array("BPC vs Trailer", 7*n), array("BPC vs RL
B", 7*n), array("Trailer vs RLB", 7*n))
year.array.CA <- rep(c(array(3,n), array(4,n), array(5,n), array(6,n),
array(7,n), array(8,n), array(9,n)),3)
LCC.DIFF <- (c(BPC.TRA.3YR, BPC.TRA.4YR, BPC.TRA.5YR, BPC.TRA.6YR, BPC.
TRA.7YR, BPC.TRA.8YR, BPC.TRA.9YR, BPC.RLB.3YR, BPC.RLB.4YR, BPC.RLB.5Y
R, BPC.RLB.6YR, BPC.RLB.7YR, BPC.RLB.8YR, BPC.RLB.9YR, TRA.RLB.3YR, TRA
.RLB.4YR, TRA.RLB.5YR, TRA.RLB.6YR, TRA.RLB.7YR, TRA.RLB.8YR, TRA.RLB.9
YR)/100000)
DIFF.data <- data.frame(Comparison = comparison.array.CA, Year = year.a
rray.CA, Difference = LCC.DIFF)
DIFF.data.Sum <- summarySE(DIFF.data, measurevar = "Difference", groupv
ars = c("Comparison", "Year"), conf.interval = .90)
```

```
BPC.TRA.Lower <- c(quantile(BPC.TRA.3YR,c(0.05)),quantile(BPC.TRA.4YR,c
(0.05)), quantile(BPC.TRA.5YR,c(0.05)), quantile(BPC.TRA.6YR,c(0.05)),q
uantile(BPC.TRA.7YR,c(0.05)), quantile(BPC.TRA.8YR,c(0.05)), quantile(B
PC.TRA.9YR,c(0.05)))
BPC.TRA.Upper <- c(quantile(BPC.TRA.3YR,c(0.95)),quantile(BPC.TRA.4YR,c
(0.95)), quantile(BPC.RLB.5YR,c(0.95)), quantile(BPC.RLB.6YR,c(0.95)),q
uantile(BPC.RLB.7YR,c(0.95)), quantile(BPC.RLB.8YR,c(0.95)), quantile(B
PC.RLB.9YR,c(0.95)))
BPC.RLB.Lower <- c(quantile(BPC.RLB.3YR,c(0.05)),quantile(BPC.RLB.4YR,c
(0.05)), quantile(BPC.RLB.5YR,c(0.05)), quantile(BPC.RLB.6YR,c(0.05)),q
uantile(BPC.RLB.7YR,c(0.05)), quantile(BPC.RLB.8YR,c(0.05)), quantile(B
PC.RLB.9YR,c(0.05)))
BPC.RLB.Upper <- c(quantile(BPC.RLB.3YR,c(0.95)),quantile(BPC.RLB.4YR,c
(0.95)), quantile(BPC.RLB.5YR,c(0.95)), quantile(BPC.RLB.6YR,c(0.95)),q
uantile(BPC.RLB.7YR,c(0.95)), quantile(BPC.RLB.8YR,c(0.95)), quantile(B
PC.RLB.9YR,c(0.95)))
TRA.RLB.Lower <- c(quantile(TRA.RLB.3YR,c(0.05)),quantile(TRA.RLB.4YR,c
(0.05)), quantile(TRA.RLB.5YR,c(0.05)), quantile(TRA.RLB.6YR,c(0.05)),q
uantile(TRA.RLB.7YR,c(0.05)), quantile(TRA.RLB.8YR,c(0.05)), quantile(T
RA.RLB.9YR,c(0.05)))
TRA.RLB.Upper <- c(quantile(TRA.RLB.3YR,c(0.95)),quantile(TRA.RLB.4YR,c
(0.95)), quantile(TRA.RLB.5YR,c(0.95)), quantile(TRA.RLB.6YR,c(0.95)),q
uantile(TRA.RLB.7YR,c(0.95)), quantile(TRA.RLB.8YR,c(0.95)), quantile(T
RA.RLB.9YR,c(0.95)))
Lower <- c(BPC.TRA.Lower,BPC.RLB.Lower,TRA.RLB.Lower)
Upper <- c(BPC.TRA.Upper,BPC.RLB.Upper,TRA.RLB.Upper)
DIFF.data.Sum <- cbind(DIFF.data.Sum,Lower)
DIFF.data.Sum <- cbind(DIFF.data.Sum,Upper)
DIFF.data.Sum <- rename(DIFF.data.Sum, replace = c("Difference" = "Mean
","sd" = "Standard Deviation", "se" = "Standard Error", "ci" = "Confide
nce Interval", "Lower" = "5th Percentile", "Upper" = "95th Percentile")
)
write.csv(DIFF.data.Sum, "3b_Differences_data.csv")

DIFF.BPC.TRA <- subset(DIFF.data, Comparison == "BPC vs Trailer", selec
t = c(Comparison, Year, Difference))
DIFF.BPC.RLB <- subset(DIFF.data, Comparison == "BPC vs RLB", select =
c(Comparison, Year, Difference))
DIFF.TRA.RLB <- subset(DIFF.data, Comparison == "Trailer vs RLB", selec
t = c(Comparison, Year, Difference))

# Plot Construction
# Simulation Means Plots
Designs.AC.Sum <- subset(Cost.Data.Summary, Type == "Acquisition" , sel
ect = c(Design, Year, Type, N, Cost, sd, se, ci))
Designs.MX.Year.Sum <- summarySE(Designs.MX.Year, measurevar = "Cost",
```

```
groupvars = c("Design","Year"), conf.interval = .90)
Designs.MX.Sum <- subset(Cost.Data.Summary, Type == "Maintenance", sele
ct = c(Design, Year, Type, N, Cost, sd, se, ci))
Designs.DC.Sum <- subset(Cost.Data.Summary, Type == "Disposal", select
= c(Design, Year, Type, N, Cost, sd, se, ci))
Designs.LCC.Sum <- subset(Cost.Data.Summary, Type == "Life Cycle" , sel
ect = c(Design, Year, Type, N, Cost, sd, se, ci))

LCC.Means.Plot <- ggplot(data=Designs.LCC.Sum) +
  geom_line(aes(x=Year,y=Cost,colour=Design)) +
  labs(title = "Means of Life Cycle Cost") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold"), legend.position=c(.9,.6)) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_y_continuous(name="Cost ($100K)")

# Simulation Histograms
Designs.LCC <- subset(Cost.Data, Type == "Life Cycle", select = c("Desi
gn","Year","Cost"))
LCC.Sum <- summarySE(Designs.LCC, measurevar = "Cost", groupvars = c("D
esign","Year"),conf.interval = .90)
BPC.Lower <- c(quantile(BPC.LCC.3, c(.05)), quantile(BPC.LCC.4, c(.05))
,quantile(BPC.LCC.5, c(.05)),quantile(BPC.LCC.6, c(.05)),quantile(BPC.L
CC.7, c(.05)),quantile(BPC.LCC.8, c(.05)),quantile(BPC.LCC.9, c(.05)))
BPC.Upper <- c(quantile(BPC.LCC.3, c(.95)), quantile(BPC.LCC.4, c(.95))
,quantile(BPC.LCC.5, c(.95)),quantile(BPC.LCC.6, c(.95)),quantile(BPC.L
CC.7, c(.95)),quantile(BPC.LCC.8, c(.95)),quantile(BPC.LCC.9, c(.95)))
TRA.Lower <- c(quantile(TRA.LCC.3, c(.05)), quantile(TRA.LCC.4, c(.05))
,quantile(TRA.LCC.5, c(.05)),quantile(TRA.LCC.6, c(.05)),quantile(TRA.L
CC.7, c(.05)),quantile(TRA.LCC.8, c(.05)),quantile(TRA.LCC.9, c(.05)))
TRA.Upper <- c(quantile(TRA.LCC.3, c(.95)), quantile(TRA.LCC.4, c(.95))
,quantile(TRA.LCC.5, c(.95)),quantile(TRA.LCC.6, c(.95)),quantile(TRA.L
CC.7, c(.95)),quantile(TRA.LCC.8, c(.95)),quantile(TRA.LCC.9, c(.95)))
RLB.Lower <- c(quantile(RLB.LCC.3, c(.05)), quantile(RLB.LCC.4, c(.05))
,quantile(RLB.LCC.5, c(.05)),quantile(RLB.LCC.6, c(.05)),quantile(RLB.L
CC.7, c(.05)),quantile(RLB.LCC.8, c(.05)),quantile(RLB.LCC.9, c(.05)))
RLB.Upper <- c(quantile(RLB.LCC.3, c(.95)), quantile(RLB.LCC.4, c(.95))
,quantile(RLB.LCC.5, c(.95)),quantile(RLB.LCC.6, c(.95)),quantile(RLB.L
CC.7, c(.95)),quantile(RLB.LCC.8, c(.95)),quantile(RLB.LCC.9, c(.95)))
Lower = (c(BPC.Lower,RLB.Lower,TRA.Lower)/100000)
Upper = (c(BPC.Upper,RLB.Upper,TRA.Upper)/100000)
```

```
LCC.Sum <- cbind(LCC.Sum, Lower)
LCC.Sum <- cbind(LCC.Sum, Upper)
LCC.Sum <- rename(LCC.Sum, replace = c("Cost" = "Mean","sd" = "Standard
Deviation", "se" = "Standard Error", "ci" = "Confidence Interval", "Low
er" = "5th Percentile", "Upper" = "95th Percentile"))
write.csv(LCC.Sum,file = "3b_cost_data.csv")

Year.Design.Hist.free <- ggplot(Designs.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, colour = "black") +
  facet_grid(Design ~ Year, scale = "free") +
  labs(title = "Simulated LCCs per Designs") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold"), legend.position=c(.9,.6)) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_x_continuous(name="Cost ($100K)")



Year.3.LCC <- subset(Cost.Data, Year == 3 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.3.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.3), mean(RLB.LCC
.3), mean(TRA.LCC.3))/100000), Design = c("BPC","RLB","TRA"))
Year.3.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.3, c(.05))
, quantile(RLB.LCC.3, c(.05)), quantile(TRA.LCC.3, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.3.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.3, c(.95))
, quantile(RLB.LCC.3, c(.95)), quantile(TRA.LCC.3, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.3.Hist <- ggplot(Year.3.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.3.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.3.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.3.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 3 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
```

```
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.3.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.3),mean(RLB.LCC.3),mean(TRA.LCC.3))/100000))
Year.3.Hist.Overlay <- ggplot(Year.3.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.3.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 3 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.4.LCC <- subset(Cost.Data, Year == 4 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.4.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.4), mean(RLB.LCC
.4), mean(TRA.LCC.4))/100000), Design = c("BPC","RLB","TRA"))
Year.4.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.4, c(.05))
, quantile(RLB.LCC.4, c(.05)), quantile(TRA.LCC.4, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.4.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.4, c(.95))
, quantile(RLB.LCC.4, c(.95)), quantile(TRA.LCC.4, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.4.Hist <- ggplot(Year.4.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.4.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.4.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.4.vline.upper, size = .5) +
```

```
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 4 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.4.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.4),mean(RLB.LCC.4),mean(TRA.LCC.4))/100000))
Year.4.Hist.Overlay <- ggplot(Year.4.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.4.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 4 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.5.LCC <- subset(Cost.Data, Year == 5 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.5.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.5), mean(RLB.LCC
.5), mean(TRA.LCC.5))/100000), Design = c("BPC","RLB","TRA"))
Year.5.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.5, c(.05))
, quantile(RLB.LCC.5, c(.05)), quantile(TRA.LCC.5, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.5.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.5, c(.95))
, quantile(RLB.LCC.5, c(.95)), quantile(TRA.LCC.5, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.5.Hist <- ggplot(Year.5.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.5.vline.me
an, size = .5) +
```

```
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.5.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.5.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 5 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.5.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.5),mean(RLB.LCC.5),mean(TRA.LCC.5))/100000))
Year.5.Hist.Overlay <- ggplot(Year.5.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.5.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 5 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.6.LCC <- subset(Cost.Data, Year == 6 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.6.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.6), mean(RLB.LCC
.6), mean(TRA.LCC.6))/100000), Design = c("BPC","RLB","TRA"))
Year.6.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.6, c(.05))
, quantile(RLB.LCC.6, c(.05)), quantile(TRA.LCC.6, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.6.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.6, c(.95))
, quantile(RLB.LCC.6, c(.95)), quantile(TRA.LCC.6, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.6.Hist <- ggplot(Year.6.LCC, aes(x = Cost)) +
```

```
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.6.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.6.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.6.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 6 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.6.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.6),mean(RLB.LCC.6),mean(TRA.LCC.6))/100000))
Year.6.Hist.Overlay <- ggplot(Year.6.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.6.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 6 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.7.LCC <- subset(Cost.Data, Year == 7 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.7.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.7), mean(RLB.LCC
.7), mean(TRA.LCC.7))/100000), Design = c("BPC","RLB","TRA"))
Year.7.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.7, c(.05))
, quantile(RLB.LCC.7, c(.05)), quantile(TRA.LCC.7, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
```

```
Year.7.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.7, c(.95))
, quantile(RLB.LCC.7, c(.95)), quantile(TRA.LCC.7, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.7.Hist <- ggplot(Year.7.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.7.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.7.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.7.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 7 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.7.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.7),mean(RLB.LCC.7),mean(TRA.LCC.7))/100000))
Year.7.Hist.Overlay <- ggplot(Year.7.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.7.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 7 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.8.LCC <- subset(Cost.Data, Year == 8 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.8.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.8), mean(RLB.LCC
```

```
.8), mean(TRA.LCC.8))/100000), Design = c("BPC","RLB","TRA"))
Year.8.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.8, c(.05))
, quantile(RLB.LCC.8, c(.05)), quantile(TRA.LCC.8, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.8.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.8, c(.95))
, quantile(RLB.LCC.8, c(.95)), quantile(TRA.LCC.8, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.8.Hist <- ggplot(Year.8.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.8.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.8.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.8.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 8 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.8.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.8),mean(RLB.LCC.8),mean(TRA.LCC.8))/100000))
Year.8.Hist.Overlay <- ggplot(Year.8.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.8.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 8 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))
```

```
Year.9.LCC <- subset(Cost.Data, Year == 9 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.9.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.9), mean(RLB.LCC
.9), mean(TRA.LCC.9))/100000), Design = c("BPC","RLB","TRA"))
Year.9.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.9, c(.05))
, quantile(RLB.LCC.9, c(.05)), quantile(TRA.LCC.9, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.9.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.9, c(.95))
, quantile(RLB.LCC.9, c(.95)), quantile(TRA.LCC.9, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.9.Hist <- ggplot(Year.9.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.9.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.9.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.9.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Simulated LCC for 9 Years of Use") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.9.Means <- data.frame(Mean = c("BPC","RLB","TRA"), Value = (c(mean
(BPC.LCC.9),mean(RLB.LCC.9),mean(TRA.LCC.9))/100000))
Year.9.Hist.Overlay <- ggplot(Year.9.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.9.Means, aes(xintercept = Value,  colour = Mean)
,linetype="dashed", size=1) +
  labs(title = "Simulated LCC for 9 Years of Use Adjusted") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
```

```
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))


# Comparison Analysis Histograms
BPC.TRA.vline.mean <- data.frame(Mean = (c(mean(BPC.TRA.3YR), mean(BPC.
TRA.4YR), mean(BPC.TRA.5YR), mean(BPC.TRA.6YR), mean(BPC.TRA.7YR), mean
(BPC.TRA.8YR), mean(BPC.TRA.9YR))/100000), Year = c(3,4,5,6,7,8,9))
BPC.TRA.vline.lower <- data.frame(Lower = (c(quantile(BPC.TRA.3YR, c(.0
5)), quantile(BPC.TRA.4YR, c(.05)), quantile(BPC.TRA.5YR, c(.05)), quan
tile(BPC.TRA.6YR, c(.05)), quantile(BPC.TRA.7YR, c(.05)), quantile(BPC.
TRA.8YR, c(.05)), quantile(BPC.TRA.9YR, c(.05)))/100000), Year = c(3,4,
5,6,7,8,9))
BPC.TRA.vline.upper <- data.frame(Upper = (c(quantile(BPC.TRA.3YR, c(.9
5)), quantile(BPC.TRA.4YR, c(.95)), quantile(BPC.TRA.5YR, c(.95)), quan
tile(BPC.TRA.6YR, c(.95)), quantile(BPC.TRA.7YR, c(.95)), quantile(BPC.
TRA.8YR, c(.95)), quantile(BPC.TRA.9YR, c(.95)))/100000), Year = c(3,4,
5,6,7,8,9))
BPC.TRA.CA.Hist <- ggplot(DIFF.BPC.TRA, aes(x = Difference)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Year, scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), BPC.TRA.vline.m
ean, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), BPC.TRA.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), BPC.TRA.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Comparison of BPC to Trailer Adjusted") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.position="none")

BPC.RLB.vline.mean <- data.frame(Mean = (c(mean(BPC.RLB.3YR), mean(BPC.
RLB.4YR), mean(BPC.RLB.5YR), mean(BPC.RLB.6YR), mean(BPC.RLB.7YR), mean
(BPC.RLB.8YR), mean(BPC.RLB.9YR))/100000), Year = c(3,4,5,6,7,8,9))
BPC.RLB.vline.lower <- data.frame(Lower = (c(quantile(BPC.RLB.3YR, c(.0
5)), quantile(BPC.RLB.4YR, c(.05)), quantile(BPC.RLB.5YR, c(.05)), quan
tile(BPC.RLB.6YR, c(.05)), quantile(BPC.RLB.7YR, c(.05)), quantile(BPC.
RLB.8YR, c(.05)), quantile(BPC.RLB.9YR, c(.05)))/100000), Year = c(3,4,
```

```
5,6,7,8,9))
BPC.RLB.vline.upper <- data.frame(Upper = (c(quantile(BPC.RLB.3YR, c(.9
5)), quantile(BPC.RLB.4YR, c(.95)), quantile(BPC.RLB.5YR, c(.95)), quan
tile(BPC.RLB.6YR, c(.95)), quantile(BPC.RLB.7YR, c(.95)), quantile(BPC.
RLB.8YR, c(.95)), quantile(BPC.RLB.9YR, c(.95)))/100000), Year = c(3,4,
5,6,7,8,9))
BPC.RLB.CA.Hist <- ggplot(DIFF.BPC.RLB, aes(x = Difference)) +
  geom_histogram(binwidth = 10, colour = "black") +
  facet_grid(.~Year, scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), BPC.RLB.vline.m
ean, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th & 95th\nPercentile
"), BPC.RLB.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th  95th\nPercentile"
), BPC.RLB.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Comparison of BPC to RLBs Adjusted") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.position="none")

TRA.RLB.vline.mean <- data.frame(Mean = (c(mean(TRA.RLB.3YR), mean(TRA.
RLB.4YR), mean(TRA.RLB.5YR), mean(TRA.RLB.6YR), mean(TRA.RLB.7YR), mean
(TRA.RLB.8YR), mean(TRA.RLB.9YR))/100000), Year = c(3,4,5,6,7,8,9))
TRA.RLB.vline.lower <- data.frame(Lower = (c(quantile(TRA.RLB.3YR, c(.0
5)), quantile(TRA.RLB.4YR, c(.05)), quantile(TRA.RLB.5YR, c(.05)), quan
tile(TRA.RLB.6YR, c(.05)), quantile(TRA.RLB.7YR, c(.05)), quantile(TRA.
RLB.8YR, c(.05)), quantile(TRA.RLB.9YR, c(.05)))/100000), Year = c(3,4,
5,6,7,8,9))
TRA.RLB.vline.upper <- data.frame(Upper = (c(quantile(TRA.RLB.3YR, c(.9
5)), quantile(TRA.RLB.4YR, c(.95)), quantile(TRA.RLB.5YR, c(.95)), quan
tile(TRA.RLB.6YR, c(.95)), quantile(TRA.RLB.7YR, c(.95)), quantile(TRA.
RLB.8YR, c(.95)), quantile(TRA.RLB.9YR, c(.95)))/100000), Year = c(3,4,
5,6,7,8,9))
TRA.RLB.CA.Hist <- ggplot(DIFF.TRA.RLB, aes(x = Difference)) +
  geom_histogram(binwidth = 10, colour = "black") +
  facet_grid(.~Year, scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), TRA.RLB.vline.m
ean, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), TRA.RLB.vline.lower, size = .5) +
```

```r
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), TRA.RLB.vline.upper, size = .5) +
  theme(legend.title=element_blank()) +
  labs(title = "Comparison of Trailers to RLBs Adjusted") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.position="none")


# Print All Plots
LCC.Means.Plot
```

```r
ggsave("LCC_Means_Plot.jpg", width = 5, height = 5)
Year.Design.Hist.free
```

```r
ggsave("Facet_Plot.jpg", width = 7, height = 7)
Year.3.Hist
```

```r
ggsave("Year3_Designs_Plot.jpg", width = 7, height = 5)
Year.3.Hist.Overlay
```

```r
ggsave("Year3_OL_Plot.jpg", width = 7, height = 5)
Year.4.Hist
```

```r
ggsave("Year4_Designs_Plot.jpg", width = 7, height = 5)
Year.4.Hist.Overlay
```

```r
ggsave("Year4_OL_Plot.jpg", width = 7, height = 5)
Year.5.Hist
```

```r
ggsave("Year5_Designs_Plot.jpg", width = 7, height = 5)
Year.5.Hist.Overlay
```

```r
ggsave("Year5_OL_Plot.jpg", width = 7, height = 5)
Year.6.Hist
```

```r
ggsave("Year6_Designs_Plot.jpg", width = 7, height = 5)
Year.6.Hist.Overlay
```

```r
ggsave("Year6_OL_Plot.jpg", width = 7, height = 5)
Year.7.Hist
```

```r
ggsave("Year7_Design_Plot.jpg", width = 7, height = 5)
Year.7.Hist.Overlay
```

```r
ggsave("Year7_OL_Plot.jpg", width = 7, height = 5)
Year.8.Hist
```

```r
ggsave("Year8_Designs_Plot.jpg", width = 7, height = 5)
Year.8.Hist.Overlay
```

```r
ggsave("Year8_OL_Plot.jpg", width = 7, height = 5)
Year.9.Hist
```

```r
ggsave("Year9_Designs_Plot.jpg", width = 7, height = 5)
Year.9.Hist.Overlay
```

```r
ggsave("Year9_OL_Plot.jpg", width = 7, height = 5)
BPC.TRA.CA.Hist
```

```r
ggsave("BPC_TRA_CA_Plot.jpg", width = 7, height = 5)
BPC.RLB.CA.Hist
```

```r
ggsave("BPC_RLB_CA_Plot.jpg", width = 7, height = 5)
TRA.RLB.CA.Hist
```

```r
ggsave("TRA_RLB_CA_Plot.jpg", width = 7, height = 5)


##Results
# 3 Years
wilcox.test(BPC.LCC.3/100000, TRA.LCC.3/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.3/1e+05 and TRA.LCC.3/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  15.17860 15.24376
## sample estimates:
## difference in location
##                15.2112

wilcox.test(BPC.LCC.3/100000, RLB.LCC.3/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.3/1e+05 and RLB.LCC.3/1e+05
## W = 19046000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -23.61816 -22.66132
## sample estimates:
## difference in location
##              -23.13043

wilcox.test(TRA.LCC.3/100000, RLB.LCC.3/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  TRA.LCC.3/1e+05 and RLB.LCC.3/1e+05
## W = 4282000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -38.83359 -37.86557
## sample estimates:
## difference in location
##              -38.34673
```

```
# 4 Years
wilcox.test(BPC.LCC.4/100000, TRA.LCC.4/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.4/1e+05 and TRA.LCC.4/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  15.81608 15.88162
## sample estimates:
## difference in location
##               15.84887
```

```
wilcox.test(BPC.LCC.4/100000, RLB.LCC.4/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.4/1e+05 and RLB.LCC.4/1e+05
## W = 14514000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -26.71892 -25.65760
## sample estimates:
## difference in location
##              -26.18819
```

```
wilcox.test(TRA.LCC.4/100000, RLB.LCC.4/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
```

```
##
## data:  TRA.LCC.4/1e+05 and RLB.LCC.4/1e+05
## W = 2481300, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.55526 -41.50466
## sample estimates:
## difference in location
##              -42.03183
```

```
# 5 Years
wilcox.test(BPC.LCC.5/100000, TRA.LCC.5/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.5/1e+05 and TRA.LCC.5/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  16.21399 16.27990
## sample estimates:
## difference in location
##               16.24694
```

```
wilcox.test(BPC.LCC.5/100000, RLB.LCC.5/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.5/1e+05 and RLB.LCC.5/1e+05
## W = 11599000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -29.14394 -28.09799
## sample estimates:
## difference in location
##              -28.62339
```

```
wilcox.test(TRA.LCC.5/100000, RLB.LCC.5/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  TRA.LCC.5/1e+05 and RLB.LCC.5/1e+05
```

```
## W = 1457400, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -45.38625 -44.33790
## sample estimates:
## difference in location
##              -44.86151
```

```r
# 6 Years
wilcox.test(BPC.LCC.6/100000, TRA.LCC.6/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90,conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.6/1e+05 and TRA.LCC.6/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  16.49590 16.56162
## sample estimates:
## difference in location
##               16.52875
```

```r
wilcox.test(BPC.LCC.6/100000, RLB.LCC.6/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90,conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.6/1e+05 and RLB.LCC.6/1e+05
## W = 9847800, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -31.88382 -30.80074
## sample estimates:
## difference in location
##              -31.33813
```

```r
wilcox.test(TRA.LCC.6/100000, RLB.LCC.6/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90,conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  TRA.LCC.6/1e+05 and RLB.LCC.6/1e+05
## W = 901040, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
```

```
## 90 percent confidence interval:
##  -48.40566 -47.32172
## sample estimates:
## difference in location
##              -47.86306
```

```
# 7 Years
wilcox.test(BPC.LCC.7/100000, TRA.LCC.7/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.7/1e+05 and TRA.LCC.7/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  17.84252 17.91016
## sample estimates:
## difference in location
##               17.87636
```

```
wilcox.test(BPC.LCC.7/100000, RLB.LCC.7/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.7/1e+05 and RLB.LCC.7/1e+05
## W = 7756700, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -33.28299 -32.35374
## sample estimates:
## difference in location
##               -32.8161
```

```
wilcox.test(TRA.LCC.7/100000, RLB.LCC.7/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  TRA.LCC.7/1e+05 and RLB.LCC.7/1e+05
## W = 441840, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -51.16344 -50.23206
```

```
## sample estimates:
## difference in location
##              -50.69701
```

```r
# 8 Years
wilcox.test(BPC.LCC.8/100000, TRA.LCC.8/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90,conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.8/1e+05 and TRA.LCC.8/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  18.78043 18.84820
## sample estimates:
## difference in location
##                18.8143
```

```r
wilcox.test(BPC.LCC.8/100000, RLB.LCC.8/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90,conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.8/1e+05 and RLB.LCC.8/1e+05
## W = 7111200, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -35.81114 -34.80860
## sample estimates:
## difference in location
##               -35.3097
```

```r
wilcox.test(TRA.LCC.8/100000, RLB.LCC.8/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90,conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  TRA.LCC.8/1e+05 and RLB.LCC.8/1e+05
## W = 269320, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -54.62107 -53.61685
## sample estimates:
```

```
## difference in location
##             -54.11754
```

```r
# 9 Years
wilcox.test(BPC.LCC.9/100000, TRA.LCC.9/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.9/1e+05 and TRA.LCC.9/1e+05
## W = 1e+08, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.62749 19.69570
## sample estimates:
## difference in location
##               19.6616
```

```r
wilcox.test(BPC.LCC.9/100000, RLB.LCC.9/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  BPC.LCC.9/1e+05 and RLB.LCC.9/1e+05
## W = 4473800, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -39.74989 -38.73603
## sample estimates:
## difference in location
##             -39.24348
```

```r
wilcox.test(TRA.LCC.9/100000, RLB.LCC.9/100000, alternative = "two.side
d", mu = 0, paired = FALSE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  TRA.LCC.9/1e+05 and RLB.LCC.9/1e+05
## W = 70168, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -59.40382 -58.39526
## sample estimates:
## difference in location
##             -58.89902
```

```
#Comparisons
Comparison.data <- data.frame(Year = c(3,4,5,6,7,8,9), One = c((sum(BPC
.LCC.3 < TRA.LCC.3)/10000), (sum(BPC.LCC.4 < TRA.LCC.4)/10000), (sum(BP
C.LCC.5 < TRA.LCC.5)/10000), (sum(BPC.LCC.6 < TRA.LCC.6)/10000), (sum(B
PC.LCC.7 < TRA.LCC.7)/10000), (sum(BPC.LCC.8 < TRA.LCC.8)/10000), (sum(
BPC.LCC.9 < TRA.LCC.9)/10000)), Two = c((sum(BPC.LCC.3 < RLB.LCC.3)/100
00), (sum(BPC.LCC.4 < RLB.LCC.4)/10000), (sum(BPC.LCC.5 < RLB.LCC.5)/10
000), (sum(BPC.LCC.6 < RLB.LCC.6)/10000), (sum(BPC.LCC.7 < RLB.LCC.7)/1
0000), (sum(BPC.LCC.8 < RLB.LCC.8)/10000), (sum(BPC.LCC.9 < RLB.LCC.9)/
10000)), Three = c((sum(TRA.LCC.3 < RLB.LCC.3)/10000), (sum(TRA.LCC.4 <
RLB.LCC.4)/10000), (sum(TRA.LCC.5 < RLB.LCC.5)/10000), (sum(TRA.LCC.6 <
RLB.LCC.6)/10000), (sum(TRA.LCC.7 < RLB.LCC.7)/10000), (sum(TRA.LCC.8 <
RLB.LCC.8)/10000), (sum(TRA.LCC.9 < RLB.LCC.9)/10000)))
Comparison.data <- rename(Comparison.data, replace = c("One"= "BPC < TR
A", "Two" = "BPC < RLB", "Three" = "TRA < RLB"))
write.csv(Comparison.data,file = "3b_Comparison_results.csv")
```

50_Year_Horizon.R

Ryan

Thu Feb 11 05:52:05 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/50 Year Hori
zon")


# Assumptions
TRA.Adjustment.Factor <- 4
RLB.Adjustment.Factor <- 49
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06

# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
BPC.DCPSF3 <- 15.60
```

```
BPC.DCPSF4 <- 21.00
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
RLB2.MX2015.mean <- 5.333
```

```r
RLB2.MX2015.stdev <- 0.690
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Present Worth of Life Cycle Cost Function (Definite Use)
LCC <- function (t, design, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  if(design == "BPC"){
    ifelse(t == 1, LCC <- AC, NA)
    ifelse(t == 2, LCC <- AC + DC, NA)
    ifelse(t == 3, LCC <- AC + MX1 + DC, NA)
    ifelse(t == 4, LCC <- AC + MX1 + MX2 + DC, NA)
    ifelse(t == 5, LCC <- AC + MX1 + MX2 + MX3 + DC, NA)
    ifelse(t == 6, LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC, NA)
    ifelse(t == 7, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC, NA)
    ifelse(t == 8, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC,
NA)
    ifelse(t == 9, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7
+ DC, NA)
    ifelse(t == 10, LCC <- AC + (MX1*2) + MX2 + MX3 + MX4 + MX5 + MX6 +
MX7 + DC, NA)
    ifelse(t == 11, LCC <- AC + (MX1*2) + (MX2*2) + MX3 + MX4 + MX5 + M
X6 + MX7 + DC, NA)
    ifelse(t == 12, LCC <- AC + (MX1*2) + (MX2*2) + (MX3*2) + MX4 + MX5
+ MX6 + MX7 + DC, NA)
    ifelse(t == 13, LCC <- AC + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*2) +
MX5 + MX6 + MX7 + DC, NA)
    ifelse(t == 14, LCC <- AC + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*2) +
(MX5*2) + MX6 + MX7 + DC, NA)
    ifelse(t == 15, LCC <- AC + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*2) +
(MX5*2) + (MX6*2) + MX7 + DC, NA)
    ifelse(t == 16, LCC <- AC + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*2) +
(MX5*2) + (MX6*2) + (MX7*2) + DC, NA)
    ifelse(t == 17, LCC <- AC + (MX1*3) + (MX2*2) + (MX3*2) + (MX4*2) +
(MX5*2) + (MX6*2) + (MX7*2) + DC, NA)
```

```
    ifelse(t == 18, LCC <- AC + (MX1*3) + (MX2*3) + (MX3*2) + (MX4*2) +
(MX5*2) + (MX6*2) + (MX7*2) + DC, NA)
    ifelse(t == 19, LCC <- AC + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*2) +
(MX5*2) + (MX6*2) + (MX7*2) + DC, NA)
    ifelse(t == 20, LCC <- AC + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*3) +
(MX5*2) + (MX6*2) + (MX7*2) + DC, NA)
    ifelse(t == 21, LCC <- AC + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*3) +
(MX5*3) + (MX6*2) + (MX7*2) + DC, NA)
    ifelse(t == 22, LCC <- AC + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*3) +
(MX5*3) + (MX6*3) + (MX7*2) + DC, NA)
    ifelse(t == 23, LCC <- AC + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*3) +
(MX5*3) + (MX6*3) + (MX7*3) + DC, NA)
    ifelse(t == 24, LCC <- AC + (MX1*4) + (MX2*3) + (MX3*3) + (MX4*3) +
(MX5*3) + (MX6*3) + (MX7*3) + DC, NA)
    ifelse(t == 25, LCC <- AC + (MX1*4) + (MX2*4) + (MX3*3) + (MX4*3) +
(MX5*3) + (MX6*3) + (MX7*3) + DC, NA)
    ifelse(t == 26, LCC <- AC + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*3) +
(MX5*3) + (MX6*3) + (MX7*3) + DC, NA)
    ifelse(t == 27, LCC <- AC + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*4) +
(MX5*3) + (MX6*3) + (MX7*3) + DC, NA)
    ifelse(t == 28, LCC <- AC + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*4) +
(MX5*4) + (MX6*3) + (MX7*3) + DC, NA)
    ifelse(t == 29, LCC <- AC + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*4) +
(MX5*4) + (MX6*4) + (MX7*3) + DC, NA)
    ifelse(t == 30, LCC <- AC + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*4) +
(MX5*4) + (MX6*4) + (MX7*4) + DC, NA)
    ifelse(t == 31, LCC <- AC + (MX1*5) + (MX2*4) + (MX3*4) + (MX4*4) +
(MX5*4) + (MX6*4) + (MX7*4) + DC, NA)
    ifelse(t == 32, LCC <- AC + (MX1*5) + (MX2*5) + (MX3*4) + (MX4*4) +
(MX5*4) + (MX6*4) + (MX7*4) + DC, NA)
    ifelse(t == 33, LCC <- AC + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*4) +
(MX5*4) + (MX6*4) + (MX7*4) + DC, NA)
    ifelse(t == 34, LCC <- AC + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*5) +
(MX5*4) + (MX6*4) + (MX7*4) + DC, NA)
    ifelse(t == 35, LCC <- AC + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*5) +
(MX5*5) + (MX6*4) + (MX7*4) + DC, NA)
    ifelse(t == 36, LCC <- AC + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*5) +
(MX5*5) + (MX6*5) + (MX7*4) + DC, NA)
    ifelse(t == 37, LCC <- AC + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*5) +
(MX5*5) + (MX6*5) + (MX7*5) + DC, NA)
    ifelse(t == 38, LCC <- AC + (MX1*6) + (MX2*5) + (MX3*5) + (MX4*5) +
(MX5*5) + (MX6*5) + (MX7*5) + DC, NA)
    ifelse(t == 39, LCC <- AC + (MX1*6) + (MX2*6) + (MX3*5) + (MX4*5) +
(MX5*5) + (MX6*5) + (MX7*5) + DC, NA)
    ifelse(t == 40, LCC <- AC + (MX1*6) + (MX2*6) + (MX3*6) + (MX4*5) +
(MX5*5) + (MX6*5) + (MX7*5) + DC, NA)
```

```
    ifelse(t == 41, LCC <- AC + (MX1*6) + (MX2*6) + (MX3*6) + (MX4*6) +
(MX5*5) + (MX6*5) + (MX7*5) + DC, NA)
    ifelse(t == 42, LCC <- AC + (MX1*6) + (MX2*6) + (MX3*6) + (MX4*6) +
(MX5*6) + (MX6*5) + (MX7*5) + DC, NA)
    ifelse(t == 43, LCC <- AC + (MX1*6) + (MX2*6) + (MX3*6) + (MX4*6) +
(MX5*6) + (MX6*6) + (MX7*5) + DC, NA)
    ifelse(t == 44, LCC <- AC + (MX1*6) + (MX2*6) + (MX3*6) + (MX4*6) +
(MX5*6) + (MX6*6) + (MX7*6) + DC, NA)
    ifelse(t == 45, LCC <- AC + (MX1*7) + (MX2*6) + (MX3*6) + (MX4*6) +
(MX5*6) + (MX6*6) + (MX7*6) + DC, NA)
    ifelse(t == 46, LCC <- AC + (MX1*7) + (MX2*7) + (MX3*6) + (MX4*6) +
(MX5*6) + (MX6*6) + (MX7*6) + DC, NA)
    ifelse(t == 47, LCC <- AC + (MX1*7) + (MX2*7) + (MX3*7) + (MX4*6) +
(MX5*6) + (MX6*6) + (MX7*6) + DC, NA)
    ifelse(t == 48, LCC <- AC + (MX1*7) + (MX2*7) + (MX3*7) + (MX4*7) +
(MX5*6) + (MX6*6) + (MX7*6) + DC, NA)
    ifelse(t == 49, LCC <- AC + (MX1*7) + (MX2*7) + (MX3*7) + (MX4*7) +
(MX5*7) + (MX6*6) + (MX7*6) + DC, NA)
    ifelse(t == 50, LCC <- AC + (MX1*7) + (MX2*7) + (MX3*7) + (MX4*7) +
(MX5*7) + (MX6*7) + (MX7*6) + DC, NA)
    return(LCC)
  }
  if(design == "TRA"){
    ifelse(t == 1, LCC <- AC, NA)
    ifelse(t == 2, LCC <- AC + DC, NA)
    ifelse(t == 3, LCC <- AC + MX1 + DC, NA)
    ifelse(t == 4, LCC <- AC + MX1 + MX2 + DC, NA)
    ifelse(t == 5, LCC <- AC + MX1 + MX2 + MX3 + DC, NA)
    ifelse(t == 6, LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC, NA)
    ifelse(t == 7, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC, NA)
    ifelse(t == 8, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC,
NA)
    ifelse(t == 9, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7
+ DC, NA)
    ifelse(t == 10, LCC <- AC + MX1 + MX2 + MX3 + MX4 + (MX5*2) + MX6 +
MX7 + DC, NA)
    ifelse(t == 11, LCC <- AC + MX1 + MX2 + MX3 + MX4 + (MX5*2) + (MX6*
2) + MX7 + DC, NA)
    ifelse(t == 12, LCC <- AC + MX1 + MX2 + MX3 + MX4 + (MX5*2) + (MX6*
2) + (MX7*2) + DC, NA)
    ifelse(t == 13, LCC <- (AC*2) + (MX1*2) + MX2 + MX3 + MX4 + (MX5*2)
+ (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 14, LCC <- (AC*2) + (MX1*2) + (MX2*2) + MX3 + MX4 + (MX
5*2) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 15, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + MX4 +
(MX5*2) + (MX6*2) + (MX7*2) + (DC*2), NA)
```

```
    ifelse(t == 16, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*2) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 17, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*3) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 18, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*3) + (MX6*3) + (MX7*2) + (DC*2), NA)
    ifelse(t == 19, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*3) + (MX6*3) + (MX7*3) + (DC*2), NA)
    ifelse(t == 20, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*3) + (MX7*3) + (DC*2), NA)
    ifelse(t == 21, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*3) + (DC*2), NA)
    ifelse(t == 22, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*2), NA)
    ifelse(t == 23, LCC <- (AC*3) + (MX1*3) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 24, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 25, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 26, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 27, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*5) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 28, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*5) + (MX6*5) + (MX7*4) + (DC*3), NA)
    ifelse(t == 29, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*5) + (MX6*5) + (MX7*5) + (DC*3), NA)
    ifelse(t == 30, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*5) + (MX7*5) + (DC*3), NA)
    ifelse(t == 31, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*5) + (DC*3), NA)
    ifelse(t == 32, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*3), NA)
    ifelse(t == 33, LCC <- (AC*4) + (MX1*4) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 34, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 35, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 36, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 37, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*7) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 38, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*7) + (MX6*7) + (MX7*6) + (DC*4), NA)
```

```
    ifelse(t == 39, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*7) + (MX6*7) + (MX7*7) + (DC*4), NA)
    ifelse(t == 40, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*7) + (MX7*7) + (DC*4), NA)
    ifelse(t == 41, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*7) + (DC*4), NA)
    ifelse(t == 42, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*4), NA)
    ifelse(t == 43, LCC <- (AC*5) + (MX1*5) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 44, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 45, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 46, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 47, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*9) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 48, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*9) + (MX6*9) + (MX7*8) + (DC*5), NA)
    ifelse(t == 49, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*9) + (MX6*9) + (MX7*9) + (DC*5), NA)
    ifelse(t == 50, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*10) + (MX6*9) + (MX7*9) + (DC*5), NA)
    return(LCC)
  }
  if(design == "RLB"){
    ifelse(t == 1, LCC <- AC, NA)
    ifelse(t == 2, LCC <- AC + DC, NA)
    ifelse(t == 3, LCC <- AC + MX1 + DC, NA)
    ifelse(t == 4, LCC <- AC + MX1 + MX2 + DC, NA)
    ifelse(t == 5, LCC <- AC + MX1 + MX2 + MX3 + DC, NA)
    ifelse(t == 6, LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC, NA)
    ifelse(t == 7, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC, NA)
    ifelse(t == 8, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC,
NA)
    ifelse(t == 9, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7
+ DC, NA)
    ifelse(t == 10, LCC <- AC + MX1 + MX2 + MX3 + MX4 + (MX5*2) + MX6 +
MX7 + DC, NA)
    ifelse(t == 11, LCC <- AC + MX1 + MX2 + MX3 + MX4 + (MX5*2) + (MX6*
2) + MX7 + DC, NA)
    ifelse(t == 12, LCC <- AC + MX1 + MX2 + MX3 + MX4 + (MX5*2) + (MX6*
2) + (MX7*2) + DC, NA)
    ifelse(t == 13, LCC <- (AC*2) + (MX1*2) + MX2 + MX3 + MX4 + (MX5*2)
+ (MX6*2) + (MX7*2) + (DC*2), NA)
```

```
    ifelse(t == 14, LCC <- (AC*2) + (MX1*2) + (MX2*2) + MX3 + MX4 + (MX
5*2) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 15, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + MX4 +
(MX5*2) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 16, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*2) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 17, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*3) + (MX6*2) + (MX7*2) + (DC*2), NA)
    ifelse(t == 18, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*3) + (MX6*3) + (MX7*2) + (DC*2), NA)
    ifelse(t == 19, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*3) + (MX6*3) + (MX7*3) + (DC*2), NA)
    ifelse(t == 20, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*3) + (MX7*3) + (DC*2), NA)
    ifelse(t == 21, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*3) + (DC*2), NA)
    ifelse(t == 22, LCC <- (AC*2) + (MX1*2) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*2), NA)
    ifelse(t == 23, LCC <- (AC*3) + (MX1*3) + (MX2*2) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 24, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*2) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 25, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
2) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 26, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*4) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 27, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*5) + (MX6*4) + (MX7*4) + (DC*3), NA)
    ifelse(t == 28, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*5) + (MX6*5) + (MX7*4) + (DC*3), NA)
    ifelse(t == 29, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*5) + (MX6*5) + (MX7*5) + (DC*3), NA)
    ifelse(t == 30, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*5) + (MX7*5) + (DC*3), NA)
    ifelse(t == 31, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*5) + (DC*3), NA)
    ifelse(t == 32, LCC <- (AC*3) + (MX1*3) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*3), NA)
    ifelse(t == 33, LCC <- (AC*4) + (MX1*4) + (MX2*3) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 34, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*3) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 35, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
3) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 36, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*6) + (MX6*6) + (MX7*6) + (DC*4), NA)
```

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    ifelse(t == 37, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*7) + (MX6*6) + (MX7*6) + (DC*4), NA)
    ifelse(t == 38, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*7) + (MX6*7) + (MX7*6) + (DC*4), NA)
    ifelse(t == 39, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*7) + (MX6*7) + (MX7*7) + (DC*4), NA)
    ifelse(t == 40, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*7) + (MX7*7) + (DC*4), NA)
    ifelse(t == 41, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*7) + (DC*4), NA)
    ifelse(t == 42, LCC <- (AC*4) + (MX1*4) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*4), NA)
    ifelse(t == 43, LCC <- (AC*5) + (MX1*5) + (MX2*4) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 44, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*4) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 45, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
4) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 46, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*8) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 47, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*9) + (MX6*8) + (MX7*8) + (DC*5), NA)
    ifelse(t == 48, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*9) + (MX6*9) + (MX7*8) + (DC*5), NA)
    ifelse(t == 49, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*9) + (MX6*9) + (MX7*9) + (DC*5), NA)
    ifelse(t == 50, LCC <- (AC*5) + (MX1*5) + (MX2*5) + (MX3*5) + (MX4*
5) + (MX5*10) + (MX6*9) + (MX7*9) + (DC*5), NA)
    return(LCC)
  }
}

##Simulation
BPC.AC <- BPC.AC * FGP(8,i)
BPC.MX1 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.shop
.rate * FGP(7,i)
BPC.MX2 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.shop
.rate * FGP(6,i)
BPC.MX3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.sh
op.rate * FGP(5,i)
BPC.MX4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.shop
.rate * FGP(4,i)
BPC.MX5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.shop
.rate * FGP(3,i)
BPC.MX6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.shop
.rate * FGP(2,i)
```

```
BPC.MX7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.shop
.rate * FGP(1,i)
BPC.DC <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.Adj
ustment.Factor
TRA.MX1 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.shop
.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.shop
.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.sh
op.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.shop
.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.shop
.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.shop
.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.shop
.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.Adj
ustment.Factor
RLB.MX1 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.sh
op.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.sh
op.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.sh
op.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rate
* (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.sh
op.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.sh
op.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.sh
op.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

##Calculations
BPC.1 <- LCC(1, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.2 <- LCC(2, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.3 <- LCC(3, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
```

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MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.4 <- LCC(4, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.5 <- LCC(5, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.6 <- LCC(6, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.7 <- LCC(7, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.8 <- LCC(8, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.9 <- LCC(9, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.
MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.10 <- LCC(10, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.11 <- LCC(11, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.12 <- LCC(12, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.13 <- LCC(13, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.14 <- LCC(14, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.15 <- LCC(15, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.16 <- LCC(16, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.17 <- LCC(17, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.18 <- LCC(18, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.19 <- LCC(19, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.20 <- LCC(20, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.21 <- LCC(21, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.22 <- LCC(22, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.23 <- LCC(23, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.24 <- LCC(24, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.25 <- LCC(25, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.26 <- LCC(26, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
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C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.27 <- LCC(27, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.28 <- LCC(28, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.29 <- LCC(29, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.30 <- LCC(30, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.31 <- LCC(31, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.32 <- LCC(32, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.33 <- LCC(33, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.34 <- LCC(34, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.35 <- LCC(35, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.36 <- LCC(36, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.37 <- LCC(37, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.38 <- LCC(38, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.39 <- LCC(39, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.30 <- LCC(30, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.31 <- LCC(31, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.32 <- LCC(32, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.33 <- LCC(33, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.34 <- LCC(34, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.35 <- LCC(35, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.36 <- LCC(36, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.37 <- LCC(37, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.38 <- LCC(38, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.39 <- LCC(39, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
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C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.40 <- LCC(40, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.41 <- LCC(41, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.42 <- LCC(42, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.43 <- LCC(43, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.44 <- LCC(44, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.45 <- LCC(45, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.46 <- LCC(46, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.47 <- LCC(47, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.48 <- LCC(48, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.49 <- LCC(49, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
BPC.50 <- LCC(50, "BPC", BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)

TRA.1 <- LCC(1, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.2 <- LCC(2, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.3 <- LCC(3, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.4 <- LCC(4, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.5 <- LCC(5, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.6 <- LCC(6, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.7 <- LCC(7, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.8 <- LCC(8, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.9 <- LCC(9, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.
MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.10 <- LCC(10, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.11 <- LCC(11, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
```

```
TRA.12 <- LCC(12, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.13 <- LCC(13, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.14 <- LCC(14, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.15 <- LCC(15, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.16 <- LCC(16, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.17 <- LCC(17, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.18 <- LCC(18, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.19 <- LCC(19, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.20 <- LCC(20, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.21 <- LCC(21, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.22 <- LCC(22, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.23 <- LCC(23, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.24 <- LCC(24, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.25 <- LCC(25, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.26 <- LCC(26, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.27 <- LCC(27, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.28 <- LCC(28, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.29 <- LCC(29, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.30 <- LCC(30, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.31 <- LCC(31, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.32 <- LCC(32, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.33 <- LCC(33, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.34 <- LCC(34, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
```

```
TRA.35 <- LCC(35, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.36 <- LCC(36, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.37 <- LCC(37, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.38 <- LCC(38, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.39 <- LCC(39, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.30 <- LCC(30, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.31 <- LCC(31, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.32 <- LCC(32, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.33 <- LCC(33, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.34 <- LCC(34, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.35 <- LCC(35, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.36 <- LCC(36, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.37 <- LCC(37, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.38 <- LCC(38, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.39 <- LCC(39, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.40 <- LCC(40, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.41 <- LCC(41, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.42 <- LCC(42, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.43 <- LCC(43, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.44 <- LCC(44, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.45 <- LCC(45, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.46 <- LCC(46, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.47 <- LCC(47, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
```

```
TRA.48 <- LCC(48, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.49 <- LCC(49, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
TRA.50 <- LCC(50, "TRA", TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)

RLB.1 <- LCC(1, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.2 <- LCC(2, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.3 <- LCC(3, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.4 <- LCC(4, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.5 <- LCC(5, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.6 <- LCC(6, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.7 <- LCC(7, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.8 <- LCC(8, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.9 <- LCC(9, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.
MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.10 <- LCC(10, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.11 <- LCC(11, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.12 <- LCC(12, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.13 <- LCC(13, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.14 <- LCC(14, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.15 <- LCC(15, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.16 <- LCC(16, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.17 <- LCC(17, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.18 <- LCC(18, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.19 <- LCC(19, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.20 <- LCC(20, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
```

```
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.21 <- LCC(21, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.22 <- LCC(22, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.23 <- LCC(23, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.24 <- LCC(24, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.25 <- LCC(25, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.26 <- LCC(26, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.27 <- LCC(27, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.28 <- LCC(28, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.29 <- LCC(29, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.30 <- LCC(30, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.31 <- LCC(31, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.32 <- LCC(32, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.33 <- LCC(33, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.34 <- LCC(34, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.35 <- LCC(35, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.36 <- LCC(36, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.37 <- LCC(37, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.38 <- LCC(38, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.39 <- LCC(39, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.30 <- LCC(30, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.31 <- LCC(31, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.32 <- LCC(32, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.33 <- LCC(33, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
```

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B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.34 <- LCC(34, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.35 <- LCC(35, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.36 <- LCC(36, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.37 <- LCC(37, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.38 <- LCC(38, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.39 <- LCC(39, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.40 <- LCC(40, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.41 <- LCC(41, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.42 <- LCC(42, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.43 <- LCC(43, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.44 <- LCC(44, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.45 <- LCC(45, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.46 <- LCC(46, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.47 <- LCC(47, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.48 <- LCC(48, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.49 <- LCC(49, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
RLB.50 <- LCC(50, "RLB", RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)

design.array <- c(array("BPC",50*n), array("TRA",50*n), array("RLB",50*
n))
year.array <- rep(c(array(1,n),array(2,n,),array(3,n), array(4,n), arra
y(5,n), array(6,n), array(7,n), array(8,n), array(9,n),array(10,n),arra
y(11,n),array(12,n),array(13,n), array(14,n), array(15,n), array(16,n),
array(17,n), array(18,n), array(19,n),array(20,n),array(21,n),array(22,
n),array(23,n), array(24,n), array(25,n), array(26,n), array(27,n), arr
ay(28,n), array(29,n),array(30,n),array(31,n),array(32,n),array(33,n),
array(34,n), array(35,n), array(36,n), array(37,n), array(38,n), array(
39,n),array(40,n),array(41,n),array(42,n),array(43,n), array(44,n), arr
```

```
ay(45,n), array(46,n), array(47,n), array(48,n), array(49,n),array(50,n
)),3)
BPC.LCC.array <- c(BPC.1,BPC.2,BPC.3,BPC.4,BPC.5,BPC.6,BPC.7,BPC.8,BPC.
9,BPC.10,BPC.11,BPC.12,BPC.13,BPC.14,BPC.15,BPC.16,BPC.17,BPC.18,BPC.19
,BPC.20,BPC.21,BPC.22,BPC.23,BPC.24,BPC.25,BPC.26,BPC.27,BPC.28,BPC.29,
BPC.30,BPC.31,BPC.32,BPC.33,BPC.34,BPC.35,BPC.36,BPC.37,BPC.38,BPC.39,B
PC.40,BPC.41,BPC.42,BPC.43,BPC.44,BPC.45,BPC.46,BPC.47,BPC.48,BPC.49,BP
C.50)
TRA.LCC.array <- c(TRA.1,TRA.2,TRA.3,TRA.4,TRA.5,TRA.6,TRA.7,TRA.8,TRA.
9,TRA.10,TRA.11,TRA.12,TRA.13,TRA.14,TRA.15,TRA.16,TRA.17,TRA.18,TRA.19
,TRA.20,TRA.21,TRA.22,TRA.23,TRA.24,TRA.25,TRA.26,TRA.27,TRA.28,TRA.29,
TRA.30,TRA.31,TRA.32,TRA.33,TRA.34,TRA.35,TRA.36,TRA.37,TRA.38,TRA.39,T
RA.40,TRA.41,TRA.42,TRA.43,TRA.44,TRA.45,TRA.46,TRA.47,TRA.48,TRA.49,TR
A.50)
RLB.LCC.array <- c(RLB.1,RLB.2,RLB.3,RLB.4,RLB.5,RLB.6,RLB.7,RLB.8,RLB.
9,RLB.10,RLB.11,RLB.12,RLB.13,RLB.14,RLB.15,RLB.16,RLB.17,RLB.18,RLB.19
,RLB.20,RLB.21,RLB.22,RLB.23,RLB.24,RLB.25,RLB.26,RLB.27,RLB.28,RLB.29,
RLB.30,RLB.31,RLB.32,RLB.33,RLB.34,RLB.35,RLB.36,RLB.37,RLB.38,RLB.39,R
LB.40,RLB.41,RLB.42,RLB.43,RLB.44,RLB.45,RLB.46,RLB.47,RLB.48,RLB.49,RL
B.50)
LCC.array <- (c(BPC.LCC.array,TRA.LCC.array,RLB.LCC.array)/100000)

LCC.data <- data.frame(Design = design.array, Year = year.array, Cost =
LCC.array)
LCC.summary <- summarySE(LCC.data, measurevar = "Cost", groupvars = c("
Design","Year"), conf.interval = .90)
BPC.Lower <- c(quantile(BPC.1, c(.05)),quantile(BPC.2, c(.05)),quantile
(BPC.3, c(.05)),quantile(BPC.4, c(.05)),quantile(BPC.5, c(.05)),quantil
e(BPC.6, c(.05)),quantile(BPC.7, c(.05)),quantile(BPC.8, c(.05)),quanti
le(BPC.9, c(.05)), quantile(BPC.10, c(.05)), quantile(BPC.11, c(.05)),q
uantile(BPC.12, c(.05)),quantile(BPC.13, c(.05)),quantile(BPC.14, c(.05
)),quantile(BPC.15, c(.05)),quantile(BPC.16, c(.05)),quantile(BPC.17, c
(.05)),quantile(BPC.18, c(.05)),quantile(BPC.19, c(.05)),quantile(BPC.2
0, c(.05)), quantile(BPC.21, c(.05)),quantile(BPC.22, c(.05)),quantile(
BPC.23, c(.05)),quantile(BPC.24, c(.05)),quantile(BPC.25, c(.05)),quant
ile(BPC.26, c(.05)),quantile(BPC.27, c(.05)),quantile(BPC.28, c(.05)),q
uantile(BPC.29, c(.05)),quantile(BPC.30, c(.05)), quantile(BPC.31, c(.0
5)),quantile(BPC.32, c(.05)),quantile(BPC.33, c(.05)),quantile(BPC.34,
c(.05)),quantile(BPC.35, c(.05)),quantile(BPC.36, c(.05)),quantile(BPC.
37, c(.05)),quantile(BPC.38, c(.05)),quantile(BPC.39, c(.05)),quantile(
BPC.40, c(.05)), quantile(BPC.41, c(.05)),quantile(BPC.42, c(.05)),quan
tile(BPC.43, c(.05)),quantile(BPC.44, c(.05)),quantile(BPC.45, c(.05)),
quantile(BPC.46, c(.05)),quantile(BPC.47, c(.05)),quantile(BPC.48, c(.0
5)),quantile(BPC.49, c(.05)),quantile(BPC.50,c(.05)))
BPC.Upper <- c(quantile(BPC.1, c(.95)),quantile(BPC.2, c(.95)),quantile
(BPC.3, c(.95)),quantile(BPC.4, c(.95)),quantile(BPC.5, c(.95)),quantil
```

```
e(BPC.6, c(.95)),quantile(BPC.7, c(.95)),quantile(BPC.8, c(.95)),quanti
le(BPC.9, c(.95)), quantile(BPC.10, c(.95)), quantile(BPC.11, c(.95)),q
uantile(BPC.12, c(.95)),quantile(BPC.13, c(.95)),quantile(BPC.14, c(.95
)),quantile(BPC.15, c(.95)),quantile(BPC.16, c(.95)),quantile(BPC.17, c
(.95)),quantile(BPC.18, c(.95)),quantile(BPC.19, c(.95)),quantile(BPC.2
0, c(.95)), quantile(BPC.21, c(.95)),quantile(BPC.22, c(.95)),quantile(
BPC.23, c(.95)),quantile(BPC.24, c(.95)),quantile(BPC.25, c(.95)),quant
ile(BPC.26, c(.95)),quantile(BPC.27, c(.95)),quantile(BPC.28, c(.95)),q
uantile(BPC.29, c(.95)),quantile(BPC.30, c(.95)), quantile(BPC.31, c(.9
5)),quantile(BPC.32, c(.95)),quantile(BPC.33, c(.95)),quantile(BPC.34,
c(.95)),quantile(BPC.35, c(.95)),quantile(BPC.36, c(.95)),quantile(BPC.
37, c(.95)),quantile(BPC.38, c(.95)),quantile(BPC.39, c(.95)),quantile(
BPC.40, c(.95)), quantile(BPC.41, c(.95)),quantile(BPC.42, c(.95)),quan
tile(BPC.43, c(.95)),quantile(BPC.44, c(.95)),quantile(BPC.45, c(.95)),
quantile(BPC.46, c(.95)),quantile(BPC.47, c(.95)),quantile(BPC.48, c(.9
5)),quantile(BPC.49, c(.95)),quantile(BPC.50,c(.95)))
TRA.Lower <- c(quantile(TRA.1, c(.05)),quantile(TRA.2, c(.05)),quantile
(TRA.3, c(.05)),quantile(TRA.4, c(.05)),quantile(TRA.5, c(.05)),quantil
e(TRA.6, c(.05)),quantile(TRA.7, c(.05)),quantile(TRA.8, c(.05)),quanti
le(TRA.9, c(.05)), quantile(TRA.10, c(.05)), quantile(TRA.11, c(.05)),q
uantile(TRA.12, c(.05)),quantile(TRA.13, c(.05)),quantile(TRA.14, c(.05
)),quantile(TRA.15, c(.05)),quantile(TRA.16, c(.05)),quantile(TRA.17, c
(.05)),quantile(TRA.18, c(.05)),quantile(TRA.19, c(.05)),quantile(TRA.2
0, c(.05)), quantile(TRA.21, c(.05)),quantile(TRA.22, c(.05)),quantile(
TRA.23, c(.05)),quantile(TRA.24, c(.05)),quantile(TRA.25, c(.05)),quant
ile(TRA.26, c(.05)),quantile(TRA.27, c(.05)),quantile(TRA.28, c(.05)),q
uantile(TRA.29, c(.05)),quantile(TRA.30, c(.05)), quantile(TRA.31, c(.0
5)),quantile(TRA.32, c(.05)),quantile(TRA.33, c(.05)),quantile(TRA.34,
c(.05)),quantile(TRA.35, c(.05)),quantile(TRA.36, c(.05)),quantile(TRA.
37, c(.05)),quantile(TRA.38, c(.05)),quantile(TRA.39, c(.05)),quantile(
TRA.40, c(.05)), quantile(TRA.41, c(.05)),quantile(TRA.42, c(.05)),quan
tile(TRA.43, c(.05)),quantile(TRA.44, c(.05)),quantile(TRA.45, c(.05)),
quantile(TRA.46, c(.05)),quantile(TRA.47, c(.05)),quantile(TRA.48, c(.0
5)),quantile(TRA.49, c(.05)),quantile(TRA.50,c(.05)))
TRA.Upper <- c(quantile(TRA.1, c(.95)),quantile(TRA.2, c(.95)),quantile
(TRA.3, c(.95)),quantile(TRA.4, c(.95)),quantile(TRA.5, c(.95)),quantil
e(TRA.6, c(.95)),quantile(TRA.7, c(.95)),quantile(TRA.8, c(.95)),quanti
le(TRA.9, c(.95)), quantile(TRA.10, c(.95)), quantile(TRA.11, c(.95)),q
uantile(TRA.12, c(.95)),quantile(TRA.13, c(.95)),quantile(TRA.14, c(.95
)),quantile(TRA.15, c(.95)),quantile(TRA.16, c(.95)),quantile(TRA.17, c
(.95)),quantile(TRA.18, c(.95)),quantile(TRA.19, c(.95)),quantile(TRA.2
0, c(.95)), quantile(TRA.21, c(.95)),quantile(TRA.22, c(.95)),quantile(
TRA.23, c(.95)),quantile(TRA.24, c(.95)),quantile(TRA.25, c(.95)),quant
ile(TRA.26, c(.95)),quantile(TRA.27, c(.95)),quantile(TRA.28, c(.95)),q
uantile(TRA.29, c(.95)),quantile(TRA.30, c(.95)), quantile(TRA.31, c(.9
5)),quantile(TRA.32, c(.95)),quantile(TRA.33, c(.95)),quantile(TRA.34,
```

```
c(.95)),quantile(TRA.35, c(.95)),quantile(TRA.36, c(.95)),quantile(TRA.
37, c(.95)),quantile(TRA.38, c(.95)),quantile(TRA.39, c(.95)),quantile(
TRA.40, c(.95)), quantile(TRA.41, c(.95)),quantile(TRA.42, c(.95)),quan
tile(TRA.43, c(.95)),quantile(TRA.44, c(.95)),quantile(TRA.45, c(.95)),
quantile(TRA.46, c(.95)),quantile(TRA.47, c(.95)),quantile(TRA.48, c(.9
5)),quantile(TRA.49, c(.95)),quantile(TRA.50,c(.95)))
RLB.Lower <- c(quantile(RLB.1, c(.05)),quantile(RLB.2, c(.05)),quantile
(RLB.3, c(.05)),quantile(RLB.4, c(.05)),quantile(RLB.5, c(.05)),quantil
e(RLB.6, c(.05)),quantile(RLB.7, c(.05)),quantile(RLB.8, c(.05)),quanti
le(RLB.9, c(.05)), quantile(RLB.10, c(.05)), quantile(RLB.11, c(.05)),q
uantile(RLB.12, c(.05)),quantile(RLB.13, c(.05)),quantile(RLB.14, c(.05
)),quantile(RLB.15, c(.05)),quantile(RLB.16, c(.05)),quantile(RLB.17, c
(.05)),quantile(RLB.18, c(.05)),quantile(RLB.19, c(.05)),quantile(RLB.2
0, c(.05)), quantile(RLB.21, c(.05)),quantile(RLB.22, c(.05)),quantile(
RLB.23, c(.05)),quantile(RLB.24, c(.05)),quantile(RLB.25, c(.05)),quant
ile(RLB.26, c(.05)),quantile(RLB.27, c(.05)),quantile(RLB.28, c(.05)),q
uantile(RLB.29, c(.05)),quantile(RLB.30, c(.05)), quantile(RLB.31, c(.0
5)),quantile(RLB.32, c(.05)),quantile(RLB.33, c(.05)),quantile(RLB.34,
c(.05)),quantile(RLB.35, c(.05)),quantile(RLB.36, c(.05)),quantile(RLB.
37, c(.05)),quantile(RLB.38, c(.05)),quantile(RLB.39, c(.05)),quantile(
RLB.40, c(.05)), quantile(RLB.41, c(.05)),quantile(RLB.42, c(.05)),quan
tile(RLB.43, c(.05)),quantile(RLB.44, c(.05)),quantile(RLB.45, c(.05)),
quantile(RLB.46, c(.05)),quantile(RLB.47, c(.05)),quantile(RLB.48, c(.0
5)),quantile(RLB.49, c(.05)),quantile(RLB.50,c(.05)))
RLB.Upper <- c(quantile(RLB.1, c(.95)),quantile(RLB.2, c(.95)),quantile
(RLB.3, c(.95)),quantile(RLB.4, c(.95)),quantile(RLB.5, c(.95)),quantil
e(RLB.6, c(.95)),quantile(RLB.7, c(.95)),quantile(RLB.8, c(.95)),quanti
le(RLB.9, c(.95)), quantile(RLB.10, c(.95)), quantile(RLB.11, c(.95)),q
uantile(RLB.12, c(.95)),quantile(RLB.13, c(.95)),quantile(RLB.14, c(.95
)),quantile(RLB.15, c(.95)),quantile(RLB.16, c(.95)),quantile(RLB.17, c
(.95)),quantile(RLB.18, c(.95)),quantile(RLB.19, c(.95)),quantile(RLB.2
0, c(.95)), quantile(RLB.21, c(.95)),quantile(RLB.22, c(.95)),quantile(
RLB.23, c(.95)),quantile(RLB.24, c(.95)),quantile(RLB.25, c(.95)),quant
ile(RLB.26, c(.95)),quantile(RLB.27, c(.95)),quantile(RLB.28, c(.95)),q
uantile(RLB.29, c(.95)),quantile(RLB.30, c(.95)), quantile(RLB.31, c(.9
5)),quantile(RLB.32, c(.95)),quantile(RLB.33, c(.95)),quantile(RLB.34,
c(.95)),quantile(RLB.35, c(.95)),quantile(RLB.36, c(.95)),quantile(RLB.
37, c(.95)),quantile(RLB.38, c(.95)),quantile(RLB.39, c(.95)),quantile(
RLB.40, c(.95)), quantile(RLB.41, c(.95)),quantile(RLB.42, c(.95)),quan
tile(RLB.43, c(.95)),quantile(RLB.44, c(.95)),quantile(RLB.45, c(.95)),
quantile(RLB.46, c(.95)),quantile(RLB.47, c(.95)),quantile(RLB.48, c(.9
5)),quantile(RLB.49, c(.95)),quantile(RLB.50,c(.95)))
Lower <- (c(BPC.Lower,RLB.Lower,TRA.Lower)/100000)
Upper <- (c(BPC.Upper,RLB.Upper,TRA.Upper)/100000)
LCC.summary <- cbind(LCC.summary,Lower)
LCC.summary <- cbind(LCC.summary,Upper)
```

```
LCC.Means.Plot <- ggplot(data=LCC.summary) +
  geom_line(aes(x=Year,y=Cost,colour=Design)) +
  geom_errorbar(aes(x=Year,ymin = Cost-sd ,ymax= Cost+sd), width = 0.1)
+
  labs(title = "Simulated Means of Life Cycle Cost") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold"), legend.position=c(.1,.6)) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_y_continuous(name="Cost ($100K)")


LCC.Means.Plot
```

```
ggsave("Plot.jpg", width = 7, height = 5)
LCC.summary <- rename(LCC.summary,replace = c("Cost"= "Mean", "sd"="Sta
ndard Deviation", "se"="Standard Error", "ci"= "Confidence Interval", "
Lower"="5th Percentile", "Upper"="95th Percentile"))
write.csv(LCC.summary, file = "50_Year_Horizon_data.csv")
```

OEF FOB Simulation.R

Ryan

Thu Feb 11 05:30:19 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/Question 4a"
)

# Assumptions
TRA.Adjustment.Factor <- 3.266667
RLB.Adjustment.Factor <- 49
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06
t <- rpois(n, 5.962)

# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
BPC.DCPSF3 <- 15.60
```

```
BPC.DCPSF4 <- 21.00
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
RLB2.MX2015.mean <- 5.333
```

```
RLB2.MX2015.stdev <- 0.690
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Present Worth of Life Cycle Cost Function
LCC <- function (t, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  ifelse(t <= 3, LCC <- AC + MX1 + DC, NA)
  ifelse(t == 4, LCC <- AC + MX1 + MX2 + DC, NA)
  ifelse(t == 5, LCC <- AC + MX1 + MX2 + MX3 + DC, NA)
  ifelse(t == 6, LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC, NA)
  ifelse(t == 7, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC, NA)
  ifelse(t == 8, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC, NA
)
  ifelse(t >= 9, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7 +
DC, NA)
  return(LCC)
}

# Simulation
BPC.AC <- BPC.AC * FGP(8,i)
BPC.MX1 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.shop
.rate * FGP(7,i)
BPC.MX2 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.shop
.rate * FGP(6,i)
BPC.MX3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.sh
op.rate * FGP(5,i)
BPC.MX4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.shop
.rate * FGP(4,i)
BPC.MX5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.shop
.rate * FGP(3,i)
BPC.MX6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.shop
.rate * FGP(2,i)
BPC.MX7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.shop
.rate * FGP(1,i)
```

```
BPC.DC <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.Adj
ustment.Factor
TRA.MX1 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.shop
.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.shop
.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.sh
op.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.shop
.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.shop
.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.shop
.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.shop
.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.Adj
ustment.Factor
RLB.MX1 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.sh
op.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.sh
op.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.sh
op.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rate
* (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.sh
op.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.sh
op.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.sh
op.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC <- LCC(t, BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BPC.MX5,
BPC.MX6, BPC.MX7, BPC.DC)
TRA.LCC <- LCC(t, TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TRA.MX5,
TRA.MX6, TRA.MX7, TRA.DC)
RLB.LCC <- LCC(t, RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RLB.MX5,
RLB.MX6, RLB.MX7, RLB.DC)

## Histograms Construction
```

```
BPC.array <- array("BPC",n)
TRA.array <- array("TRA",n)
RLB.array <- array("RLB",n)

BPC.data <- data.frame(Design = BPC.array, LCC = BPC.LCC/100000)
TRA.data <- data.frame(Design = TRA.array, LCC = TRA.LCC/100000)
RLB.data <- data.frame(Design = RLB.array, LCC = RLB.LCC/100000)
LCC.data <- data.frame(Design = c(BPC.array, TRA.array, RLB.array), LCC
= (c(BPC.LCC, TRA.LCC, RLB.LCC)/100000))
LCC.Means <- data.frame(Median = c("BPC", "TRA", "RLB"), Value = (c(med
ian(BPC.LCC),median(TRA.LCC), median(RLB.LCC))/100000))

BPC.hist <- ggplot(BPC.data, aes(x = LCC)) +
  geom_histogram(binwidth = .5, colour = "black", fill = "white")  +
  geom_vline(aes(xintercept = mean(LCC), linetype = "Estimated Mean"),
size = 1) +
  geom_vline(aes(xintercept = quantile(LCC, c(.05)), linetype = "5th &
95th\nPercentile"), size = 1) +
  geom_vline(aes(xintercept=quantile(LCC, c(.95)), linetype="5th & 95th
\nPercentile"), size=1) +
  geom_vline(aes(xintercept=median(LCC), linetype = "Median"), size = 2
) +
  labs(title = "Simulated LCC Histogram of BPC") +
  scale_linetype_discrete(name = "Legend") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))

TRA.hist <- ggplot(TRA.data, aes(x = LCC)) +
  geom_histogram(binwidth = .5, colour = "black", fill = "white")  +
  geom_vline(aes(xintercept = mean(LCC), linetype = "Estimated Mean"),
size = 1) +
  geom_vline(aes(xintercept = quantile(LCC, c(.05)), linetype = "5th &
95th\nPercentile"), size = 1) +
  geom_vline(aes(xintercept=quantile(LCC, c(.95)), linetype="5th & 95th
\nPercentile"), size=1) +
  geom_vline(aes(xintercept=median(LCC), linetype = "Median"), size = 2
) +
  labs(title = "Simulated LCC Histogram of Trailers") +
  scale_linetype_discrete(name = "Legend") +
```

```
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))

RLB.hist <- ggplot(RLB.data, aes(x = LCC)) +
  geom_histogram(binwidth = 10, colour = "black", fill = "white") +
  geom_vline(aes(xintercept = mean(LCC), linetype = "Estimated Mean"),
size = 1) +
  geom_vline(aes(xintercept = quantile(LCC, c(.05)), linetype = "5th &
95th\nPercentile"), size = 1) +
  geom_vline(aes(xintercept=quantile(LCC, c(.95)), linetype="5th & 95th
\nPercentile"), size=1) +
  geom_vline(aes(xintercept=median(LCC), linetype = "Median"), size = 2
) +
  labs(title = "Simulated LCC Histogram of Relocatable Buildings") +
  scale_linetype_discrete(name = "Legend") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))


LCC.hist <- ggplot(LCC.data, aes(x = LCC)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=LCC.Means, aes(xintercept = Value,  colour = Median),
linetype="dashed", size=1) +
  labs(title = "Histogram Comparison of Designs") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
```

```
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


# Print Plots
BPC.hist

## Warning in data.frame(xintercept = structure(65.7470670193022, .Name
s =
## "5%"), : row names were found from a short variable and have been di
scarded

## Warning in data.frame(xintercept = structure(69.9866700247191, .Name
s
## = "95%"), : row names were found from a short variable and have been
## discarded
```

```
ggsave("BPC_Plot.jpg", width = 7, height = 5)

## Warning in data.frame(xintercept = structure(65.7470670193022, .Name
s =
## "5%"), : row names were found from a short variable and have been di
scarded

## Warning in data.frame(xintercept = structure(69.9866700247191, .Name
s
## = "95%"), : row names were found from a short variable and have been
## discarded

TRA.hist

## Warning in data.frame(xintercept = structure(45.8580929160928, .Name
s =
## "5%"), : row names were found from a short variable and have been di
scarded

## Warning in data.frame(xintercept = structure(50.5344548015969, .Name
s
## = "95%"), : row names were found from a short variable and have been
## discarded
```

```
ggsave("TRA_Plot.jpg", width = 7, height = 5)

## Warning in data.frame(xintercept = structure(45.8580929160928, .Name
s =
## "5%"), : row names were found from a short variable and have been di
scarded

## Warning in data.frame(xintercept = structure(50.5344548015969, .Name
s
## = "95%"), : row names were found from a short variable and have been
## discarded

RLB.hist

## Warning in data.frame(xintercept = structure(68.8400319146533, .Name
s =
## "5%"), : row names were found from a short variable and have been di
scarded

## Warning in data.frame(xintercept = structure(176.154222049055, .Name
s
## = "95%"), : row names were found from a short variable and have been
## discarded
```

```
ggsave("RLB_Plot.jpg", width = 7, height = 5)

## Warning in data.frame(xintercept = structure(68.8400319146533, .Name
s =
## "5%"), : row names were found from a short variable and have been di
scarded

## Warning in data.frame(xintercept = structure(176.154222049055, .Name
s
## = "95%"), : row names were found from a short variable and have been
## discarded

LCC.hist
```

```
ggsave("LCC_Plot.jpg", width = 7, height = 5)


#Results
wilcox.test(BPC.LCC/100000, TRA.LCC/100000, alternative = "two.sided",
mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC/1e+05 and TRA.LCC/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.66898 19.70610
## sample estimates:
## (pseudo)median
##       19.68758
```

```
wilcox.test(BPC.LCC/100000, RLB.LCC/100000, alternative = "two.sided",
mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC/1e+05 and RLB.LCC/1e+05
## V = 295030, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.60030 -41.51152
## sample estimates:
## (pseudo)median
##      -42.05539
```

```
wilcox.test(TRA.LCC/100000, RLB.LCC/100000, alternative = "two.sided",
mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC/1e+05 and RLB.LCC/1e+05
## V = 40, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -62.28492 -61.19659
## sample estimates:
## (pseudo)median
##      -61.73922
```

```
LCC.stats <- data.frame(Design = c("BPC","Trailer","RLB"), Lower = (c(q
uantile(BPC.LCC, c(0.05)), quantile(TRA.LCC, c(0.05)), quantile(RLB.LCC
, c(0.05)))/100000), Mean = (c(mean(BPC.LCC), mean(TRA.LCC), mean(RLB.L
CC))/100000), Upper = (c(quantile(BPC.LCC, c(0.95)), quantile(TRA.LCC,
c(0.95)), quantile(RLB.LCC, c(0.95)))/100000), sd = (c(sd(BPC.LCC),sd(T
RA.LCC),sd(RLB.LCC))/100000), se = (c((sd(BPC.LCC)/sqrt(length(BPC.LCC)
```

```
)), (sd(TRA.LCC)/sqrt(length(TRA.LCC))), (sd(RLB.LCC)/sqrt(length(RLB.L
CC))))/100000),Median = (c(median(BPC.LCC),median(TRA.LCC),median(RLB.L
CC))/100000))
LCC.stats <- rename(LCC.stats, replace = c("Lower"="5th Percentile", "U
pper"="95th Percentile", "sd"="Standard Deviation", "se"="Standard Erro
r"))
write.csv(LCC.stats, file = "4a_LCC_stats.csv")

Comparison.data <- data.frame(Comparison = c("BPC < TRA","BPC < RLB", "
TRA < RLB"), Probability = c((sum(BPC.LCC < TRA.LCC)/10000),(sum(BPC.LC
C < RLB.LCC)/10000),(sum(TRA.LCC < RLB.LCC)/10000)))
write.csv(Comparison.data,file = "4a_comparsions.csv")
```

Lack of Knowledge Simulations.R

Ryan

Thu Feb 11 05:38:39 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

library(triangle)
setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/Question 4b"
)


# Assumptions
TRA.Adjustment.Factor <- 3.266667
RLB.Adjustment.Factor <- 49
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06

# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
```

```
BPC.DCPSF3 <- 15.60
BPC.DCPSF4 <- 21.00
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
```

```
RLB2.MX2015.mean <- 5.333
RLB2.MX2015.stdev <- 0.690
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Present Worth of Life Cycle Cost Function
LCC<- function (t, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  ifelse(t <= 3, LCC <- AC + MX1 + DC, NA)
  ifelse(t == 4, LCC <- AC + MX1 + MX2 + DC, NA)
  ifelse(t == 5, LCC <- AC + MX1 + MX2 + MX3 + DC, NA)
  ifelse(t == 6, LCC <- AC + MX1 + MX2 + MX3 + MX4 + DC, NA)
  ifelse(t == 7, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC, NA)
  ifelse(t == 8, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + DC, NA
)
  ifelse(t >= 9, LCC <- AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 + MX7 +
DC, NA)
  return(LCC)
}

# Comparisons for Uncertain Duration - Year 3 Most Probable
t3 <- round(rtriangle(n,3,9,3), 0)

BPC.AC.3 <- BPC.AC * FGP(8,i)
BPC.MX1.3 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.3 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.3 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.3 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.3 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
```

```
op.rate * FGP(2,i)
BPC.MX7.3 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.3 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.3 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.3 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.3 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.3 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.3 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.3 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.3 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.3 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.3 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.3 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.3 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.3 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.3 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.3 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.3 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.3 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.MX.3 <- BPC.MX1.3
TRA.MX.3 <- TRA.MX1.3
RLB.MX.3 <- RLB.MX1.3

BPC.LCC.3 <- LCC(t3, BPC.AC.3, BPC.MX1.3, BPC.MX2.3, BPC.MX3.3, BPC.MX4
```

```
.3, BPC.MX5.3, BPC.MX6.3, BPC.MX7.3, BPC.DC.3)
TRA.LCC.3 <- LCC(t3, TRA.AC.3, TRA.MX1.3, TRA.MX2.3, TRA.MX3.3, TRA.MX4
.3, TRA.MX5.3, TRA.MX6.3, TRA.MX7.3, TRA.DC.3)
RLB.LCC.3 <- LCC(t3, RLB.AC.3, RLB.MX1.3, RLB.MX2.3, RLB.MX3.3, RLB.MX4
.3, RLB.MX5.3, RLB.MX6.3, RLB.MX7.3, RLB.DC.3)

# Comparisons for Uncertain Duration - Year 4 Most Probable
t4 <- round(rtriangle(n,3,9,4), 0)

BPC.AC.4 <- BPC.AC * FGP(8,i)
BPC.MX1.4 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.4 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.4 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.4 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.4 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.4 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.4 <- BPC.MX1.4 + BPC.MX2.4
BPC.DC.4 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.4 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.4 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.4 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.4 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.4 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.4 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.4 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.4 <- TRA.MX1.4 + TRA.MX2.4
TRA.DC.4 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor
```

```
RLB.AC.4 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.4 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.4 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.4 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.4 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.4 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.4 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.4 <- RLB.MX1.4 + RLB.MX2.4
RLB.DC.4 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.4 <- LCC(t3, BPC.AC.4, BPC.MX1.4, BPC.MX2.4, BPC.MX3.4, BPC.MX4
.4, BPC.MX5.4, BPC.MX6.4, BPC.MX7.4, BPC.DC.4)
TRA.LCC.4 <- LCC(t3, TRA.AC.4, TRA.MX1.4, TRA.MX2.4, TRA.MX3.4, TRA.MX4
.4, TRA.MX5.4, TRA.MX6.4, TRA.MX7.4, TRA.DC.4)
RLB.LCC.4 <- LCC(t3, RLB.AC.4, RLB.MX1.4, RLB.MX2.4, RLB.MX3.4, RLB.MX4
.4, RLB.MX5.4, RLB.MX6.4, RLB.MX7.4, RLB.DC.4)

# Comparisons for Uncertain Duration - Year 5 Most Probable
t5 <- round(rtriangle(n,3,9,5), 0)

BPC.AC.5 <- BPC.AC * FGP(8,i)
BPC.MX1.5 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.5 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.5 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.5 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.5 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.5 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.5 <- BPC.MX1.5 + BPC.MX2.5 + BPC.MX3.5
BPC.DC.5 <- array(BPC.DC.AVG, n) * BPC.size
```

```
TRA.AC.5 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.5 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.5 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.5 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.5 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.5 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.5 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.5 <- TRA.MX1.5 + TRA.MX2.5 + TRA.MX3.5
TRA.DC.5 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.5 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.5 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.5 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.5 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.5 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.5 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.5 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.5 <- RLB.MX1.5 + RLB.MX2.5 + RLB.MX3.5
RLB.DC.5 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.5 <- LCC(t3, BPC.AC.5, BPC.MX1.5, BPC.MX2.5, BPC.MX3.5, BPC.MX4
.5, BPC.MX5.5, BPC.MX6.5, BPC.MX7.5, BPC.DC.5)
TRA.LCC.5 <- LCC(t3, TRA.AC.5, TRA.MX1.5, TRA.MX2.5, TRA.MX3.5, TRA.MX4
.5, TRA.MX5.5, TRA.MX6.5, TRA.MX7.5, TRA.DC.5)
RLB.LCC.5 <- LCC(t3, RLB.AC.5, RLB.MX1.5, RLB.MX2.5, RLB.MX3.5, RLB.MX4
.5, RLB.MX5.5, RLB.MX6.5, RLB.MX7.5, RLB.DC.5)
```

```
# Comparisons for Uncertain Duration - Year 6 Most Probable
t6 <- round(rtriangle(n,3,9,6), 0)

BPC.AC.6 <- BPC.AC * FGP(8,i)
BPC.MX1.6 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.6 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.6 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.6 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.6 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.6 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.6 <- BPC.MX1.6 + BPC.MX2.6 + BPC.MX3.6 + BPC.MX4.6
BPC.DC.6 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.6 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.6 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.6 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.6 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.6 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.6 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.6 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.6 <- TRA.MX1.6 + TRA.MX2.6 + TRA.MX3.6 + TRA.MX4.6
TRA.DC.6 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.6 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.6 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.6 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
```

```
RLB.MX3.6 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.6 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.6 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.6 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.6 <- RLB.MX1.6 + RLB.MX2.6 + RLB.MX3.6 + RLB.MX4.6
RLB.DC.6 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.6 <- LCC(t3, BPC.AC.6, BPC.MX1.6, BPC.MX2.6, BPC.MX3.6, BPC.MX4
.6, BPC.MX5.6, BPC.MX6.6, BPC.MX7.6, BPC.DC.6)
TRA.LCC.6 <- LCC(t3, TRA.AC.6, TRA.MX1.6, TRA.MX2.6, TRA.MX3.6, TRA.MX4
.6, TRA.MX5.6, TRA.MX6.6, TRA.MX7.6, TRA.DC.6)
RLB.LCC.6 <- LCC(t3, RLB.AC.6, RLB.MX1.6, RLB.MX2.6, RLB.MX3.6, RLB.MX4
.6, RLB.MX5.6, RLB.MX6.6, RLB.MX7.6, RLB.DC.6)

# Comparisons for Uncertain Duration - Year 7 Most Probable
t7 <- round(rtriangle(n,3,9,7), 0)

BPC.AC.7 <- BPC.AC * FGP(8,i)
BPC.MX1.7 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.7 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.7 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.7 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.7 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.7 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.7 <- BPC.MX1.7 + BPC.MX2.7 + BPC.MX3.7 + BPC.MX4.7 + BPC.MX5.7
BPC.DC.7 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.7 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.7 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.7 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
```

```
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.7 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.7 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.7 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.7 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.7 <- TRA.MX1.7 + TRA.MX2.7 + TRA.MX3.7 + TRA.MX4.7 + TRA.MX5.7
TRA.DC.7 <- array(TRA.DC.AVG, n) * TRA.size * TRA.Adjustment.Factor

RLB.AC.7 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.7 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.7 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.7 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.7 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.7 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.7 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.7 <- RLB.MX1.7 + RLB.MX2.7 + RLB.MX3.7 + RLB.MX4.7 + RLB.MX5.7
RLB.DC.7 <- array(RLB.DC.AVG, n) * RLB.size * RLB.Adjustment.Factor

BPC.LCC.7 <- LCC(t3, BPC.AC.7, BPC.MX1.7, BPC.MX2.7, BPC.MX3.7, BPC.MX4
.7, BPC.MX5.7, BPC.MX6.7, BPC.MX7.7, BPC.DC.7)
TRA.LCC.7 <- LCC(t3, TRA.AC.7, TRA.MX1.7, TRA.MX2.7, TRA.MX3.7, TRA.MX4
.7, TRA.MX5.7, TRA.MX6.7, TRA.MX7.7, TRA.DC.7)
RLB.LCC.7 <- LCC(t3, RLB.AC.7, RLB.MX1.7, RLB.MX2.7, RLB.MX3.7, RLB.MX4
.7, RLB.MX5.7, RLB.MX6.7, RLB.MX7.7, RLB.DC.7)

# Comparisons for Uncertain Duration - Year 8 Most Probable
t8 <- round(rtriangle(n,3,9,8), 0)

BPC.AC.8 <- BPC.AC * FGP(8,i)
BPC.MX1.8 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
```

```
BPC.MX2.8 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.8 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.8 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.8 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.8 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.8 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.8 <- BPC.MX1.8 + BPC.MX2.8 + BPC.MX3.8 + BPC.MX4.8 + BPC.MX5.8 +
BPC.MX6.8
BPC.DC.8 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.8 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.8 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.8 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.8 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.8 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.8 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.8 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.8 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.8 <- TRA.MX1.8 + TRA.MX2.8 + TRA.MX3.8 + TRA.MX4.8 + TRA.MX5.8 +
TRA.MX6.8
TRA.DC.8 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.8 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.8 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.8 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.8 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.8 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
```

```
RLB.MX5.8 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.8 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.8 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.8 <- RLB.MX1.8 + RLB.MX2.8 + RLB.MX3.8 + RLB.MX4.8 + RLB.MX5.8 +
RLB.MX6.8
RLB.DC.8 <- array(RLB.DC.AVG, n) * RLB.size * RLB.Adjustment.Factor

BPC.LCC.8 <- LCC(t3, BPC.AC.8, BPC.MX1.8, BPC.MX2.8, BPC.MX3.8, BPC.MX4
.8, BPC.MX5.8, BPC.MX6.8, BPC.MX7.8, BPC.DC.8)
TRA.LCC.8 <- LCC(t3, TRA.AC.8, TRA.MX1.8, TRA.MX2.8, TRA.MX3.8, TRA.MX4
.8, TRA.MX5.8, TRA.MX6.8, TRA.MX7.8, TRA.DC.8)
RLB.LCC.8 <- LCC(t3, RLB.AC.8, RLB.MX1.8, RLB.MX2.8, RLB.MX3.8, RLB.MX4
.8, RLB.MX5.8, RLB.MX6.8, RLB.MX7.8, RLB.DC.8)

# Comparisons for Uncertain Duration - Year 9 Most Probable
t9 <- round(rtriangle(n,3,9,9), 0)

BPC.AC.9 <- BPC.AC * FGP(8,i)
BPC.MX1.9 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.9 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.9 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.9 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.9 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.9 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.9 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.MX.9 <- BPC.MX1.9 + BPC.MX2.9 + BPC.MX3.9 + BPC.MX4.9 + BPC.MX5.9 +
BPC.MX6.9 + BPC.MX7.9
BPC.DC.9 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.9 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.9 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.9 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.9 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
```

```
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.9 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.9 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.9 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.9 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.MX.9 <- TRA.MX1.9 + TRA.MX2.9 + TRA.MX3.9 + TRA.MX4.9 + TRA.MX5.9 +
TRA.MX6.9 + TRA.MX7.9
TRA.DC.9 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.9 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.9 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.9 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.9 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.9 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.9 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.9 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.9 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX.9 <- RLB.MX1.9 + RLB.MX2.9 + RLB.MX3.9 + RLB.MX4.9 + RLB.MX5.9 +
RLB.MX6.9 + RLB.MX7.9
RLB.DC.9 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.LCC.9 <- LCC(t3, BPC.AC.9, BPC.MX1.9, BPC.MX2.9, BPC.MX3.9, BPC.MX4
.9, BPC.MX5.9, BPC.MX6.9, BPC.MX7.9, BPC.DC.9)
TRA.LCC.9 <- LCC(t3, TRA.AC.9, TRA.MX1.9, TRA.MX2.9, TRA.MX3.9, TRA.MX4
.9, TRA.MX5.9, TRA.MX6.9, TRA.MX7.9, TRA.DC.9)
RLB.LCC.9 <- LCC(t3, RLB.AC.9, RLB.MX1.9, RLB.MX2.9, RLB.MX3.9, RLB.MX4
.9, RLB.MX5.9, RLB.MX6.9, RLB.MX7.9, RLB.DC.9)

# Data Frame Construction
# Simulation Histograms and Means Plots Data Frames
design.array <- c(array("BPC",28*n),array("TRA",28*n),array("RLB",28*n)
)
year.array <- rep(c(array(3,n), array(4,n), array(5,n), array(6,n), arr
ay(7,n), array(8,n), array(9,n)),12)
```

```
cost.type.array <- rep(c(array("Acquisition",7*n), array("Maintenance",
7*n), array("Disposal",7*n), array("Life Cycle",7*n)),3)

BPC.AC <- c(BPC.AC.3, BPC.AC.4, BPC.AC.5, BPC.AC.6, BPC.AC.7, BPC.AC.8,
BPC.AC.9)
BPC.MX <- c(BPC.MX.3, BPC.MX.4, BPC.MX.5, BPC.MX.6, BPC.MX.7, BPC.MX.8,
BPC.MX.9)
BPC.DC <- c(BPC.DC.3, BPC.DC.4, BPC.DC.5, BPC.DC.6, BPC.DC.7, BPC.DC.8,
BPC.DC.9)
BPC.LCC <- c(BPC.LCC.3, BPC.LCC.4, BPC.LCC.5, BPC.LCC.6, BPC.LCC.7, BPC
.LCC.8, BPC.LCC.9)

BPC <- c(BPC.AC, BPC.MX, BPC.DC, BPC.LCC)

TRA.AC <- c(TRA.AC.3, TRA.AC.4, TRA.AC.5, TRA.AC.6, TRA.AC.7, TRA.AC.8,
TRA.AC.9)
TRA.MX <- c(TRA.MX.3, TRA.MX.4, TRA.MX.5, TRA.MX.6, TRA.MX.7, TRA.MX.8,
TRA.MX.9)
TRA.DC <- c(TRA.DC.3, TRA.DC.4, TRA.DC.5, TRA.DC.6, TRA.DC.7, TRA.DC.8,
TRA.DC.9)
TRA.LCC <- c(TRA.LCC.3, TRA.LCC.4, TRA.LCC.5, TRA.LCC.6, TRA.LCC.7, TRA
.LCC.8, TRA.LCC.9)
TRA <- c(TRA.AC, TRA.MX, TRA.DC, TRA.LCC)

RLB.AC <- c(RLB.AC.3, RLB.AC.4, RLB.AC.5, RLB.AC.6, RLB.AC.7, RLB.AC.8,
RLB.AC.9)
RLB.MX <- c(RLB.MX.3, RLB.MX.4, RLB.MX.5, RLB.MX.6, RLB.MX.7, RLB.MX.8,
RLB.MX.9)
RLB.DC <- c(RLB.DC.3, RLB.DC.4, RLB.DC.5, RLB.DC.6, RLB.DC.7, RLB.DC.8,
RLB.DC.9)
RLB.LCC <- c(RLB.LCC.3, RLB.LCC.4, RLB.LCC.5, RLB.LCC.6, RLB.LCC.7, RLB
.LCC.8, RLB.LCC.9)
RLB <- c(RLB.AC, RLB.MX, RLB.DC, RLB.LCC)

cost.array <- (c(BPC, TRA, RLB)/100000)
Cost.Data <- data.frame(Design = design.array, Year = year.array, Type
= cost.type.array, Cost = cost.array)
Cost.Data.Summary <- summarySE(Cost.Data, measurevar = "Cost", groupvar
s = c("Design", "Year", "Type"))

# Plot Construction
# Simulation Means Plots
Designs.LCC.Sum <- subset(Cost.Data.Summary, Type == "Life Cycle", sele
ct = c(Design, Year, Type, N, Cost, sd, se, ci))
LCC.Means.Plot <- ggplot(data=Designs.LCC.Sum) + geom_line(aes(x=Year,y
=Cost,colour=Design)) + geom_errorbar(aes(x=Year,ymin = Cost-ci ,ymax=
```

```
Cost+ci), width = 0.1) + labs(title = "Simulated Means of Life Cycle Co
st")
BPC.Lower <- c(quantile(BPC.LCC.3, c(.05)), quantile(BPC.LCC.4, c(.05))
,quantile(BPC.LCC.5, c(.05)),quantile(BPC.LCC.6, c(.05)),quantile(BPC.L
CC.7, c(.05)),quantile(BPC.LCC.8, c(.05)),quantile(BPC.LCC.9, c(.05)))
BPC.Upper <- c(quantile(BPC.LCC.3, c(.95)), quantile(BPC.LCC.4, c(.95))
,quantile(BPC.LCC.5, c(.95)),quantile(BPC.LCC.6, c(.95)),quantile(BPC.L
CC.7, c(.95)),quantile(BPC.LCC.8, c(.95)),quantile(BPC.LCC.9, c(.95)))
TRA.Lower <- c(quantile(TRA.LCC.3, c(.05)), quantile(TRA.LCC.4, c(.05))
,quantile(TRA.LCC.5, c(.05)),quantile(TRA.LCC.6, c(.05)),quantile(TRA.L
CC.7, c(.05)),quantile(TRA.LCC.8, c(.05)),quantile(TRA.LCC.9, c(.05)))
TRA.Upper <- c(quantile(TRA.LCC.3, c(.95)), quantile(TRA.LCC.4, c(.95))
,quantile(TRA.LCC.5, c(.95)),quantile(TRA.LCC.6, c(.95)),quantile(TRA.L
CC.7, c(.95)),quantile(TRA.LCC.8, c(.95)),quantile(TRA.LCC.9, c(.95)))
RLB.Lower <- c(quantile(RLB.LCC.3, c(.05)), quantile(RLB.LCC.4, c(.05))
,quantile(RLB.LCC.5, c(.05)),quantile(RLB.LCC.6, c(.05)),quantile(RLB.L
CC.7, c(.05)),quantile(RLB.LCC.8, c(.05)),quantile(RLB.LCC.9, c(.05)))
RLB.Upper <- c(quantile(RLB.LCC.3, c(.95)), quantile(RLB.LCC.4, c(.95))
,quantile(RLB.LCC.5, c(.95)),quantile(RLB.LCC.6, c(.95)),quantile(RLB.L
CC.7, c(.95)),quantile(RLB.LCC.8, c(.95)),quantile(RLB.LCC.9, c(.95)))
Lower <- (c(BPC.Lower,RLB.Lower,TRA.Lower)/100000)
Upper <- (c(BPC.Upper,RLB.Upper,TRA.Upper)/100000)
BPC.Median <- c(median(BPC.LCC.3),median(BPC.LCC.4),median(BPC.LCC.5),m
edian(BPC.LCC.6),median(BPC.LCC.7),median(BPC.LCC.8),median(BPC.LCC.9))
TRA.Median <- c(median(TRA.LCC.3),median(TRA.LCC.4),median(TRA.LCC.5),m
edian(TRA.LCC.6),median(TRA.LCC.7),median(TRA.LCC.8),median(TRA.LCC.9))
RLB.Median <- c(median(RLB.LCC.3),median(RLB.LCC.4),median(RLB.LCC.5),m
edian(RLB.LCC.6),median(RLB.LCC.7),median(RLB.LCC.8),median(RLB.LCC.9))
Median <- (c(BPC.Median,RLB.Median,TRA.Median)/100000)
Designs.LCC.Sum <- cbind(Designs.LCC.Sum, Lower)
Designs.LCC.Sum <- cbind(Designs.LCC.Sum, Upper)
Designs.LCC.Sum <- cbind(Designs.LCC.Sum, Median)
Designs.LCC.Sum <- rename(Designs.LCC.Sum, replace = c("Cost" = "Mean",
"sd" = "Standard Deviation", "se" = "Standard Error", "ci" = "Confidenc
e Interval", "Lower" = "5th Percentile", "Upper" = "95th Percentile"))
write.csv(Designs.LCC.Sum,file = "4b_cost_data.csv")


# Simulation Histograms
Designs.LCC <- subset(Cost.Data, Type == "Life Cycle", select = c("Desi
gn","Year","Cost"))


Year.Design.Hist.free <- ggplot(Designs.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, colour = "black") +
  facet_grid(Design ~ Year, scale = "free") +
```

```
  labs(title = "Simulated LCCs per Designs") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), plot.title = element_text(li
neheight=.8, face="bold", size = 20), legend.title = element_text(colou
r="black", size=15, face="bold"), legend.position=c(.9,.6)) +
  scale_colour_discrete(name  ="Design\nAlternative", breaks=c("BPC", "
RLB","TRA"), labels=c("BPC", "RLB","Trailer")) +
  scale_x_continuous(name="Cost ($100K)")


Year.3.LCC <- subset(Cost.Data, Year == 3 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.3.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.3), mean(RLB.LCC
.3), mean(TRA.LCC.3))/100000), Design = c("BPC","RLB","TRA"))
Year.3.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.3, c(.05))
, quantile(RLB.LCC.3, c(.05)), quantile(TRA.LCC.3, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.3.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.3, c(.95))
, quantile(RLB.LCC.3, c(.95)), quantile(TRA.LCC.3, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.3.vline.median <- data.frame(Median = (c(median(BPC.LCC.3), median
(RLB.LCC.3), median(TRA.LCC.3))/100000), Design = c("BPC","RLB","TRA"))
Year.3.Hist <- ggplot(Year.3.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.3.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.3.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.3.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.3.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "3 Years of Use Expected") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))
```

```
Year.3.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.3),median(RLB.LCC.3),median(TRA.LCC.3))/100000))
Year.3.Hist.Overlay <- ggplot(Year.3.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.3.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "3 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))


Year.4.LCC <- subset(Cost.Data, Year == 4 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.4.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.4), mean(RLB.LCC
.4), mean(TRA.LCC.4))/100000), Design = c("BPC","RLB","TRA"))
Year.4.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.4, c(.05))
, quantile(RLB.LCC.4, c(.05)), quantile(TRA.LCC.4, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.4.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.4, c(.95))
, quantile(RLB.LCC.4, c(.95)), quantile(TRA.LCC.4, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.4.vline.median <- data.frame(Median = (c(median(BPC.LCC.4), median
(RLB.LCC.4), median(TRA.LCC.4))/100000), Design = c("BPC","RLB","TRA"))
Year.4.Hist <- ggplot(Year.4.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.4.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.4.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.4.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.4.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "4 Years of Use Expected") +
```

```
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.4.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.4),median(RLB.LCC.4),median(TRA.LCC.4))/100000))
Year.4.Hist.Overlay <- ggplot(Year.4.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.4.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "4 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.5.LCC <- subset(Cost.Data, Year == 5 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.5.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.5), mean(RLB.LCC
.5), mean(TRA.LCC.5))/100000), Design = c("BPC","RLB","TRA"))
Year.5.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.5, c(.05))
, quantile(RLB.LCC.5, c(.05)), quantile(TRA.LCC.5, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.5.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.5, c(.95))
, quantile(RLB.LCC.5, c(.95)), quantile(TRA.LCC.5, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.5.vline.median <- data.frame(Median = (c(median(BPC.LCC.5), median
(RLB.LCC.5), median(TRA.LCC.5))/100000), Design = c("BPC","RLB","TRA"))
Year.5.Hist <- ggplot(Year.5.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.5.vline.me
an, size = .5) +
```

```
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.5.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.5.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.5.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "5 Years of Use Expected") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.5.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.5),median(RLB.LCC.5),median(TRA.LCC.5))/100000))
Year.5.Hist.Overlay <- ggplot(Year.5.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.5.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "5 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.6.LCC <- subset(Cost.Data, Year == 6 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.6.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.6), mean(RLB.LCC
.6), mean(TRA.LCC.6))/100000), Design = c("BPC","RLB","TRA"))
Year.6.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.6, c(.05))
, quantile(RLB.LCC.6, c(.05)), quantile(TRA.LCC.6, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.6.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.6, c(.95))
, quantile(RLB.LCC.6, c(.95)), quantile(TRA.LCC.6, c(.95)))/100000), De
```

```
sign = c("BPC","RLB","TRA"))
Year.6.vline.median <- data.frame(Median = (c(median(BPC.LCC.6), median
(RLB.LCC.6), median(TRA.LCC.6))/100000), Design = c("BPC","RLB","TRA"))
Year.6.Hist <- ggplot(Year.6.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.6.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.6.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.6.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.6.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "6 Years of Use Expected") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.6.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.6),median(RLB.LCC.6),median(TRA.LCC.6))/100000))
Year.6.Hist.Overlay <- ggplot(Year.6.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.6.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "6 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))



Year.7.LCC <- subset(Cost.Data, Year == 7 & Type == "Life Cycle", selec
```

```
t = c("Design", "Type", "Cost"))
Year.7.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.7), mean(RLB.LCC
.7), mean(TRA.LCC.7))/100000), Design = c("BPC","RLB","TRA"))
Year.7.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.7, c(.05))
, quantile(RLB.LCC.7, c(.05)), quantile(TRA.LCC.7, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.7.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.7, c(.95))
, quantile(RLB.LCC.7, c(.95)), quantile(TRA.LCC.7, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.7.vline.median <- data.frame(Median = (c(median(BPC.LCC.6), median
(RLB.LCC.6), median(TRA.LCC.6))/100000), Design = c("BPC","RLB","TRA"))
Year.7.Hist <- ggplot(Year.7.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.7.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.7.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.7.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.7.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "7 Years of Use Expected") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.7.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.7),median(RLB.LCC.7),median(TRA.LCC.7))/100000))
Year.7.Hist.Overlay <- ggplot(Year.7.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.7.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "7 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
```

```
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))


Year.8.LCC <- subset(Cost.Data, Year == 8 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.8.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.8), mean(RLB.LCC
.8), mean(TRA.LCC.8))/100000), Design = c("BPC","RLB","TRA"))
Year.8.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.8, c(.05))
, quantile(RLB.LCC.8, c(.05)), quantile(TRA.LCC.8, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.8.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.8, c(.95))
, quantile(RLB.LCC.8, c(.95)), quantile(TRA.LCC.8, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.8.vline.median <- data.frame(Median = (c(median(BPC.LCC.8), median
(RLB.LCC.8), median(TRA.LCC.8))/100000), Design = c("BPC","RLB","TRA"))
Year.8.Hist <- ggplot(Year.8.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.8.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.8.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.8.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.8.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "8 Years of Use Expected") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.8.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.8),median(RLB.LCC.8),median(TRA.LCC.8))/100000))
Year.8.Hist.Overlay <- ggplot(Year.8.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
```

```
  geom_vline(data=Year.8.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "8 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))


Year.9.LCC <- subset(Cost.Data, Year == 9 & Type == "Life Cycle", selec
t = c("Design", "Type", "Cost"))
Year.9.vline.mean <- data.frame(Mean = (c(mean(BPC.LCC.9), mean(RLB.LCC
.9), mean(TRA.LCC.9))/100000), Design = c("BPC","RLB","TRA"))
Year.9.vline.lower <- data.frame(Lower = (c(quantile(BPC.LCC.9, c(.05))
, quantile(RLB.LCC.9, c(.05)), quantile(TRA.LCC.9, c(.05)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.9.vline.upper <- data.frame(Upper = (c(quantile(BPC.LCC.9, c(.95))
, quantile(RLB.LCC.9, c(.95)), quantile(TRA.LCC.9, c(.95)))/100000), De
sign = c("BPC","RLB","TRA"))
Year.9.vline.median <- data.frame(Median = (c(median(BPC.LCC.9), median
(RLB.LCC.9), median(TRA.LCC.9))/100000), Design = c("BPC","RLB","TRA"))
Year.9.Hist <- ggplot(Year.9.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = .5, colour = "black") +
  facet_grid(.~Design , scale = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), Year.9.vline.me
an, size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th\nPercenti
le"), Year.9.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th\nPercenti
le"), Year.9.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), Year.8.vlin
e.median, size = 1) +
  theme(legend.title=element_blank()) +
  labs(title = "9 Years of Use Expected") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
```

```
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10))

Year.9.Medians <- data.frame(Median = c("BPC","RLB","TRA"), Value = (c(
median(BPC.LCC.9),median(RLB.LCC.9),median(TRA.LCC.9))/100000))
Year.9.Hist.Overlay <- ggplot(Year.9.LCC, aes(x = Cost)) +
  geom_histogram(binwidth = 1, alpha =0.5, aes(fill = Design), position
= "identity") +
  geom_vline(data=Year.9.Medians, aes(xintercept = Value,  colour = Med
ian),linetype="dashed", size=1) +
  labs(title = "9 Years of Use Expected") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.6))

# Print All Plots
LCC.Means.Plot
```

```
ggsave("LCC_Means_Plot.jpg", width = 7, height = 5)
Year.Design.Hist.free
```

```
ggsave("Facet_Plot.jpg", width = 7, height = 7)
Year.3.Hist
```

```
ggsave("Year3_Designs_Plot.jpg", width = 7, height = 5)
Year.3.Hist.Overlay
```

```
ggsave("Year3_OL_Plot.jpg", width = 7, height = 5)
Year.4.Hist
```

```
ggsave("Year4_Designs_Plot.jpg", width = 7, height = 5)
Year.4.Hist.Overlay
```

```r
ggsave("Year4_OL_Plot.jpg", width = 7, height = 5)
Year.5.Hist
```

```r
ggsave("Year5_Designs_Plot.jpg", width = 7, height = 5)
Year.5.Hist.Overlay
```

```r
ggsave("Year5_OL_Plot.jpg", width = 7, height = 5)
Year.6.Hist
```

```r
ggsave("Year6_Designs_Plot.jpg", width = 7, height = 5)
Year.6.Hist.Overlay
```

```r
ggsave("Year6_OL_Plot.jpg", width = 7, height = 5)
Year.7.Hist
```

```r
ggsave("Year7_Design_Plot.jpg", width = 7, height = 5)
Year.7.Hist.Overlay
```

```r
ggsave("Year7_OL_Plot.jpg", width = 7, height = 5)
Year.8.Hist
```

```r
ggsave("Year8_Designs_Plot.jpg", width = 7, height = 5)
Year.8.Hist.Overlay
```

```r
ggsave("Year8_OL_Plot.jpg", width = 7, height = 5)
Year.9.Hist
```

```r
ggsave("Year9_Designs_Plot.jpg", width = 7, height = 5)
Year.9.Hist.Overlay
```

```
ggsave("Year9_OL_Plot.jpg", width = 7, height = 5)

##Results
# 3 Years
wilcox.test(BPC.LCC.3/100000, TRA.LCC.3/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.3/1e+05 and TRA.LCC.3/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.65846 19.69632
## sample estimates:
## (pseudo)median
##       19.67741

wilcox.test(BPC.LCC.3/100000, RLB.LCC.3/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.3/1e+05 and RLB.LCC.3/1e+05
## V = 268040, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.49165 -41.39255
## sample estimates:
## (pseudo)median
##      -41.94035

wilcox.test(TRA.LCC.3/100000, RLB.LCC.3/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.3/1e+05 and RLB.LCC.3/1e+05
## V = 115, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -62.17162 -61.07246
## sample estimates:
## (pseudo)median
##      -61.62009
```

```r
# 4 Years
wilcox.test(BPC.LCC.4/100000, TRA.LCC.4/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.4/1e+05 and TRA.LCC.4/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.65230 19.69035
## sample estimates:
## (pseudo)median
##       19.67134

wilcox.test(BPC.LCC.4/100000, RLB.LCC.4/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.4/1e+05 and RLB.LCC.4/1e+05
## V = 290370, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -41.84872 -40.78379
## sample estimates:
## (pseudo)median
##      -41.31453

wilcox.test(TRA.LCC.4/100000, RLB.LCC.4/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.4/1e+05 and RLB.LCC.4/1e+05
## V = 104, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -61.52227 -60.45635
## sample estimates:
## (pseudo)median
##      -60.98655
```

```r
# 5 Years
wilcox.test(BPC.LCC.5/100000, TRA.LCC.5/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.5/1e+05 and TRA.LCC.5/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.65679 19.69415
## sample estimates:
## (pseudo)median
##       19.67548
```

```r
wilcox.test(BPC.LCC.5/100000, RLB.LCC.5/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.5/1e+05 and RLB.LCC.5/1e+05
## V = 340640, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -41.92362 -40.84122
## sample estimates:
## (pseudo)median
##      -41.38064
```

```r
wilcox.test(TRA.LCC.5/100000, RLB.LCC.5/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.5/1e+05 and RLB.LCC.5/1e+05
## V = 370, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -61.60155 -60.51750
## sample estimates:
## (pseudo)median
##      -61.05853
```

```r
# 6 Years
wilcox.test(BPC.LCC.6/100000, TRA.LCC.6/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90,conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.6/1e+05 and TRA.LCC.6/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.65955 19.69710
## sample estimates:
## (pseudo)median
##       19.67831

wilcox.test(BPC.LCC.6/100000, RLB.LCC.6/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90,conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.6/1e+05 and RLB.LCC.6/1e+05
## V = 297140, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.05282 -40.96639
## sample estimates:
## (pseudo)median
##      -41.50803

wilcox.test(TRA.LCC.6/100000, RLB.LCC.6/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90,conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.6/1e+05 and RLB.LCC.6/1e+05
## V = 2, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -61.72722 -60.63982
## sample estimates:
## (pseudo)median
##      -61.18314
```

```
# 7 Years
wilcox.test(BPC.LCC.7/100000, TRA.LCC.7/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.7/1e+05 and TRA.LCC.7/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.63832 19.67600
## sample estimates:
## (pseudo)median
##       19.65712

wilcox.test(BPC.LCC.7/100000, RLB.LCC.7/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.7/1e+05 and RLB.LCC.7/1e+05
## V = 296840, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.24897 -41.16038
## sample estimates:
## (pseudo)median
##       -41.7026

wilcox.test(TRA.LCC.7/100000, RLB.LCC.7/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.7/1e+05 and RLB.LCC.7/1e+05
## V = 98, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -61.91466 -60.82807
## sample estimates:
## (pseudo)median
##      -61.36833
```

```r
# 8 Years
wilcox.test(BPC.LCC.8/100000, TRA.LCC.8/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90,conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.8/1e+05 and TRA.LCC.8/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.63557 19.67293
## sample estimates:
## (pseudo)median
##       19.65423

wilcox.test(BPC.LCC.8/100000, RLB.LCC.8/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90,conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.8/1e+05 and RLB.LCC.8/1e+05
## V = 328900, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.29344 -41.20035
## sample estimates:
## (pseudo)median
##      -41.74517

wilcox.test(TRA.LCC.8/100000, RLB.LCC.8/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90,conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.8/1e+05 and RLB.LCC.8/1e+05
## V = 137, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -61.95194 -60.86043
## sample estimates:
## (pseudo)median
##      -61.40474
```

```
# 9 Years
wilcox.test(BPC.LCC.9/100000, TRA.LCC.9/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.9/1e+05 and TRA.LCC.9/1e+05
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  19.63485 19.67260
## sample estimates:
## (pseudo)median
##       19.65367

wilcox.test(BPC.LCC.9/100000, RLB.LCC.9/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.LCC.9/1e+05 and RLB.LCC.9/1e+05
## V = 315960, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -42.08228 -40.98610
## sample estimates:
## (pseudo)median
##      -41.53222

wilcox.test(TRA.LCC.9/100000, RLB.LCC.9/100000, alternative = "two.side
d", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.LCC.9/1e+05 and RLB.LCC.9/1e+05
## V = 20, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -61.74359 -60.64576
## sample estimates:
## (pseudo)median
##      -61.19317

#Comparisons
Comparison.data <- data.frame(Year = c(3,4,5,6,7,8,9), One = c((sum(BPC
```

```
.LCC.3 < TRA.LCC.3)/10000), (sum(BPC.LCC.4 < TRA.LCC.4)/10000), (sum(BP
C.LCC.5 < TRA.LCC.5)/10000), (sum(BPC.LCC.6 < TRA.LCC.6)/10000), (sum(B
PC.LCC.7 < TRA.LCC.7)/10000), (sum(BPC.LCC.8 < TRA.LCC.8)/10000), (sum(
BPC.LCC.9 < TRA.LCC.9)/10000)), Two = c((sum(BPC.LCC.3 < RLB.LCC.3)/100
00), (sum(BPC.LCC.4 < RLB.LCC.4)/10000), (sum(BPC.LCC.5 < RLB.LCC.5)/10
000), (sum(BPC.LCC.6 < RLB.LCC.6)/10000), (sum(BPC.LCC.7 < RLB.LCC.7)/1
0000), (sum(BPC.LCC.8 < RLB.LCC.8)/10000), (sum(BPC.LCC.9 < RLB.LCC.9)/
10000)), Three = c((sum(TRA.LCC.3 < RLB.LCC.3)/10000), (sum(TRA.LCC.4 <
RLB.LCC.4)/10000), (sum(TRA.LCC.5 < RLB.LCC.5)/10000), (sum(TRA.LCC.6 <
RLB.LCC.6)/10000), (sum(TRA.LCC.7 < RLB.LCC.7)/10000), (sum(TRA.LCC.8 <
RLB.LCC.8)/10000), (sum(TRA.LCC.9 < RLB.LCC.9)/10000)))
Comparison.data <- rename(Comparison.data, replace = c("One"= "BPC < TR
A", "Two" = "BPC < RLB", "Three" = "TRA < RLB"))
write.csv(Comparison.data,file = "4b_Comparison_results.csv")
```

OEF Risk Analysis.R

Ryan

Thu Feb 11 05:40:50 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/Question 5a"
)

# Assumptions
rt1 <- 30000000
rt2 <- 5000000
TRA.Adjustment.Factor <- 3.266667
RLB.Adjustment.Factor <- 49
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06
t <- rpois(n, 5.962)


# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
```

```
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
BPC.DCPSF3 <- 15.60
BPC.DCPSF4 <- 21.00
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
```

```
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
RLB2.MX2015.mean <- 5.333
RLB2.MX2015.stdev <- 0.690
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Expected Utility of Life Cycle Cost Function
EU <- function (t, rt, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  PWF <- function(t,i){
    PWF <- 1/((1+i)^t)
  }
  ifelse(t <= 3, EU <- 1-exp(-(AC + MX1 + DC)/rt), NA)
  ifelse(t == 4, EU <- 1-exp(-(AC + MX1 + MX2 + DC)/rt), NA)
  ifelse(t == 5, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + DC)/rt), NA)
  ifelse(t == 6, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + DC)/rt), NA
)
  ifelse(t == 7, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC)/r
t), NA)
  ifelse(t == 8, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 +
DC)/rt), NA)
  ifelse(t >= 9, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 +
MX7 + DC)/rt), NA)
  return(EU)
}

# Simulation
BPC.AC <- BPC.AC * FGP(8,i)
BPC.MX1 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.shop
.rate * FGP(7,i)
BPC.MX2 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.shop
.rate * FGP(6,i)
BPC.MX3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.sh
op.rate * FGP(5,i)
```

```
BPC.MX4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.shop
.rate * FGP(4,i)
BPC.MX5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.shop
.rate * FGP(3,i)
BPC.MX6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.shop
.rate * FGP(2,i)
BPC.MX7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.shop
.rate * FGP(1,i)
BPC.DC <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.Adj
ustment.Factor
TRA.MX1 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.shop
.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.shop
.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.sh
op.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.shop
.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.shop
.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.shop
.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.shop
.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.Adj
ustment.Factor
RLB.MX1 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.sh
op.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.sh
op.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.sh
op.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rate
* (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.sh
op.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.sh
op.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.sh
op.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor
```

```
BPC.EU.rt1 <- EU(t, rt1, BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
TRA.EU.rt1 <- EU(t, rt1, TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
RLB.EU.rt1 <- EU(t, rt1, RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)
BPC.EU.rt2 <- EU(t, rt2, BPC.AC, BPC.MX1, BPC.MX2, BPC.MX3, BPC.MX4, BP
C.MX5, BPC.MX6, BPC.MX7, BPC.DC)
TRA.EU.rt2 <- EU(t, rt2, TRA.AC, TRA.MX1, TRA.MX2, TRA.MX3, TRA.MX4, TR
A.MX5, TRA.MX6, TRA.MX7, TRA.DC)
RLB.EU.rt2 <- EU(t, rt2, RLB.AC, RLB.MX1, RLB.MX2, RLB.MX3, RLB.MX4, RL
B.MX5, RLB.MX6, RLB.MX7, RLB.DC)

# Histogram Construction
Risk.Data <- data.frame(Profile = rep(c(array("Risk Profile 1",n), arra
y("Risk Profile 2",n))), Design = c(array("BPC",2*n),array("TRA",2*n),a
rray("RLB",2*n)), Utility = c(BPC.EU.rt1,BPC.EU.rt2,TRA.EU.rt1,TRA.EU.r
t2,RLB.EU.rt1,RLB.EU.rt2))

BPC.data <- subset(Risk.Data, Design == "BPC", select = c(Profile,Desig
n,Utility))
BPC.vline.mean <- data.frame(Mean = c(mean(BPC.EU.rt1), mean(BPC.EU.rt2
)), Profile = c("Risk Profile 1","Risk Profile 2"))
BPC.vline.lower <- data.frame(Lower = c(quantile(BPC.EU.rt1, c(.05)), q
uantile(BPC.EU.rt2, c(.05))), Profile = c("Risk Profile 1","Risk Profil
e 2"))
BPC.vline.upper <- data.frame(Upper = c(quantile(BPC.EU.rt1, c(.95)), q
uantile(BPC.EU.rt2, c(.95))), Profile = c("Risk Profile 1","Risk Profil
e 2"))
BPC.vline.median <- data.frame(Median = c(median(BPC.EU.rt1), median(BP
C.EU.rt2)), Profile = c("Risk Profile 1","Risk Profile 2"))
TRA.data <- subset(Risk.Data, Design == "TRA", select = c(Profile,Desig
n,Utility))
TRA.vline.mean <- data.frame(Mean = c(mean(TRA.EU.rt1), mean(TRA.EU.rt2
)),Profile = c("Risk Profile 1","Risk Profile 2"))
TRA.vline.lower <- data.frame(Lower = c(quantile(TRA.EU.rt1, c(.05)), q
uantile(TRA.EU.rt2, c(.05))), Profile = c("Risk Profile 1","Risk Profil
e 2"))
TRA.vline.upper <- data.frame(Upper = c(quantile(TRA.EU.rt1, c(.95)), q
uantile(TRA.EU.rt2, c(.95))), Profile = c("Risk Profile 1","Risk Profil
e 2"))
TRA.vline.median <- data.frame(Median = c(median(TRA.EU.rt1), median(TR
A.EU.rt2)), Profile = c("Risk Profile 1","Risk Profile 2"))
RLB.data <- subset(Risk.Data, Design == "RLB", select = c(Profile,Desig
n,Utility))
RLB.vline.mean <- data.frame(Mean = c(mean(RLB.EU.rt1), mean(RLB.EU.rt2
```

```
)), Profile = c("Risk Profile 1","Risk Profile 2"))
RLB.vline.lower <- data.frame(Lower = c(quantile(RLB.EU.rt1, c(.05)), q
uantile(RLB.EU.rt2, c(.05))), Profile = c("Risk Profile 1","Risk Profil
e 2"))
RLB.vline.upper <- data.frame(Upper = c(quantile(RLB.EU.rt1, c(.95)), q
uantile(RLB.EU.rt2, c(.95))), Profile = c("Risk Profile 1","Risk Profil
e 2"))
RLB.vline.median <- data.frame(Median = c(median(RLB.EU.rt1), median(RL
B.EU.rt2)), Profile = c("Risk Profile 1","Risk Profile 2"))

EU.vline.mean <- data.frame(Value = c(median(BPC.EU.rt1),median(TRA.EU.
rt1),median(RLB.EU.rt1), median(BPC.EU.rt2), median(TRA.EU.rt2), median
(RLB.EU.rt2)), Profile = c(array("Risk Profile 1",3),array("Risk Profil
e 2",3)), Median = rep(c("BPC","TRA","RLB"),2))

BPC.hist <- ggplot(BPC.data, aes(x = Utility)) +
  geom_histogram(binwidth = .001, colour = "black", fill = "white") +
  facet_grid(. ~  Profile, scales = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), BPC.vline.mean,
size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th Percentil
e"), BPC.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th Percentil
e"), BPC.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), BPC.vline.m
edian, size = 1) +
  labs(title= "BPC Expected Utility") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(legend.title=element_blank()) +
  scale_linetype_discrete(name = "Legend") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.8))

TRA.hist <- ggplot(TRA.data, aes(x = Utility)) +
  geom_histogram(binwidth = .001, colour = "black", fill = "white") +
  facet_grid(. ~  Profile, scales = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), TRA.vline.mean,
size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th Percentil
```

```
e"), TRA.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th Percentil
e"), TRA.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), TRA.vline.m
edian, size = 1) +
  labs(title= "Trailer Expected Utility") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(legend.title=element_blank()) +
  scale_linetype_discrete(name = "Legend") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.9,.8))

RLB.hist <- ggplot(RLB.data, aes(x = Utility)) +
  geom_histogram(binwidth = .01, colour = "black", fill = "white") +
  facet_grid(. ~  Profile, scales = "free_x") +
  geom_vline(aes(xintercept = Mean, linetype = "Mean"), RLB.vline.mean,
size = .5) +
  geom_vline(aes(xintercept = Lower, linetype = "5th and 95th Percentil
e"), RLB.vline.lower, size = .5) +
  geom_vline(aes(xintercept = Upper, linetype = "5th and 95th Percentil
e"), RLB.vline.upper, size = .5) +
  geom_vline(aes(xintercept = Median, linetype = "Median"), RLB.vline.m
edian, size = 1) +
  labs(title= "RLB Expected Utility") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(legend.title=element_blank()) +
  scale_linetype_discrete(name = "Legend") +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"), legend.position=c(.6,.8))

EU.hist <- ggplot(Risk.Data, aes(x = Utility)) +
  geom_histogram(binwidth = .001, alpha =0.5, aes(fill = Design), posit
```

```
ion = "identity") +
  facet_grid(. ~  Profile, scales = "free_x") +
  geom_vline(data=EU.vline.mean, aes(xintercept = Value,  colour = Medi
an),linetype="dashed", size=1) +
  labs(title= "Expected Utility Per Risk Profile") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Cost ($100K)") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


#Print All Plots
BPC.hist
```

```
ggsave("BPC_Plot.jpg", width = 7, height = 5)
TRA.hist
```

```
ggsave("TRA_Plot.jpg", width = 7, height = 5)
RLB.hist
```

```
ggsave("RLB_Plot.jpg", width = 7, height = 5)
EU.hist
```

```
ggsave("EU_Plot.jpg", width = 7, height = 5)


#Results
wilcox.test(BPC.EU.rt1, TRA.EU.rt1, alternative = "two.sided", mu = 0,
paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.rt1 and TRA.EU.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05394020 0.05407077
## sample estimates:
## (pseudo)median
##      0.0540147
```

```
wilcox.test(BPC.EU.rt1, RLB.EU.rt1, alternative = "two.sided", mu = 0,
paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.rt1 and RLB.EU.rt1
## V = 303980, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1033652 -0.1008845
## sample estimates:
## (pseudo)median
##     -0.1021219
```

```
wilcox.test(TRA.EU.rt1, RLB.EU.rt1, alternative = "two.sided", mu = 0,
paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.rt1 and RLB.EU.rt1
## V = 17, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1573896 -0.1549090
## sample estimates:
## (pseudo)median
##     -0.1561495
```

```
wilcox.test(BPC.EU.rt2, TRA.EU.rt2, alternative = "two.sided", mu = 0,
paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
```

```
## data:  BPC.EU.rt2 and TRA.EU.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1239150 0.1242116
## sample estimates:
## (pseudo)median
##      0.1240717
```

```
wilcox.test(BPC.EU.rt2, RLB.EU.rt2, alternative = "two.sided", mu = 0,
paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.rt2 and RLB.EU.rt2
## V = 366400, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1361875 -0.1337845
## sample estimates:
## (pseudo)median
##     -0.1349634
```

```
wilcox.test(TRA.EU.rt2, RLB.EU.rt2, alternative = "two.sided", mu = 0,
paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.rt2 and RLB.EU.rt2
## V = 17, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2601823 -0.2577937
## sample estimates:
## (pseudo)median
##     -0.2589995
```

```
Risk.data.summary <- summarySE(Risk.Data,measurevar = "Utility", groupv
ars = c("Profile","Design"), conf.interval = 0.90)
Median.data <- c(median(BPC.EU.rt1), median(TRA.EU.rt1), median(RLB.EU.
rt1), median(BPC.EU.rt2), median(TRA.EU.rt2), median(RLB.EU.rt2))
Lower <- c(quantile(BPC.EU.rt1,c(0.05)), quantile(RLB.EU.rt1,c(0.05)),
quantile(TRA.EU.rt1,c(0.05)), quantile(BPC.EU.rt2,c(0.05)),quantile(RLB
.EU.rt2,c(0.05)),quantile(TRA.EU.rt2,c(0.05)))
Upper <- c(quantile(BPC.EU.rt1,c(0.95)), quantile(RLB.EU.rt1,c(0.95)),
quantile(TRA.EU.rt1,c(0.95)), quantile(BPC.EU.rt2,c(0.95)),quantile(RLB
```

```
.EU.rt2,c(0.95)),quantile(TRA.EU.rt2,c(0.95)))
Risk.data.summary <- cbind(Risk.data.summary,Lower)
Risk.data.summary <- cbind(Risk.data.summary,Upper)
Risk.data.summary <- cbind(Risk.data.summary,Median.data)
Risk.data.summary <- rename(Risk.data.summary, replace = c("Utility"= "
Mean","sd"= "Standard Deviation", "se"="Standard Error","ci"="Confidenc
e Interval","Median.data"="Median", "Lower"= "5th Percentile", "Upper"=
"95th Percentile"))
write.csv(Risk.data.summary, file = "5a_Riskdata.csv")

Comparison.data <- data.frame(Profile = c(1,2), One = c((sum(BPC.EU.rt1
< TRA.EU.rt1)/10000),(sum(BPC.EU.rt2 < TRA.EU.rt2)/10000)), Two = c((su
m(BPC.EU.rt1 < RLB.EU.rt1)/10000),(sum(BPC.EU.rt2 < RLB.EU.rt2)/10000))
, Three = c((sum(TRA.EU.rt1 < RLB.EU.rt1)/10000),(sum(TRA.EU.rt2 < RLB.
EU.rt2)/10000)))
Comparison.data <- rename(Comparison.data, replace = c("Profile" = "Ris
k Profile", "One"="BPC < Trailer","Two"="BPC < RLB", "Three"="Trailer <
RLB"))
write.csv(Comparison.data, file = "5a_Comparisons.csv")
```

Lack of Knowledge Risk Analysis.R

Ryan

Thu Feb 11 05:44:13 2016

```
library(Rmisc)

## Loading required package: lattice
## Loading required package: plyr

library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.2.3

library(triangle)
rt1 <- 30000000
rt2 <- 5000000
setwd("/Users/Ryan/Desktop/Thesis/Data Analysis/R - Output/Question 5b"
)


# Assumptions
TRA.Adjustment.Factor <- 3.266667
RLB.Adjustment.Factor <- 49
n <- 10000
i <- runif(n,.02,.03)
ADAB.shop.rate <- 38.00
AUAB.shop.rate <- 44.06

# BPC Data
BPC.size <- 77016
BPC.AC <- array(4362453.80, n)
BPC.MX2009.mean <- 3.772
BPC.MX2009.stdev <- 0.118
BPC.MX2010.mean <- 7.283
BPC.MX2010.stdev <- 0.310
BPC.MX2012.mean <- 6.556
BPC.MX2012.stdev <- 0.171
BPC.MX2013.mean <- 8.139
BPC.MX2013.stdev <- 0.216
BPC.MX2014.mean <- 7.854
BPC.MX2014.stdev <- 0.086
BPC.MX2015.mean <- 7.791
BPC.MX2015.stdev <- 0.171
BPC.MXA2011.mean <- ((BPC.MX2010.mean + BPC.MX2012.mean)/2)
BPC.MXA2011.stdev <- ((BPC.MX2010.stdev + BPC.MX2012.stdev)/2)
```

```
BPC.DCPSF1 <- 5.34
BPC.DCPSF2 <- 10.50
BPC.DCPSF3 <- 15.60
BPC.DCPSF4 <- 21.00
BPC.DCPSF5 <- 6.36
BPC.DC.AVG <- mean(c(BPC.DCPSF1,BPC.DCPSF2,BPC.DCPSF3,BPC.DCPSF4,BPC.DC
PSF5))

# Trailer Data
TRA.size <- 4100
TRA.AC.mean <- 13.942
TRA.AC.stdev <- 0.021
TRA.MX2009.mean <- 4.728
TRA.MX2009.stdev <- 0.338
TRA.MX2010.mean <- 4.501
TRA.MX2010.stdev <- 0.468
TRA.MX2012.mean <- 3.750
TRA.MX2012.stdev <- 0.288
TRA.MX2013.mean <- 5.206
TRA.MX2013.stdev <- 0.329
TRA.MX2014.mean <- 5.124
TRA.MX2014.stdev <- 0.412
TRA.MX2015.mean <- 5.058
TRA.MX2015.stdev <- 0.324
TRA.MXA2011.mean <- ((TRA.MX2010.mean+TRA.MX2012.mean)/2)
TRA.MXA2011.stdev <- ((TRA.MX2010.stdev+TRA.MX2012.stdev)/2)
TRA.DCPSF1 <- 4.08
TRA.DCPSF2 <- 11.10
TRA.DCPSF3 <- 17.40
TRA.DCPSF4 <- 23.40
TRA.DCPSF5 <- 4.92
TRA.DC.AVG <- mean(c(TRA.DCPSF1,TRA.DCPSF2,TRA.DCPSF3,TRA.DCPSF4,TRA.DC
PSF5))

# RLB Data
RLB.size <- 1350
RLB.AC.mean <- 11.848
RLB.AC.stdev <- 0.400
RLB1.MX2013.mean <- 3.772
RLB1.MX2013.stdev <- 0.660
RLB1.MX2014.mean <- 5.221
RLB1.MX2014.stdev <- 0.444
RLB1.MX2015.mean <- 4.850
RLB1.MX2015.stdev <- 0.422
RLB2.MX2013.mean <- 5.059
RLB2.MX2013.stdev <- 0.479
```

```
RLB2.MX2014.mean <- 4.891
RLB2.MX2014.stdev <- 0.739
RLB2.MX2015.mean <- 5.333
RLB2.MX2015.stdev <- 0.690
RLB.MXA.mean <- ((RLB1.MX2015.mean+RLB2.MX2013.mean)/2)
RLB.MXA.stdev <-  ((RLB1.MX2015.stdev+RLB2.MX2013.stdev)/2)
RLB.DCPSF1 <- 4.68
RLB.DCPSF2 <- 11.10
RLB.DCPSF3 <- 17.40
RLB.DCPSF4 <- 24.00
RLB.DCPSF5 <- 4.44
RLB.DC.AVG <- mean(c(RLB.DCPSF1,RLB.DCPSF2,RLB.DCPSF3,RLB.DCPSF4,RLB.DC
PSF5))

# F/P Tranformation Function
FGP <- function(t,i){
  FGP <- (1+i)^t
}

# Expected Utility of Life Cycle Cost Function
EU <- function (t, rt, AC, MX1, MX2, MX3, MX4, MX5, MX6, MX7, DC){
  PWF <- function(t,i){
    PWF <- 1/((1+i)^t)
  }
  ifelse(t <= 3, EU <- 1-exp(-(AC + MX1 + DC)/rt), NA)
  ifelse(t == 4, EU <- 1-exp(-(AC + MX1 + MX2 + DC)/rt), NA)
  ifelse(t == 5, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + DC)/rt), NA)
  ifelse(t == 6, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + DC)/rt), NA
)
  ifelse(t == 7, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + MX5 + DC)/r
t), NA)
  ifelse(t == 8, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 +
DC)/rt), NA)
  ifelse(t >= 9, EU <- 1-exp(-(AC + MX1 + MX2 + MX3 + MX4 + MX5 + MX6 +
MX7 + DC)/rt), NA)
         return(EU)
}

# Comparisons for Uncertain Duration - Year 3 Most Probable
t3 <- round(rtriangle(n,3,9,3), 0)

BPC.AC.3 <- BPC.AC * FGP(8,i)
BPC.MX1.3 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.3 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
```

```
BPC.MX3.3 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.3 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.3 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.3 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.3 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.3 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.3 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.3 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.3 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.3 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.3 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.3 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.3 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.3 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.3 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.3 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.3 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.3 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.3 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.3 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.3 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.3 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.3 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
```

```
RLB.DC.3 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.3.rt1 <- EU(t3, rt1, BPC.AC.3, BPC.MX1.3, BPC.MX2.3, BPC.MX3.3,
BPC.MX4.3, BPC.MX5.3, BPC.MX6.3, BPC.MX7.3, BPC.DC.3)
TRA.EU.3.rt1 <- EU(t3, rt1, TRA.AC.3, TRA.MX1.3, TRA.MX2.3, TRA.MX3.3,
TRA.MX4.3, TRA.MX5.3, TRA.MX6.3, TRA.MX7.3, TRA.DC.3)
RLB.EU.3.rt1 <- EU(t3, rt1, RLB.AC.3, RLB.MX1.3, RLB.MX2.3, RLB.MX3.3,
RLB.MX4.3, RLB.MX5.3, RLB.MX6.3, RLB.MX7.3, RLB.DC.3)
BPC.EU.3.rt2 <- EU(t3, rt2, BPC.AC.3, BPC.MX1.3, BPC.MX2.3, BPC.MX3.3,
BPC.MX4.3, BPC.MX5.3, BPC.MX6.3, BPC.MX7.3, BPC.DC.3)
TRA.EU.3.rt2 <- EU(t3, rt2, TRA.AC.3, TRA.MX1.3, TRA.MX2.3, TRA.MX3.3,
TRA.MX4.3, TRA.MX5.3, TRA.MX6.3, TRA.MX7.3, TRA.DC.3)
RLB.EU.3.rt2 <- EU(t3, rt2, RLB.AC.3, RLB.MX1.3, RLB.MX2.3, RLB.MX3.3,
RLB.MX4.3, RLB.MX5.3, RLB.MX6.3, RLB.MX7.3, RLB.DC.3)

Risk.Data.Yr3 <- data.frame(Year = array(3,6*n),Profile = c(array("Risk
Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("BP
C",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.3.rt1,TRA.E
U.3.rt1,RLB.EU.3.rt1,BPC.EU.3.rt2,TRA.EU.3.rt2,RLB.EU.3.rt2))



# Comparisons for Uncertain Duration - Year 4 Most Probable
t4 <- round(rtriangle(n,3,9,4), 0)

BPC.AC.4 <- BPC.AC * FGP(8,i)
BPC.MX1.4 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.4 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.4 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.4 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.4 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.4 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.4 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.4 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.4 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.4 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.4 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
```

```
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.4 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.4 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.4 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.4 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.4 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.4 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.4 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.4 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.4 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.4 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.4 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.4 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.4 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.4 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.4 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.4.rt1 <- EU(t4, rt1, BPC.AC.4, BPC.MX1.4, BPC.MX2.4, BPC.MX3.4,
BPC.MX4.4, BPC.MX5.4, BPC.MX6.4, BPC.MX7.4, BPC.DC.4)
TRA.EU.4.rt1 <- EU(t4, rt1, TRA.AC.4, TRA.MX1.4, TRA.MX2.4, TRA.MX3.4,
TRA.MX4.4, TRA.MX5.4, TRA.MX6.4, TRA.MX7.4, TRA.DC.4)
RLB.EU.4.rt1 <- EU(t4, rt1, RLB.AC.4, RLB.MX1.4, RLB.MX2.4, RLB.MX3.4,
RLB.MX4.4, RLB.MX5.4, RLB.MX6.4, RLB.MX7.4, RLB.DC.4)
BPC.EU.4.rt2 <- EU(t4, rt2, BPC.AC.4, BPC.MX1.4, BPC.MX2.4, BPC.MX3.4,
BPC.MX4.4, BPC.MX5.4, BPC.MX6.4, BPC.MX7.4, BPC.DC.4)
TRA.EU.4.rt2 <- EU(t4, rt2, TRA.AC.4, TRA.MX1.4, TRA.MX2.4, TRA.MX3.4,
TRA.MX4.4, TRA.MX5.4, TRA.MX6.4, TRA.MX7.4, TRA.DC.4)
RLB.EU.4.rt2 <- EU(t4, rt2, RLB.AC.4, RLB.MX1.4, RLB.MX2.4, RLB.MX3.4,
RLB.MX4.4, RLB.MX5.4, RLB.MX6.4, RLB.MX7.4, RLB.DC.4)

Risk.Data.Yr4 <- data.frame(Year = array(4,6*n),Profile = c(array("Risk
Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("BP
```

```
C",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.4.rt1,TRA.E
U.4.rt1,RLB.EU.4.rt1,BPC.EU.4.rt2,TRA.EU.4.rt2,RLB.EU.4.rt2))

# Comparisons for Uncertain Duration - Year 5 Most Probable
t5 <- round(rtriangle(n,3,9,5), 0)

BPC.AC.5 <- BPC.AC * FGP(8,i)
BPC.MX1.5 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.5 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.5 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.5 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.5 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.5 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.5 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.5 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.5 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.5 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.5 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.5 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.5 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.5 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.5 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.5 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.5 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.5 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.5 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.5 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
```

```
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.5 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.5 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.5 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.5 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.5 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.5 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.5.rt1 <- EU(t5, rt1, BPC.AC.5, BPC.MX1.5, BPC.MX2.5, BPC.MX3.5,
BPC.MX4.5, BPC.MX5.5, BPC.MX6.5, BPC.MX7.5, BPC.DC.5)
TRA.EU.5.rt1 <- EU(t5, rt1, TRA.AC.5, TRA.MX1.5, TRA.MX2.5, TRA.MX3.5,
TRA.MX4.5, TRA.MX5.5, TRA.MX6.5, TRA.MX7.5, TRA.DC.5)
RLB.EU.5.rt1 <- EU(t5, rt1, RLB.AC.5, RLB.MX1.5, RLB.MX2.5, RLB.MX3.5,
RLB.MX4.5, RLB.MX5.5, RLB.MX6.5, RLB.MX7.5, RLB.DC.5)
BPC.EU.5.rt2 <- EU(t5, rt2, BPC.AC.5, BPC.MX1.5, BPC.MX2.5, BPC.MX3.5,
BPC.MX4.5, BPC.MX5.5, BPC.MX6.5, BPC.MX7.5, BPC.DC.5)
TRA.EU.5.rt2 <- EU(t5, rt2, TRA.AC.5, TRA.MX1.5, TRA.MX2.5, TRA.MX3.5,
TRA.MX4.5, TRA.MX5.5, TRA.MX6.5, TRA.MX7.5, TRA.DC.5)
RLB.EU.5.rt2 <- EU(t5, rt2, RLB.AC.5, RLB.MX1.5, RLB.MX2.5, RLB.MX3.5,
RLB.MX4.5, RLB.MX5.5, RLB.MX6.5, RLB.MX7.5, RLB.DC.5)

Risk.Data.Yr5 <- data.frame(Year = array(5,6*n),Profile = c(array("Risk
Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("BP
C",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.5.rt1,TRA.E
U.5.rt1,RLB.EU.5.rt1,BPC.EU.5.rt2,TRA.EU.5.rt2,RLB.EU.5.rt2))

# Comparisons for Uncertain Duration - Year 6 Most Probable
t6 <- round(rtriangle(n,3,9,6), 0)

BPC.AC.6 <- BPC.AC * FGP(8,i)
BPC.MX1.6 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.6 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.6 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.6 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.6 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.6 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
```

```
op.rate * FGP(2,i)
BPC.MX7.6 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.6 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.6 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.6 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.6 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.6 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.6 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.6 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.6 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.6 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.6 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.6 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.6 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.6 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.6 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.6 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.6 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.6 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.6 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.6 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.6.rt1 <- EU(t6, rt1, BPC.AC.6, BPC.MX1.6, BPC.MX2.6, BPC.MX3.6,
BPC.MX4.6, BPC.MX5.6, BPC.MX6.6, BPC.MX7.6, BPC.DC.6)
TRA.EU.6.rt1 <- EU(t6, rt1, TRA.AC.6, TRA.MX1.6, TRA.MX2.6, TRA.MX3.6,
TRA.MX4.6, TRA.MX5.6, TRA.MX6.6, TRA.MX7.6, TRA.DC.6)
RLB.EU.6.rt1 <- EU(t6, rt1, RLB.AC.6, RLB.MX1.6, RLB.MX2.6, RLB.MX3.6,
```

```
RLB.MX4.6, RLB.MX5.6, RLB.MX6.6, RLB.MX7.6, RLB.DC.6)
BPC.EU.6.rt2 <- EU(t6, rt2, BPC.AC.6, BPC.MX1.6, BPC.MX2.6, BPC.MX3.6,
BPC.MX4.6, BPC.MX5.6, BPC.MX6.6, BPC.MX7.6, BPC.DC.6)
TRA.EU.6.rt2 <- EU(t6, rt2, TRA.AC.6, TRA.MX1.6, TRA.MX2.6, TRA.MX3.6,
TRA.MX4.6, TRA.MX5.6, TRA.MX6.6, TRA.MX7.6, TRA.DC.6)
RLB.EU.6.rt2 <- EU(t6, rt2, RLB.AC.6, RLB.MX1.6, RLB.MX2.6, RLB.MX3.6,
RLB.MX4.6, RLB.MX5.6, RLB.MX6.6, RLB.MX7.6, RLB.DC.6)

Risk.Data.Yr6 <- data.frame(Year = array(6,6*n),Profile = c(array("Risk
Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("BP
C",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.6.rt1,TRA.E
U.6.rt1,RLB.EU.6.rt1,BPC.EU.6.rt2,TRA.EU.6.rt2,RLB.EU.6.rt2))

# Comparisons for Uncertain Duration - Year 7 Most Probable
t7 <- round(rtriangle(n,3,9,7), 0)

BPC.AC.7 <- BPC.AC * FGP(8,i)
BPC.MX1.7 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.7 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.7 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.7 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.7 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.7 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.7 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.7 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.7 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.7 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.7 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.7 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.7 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.7 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.7 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
```

```
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.7 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.7 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.7 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.7 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.7 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.7 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.7 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.7 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.7 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.7 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.7 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.7.rt1 <- EU(t7, rt1, BPC.AC.7, BPC.MX1.7, BPC.MX2.7, BPC.MX3.7,
BPC.MX4.7, BPC.MX5.7, BPC.MX6.7, BPC.MX7.7, BPC.DC.7)
TRA.EU.7.rt1 <- EU(t7, rt1, TRA.AC.7, TRA.MX1.7, TRA.MX2.7, TRA.MX3.7,
TRA.MX4.7, TRA.MX5.7, TRA.MX6.7, TRA.MX7.7, TRA.DC.7)
RLB.EU.7.rt1 <- EU(t7, rt1, RLB.AC.7, RLB.MX1.7, RLB.MX2.7, RLB.MX3.7,
RLB.MX4.7, RLB.MX5.7, RLB.MX6.7, RLB.MX7.7, RLB.DC.7)
BPC.EU.7.rt2 <- EU(t7, rt2, BPC.AC.7, BPC.MX1.7, BPC.MX2.7, BPC.MX3.7,
BPC.MX4.7, BPC.MX5.7, BPC.MX6.7, BPC.MX7.7, BPC.DC.7)
TRA.EU.7.rt2 <- EU(t7, rt2, TRA.AC.7, TRA.MX1.7, TRA.MX2.7, TRA.MX3.7,
TRA.MX4.7, TRA.MX5.7, TRA.MX6.7, TRA.MX7.7, TRA.DC.7)
RLB.EU.7.rt2 <- EU(t7, rt2, RLB.AC.7, RLB.MX1.7, RLB.MX2.7, RLB.MX3.7,
RLB.MX4.7, RLB.MX5.7, RLB.MX6.7, RLB.MX7.7, RLB.DC.7)

Risk.Data.Yr7 <- data.frame(Year = array(7,6*n),Profile = c(array("Risk
Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("BP
C",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.7.rt1,TRA.E
U.7.rt1,RLB.EU.7.rt1,BPC.EU.7.rt2,TRA.EU.7.rt2,RLB.EU.7.rt2))

# Comparisons for Uncertain Duration - Year 8 Most Probable
t8 <- round(rtriangle(n,3,9,8), 0)

BPC.AC.8 <- BPC.AC * FGP(8,i)
BPC.MX1.8 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
```

```
op.rate * FGP(7,i)
BPC.MX2.8 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.8 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.8 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.8 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.8 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.8 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.8 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.8 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.8 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.8 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.8 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.8 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.8 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.8 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.8 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.8 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.8 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.8 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.8 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.8 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.8 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.8 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.8 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
```

```
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.8 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.8 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.8.rt1 <- EU(t8, rt1, BPC.AC.8, BPC.MX1.8, BPC.MX2.8, BPC.MX3.8,
BPC.MX4.8, BPC.MX5.8, BPC.MX6.8, BPC.MX7.8, BPC.DC.8)
TRA.EU.8.rt1 <- EU(t8, rt1, TRA.AC.8, TRA.MX1.8, TRA.MX2.8, TRA.MX3.8,
TRA.MX4.8, TRA.MX5.8, TRA.MX6.8, TRA.MX7.8, TRA.DC.8)
RLB.EU.8.rt1 <- EU(t8, rt1, RLB.AC.8, RLB.MX1.8, RLB.MX2.8, RLB.MX3.8,
RLB.MX4.8, RLB.MX5.8, RLB.MX6.8, RLB.MX7.8, RLB.DC.8)
BPC.EU.8.rt2 <- EU(t8, rt2, BPC.AC.8, BPC.MX1.8, BPC.MX2.8, BPC.MX3.8,
BPC.MX4.8, BPC.MX5.8, BPC.MX6.8, BPC.MX7.8, BPC.DC.8)
TRA.EU.8.rt2 <- EU(t8, rt2, TRA.AC.8, TRA.MX1.8, TRA.MX2.8, TRA.MX3.8,
TRA.MX4.8, TRA.MX5.8, TRA.MX6.8, TRA.MX7.8, TRA.DC.8)
RLB.EU.8.rt2 <- EU(t8, rt2, RLB.AC.8, RLB.MX1.8, RLB.MX2.8, RLB.MX3.8,
RLB.MX4.8, RLB.MX5.8, RLB.MX6.8, RLB.MX7.8, RLB.DC.8)

Risk.Data.Yr8 <- data.frame(Year = array(8,6*n),Profile = c(array("Risk
Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("BP
C",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.8.rt1,TRA.E
U.8.rt1,RLB.EU.8.rt1,BPC.EU.8.rt2,TRA.EU.8.rt2,RLB.EU.8.rt2))

# Comparisons for Uncertain Duration - Year 9 Most Probable
t9 <- round(rtriangle(n,3,9,9), 0)

BPC.AC.9 <- BPC.AC * FGP(8,i)
BPC.MX1.9 <- exp(rnorm(n, BPC.MX2009.mean, BPC.MX2009.stdev)) * AUAB.sh
op.rate * FGP(7,i)
BPC.MX2.9 <- exp(rnorm(n, BPC.MX2010.mean, BPC.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i)
BPC.MX3.9 <- exp(rnorm(n, BPC.MXA2011.mean, BPC.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i)
BPC.MX4.9 <- exp(rnorm(n, BPC.MX2012.mean, BPC.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i)
BPC.MX5.9 <- exp(rnorm(n, BPC.MX2013.mean, BPC.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i)
BPC.MX6.9 <- exp(rnorm(n, BPC.MX2014.mean, BPC.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i)
BPC.MX7.9 <- exp(rnorm(n, BPC.MX2015.mean, BPC.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i)
BPC.DC.9 <- array(BPC.DC.AVG, n) * BPC.size

TRA.AC.9 <- exp(rnorm(n, TRA.AC.mean, TRA.AC.stdev)) * FGP(8,i) * TRA.A
djustment.Factor
TRA.MX1.9 <- exp(rnorm(n, TRA.MX2009.mean, TRA.MX2009.stdev)) * AUAB.sh
```

```
op.rate * FGP(7,i) * TRA.Adjustment.Factor
TRA.MX2.9 <- exp(rnorm(n, TRA.MX2010.mean, TRA.MX2010.stdev)) * AUAB.sh
op.rate * FGP(6,i) * TRA.Adjustment.Factor
TRA.MX3.9 <- exp(rnorm(n, TRA.MXA2011.mean, TRA.MXA2011.stdev)) * AUAB.
shop.rate * FGP(5,i) * TRA.Adjustment.Factor
TRA.MX4.9 <- exp(rnorm(n, TRA.MX2012.mean, TRA.MX2012.stdev)) * AUAB.sh
op.rate * FGP(4,i) * TRA.Adjustment.Factor
TRA.MX5.9 <- exp(rnorm(n, TRA.MX2013.mean, TRA.MX2013.stdev)) * AUAB.sh
op.rate * FGP(3,i) * TRA.Adjustment.Factor
TRA.MX6.9 <- exp(rnorm(n, TRA.MX2014.mean, TRA.MX2014.stdev)) * AUAB.sh
op.rate * FGP(2,i) * TRA.Adjustment.Factor
TRA.MX7.9 <- exp(rnorm(n, TRA.MX2015.mean, TRA.MX2015.stdev)) * AUAB.sh
op.rate * FGP(1,i) * TRA.Adjustment.Factor
TRA.DC.9 <- array(TRA.DC.AVG, n) * TRA.size  * TRA.Adjustment.Factor

RLB.AC.9 <- exp(rnorm(n, RLB.AC.mean, RLB.AC.stdev)) * FGP(4,i) * RLB.A
djustment.Factor
RLB.MX1.9 <- exp(rnorm(n, RLB1.MX2013.mean, RLB1.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX2.9 <- exp(rnorm(n, RLB1.MX2014.mean, RLB1.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX3.9 <- exp(rnorm(n, RLB1.MX2015.mean, RLB1.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.MX4.9 <- exp(rnorm(n, RLB.MXA.mean, RLB.MXA.stdev)) * ADAB.shop.rat
e * (FGP(2,i)) * RLB.Adjustment.Factor
RLB.MX5.9 <- exp(rnorm(n, RLB2.MX2013.mean, RLB2.MX2013.stdev)) * ADAB.
shop.rate * FGP(3,i) * RLB.Adjustment.Factor
RLB.MX6.9 <- exp(rnorm(n, RLB2.MX2014.mean, RLB2.MX2014.stdev)) * ADAB.
shop.rate * FGP(2,i) * RLB.Adjustment.Factor
RLB.MX7.9 <- exp(rnorm(n, RLB2.MX2015.mean, RLB2.MX2015.stdev)) * ADAB.
shop.rate * FGP(1,i) * RLB.Adjustment.Factor
RLB.DC.9 <- array(RLB.DC.AVG, n) * RLB.size  * RLB.Adjustment.Factor

BPC.EU.9.rt1 <- EU(t9, rt1, BPC.AC.9, BPC.MX1.9, BPC.MX2.9, BPC.MX3.9,
BPC.MX4.9, BPC.MX5.9, BPC.MX6.9, BPC.MX7.9, BPC.DC.9)
TRA.EU.9.rt1 <- EU(t9, rt1, TRA.AC.9, TRA.MX1.9, TRA.MX2.9, TRA.MX3.9,
TRA.MX4.9, TRA.MX5.9, TRA.MX6.9, TRA.MX7.9, TRA.DC.9)
RLB.EU.9.rt1 <- EU(t9, rt1, RLB.AC.9, RLB.MX1.9, RLB.MX2.9, RLB.MX3.9,
RLB.MX4.9, RLB.MX5.9, RLB.MX6.9, RLB.MX7.9, RLB.DC.9)
BPC.EU.9.rt2 <- EU(t9, rt2, BPC.AC.9, BPC.MX1.9, BPC.MX2.9, BPC.MX3.9,
BPC.MX4.9, BPC.MX5.9, BPC.MX6.9, BPC.MX7.9, BPC.DC.9)
TRA.EU.9.rt2 <- EU(t9, rt2, TRA.AC.9, TRA.MX1.9, TRA.MX2.9, TRA.MX3.9,
TRA.MX4.9, TRA.MX5.9, TRA.MX6.9, TRA.MX7.9, TRA.DC.9)
RLB.EU.9.rt2 <- EU(t9, rt2, RLB.AC.9, RLB.MX1.9, RLB.MX2.9, RLB.MX3.9,
RLB.MX4.9, RLB.MX5.9, RLB.MX6.9, RLB.MX7.9, RLB.DC.9)
```

```
Risk.Data.Yr9 <- data.frame(Year = array(9,6*n), Profile = c(array("Ris
k Profile 1",3*n), array("Risk Profile 2",3*n)), Design = rep(c(array("
BPC",n),array("TRA",n),array("RLB",n)),2), Utility = c(BPC.EU.9.rt1,TRA
.EU.9.rt1,RLB.EU.9.rt1,BPC.EU.9.rt2,TRA.EU.9.rt2,RLB.EU.9.rt2))

#Plot Construction
Year.3.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
ity = c(median(BPC.EU.3.rt1),median(RLB.EU.3.rt1),median(TRA.EU.3.rt1),
median(BPC.EU.3.rt2),median(RLB.EU.3.rt2),median(TRA.EU.3.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
3","Risk Profile 2","Risk Profile 2"))
T3.Risk.Hist <- ggplot(Risk.Data.Yr3, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.3.medians, aes(xintercept = Utility,  colour = m
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
  labs(title= "3 Years Most Probable") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))



Year.4.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
ity = c(median(BPC.EU.4.rt1),median(RLB.EU.4.rt1),median(TRA.EU.4.rt1),
median(BPC.EU.4.rt2),median(RLB.EU.4.rt2),median(TRA.EU.4.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
2","Risk Profile 2","Risk Profile 2"))
T4.Risk.Hist <- ggplot(Risk.Data.Yr4, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.4.medians, aes(xintercept = Utility,  colour = m
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
```

```
  labs(title= "4 Years Most Probable")+
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


Year.5.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
ity = c(median(BPC.EU.5.rt1),median(RLB.EU.5.rt1),median(TRA.EU.5.rt1),
median(BPC.EU.5.rt2),median(RLB.EU.5.rt2),median(TRA.EU.5.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
2","Risk Profile 2","Risk Profile 2"))
T5.Risk.Hist <- ggplot(Risk.Data.Yr5, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.5.medians, aes(xintercept = Utility,  colour = m
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
  labs(title= "5 Years Most Probable") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


Year.6.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
```

```
ity = c(median(BPC.EU.6.rt1),median(RLB.EU.6.rt1),median(TRA.EU.6.rt1),
median(BPC.EU.6.rt2),median(RLB.EU.6.rt2),median(TRA.EU.6.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
2","Risk Profile 2","Risk Profile 2"))
T6.Risk.Hist <- ggplot(Risk.Data.Yr6, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.6.medians, aes(xintercept = Utility,  colour = m
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
  labs(title= "6 Years Most Probable") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


Year.7.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
ity = c(median(BPC.EU.7.rt1),median(RLB.EU.7.rt1),median(TRA.EU.7.rt1),
median(BPC.EU.7.rt2),median(RLB.EU.7.rt2),median(TRA.EU.7.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
2","Risk Profile 2","Risk Profile 2"))
T7.Risk.Hist <- ggplot(Risk.Data.Yr7, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.7.medians, aes(xintercept = Utility,  colour = m
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
  labs(title= "7 Years Most Probable") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
```

```
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


Year.8.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
ity = c(median(BPC.EU.8.rt1),median(RLB.EU.8.rt1),median(TRA.EU.8.rt1),
median(BPC.EU.8.rt2),median(RLB.EU.8.rt2),median(TRA.EU.8.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
2","Risk Profile 2","Risk Profile 2"))
T8.Risk.Hist <- ggplot(Risk.Data.Yr8, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.8.medians, aes(xintercept = Utility,  colour = m
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
  labs(title= "8 Years Most Probable") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


Year.9.medians <- data.frame(median = rep(c("BPC","RLB","TRA"),2), Util
ity = c(median(BPC.EU.9.rt1),median(RLB.EU.9.rt1),median(TRA.EU.9.rt1),
median(BPC.EU.9.rt2),median(RLB.EU.9.rt2),median(TRA.EU.9.rt2)), Profil
e = c("Risk Profile 1","Risk Profile 1","Risk Profile 1","Risk Profile
2","Risk Profile 2","Risk Profile 2"))
T9.Risk.Hist <- ggplot(Risk.Data.Yr9, aes(x = Utility)) +
  geom_histogram(binwidth = .01, alpha =0.5, aes(fill = Design), positi
on = "identity") +
  geom_vline(data=Year.9.medians, aes(xintercept = Utility,  colour = m
```

```
edian),linetype="dashed", size=1) +
  facet_grid(. ~  Profile, scales = "free_x") +
  labs(title= "9 Years Most Probable") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  theme(plot.title = element_text(lineheight=.8, face="bold", size = 20
)) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_continuous(name="Expected Utility") +
  theme(axis.title.x = element_text(face="bold", colour="black", size=1
5), axis.title.y = element_text(face="bold", colour="black", size=15),
axis.text.x = element_text(colour = "black", size = 10), axis.text.y =
element_text(colour = "black", size = 10), legend.title = element_text(
colour="black", size=15, face="bold"))+
  scale_colour_discrete(name  ="Median", breaks=c("BPC", "RLB","TRA"),
labels=c("BPC", "RLB","Trailer")) +
  scale_fill_discrete(name  ="Design\nAlternative", breaks=c("BPC", "RL
B","TRA"), labels=c("BPC", "RLB","Trailer"))


# Print All Plots
T3.Risk.Hist
```

```
ggsave("Year3_Plot.jpg", width = 7, height = 5)
T4.Risk.Hist
```

```
ggsave("Year4_Plot.jpg", width = 7, height = 5)
T5.Risk.Hist
```

```
ggsave("Year5_Plot.jpg", width = 7, height = 5)
T6.Risk.Hist
```

```
ggsave("Year6_Plot.jpg", width = 7, height = 5)
T7.Risk.Hist
```

```
ggsave("Year7_Plot.jpg", width = 7, height = 5)
T8.Risk.Hist
```

```r
ggsave("Year8_Plot.jpg", width = 7, height = 5)
T9.Risk.Hist
```

```r
ggsave("Year9_Plot.jpg", width = 7, height = 5)

##Results
#Year 3-Risk 1
wilcox.test(BPC.EU.3.rt1, TRA.EU.3.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.3.rt1 and TRA.EU.3.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05399979 0.05410170
## sample estimates:
## (pseudo)median
##     0.05404518

wilcox.test(BPC.EU.3.rt1, RLB.EU.3.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.3.rt1 and RLB.EU.3.rt1
## V = 351420, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.10191935 -0.09948515
## sample estimates:
## (pseudo)median
##     -0.1006863

wilcox.test(TRA.EU.3.rt1, RLB.EU.3.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.3.rt1 and RLB.EU.3.rt1
## V = 144, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
```

```
## 90 percent confidence interval:
##  -0.1559663 -0.1535320
## sample estimates:
## (pseudo)median
##     -0.1547452
```

```r
#Year 3-Risk 2
wilcox.test(BPC.EU.3.rt2, TRA.EU.3.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.3.rt2 and TRA.EU.3.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1239908 0.1242190
## sample estimates:
## (pseudo)median
##       0.124109
```

```r
wilcox.test(BPC.EU.3.rt2, RLB.EU.3.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.3.rt2 and RLB.EU.3.rt2
## V = 438170, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1348929 -0.1325066
## sample estimates:
## (pseudo)median
##     -0.1337046
```

```r
wilcox.test(TRA.EU.3.rt2, RLB.EU.3.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.3.rt2 and RLB.EU.3.rt2
## V = 158, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2589467 -0.2565530
```

```
## sample estimates:
## (pseudo)median
##     -0.2577472
```

```r
#Year 4-Risk 1
wilcox.test(BPC.EU.4.rt1, TRA.EU.4.rt1, alternative = "two.sided", mu = 
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
## 
##  Wilcoxon signed rank test with continuity correction
## 
## data:  BPC.EU.4.rt1 and TRA.EU.4.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05400906 0.05408918
## sample estimates:
## (pseudo)median
##     0.05404162
```

```r
wilcox.test(BPC.EU.4.rt1, RLB.EU.4.rt1, alternative = "two.sided", mu = 
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
## 
##  Wilcoxon signed rank test with continuity correction
## 
## data:  BPC.EU.4.rt1 and RLB.EU.4.rt1
## V = 292400, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1033959 -0.1009262
## sample estimates:
## (pseudo)median
##     -0.1021634
```

```r
wilcox.test(TRA.EU.4.rt1, RLB.EU.4.rt1, alternative = "two.sided", mu = 
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
## 
##  Wilcoxon signed rank test with continuity correction
## 
## data:  TRA.EU.4.rt1 and RLB.EU.4.rt1
## V = 60, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1574268 -0.1549516
## sample estimates:
```

```
## (pseudo)median
##     -0.1561877
```

```r
#Year 4-Risk 2
wilcox.test(BPC.EU.4.rt2, TRA.EU.4.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.4.rt2 and TRA.EU.4.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1239804 0.1242536
## sample estimates:
## (pseudo)median
##      0.1241321
```

```r
wilcox.test(BPC.EU.4.rt2, RLB.EU.4.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.4.rt2 and RLB.EU.4.rt2
## V = 360350, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1361195 -0.1337468
## sample estimates:
## (pseudo)median
##     -0.1349358
```

```r
wilcox.test(TRA.EU.4.rt2, RLB.EU.4.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)
```

```
##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.4.rt2 and RLB.EU.4.rt2
## V = 63, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2601754 -0.2578289
## sample estimates:
## (pseudo)median
##     -0.2590008
```

```r
#Year 5-Risk 1
wilcox.test(BPC.EU.5.rt1, TRA.EU.5.rt1, alternative = "two.sided", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.5.rt1 and TRA.EU.5.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05403551 0.05414891
## sample estimates:
## (pseudo)median
##     0.05410315

wilcox.test(BPC.EU.5.rt1, RLB.EU.5.rt1, alternative = "two.sided", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.5.rt1 and RLB.EU.5.rt1
## V = 330460, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.10220132 -0.09972471
## sample estimates:
## (pseudo)median
##     -0.1009646

wilcox.test(TRA.EU.5.rt1, RLB.EU.5.rt1, alternative = "two.sided", mu = 0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.5.rt1 and RLB.EU.5.rt1
## V = 118, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1562902 -0.1538158
## sample estimates:
## (pseudo)median
##     -0.1550531
```

```r
#Year 5-Risk 2
wilcox.test(BPC.EU.5.rt2, TRA.EU.5.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.5.rt2 and TRA.EU.5.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1241096 0.1243586
## sample estimates:
## (pseudo)median
##      0.1242219

wilcox.test(BPC.EU.5.rt2, RLB.EU.5.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.5.rt2 and RLB.EU.5.rt2
## V = 407840, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1347128 -0.1323407
## sample estimates:
## (pseudo)median
##     -0.1335481

wilcox.test(TRA.EU.5.rt2, RLB.EU.5.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.5.rt2 and RLB.EU.5.rt2
## V = 122, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2588729 -0.2564789
## sample estimates:
## (pseudo)median
##     -0.2577013
```

```r
#Year 6-Risk 1
wilcox.test(BPC.EU.6.rt1, TRA.EU.6.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.6.rt1 and TRA.EU.6.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05395007 0.05406160
## sample estimates:
## (pseudo)median
##     0.05402189

wilcox.test(BPC.EU.6.rt1, RLB.EU.6.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.6.rt1 and RLB.EU.6.rt1
## V = 371240, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1029417 -0.1004707
## sample estimates:
## (pseudo)median
##     -0.1017052

wilcox.test(TRA.EU.6.rt1, RLB.EU.6.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.6.rt1 and RLB.EU.6.rt1
## V = 190, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1569591 -0.1544854
## sample estimates:
## (pseudo)median
##     -0.1557177
```

```r
#Year 6-Risk 2
wilcox.test(BPC.EU.6.rt2, TRA.EU.6.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.6.rt2 and TRA.EU.6.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1239145 0.1241768
## sample estimates:
## (pseudo)median
##       0.124043

wilcox.test(BPC.EU.6.rt2, RLB.EU.6.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.6.rt2 and RLB.EU.6.rt2
## V = 465730, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1356382 -0.1332408
## sample estimates:
## (pseudo)median
##      -0.134442

wilcox.test(TRA.EU.6.rt2, RLB.EU.6.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.6.rt2 and RLB.EU.6.rt2
## V = 224, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2595905 -0.2571680
## sample estimates:
## (pseudo)median
##     -0.2583774
```

```r
#Year 7-Risk 1
wilcox.test(BPC.EU.7.rt1, TRA.EU.7.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.7.rt1 and TRA.EU.7.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05402649 0.05412445
## sample estimates:
## (pseudo)median
##     0.05406795

wilcox.test(BPC.EU.7.rt1, RLB.EU.7.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.7.rt1 and RLB.EU.7.rt1
## V = 287710, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1035063 -0.1009904
## sample estimates:
## (pseudo)median
##     -0.1022268

wilcox.test(TRA.EU.7.rt1, RLB.EU.7.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.7.rt1 and RLB.EU.7.rt1
## V = 127, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1575639 -0.1550440
## sample estimates:
## (pseudo)median
##     -0.1562824
```

```
#Year 7-Risk 2
wilcox.test(BPC.EU.7.rt2, TRA.EU.7.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.7.rt2 and TRA.EU.7.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1240337 0.1242809
## sample estimates:
## (pseudo)median
##      0.1241778

wilcox.test(BPC.EU.7.rt2, RLB.EU.7.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.7.rt2 and RLB.EU.7.rt2
## V = 367700, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1363425 -0.1339816
## sample estimates:
## (pseudo)median
##     -0.1351564

wilcox.test(TRA.EU.7.rt2, RLB.EU.7.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.7.rt2 and RLB.EU.7.rt2
## V = 130, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2604004 -0.2580450
## sample estimates:
## (pseudo)median
##     -0.2592061
```

```r
#Year 8-Risk 1
wilcox.test(BPC.EU.8.rt1, TRA.EU.8.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.8.rt1 and TRA.EU.8.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05402965 0.05413740
## sample estimates:
## (pseudo)median
##     0.05405921

wilcox.test(BPC.EU.8.rt1, RLB.EU.8.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.8.rt1 and RLB.EU.8.rt1
## V = 319990, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1033710 -0.1008854
## sample estimates:
## (pseudo)median
##     -0.1021281

wilcox.test(TRA.EU.8.rt1, RLB.EU.8.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.8.rt1 and RLB.EU.8.rt1
## V = 51, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1574662 -0.1549758
## sample estimates:
## (pseudo)median
##     -0.1562249
```

```r
#Year 8-Risk 2
wilcox.test(BPC.EU.8.rt2, TRA.EU.8.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.8.rt2 and TRA.EU.8.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1240953 0.1243427
## sample estimates:
## (pseudo)median
##      0.1242406

wilcox.test(BPC.EU.8.rt2, RLB.EU.8.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.8.rt2 and RLB.EU.8.rt2
## V = 394560, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1359632 -0.1335666
## sample estimates:
## (pseudo)median
##     -0.1347617

wilcox.test(TRA.EU.8.rt2, RLB.EU.8.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.8.rt2 and RLB.EU.8.rt2
## V = 57, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2601287 -0.2577302
## sample estimates:
## (pseudo)median
##     -0.2589563
```

```
#Year 9-Risk 1
wilcox.test(BPC.EU.9.rt1, TRA.EU.9.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.9.rt1 and TRA.EU.9.rt1
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.05393808 0.05406720
## sample estimates:
## (pseudo)median
##     0.05401215

wilcox.test(BPC.EU.9.rt1, RLB.EU.9.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.9.rt1 and RLB.EU.9.rt1
## V = 318590, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1018605 -0.0993823
## sample estimates:
## (pseudo)median
##     -0.1006141

wilcox.test(TRA.EU.9.rt1, RLB.EU.9.rt1, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.9.rt1 and RLB.EU.9.rt1
## V = 85, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1558931 -0.1534132
## sample estimates:
## (pseudo)median
##     -0.1546474
```

```
#Year 9-Risk 2
wilcox.test(BPC.EU.9.rt2, TRA.EU.9.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.9.rt2 and TRA.EU.9.rt2
## V = 50005000, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  0.1238799 0.1241688
## sample estimates:
## (pseudo)median
##      0.1240387

wilcox.test(BPC.EU.9.rt2, RLB.EU.9.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  BPC.EU.9.rt2 and RLB.EU.9.rt2
## V = 386590, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.1345231 -0.1321231
## sample estimates:
## (pseudo)median
##     -0.1333183

wilcox.test(TRA.EU.9.rt2, RLB.EU.9.rt2, alternative = "two.sided", mu =
0, paired = TRUE, conf.level = 0.90, conf.int = TRUE)

##
##  Wilcoxon signed rank test with continuity correction
##
## data:  TRA.EU.9.rt2 and RLB.EU.9.rt2
## V = 88, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 90 percent confidence interval:
##  -0.2585291 -0.2560985
## sample estimates:
## (pseudo)median
##     -0.2573064

#Results
Risk.Data <- rbind(Risk.Data.Yr3,Risk.Data.Yr4,Risk.Data.Yr5,Risk.Data.
```

```
Yr6,Risk.Data.Yr7,Risk.Data.Yr8,Risk.Data.Yr9)
Risk.data.summary <- summarySE(Risk.Data,measurevar = "Utility", groupv
ars = c("Year","Profile","Design"), conf.interval = 0.90)
Median.data <- c(median(BPC.EU.3.rt1), median(TRA.EU.3.rt1), median(RLB
.EU.3.rt1), median(BPC.EU.3.rt2), median(TRA.EU.3.rt2), median(RLB.EU.3
.rt2), median(BPC.EU.4.rt1), median(TRA.EU.4.rt1), median(RLB.EU.4.rt1)
, median(BPC.EU.4.rt2), median(TRA.EU.4.rt2), median(RLB.EU.4.rt2), med
ian(BPC.EU.5.rt1), median(TRA.EU.5.rt1), median(RLB.EU.5.rt1), median(B
PC.EU.5.rt2), median(TRA.EU.5.rt2), median(RLB.EU.5.rt2), median(BPC.EU
.6.rt1), median(TRA.EU.6.rt1), median(RLB.EU.6.rt1), median(BPC.EU.6.rt
2), median(TRA.EU.6.rt2), median(RLB.EU.6.rt2), median(BPC.EU.7.rt1), m
edian(TRA.EU.7.rt1), median(RLB.EU.7.rt1), median(BPC.EU.7.rt2), median
(TRA.EU.7.rt2), median(RLB.EU.7.rt2), median(BPC.EU.8.rt1), median(TRA.
EU.8.rt1), median(RLB.EU.8.rt1), median(BPC.EU.8.rt2), median(TRA.EU.8.
rt2), median(RLB.EU.8.rt2), median(BPC.EU.9.rt1), median(TRA.EU.9.rt1),
median(RLB.EU.9.rt1), median(BPC.EU.9.rt2), median(TRA.EU.9.rt2), media
n(RLB.EU.9.rt2))
Lower <- c(quantile(BPC.EU.3.rt1, c(0.05)), quantile(TRA.EU.3.rt1, c(0.
05)), quantile(RLB.EU.3.rt1, c(0.05)), quantile(BPC.EU.3.rt1, c(0.05)),
quantile(TRA.EU.3.rt1, c(0.05)), quantile(RLB.EU.3.rt1, c(0.05)), quant
ile(BPC.EU.4.rt1, c(0.05)), quantile(TRA.EU.4.rt1, c(0.05)), quantile(R
LB.EU.4.rt1, c(0.05)), quantile(BPC.EU.4.rt1, c(0.05)), quantile(TRA.EU
.4.rt1, c(0.05)), quantile(RLB.EU.4.rt1, c(0.05)), quantile(BPC.EU.5.rt
1, c(0.05)), quantile(TRA.EU.5.rt1, c(0.05)), quantile(RLB.EU.5.rt1, c(
0.05)), quantile(BPC.EU.5.rt1, c(0.05)), quantile(TRA.EU.5.rt1, c(0.05)
), quantile(RLB.EU.5.rt1, c(0.05)), quantile(BPC.EU.6.rt1, c(0.05)), qu
antile(TRA.EU.6.rt1, c(0.05)), quantile(RLB.EU.6.rt1, c(0.05)), quantil
e(BPC.EU.6.rt1, c(0.05)), quantile(TRA.EU.6.rt1, c(0.05)), quantile(RLB
.EU.6.rt1, c(0.05)), quantile(BPC.EU.7.rt1, c(0.05)), quantile(TRA.EU.7
.rt1, c(0.05)), quantile(RLB.EU.7.rt1, c(0.05)), quantile(BPC.EU.7.rt1,
c(0.05)), quantile(TRA.EU.7.rt1, c(0.05)), quantile(RLB.EU.7.rt1, c(0.0
5)), quantile(BPC.EU.8.rt1, c(0.05)), quantile(TRA.EU.8.rt1, c(0.05)),
quantile(RLB.EU.8.rt1, c(0.05)), quantile(BPC.EU.8.rt1, c(0.05)), quant
ile(TRA.EU.8.rt1, c(0.05)), quantile(RLB.EU.8.rt1, c(0.05)), quantile(B
PC.EU.9.rt1, c(0.05)), quantile(TRA.EU.9.rt1, c(0.05)), quantile(RLB.EU
.9.rt1, c(0.05)), quantile(BPC.EU.9.rt1, c(0.05)), quantile(TRA.EU.9.rt
1, c(0.05)), quantile(RLB.EU.9.rt1, c(0.05)))
Upper <- c(quantile(BPC.EU.3.rt1, c(0.95)), quantile(TRA.EU.3.rt1, c(0.
95)), quantile(RLB.EU.3.rt1, c(0.95)), quantile(BPC.EU.3.rt1, c(0.95)),
quantile(TRA.EU.3.rt1, c(0.95)), quantile(RLB.EU.3.rt1, c(0.95)), quant
ile(BPC.EU.4.rt1, c(0.95)), quantile(TRA.EU.4.rt1, c(0.95)), quantile(R
LB.EU.4.rt1, c(0.95)), quantile(BPC.EU.4.rt1, c(0.95)), quantile(TRA.EU
.4.rt1, c(0.95)), quantile(RLB.EU.4.rt1, c(0.95)), quantile(BPC.EU.5.rt
1, c(0.95)), quantile(TRA.EU.5.rt1, c(0.95)), quantile(RLB.EU.5.rt1, c(
0.95)), quantile(BPC.EU.5.rt1, c(0.95)), quantile(TRA.EU.5.rt1, c(0.95)
), quantile(RLB.EU.5.rt1, c(0.95)), quantile(BPC.EU.6.rt1, c(0.95)), qu
```

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antile(TRA.EU.6.rt1, c(0.95)), quantile(RLB.EU.6.rt1, c(0.95)), quantil
e(BPC.EU.6.rt1, c(0.95)), quantile(TRA.EU.6.rt1, c(0.95)), quantile(RLB
.EU.6.rt1, c(0.95)), quantile(BPC.EU.7.rt1, c(0.95)), quantile(TRA.EU.7
.rt1, c(0.95)), quantile(RLB.EU.7.rt1, c(0.95)), quantile(BPC.EU.7.rt1,
c(0.95)), quantile(TRA.EU.7.rt1, c(0.95)), quantile(RLB.EU.7.rt1, c(0.9
5)), quantile(BPC.EU.8.rt1, c(0.95)), quantile(TRA.EU.8.rt1, c(0.95)),
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ile(TRA.EU.8.rt1, c(0.95)), quantile(RLB.EU.8.rt1, c(0.95)), quantile(B
PC.EU.9.rt1, c(0.95)), quantile(TRA.EU.9.rt1, c(0.95)), quantile(RLB.EU
.9.rt1, c(0.95)), quantile(BPC.EU.9.rt1, c(0.95)), quantile(TRA.EU.9.rt
1, c(0.95)), quantile(RLB.EU.9.rt1, c(0.95)))
Risk.data.summary <- cbind(Risk.data.summary,Lower)
Risk.data.summary <- cbind(Risk.data.summary,Upper)
Risk.data.summary <- cbind(Risk.data.summary,Median.data)
Risk.data.summary <- rename(Risk.data.summary, replace = c("Utility"= "
Mean","Median.data"="Median","sd"="Standard Deviation", "se"="Standard
Error", "ci"="Confidence Interval"))
write.csv(Risk.data.summary, file = "5b_Riskdata.csv")

#Comparisons
Comparison.rt1.data <- data.frame(Risk = array(30000000,7),Year = c(3,4
,5,6,7,8,9), One = c((sum(BPC.EU.3.rt1 < TRA.EU.3.rt1)/10000), (sum(BPC
.EU.4.rt1 < TRA.EU.4.rt1)/10000), (sum(BPC.EU.5.rt1 < TRA.EU.5.rt1)/100
00), (sum(BPC.EU.6.rt1 < TRA.EU.6.rt1)/10000), (sum(BPC.EU.7.rt1 < TRA.
EU.7.rt1)/10000), (sum(BPC.EU.8.rt1 < TRA.EU.8.rt1)/10000), (sum(BPC.EU
.9.rt1 < TRA.EU.9.rt1)/10000)), Two = c((sum(BPC.EU.3.rt1 < RLB.EU.3.rt
1)/10000), (sum(BPC.EU.4.rt1 < RLB.EU.4.rt1)/10000), (sum(BPC.EU.5.rt1
< RLB.EU.5.rt1)/10000), (sum(BPC.EU.6.rt1 < RLB.EU.6.rt1)/10000), (sum(
BPC.EU.7.rt1 < RLB.EU.7.rt1)/10000), (sum(BPC.EU.8.rt1 < RLB.EU.8.rt1)/
10000), (sum(BPC.EU.9.rt1 < RLB.EU.9.rt1)/10000)), Three = c((sum(TRA.E
U.3.rt1 < RLB.EU.3.rt1)/10000), (sum(TRA.EU.4.rt1 < RLB.EU.4.rt1)/10000
), (sum(TRA.EU.5.rt1 < RLB.EU.5.rt1)/10000), (sum(TRA.EU.6.rt1 < RLB.EU
.6.rt1)/10000), (sum(TRA.EU.7.rt1 < RLB.EU.7.rt1)/10000), (sum(TRA.EU.8
.rt1 < RLB.EU.8.rt1)/10000), (sum(TRA.EU.9.rt1 < RLB.EU.9.rt1)/10000)))
Comparison.rt1.data <- rename(Comparison.rt1.data, replace = c("Risk"="
Risk Profile","One"= "BPC < TRA", "Two" = "BPC < RLB", "Three" = "TRA <
RLB"))
Comparison.rt2.data <- data.frame(Risk = array(5000000,7),Year = c(3,4,
5,6,7,8,9), One = c((sum(BPC.EU.3.rt2 < TRA.EU.3.rt2)/10000), (sum(BPC.
EU.4.rt2 < TRA.EU.4.rt2)/10000), (sum(BPC.EU.5.rt2 < TRA.EU.5.rt2)/1000
0), (sum(BPC.EU.6.rt2 < TRA.EU.6.rt2)/10000), (sum(BPC.EU.7.rt2 < TRA.E
U.7.rt2)/10000), (sum(BPC.EU.8.rt2 < TRA.EU.8.rt2)/10000), (sum(BPC.EU.
9.rt2 < TRA.EU.9.rt2)/10000)), Two = c((sum(BPC.EU.3.rt2 < RLB.EU.3.rt2
)/10000), (sum(BPC.EU.4.rt2 < RLB.EU.4.rt2)/10000), (sum(BPC.EU.5.rt2 <
RLB.EU.5.rt2)/10000), (sum(BPC.EU.6.rt2 < RLB.EU.6.rt2)/10000), (sum(BP
C.EU.7.rt2 < RLB.EU.7.rt2)/10000), (sum(BPC.EU.8.rt2 < RLB.EU.8.rt2)/10
```

```
000), (sum(BPC.EU.9.rt2 < RLB.EU.9.rt2)/10000)), Three = c((sum(TRA.EU.
3.rt2 < RLB.EU.3.rt2)/10000), (sum(TRA.EU.4.rt2 < RLB.EU.4.rt2)/10000),
(sum(TRA.EU.5.rt2 < RLB.EU.5.rt2)/10000), (sum(TRA.EU.6.rt2 < RLB.EU.6.
rt2)/10000), (sum(TRA.EU.7.rt2 < RLB.EU.7.rt2)/10000), (sum(TRA.EU.8.rt
2 < RLB.EU.8.rt2)/10000), (sum(TRA.EU.9.rt2 < RLB.EU.9.rt2)/10000)))
Comparison.rt2.data <- rename(Comparison.rt2.data, replace = c("Risk"="
Risk Profile","One"= "BPC < TRA", "Two" = "BPC < RLB", "Three" = "TRA <
RLB"))
Comparison.data <- rbind(Comparison.rt1.data,Comparison.rt2.data)
write.csv(Comparison.data, file = "5b_Comparisons.csv")
```

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14. ABSTRACT

The rapid construction of expeditionary bases is associated with the forward deployment of Department of Defense (DoD) assets in response to contingency operations such as natural disasters, terrorist operations, or armed conflict. Usually expected to be transitory, expeditionary bases are constructed with temporary materials that can be erected quickly to provide an agile and flexible combat support. The Global War on Terrorism is entering its fifteenth year, and bases within Central Command that were expected to be temporary in duration have had an enduring presence. The decision to transition a base from temporary construction or semi-permanent construction to permanent construction is difficult, as it requires a substantial capital investment for facility construction. The decision is further complicated by unknown mission durations. The DoD has attempted to reduce the decision's complexity with a model that guides the development of a base with a set of construction standards with suggested time horizons.

This study evalulated the validity of the model through an economic analysis with the assumption a mission's duration is unknown. A life-cycle cost model is developed to evaluate investments in temporary and permanent construction design alternatives to determine when or if permanent construction is fiscally advantageous for a given contingency duration. Despite limitations in the availability in cost data from Air Force Civil Engineer databases, the results show that temporary construction is preferable for contingency operations lasting up to twelve years in duration, while permanent construction is preferable after twelve years. With respect to the DoD's construction standard model, this research's results provide a different time horizon for choosing construction standards, when cost is the primary objective.

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