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14. ABSTRACT

The National Space Policy of the United States of America (2010) calls on the National Security Space (NSS) community to continue to develop and apply advanced technologies and capabilities that respond to changes to the threat environment. This national policy reinforces a trend within the NSS community that places a greater emphasis on the ability of NSS systems to operate in an uncertain future. This dissertation informs policymaking by presenting three essays that address some of the challenges associated with improving the flexibility of NSS capabilities. In addition, each essay includes an application of the decision logic that would be required to optimally support the next generation of flexible space systems. The first essay explores the hypothesis that the NSS community can be more risk-tolerant when launching small satellites that are inexpensive and can be quickly replaced following a launch failure. The ability to bundle multiple payloads on a single launch vehicle is a decision unique to small satellites that adds an extra dimension to the launch risk calculation. While bundling multiple small satellites on a single launch vehicle spreads the initial launch cost across multiple payloads, this strategy also makes a launch failure more costly. This essay develops an analytic framework for constructing optimal small satellite launch strategies for a range of risk preferences. Given the available fleet of launch options, targeted small satellite launch demand, and nominal small satellite attributes, risk-adverse decisionmakers would always seek to minimize the expected cost when choosing how best to launch a set of small satellites. Simple modifications to existing technologies would have the largest impacts on cost and risk. These modifications include the ability to easily dual manifest on a medium-cost, medium-reliability launch vehicle and a secondary payload adaptor that can support three 360-kilogram payloads. Developing and fielding a low-cost, low-reliability launch option offers the greatest reductions in financial risk but would significantly increase the mission risk associated with launching small satellites. The second essay examines the potential role for ridesharing small additional payloads on launch missions purchased in support of large and expensive primary payloads. The U.S. Air Force and its commercial partners have developed a suite of secondary payload adaptors that can accommodate a wide range of potential payloads. While increasing the number of rideshare opportunities could make access to space more affordable for small satellites, challenges persist. One concern is that by increasing the complexity of the launch vehicle integration

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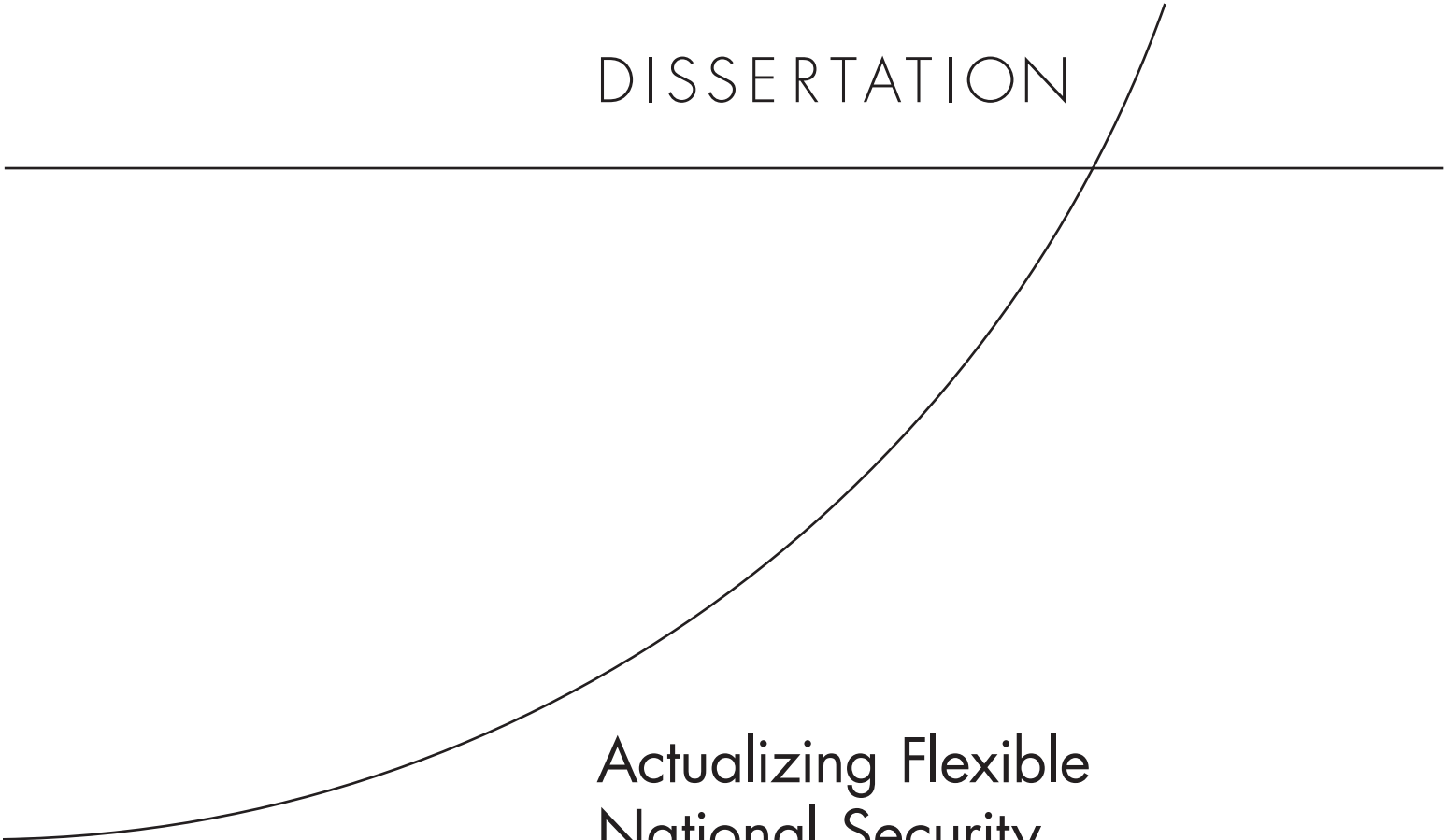
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DISSERTATION

Actualizing Flexible National Security Space Systems

Kenneth Grosselin III

This document was submitted as a dissertation in September 2011 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of William Welser IV (Chair), Brien Alkire, Adam Resnick, and Ben Van Roo.



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ABSTRACT¹

The *National Space Policy of the United States of America* (2010) calls on the National Security Space (NSS) community to continue to “develop and apply advanced technologies and capabilities that respond to changes to the threat environment.” This national policy reinforces a trend within the NSS community that places a greater emphasis on the ability of NSS systems to operate in an uncertain future. This dissertation informs policymaking by presenting three essays that address some of the challenges associated with improving the flexibility of NSS capabilities. In addition, each essay includes an application of the decision logic that would be required to optimally support the next generation of flexible space systems.

The first essay explores the hypothesis that the NSS community can be more risk-tolerant when launching small satellites that are inexpensive and can be quickly replaced following a launch failure. The ability to bundle multiple payloads on a single launch vehicle is a decision unique to small satellites that adds an extra dimension to the launch risk calculation. While bundling multiple small satellites on a single launch vehicle spreads the initial launch cost across multiple payloads, this strategy also makes a launch failure more costly. This essay develops an analytic framework for constructing optimal small satellite launch strategies for a range of risk preferences. Given the available fleet of launch options, targeted small satellite launch demand, and nominal small satellite attributes, risk-adverse decisionmakers would always seek to minimize the expected cost when choosing how best to launch a set of small satellites. Simple modifications to existing technologies would have the largest impacts on cost and risk. These modifications include the ability to easily dual

¹ This manuscript was formatted assuming that the reader would have access to a color copy. Interested readers who obtain a copy that is difficult to read may contact the author at Kenneth.Grosselin@gmail.com for a color copy.

manifest on a medium-cost, medium-reliability launch vehicle and a secondary payload adaptor that can support three 360-kilogram payloads. Developing and fielding a low-cost, low-reliability launch option offers the greatest reductions in financial risk but would significantly increase the mission risk associated with launching small satellites.

The second essay examines the potential role for ridesharing small additional payloads on launch missions purchased in support of large and expensive primary payloads. The U.S. Air Force and its commercial partners have developed a suite of secondary payload adaptors that can accommodate a wide range of potential payloads. While increasing the number of rideshare opportunities could make access to space more affordable for small satellites, challenges persist. One concern is that by increasing the complexity of the launch vehicle integration process, ridesharing auxiliary satellite systems could increase the risk exposure to the primary satellite system. In this essay, I show that, historically, ridesharing additional payloads has reduced the reliability of a launch attempt by 1.25 percentage points. Given available data, any increase in the delay of launches is difficult to detect and probably insignificant when compared to the overall development timeline of an NSS satellite system. This essay concludes with an enterprise-level assessment of the expected savings associated with a generic rideshare opportunity. Given reasonable estimates of the cost and reliability of secondary launch options, it is only cost-effective to rideshare additional payloads with primary satellite systems that cost less than \$1.4 billion. This estimate is sensitive to many input assumptions that vary across rideshare opportunities; therefore, rideshare decisions should be made on a case-by-case basis in a way that incorporates the costs across the entire NSS enterprise.

The third essay examines how uncertainty and flexibility would be incorporated into the systems analysis process for new NSS systems. While the Department of Defense (DoD) has traditionally used a cost-centric framework for systems analysis, the academic community of practice has suggested that a value-centric framework would be more appropriate for flexible space systems. This essay finds that the value-centric framework aims to identify a solution that is optimally

aligned with the preferences of the decisionmaker, while the cost-centric framework is a convenient method for identifying a solution that satisfactorily addresses the preferences of the decisionmaker. The promise of identifying an optimal solution is appealing, but practical challenges dampen the usefulness of the value-centric framework in the context of the DoD decision environment. Specifically, the incommensurable nature of military effectiveness makes it very hard to identify a consistent value model for DoD systems. This essay concludes with a discussion of how the cost-centric framework can be modified to better incorporate uncertainty into the design and selection of flexible NSS systems.

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My primary objective was to create a policy relevant dissertation and, where appropriate, develop and demonstrate analytically rigorous decision tools. Throughout the dissertation process, I have always emphasized the importance of letting the context of the policy questions determine the appropriate methodology and avoided "looking" for policy questions that are amenable to a specific analytic toolset. I hope that the organization of this document provides a discussion of the policy topics that is accessible to individuals from a broad set of backgrounds. I take full responsibility for all observations and conclusions herein, along with any remaining errors.

ABBREVIATIONS

ABS	Aft Bulkhead Carrier
AEHF	Advanced Extremely High Frequency Satellite
AF SAB	Air Force Scientific Advisory Board
AFSPC	Air Force Space Command
AF/ST	Air Force Chief Scientist
AoA	analysis of alternatives
APL	auxiliary payload
ASTRO	Autonomous Space Transport Robotic Operations
CAP+	C-Adaptor Platform Plus
CBA	Capabilities-Based Assessment
cdf	cumulative density function
DARPA	Defense Advanced Research Projects Agency
DMSP	Defense Meteorological Satellite Program
DoD	Department of Defense
DSS	Dual Satellite System
EELV	Evolved Expendable Launch Vehicle
EMD	Engineering and Manufacturing Development
ESFP	ESPA Space Flight Plan
ESPA	EELV Secondary Payload Adaptor
FAA	Federal Aviation Administration
F6	Future, Flexible, Fast, Fractionated Free-Flying Spacecraft united by Information Exchange
GAO	Government Accountability Office
GEO	geosynchronous earth orbit
GTO	geostationary transfer orbit
HCHR	high-cost, high-reliability
HLE	human lunar exploration
HME	human mars exploration
IPC	Integrated Payload Carrier
JCIDS	Joint Capabilities Integration and Development System
JROC	Joint Requirements Oversight Council
LCLR	low-cost, low-reliability

LEO	low earth orbit
LH	liquid hydrogen
LO	liquid oxygen
LV	launch vehicle
LVAP	Launch Vehicle Assignment Program
MAUT	Multi-Attribute Utility Theory
MCMR	medium-cost, medium reliability
MEO	medium earth orbit
NASA	National Aeronautics and Space Administration
NEXTSat/CSC	Next Generation Satellite and Commodities Spacecraft
NPOESS	National Polar-orbiting Operational Environmental Satellite System
NRO	National Reconnaissance Organization
NSS	National Security Space
OMB	Office of Management and Budget
ORS	Operationally Responsive Space
pdf	probability density function
PPOD	Poly Picosat Orbital Deployer
ROA	Real Options Analysis
RUG	Rideshare Users Guide
SATCOM	satellite communication
SBIRS	Space Based Infrared System
SecAF	Secretary of the Air Force
SIDV	sum of the individual downside semivariances
SMC	Space and Missile Systems Center
SMC/LR	SMC Launch and Range Systems Directorate
SMC/SD	SMC Space Development and Test Directorate
SPO	system program office
STP	DoD Space Test Program
ULA	United Launch Alliance
USAF	United States Air Force
USD	United States Dollars
VBA	Value-Based Acquisition
WGS	Wideband Global SATCOM

INTRODUCTION: UNCERTAINTY, FLEXIBILITY, AND NATIONAL SECURITY SPACE POLICY

The *National Space Policy of the United States of America* (2010, pp. 14) calls on the National Security Space (NSS) community to continue to "develop and apply advanced technologies and capabilities that respond to changes to the threat environment." This national policy reinforces a trend within the NSS community that places a greater emphasis on the ability of NSS systems to operate in an uncertain future. As the NSS community looks to develop and field the next generation of space-based capabilities, flexibility and uncertainty considerations must be incorporated into the decision process for the acquisition, fielding, employment, and sustainment of potential systems.

TECHNOLOGICAL EFFORTS TO IMPROVE THE FLEXIBILITY OF NSS CAPABILITIES

An Air Force Scientific Advisory Board (AF SAB) report on small satellites notes that "our national security satellites in general are large, complex, expensive to build and take many years to develop and launch" (AF SAB, 2007, pp. 2). The nature of these satellites makes it difficult for the NSS community to field new technologies, adapt to changing user needs, and respond to unforeseen challenges. The NSS community has recently recognized the importance of developing the capabilities required to rapidly react to changing strategic and operational environments. Section 913 of the John Warner National Defense Authorization Act for Fiscal Year 2007 called for the creation of the Operationally Responsive Space (ORS) program office. This program office was tasked with contributing to "the development of low-cost, rapid reaction payloads, busses, spacelift, and launch control capabilities in order to fulfill joint military operation requirements for on-demand space support and reconstitution."

Supplementing the current portfolio of NSS systems with smaller, cheaper, and less complex satellites could be one possible mechanism for improving the flexibility of NSS space-based capabilities. The AF SAB report on small satellites defines a small satellite as a space-based system that costs under \$100 million to develop, produce, and launch

into orbit (AF SAB, 2007). The amount roughly correlates with a 400-kilogram system. This AF SAB report found that small satellites can provide worthwhile benefits to the NSS community. Purported small satellite benefits include shorter development times, less complexity, and streamlined mission assurance (AF SAB, 2007). The proposed small satellite paradigm would limit the cost and development time of certain NSS assets by supplementing complex, multi-mission designs with simple architectures that provide capabilities designed to satisfy a single mission. These cheap satellites could potentially be quickly acquired and launched to accommodate a dynamic threat environment (e.g., unforeseen demand and changing user needs).

Once a space system is launched into orbit around the earth, it is extremely difficult to change the mission profile of that system. Fuel limitations make it difficult to repeatedly reposition satellites across different orbits without severely diminishing useable lifespan. In addition, the vast majority of satellites are inaccessible once placed in orbit, making it impossible to repair, modify, or upgrade the physical components of the system. The Defense Advanced Research Projects Agency (DARPA) Orbital Express program goal was "to validate the technical feasibility of robotic, autonomous on-orbit refueling and reconfiguration of satellites" (DARPA, 2007, pp. 1). By pursuing this project, DARPA identified and demonstrated another way in which the flexibility of space-based systems could be improved. On-orbit servicing capabilities would improve the flexibility of NSS systems by allowing the NSS community to directly modify space systems after they are placed in orbit.

The Air Force Chief Scientist (AF/ST) has identified fractionated architectures as a potential capability area for future Air Force space systems (2010). The AF/ST defines a fractionated space satellite as a set of physically separate, functionally different on-orbit modules that can act independently or cooperate to act as a single system.² After

² In contrast, a monolithic satellite system is one in which all subsystems are housed on the same satellite bus and integration occurs prior to launch.

defining a set of communication and resource-sharing protocols, the individual modules could be designed independently of each other and integrated on-orbit. The goal of the DARPA System F6³ program was to develop and demonstrate a fractionated space system. There are many purported benefits associated with fractionated space architectures. The majority of these benefits address the ability of NSS systems to respond to uncertainty. A properly designed fractionated space system could accommodate additional modules, even after the initial system has been placed into orbit around the earth. This mechanism would allow fractionated architectures to be scaled to meet unforeseen growth in demand (scalability), modified to provide a new capability (adaptability), and upgraded to improve the performance of the existing capability (upgradeability). In addition, adding redundant subsystems to the different modules would improve the survivability of NSS systems, since the system would be able to survive and operate following the loss of any single module. Other purported benefits of fractionated systems include the ability to assemble capability equal to that of large systems on-orbit at a lower overall launch cost, and the ability to lower the cost per mission set by sharing on-orbit resources across modules. In the extreme, a space-based network of fractionated resources and distributed computing would allow commercial firms to orbit very simple payloads that rely on this network for computing support, communication, and power, potentially reducing barriers to entry in the commercial space industry (Shaw and Brown, 2008).

INCORPORATING UNCERTAINTY INTO THE NSS DECISION LOGIC

While developing and fielding flexible space system architectures is an important aspect of improving the flexibility of NSS capabilities, the decision logic that supports these new architectures must also be modified to incorporate uncertainty. Small satellites, on-orbit servicing technologies, and fractionated satellite systems would offer mechanisms for responding to uncertainty that traditional NSS systems do

³ Future, Flexible, Fast, Fractionated, Free-Flying Spacecraft united by Information Exchange.

not afford. These additional uncertainty considerations would be relevant across all phases of the system life cycle and could potentially require significant modifications to the traditional NSS decision logic.

In totality, this research is intended to inform NSS policy by addressing three challenges facing NSS community efforts to improve the flexibility of space-based capabilities. While each essay addresses a different policy question related to acquiring and fielding "flexible" space systems, they share a common focus on the decision logic required to effectively develop and support these future systems.

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ESSAY ONE: RISK-TOLERANT SMALL SATELLITE LAUNCH STRATEGIES

INTRODUCTION

Background

Traditionally, NSS systems have been expensive, multi-mission platforms that can spend upwards of ten years in development.

Table 1.1
Select NSS Program Statistics

	NPOESS	AEHF	WGS	SBIRS-High
Acquisition cycle time (Months)	200	134	94	TBD
Increase from initial cycle time	16%	20%	88%	TBD
Estimated unit cost (FY08)	\$2677M	\$2272M	\$406M	\$3490M
Increase from initial unit cost	153%	88%	8%	300%

SOURCE: GAO, 2008.

NOTES: NPOESS = National Polar-orbiting Operational Environmental Satellite System (canceled February 2010), AEHF = Advanced Extremely High Frequency Satellite, WGS = Wideband Global Satellite Communication, SBIRS-High = Space Based Infrared System-High Satellite System

Table 1.1 highlights the significant cost and lengthy development times of these large, sophisticated satellites as well as the percentage change from the projected budget and schedule. The long development cycle of the traditional NSS satellite makes it difficult for the NSS community to rapidly field assets in response to changing user needs.

Small satellites⁴ have been identified as a possible supplement to the current NSS portfolio of systems that could decrease system costs and schedule overruns while also providing a way to quickly field NSS assets in response to emerging user needs. Multiple research efforts

⁴ The Air Force Scientific Advisory Board (AF SAB) defines a *small satellite* as a satellite that costs less than \$100 million to acquire and launch (AF SAB, 2007).

have presented these less sophisticated satellites as a possible way to quickly provide a new space-based product or augment an existing space-based product in a geographic region of interest (AF SAB, 2007). In theory, because they would not be as complex as traditional NSS satellite systems, small satellites would not be subject to the same budget overruns, schedule overruns, or extended development cycles.

Despite the potential benefits small satellites could provide, the AF SAB report highlights the lack of a viable small satellite launch infrastructure as a hurdle toward effectively realizing these capabilities. NSS launch capabilities are built around infrequently launching very expensive satellites that spend years in development. The current launch paradigm is extremely risk-adverse in its attempts to prevent a catastrophic launch failure because of the cost and schedule repercussions of a launch failure involving exquisite⁵ systems. This extremely risk-adverse posture translates into high launch cost and lengthy prelaunch integration and testing timelines that could effectively diminish the potential value and savings small satellites could provide. For small satellites that are relatively cheap and can be quickly reacquired, the consequences of a launch failure may not be as severe as a launch failure involving an exquisite system. If small satellites can be used to diminish the repercussions of a launch failure, it may be more cost-effective for the NSS community to utilize risk-tolerant launch strategies that trade an increased launch risk for decreased overall costs. Developing and implementing cost-effective strategies to launch small satellites are essential to realizing the operational utility of these systems. To help position the NSS community to capitalize on the potential benefits of small satellites, the AF SAB has recommended that the United States Air Force (USAF) take the lead in improving small satellite launch capabilities (AF SAB, 2007).

⁵ I define an *exquisite space system* as being any space system that is too "large" to be classified as a small satellite. Using the definition of a small satellite provided by the AF SAB, an exquisite system is a system that costs more than \$100 million to acquire and launch.

The goal of this research was to answer the question: Would a more risk-tolerant launch posture improve U.S. Air Force small satellite launch capabilities? This was done by answering three research questions:

1. How do the cost and risk considerations of small satellite launch decisions differ from those associated with the launch of larger satellites?
2. Given the current set of launch capabilities, what role should risk preferences play in the construction of small satellite launch strategies?
3. What are the cost and risk implications associated with additional capabilities purported to improve small satellite launch performance?

Three interrelated tasks were pursued to accomplish this goal and answer these research questions. I developed a framework for constructing small satellite launch strategies that takes into account a spectrum of risk preferences. This framework was used to assess the role that risk preferences and the current set of small satellite launch capabilities have on determining the optimal small satellite launch strategy. Finally, these findings were used to assess the cost and risk implications of additional capabilities designed to improve small satellite launch performance.

NSS Small Satellite Launch Capabilities and Targeted Demand

Table 1.2 contains the costs of several launch vehicles. It is not guaranteed that a launch vehicle will successfully deliver its assigned payload(s) into the correct orbit(s). In this table, the reliability of a launch vehicle is defined as the probability the launch vehicle successfully delivers its payload into the correct orbit around the earth.

Table 1.2
Unit Cost and Estimated Reliabilities for Select Launch Vehicles

Launch Vehicle	Minimum Cost (FY09)	Maximum Cost (FY09)	No. of Attempts (No. of Successes)	Predicted Reliability ^a
Athena	\$39M	\$50M	7 (5)	67%
Atlas V	\$113M	\$156M	24 (23)	92%
Delta II	\$48M	\$63M	148 (146)	98%
Delta IV	\$97M	\$135M	16 (15)	89%
Falcon 1	\$8M	\$13M	5 (2)	43%
Minotaur I	\$19M	\$25M	9 (9)	91%
Minotaur IV	\$27M	\$33M	2 (2)	75%
Pegasus	\$19M	\$27M	40 (35)	86%
Taurus	\$24M	\$31M	9 (6)	64%

NOTES: Launch vehicle cost statistics were taken from the DARPA System F6 set of suggested performance metrics for Phase 1 value modeling. All DARPA System F6 data files are openly available at <http://www.darpa.mil/tto/programs/systemf6/>. These numbers were provided to the Phase 1 design teams to be incorporated into the value-centric decision models.

^a Because of small sample sizes, launch vehicle reliability rates are difficult to calculate. Here the predicted reliability is calculated using the method described in Guikema and Paté-Cornell (2004) and is equal to $(m+1)/(n+2)$ where m is the number of successes and n is the number of attempts. This measure is based on a Bayesian estimate of the reliability rate with an uninformative prior. Launch attempts are current as of April 2, 2011.

Some launch vehicles can be modified to accommodate multiple payloads. The Delta II can easily support dual manifested payloads (ULA, 2006). Other attachments, such as the EELV Secondary Payload Adaptor Ring (ESPA ring), allows up to six additional systems (all additional payloads must be less than 180 kilograms) to rideshare on the Delta IV or the Atlas V.

The decision to retire the Delta II and migrate to the EELV (Delta IV and Atlas V) is a policy decision that could impact small satellite launch capabilities. Over the last 20 years, the Delta II has been a reliable launch option for medium sized payloads, with the USAF utilizing the Delta II launch vehicle over 50 times during that span (Ray, 2009). The last planned Air Force launch utilizing the Delta II was August 2009. NASA is expected to continue using the Delta II until 2014; however, extending the use of the Delta II past this date would

require additional funds to restart production and cover the fixed-costs associated with supporting the Delta II infrastructure.

In order to simplify the analysis, the set of available launch vehicles in Table 1.2 was reduced into four classifications. These classifications were designed to reflect the tradeoffs that exist across cost, reliability, capacity and capability.

Table 1.3
Four Classes of Considered Launch Vehicles

Launch Vehicle Class	Cost	Reliability	Total Mass Constraint	Individual Mass Constraint	Capacity
High-Cost, High-Reliability LV (HCHR LV)	Varied \$54M or \$100M	98%	3899 kg	None	1
High-Cost, High-Reliability LV with ESPA ring (ESPA LV)	Varied \$69M or \$115M	98%	3899 kg	180 kg	7
Medium-Cost, Medium-Reliability LV (MCMR LV)	\$30M	95%	1735 kg	None	Varied 1 or 2
Low-Cost, Low-Reliability (LCLR LV)	Varied Between \$5M - \$20M	Varied 85%-95%	700 kg	None	1

Notes: Because most conceivable small satellite missions would take place in low earth orbit (LEO) (AF SAB, 2007), the total mass constraint assumes that the launch vehicle is placing its payload in LEO.

Table 1.3 contains the four classes of launch vehicles used in this analysis along with their associated performance parameters. For the most part, these classes were designed to reflect the current set of launch capabilities. In terms of the total mass constraint, the HCHR LV, ESPA LV, and MCMR LV are comparable to the EELV/Delta II, EELV/Delta II with an ESPA attachment, and the Minotaur IV, respectively. Most scenarios assumed the EELV was the HCHR LV option, with an associated cost of \$100 million; however, when investigating the impact of extending the use of the Delta II as a HCHR launch option for small

satellites, the cost of the HCHR LV was assumed to be \$54 million. While the demonstrated reliability of the Atlas V and the Delta IV is less than the Delta II, the USAF hopes to eventually demonstrate reliability greater than 98 percent for these launch vehicles (Kimhan et al., 1999). The MCMR LV reflects the Minotaur IV, with one major difference. The Minotaur IV has only been launched twice, so its predicted reliability is low. A reliability of 95 percent was used because it represented a reasonably mature reliability while still providing some differentiation between itself and the HCHR LV. The LCLR LV shares capacity constraints with the Falcon 1, but assumes more mature launch vehicle reliability.

In addition to these launch vehicle attributes, an understanding of future small satellite launch demand is crucial for any research that attempts to inform small satellite launch policy. While the NSS community has yet to fully incorporate a significant small satellite program into the portfolio of operational space-based systems, it is still possible to make reasonable attempts at describing the future demand for small satellite launch. The AF SAB has recommended that the Air Force be able to support the launch of 20 domestic small satellites per year by 2015 (AF SAB, 2007). This targeted demand level was used as the baseline assumption of future demand. Estimates of small satellite cost and mass are drawn from small satellite parametric relationships published by the Aerospace Corporation (Bearden, 2001).

FRAMEWORK

Small Satellite Launch Risk and Additional Assumptions

The catastrophic launch failure of a Zenit 2 launch vehicle in 1998 demonstrates the unique tradeoffs associated with small satellite launch. The launch vehicle was carrying 12 small communication satellites that would be part of the Globalstar commercial satellite communication network. The launch failure destroyed all onboard payloads and resulted in nearly \$240 million in additional replacement costs for Globalstar ("Globalstar's Cost for Satellite System Rise \$240 Million," 1998). On one hand, the diminutive nature of small satellites

makes it feasible to share launch costs across multiple payloads by bundling them together on the same launch vehicle. This cost-saving strategy, however, also increases the severity of the repercussions of a catastrophic launch failure. Thus bundling multiple payloads on the same launch vehicle can increase the risk of the launch strategy.

Within the commercial space industry, there are five categories of risk associated with a catastrophic launch failure (Parkinson, 1998). Table 1.4 contains these risks, along with their NSS equivalent. Not all of these commercial categories are easily mapped into an equivalent NSS cost or risk.

Table 1.4
Risks Associated with Launch Failures

Commercial Failure Launch Risk	NSS Equivalent
Replacement payload, LV, and launch	Replacement payload, LV, and launch
Delays launch until failure investigation complete	Failure investigation, other launches delayed
Diminished capability while system is maintained through downtime	Unfulfilled demand for space-based products
Lost profit or value from not having a complete system	Diminished on-orbit capabilities
Insurance cost/surcharge	None

With respect to NSS systems, risk can be separated into two classifications. The first is the financial risk of having to replace and relaunch lost payloads. The second classification captures the operational impact of either temporary or permanent delay of the capabilities the lost payloads were designed to deliver. In the best-case scenario, following a launch failure the lost payloads can be reacquired and relaunched, and there is only a temporary delay in achieving the prescribed level of capability. In the worst-case scenario, the payloads cannot be quickly reacquired, and the NSS community must operate with diminished on-orbit capabilities for an extended period of time.

Initially, this research considered only the financial risk associated with potential launch failures.⁶ Incorporating mission risk into the decision process requires an in-depth understanding of the operational demand for and value of a provided small satellite capability. Estimates of how long it would take to recover from a launch failure would also be required. Currently, these attributes cannot be reasonably quantified in a way that would allow for a meaningful analysis. To overcome these limitations, additional analysis was used to understand how sensitive conclusions were to any additional mission risk component.

Throughout this research, I assume that payload sets are launched and relaunched until all payloads have been successfully placed in the correct orbit⁷ and that the required launch infrastructure is always available. For a complete list of assumptions along with justifications for these assumptions, the interested reader is directed to Appendix B.

Quantifying Launch Risk and Risk Preferences

Weigel and Hastings (2004) characterize launch decisions based on the risk preferences of the decisionmaker. A decisionmaker follows one of three possible strategies when making launch decisions. In the first strategy, the decisionmaker selects the launch strategy that minimizes

⁶ While the initial analysis considers only cost risk, later on, the portion of the analysis that examines potential USAF launch capabilities takes into account both the cost risk and the mission risk associated with the different policy levers.

⁷ Practically, this is equivalent to assuming that the USAF will always respond to a launch failure by repurchasing the lost payloads for another launch attempt. This process continues until all payloads have been orbited. Thus, there is a nonzero probability that 2, 5, 10, or 100 launches will be required. In practice, the time relevance of the payloads coupled with the ballooning costs would result in the payload set eventually being scrubbed or dispersed, and not continually relaunched until a success occurs. The high reliabilities of the launch vehicles under consideration, however, reduce the importance of these extreme events. A launch vehicle with a reliability of 89 percent has a 0.1 percent chance of requiring four or more launches. Thus, the contributions to the expected cost and the variance from the unlikely scenarios involving many relaunched (three or more) will have a minuscule additional impact on the estimated moments.

overall cost. Under the second strategy, the decisionmaker selects the launch strategy that minimizes some probabilistic cost risk metric. The third strategy is a combination of the first two, with the decisionmaker minimizing a weighted combination of cost and risk, where the weight captures their overall risk preferences.

The framework that I developed builds on this formulation by accommodating different risk preferences, but it is rooted in the economic theory of risk aversion (Arrow, 1965). A decisionmaker is defined as being risk-neutral if he or she has no preference between an uncertain decision with an expected cost of \$X and a certain decision with known cost \$X. For example, consider two decisions. Both have the same benefits, but Decision 1 is guaranteed to cost \$1,000, while there is a 50 percent probability that Decision 2 costs \$1,500, and a 50 percent probability that Decision 2 costs \$500. The long-run average cost for both decisions is \$1,000. A risk-neutral decisionmaker would have no preference between these two decisions. A risk-averse decisionmaker would prefer the guaranteed cost of \$1,000 to the lottery that could result in a loss of \$1,500.

In the context of small satellite launches, this implies that a risk-neutral decisionmaker will select the launch strategy with the lowest expected cost.⁸ On the other extreme, a completely risk-adverse decisionmaker would select the launch strategy with the lowest worst-case cost. A risk-tolerant decisionmaker lies somewhere between these two extremes, selecting the launch strategy that minimizes some cost percentile between the average and the worst-case scenario (e.g., he or she selects the launch strategy that minimizes the 80th percentile of the total cost).

⁸ The fact that the risk-neutral decisionmaker minimizes the expected cost, and not the initial cost, is important. A "low-quality" launch vehicle may have a relatively low initial cost, but also a relatively poor reliability. This low reliability increases the expected number of required launches, which in turn, increases the expected cost. Because the stakeholders incur costs following a launch failure, both the launch cost and the reliability impact the overall expected cost.

Risk measures the probability and severity of an unfortunate event. When launching satellites, the unfortunate event is a catastrophic launch failure, the reliability of the launch vehicle determines the probability that a failure occurs, and the payloads on the launch vehicle determine the severity of the loss. When constructing small satellite launch strategies, decisionmakers face two types of decisions that impact risk. The first decision involves selecting a portfolio of launch vehicles to support a small satellite launch manifest. As demonstrated in Table 1.2, there can be a tradeoff between reliability and cost. For example, the Delta II has a higher predicted reliability than the Minotaur IV, but it also costs \$11 million to \$30 million more than the Minotaur IV. Small satellite launch strategies also require the decisionmaker to determine the extent that satellites are bundled together on the same launch vehicle. Increasing the number of payloads on an individual launch vehicle spreads out launch costs across multiple payloads. For example, assume the USAF has five small satellites to launch, and each launch costs \$30 million. If all five satellites are placed on the same launch vehicle, the total launch cost is only \$30 million or \$6 million per satellite. Conversely, if each satellite is launched on its own launch vehicle, the total launch cost becomes \$150 million at \$30 million per satellite. Yet, bundling multiple satellites together increases the repercussions following a catastrophic launch failure, possibly increasing the risk exposure of a launch strategy. These two interrelated decisions must be made under the performance and capacity constraints of the available launch vehicles.

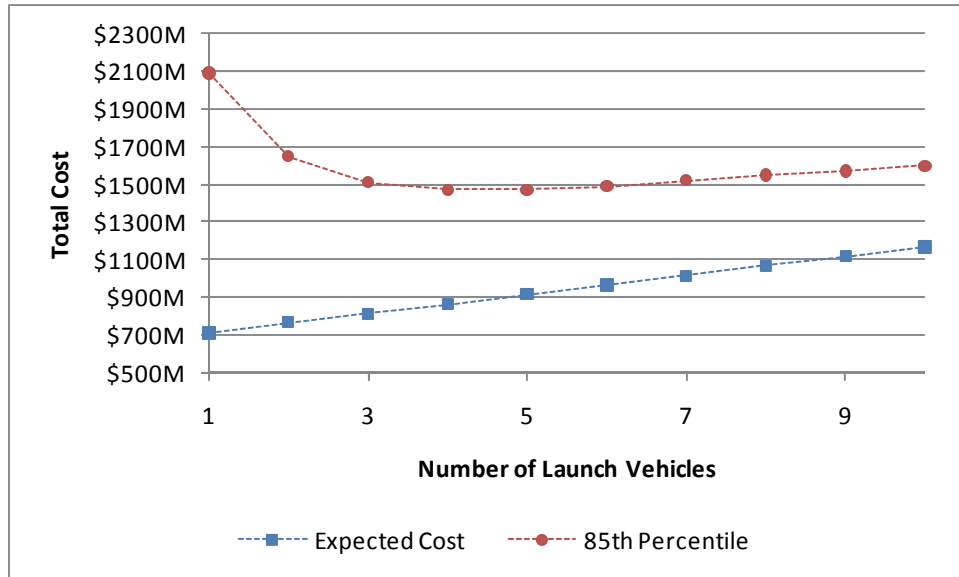
As an example, consider ten identical small satellites and a single class of launch vehicle. In this example, all payloads cost \$100 million. Each launch vehicle costs \$30 million and has a reliability of 60 percent. The decisionmaker must determine how best to orbit these ten payloads. If we ignore any mass constraints and assume that launch bundles will be launched and relaunched until successfully orbited,⁹

⁹ Throughout this research, I assume payload sets are launched and relaunched until all payloads have been orbited. Practically, this is equivalent to assuming that the USAF will always respond to a launch

initially the most cost-effective strategy would be to place all ten payloads on the same launch vehicle. Given this strategy, the repercussions of a launch failure are severe, since all ten payloads must be replaced. On the other hand, using ten launch vehicles to launch each payload individually would have the largest initial cost but spread out the repercussions of launch failures. Figure 1.1 and Figure 1.2 demonstrate how the expected cost and the upper cost percentiles change with the initial number of launch vehicles used to orbit the ten payloads.

failure by repurchasing the lost payloads for another launch attempt. This process continues until all payloads have been orbited. Thus, there is a nonzero probability that 2,5,10 or 100 launches will be required. In practice, the time relevance of the payloads coupled with the ballooning costs would result in the payload set eventually being scrubbed or dispersed, and not continually relaunched until a success. The high reliabilities of the launch vehicles under consideration, however, reduce the importance of these extreme events. A launch vehicle with a reliability of 89 percent has a 0.1 percent chance of requiring four or more launches. Thus, the contributions to the expected cost and the variance from the unlikely scenarios involving many relaunches (3 or more) will have a minuscule additional impact on the estimated moments. For a complete list of assumptions along with justifications for these assumptions, the interested reader is directed to Appendix B.

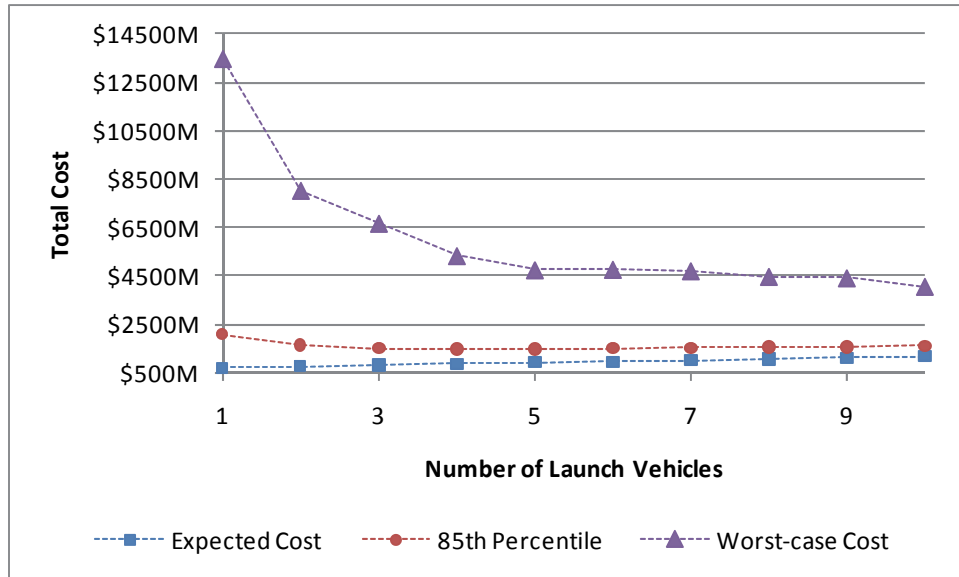
Figure 1.1
Example: Distribution of Total Program Cost for Different Launch Strategies



NOTES: Total cost is defined as the sum of the launch costs across all required launches (up to and including the first success), plus any small satellite repurchases associated with randomly generated catastrophic launch failures.

In the example in Figure 1.1, a risk-neutral decisionmaker would bundle all payloads on a single launch vehicle, since this strategy minimizes the expected cost. On the other hand, a risk-tolerant decisionmaker whose risk preferences correspond to the 85th percentile would use five launch vehicles, since this strategy minimizes the 85th percentile of the total cost (albeit narrowly over the four launch vehicle strategy). Figure 1.2 steps back to capture how the worst-case scenario changes with the payload bundling strategy.

Figure 1.2
Example: Distribution of Total Program Cost for Different Launch Strategies (Worst-Case Scenario)



NOTES: Total cost is defined as the sum of the launch costs across all required launches (up to and including the first success), plus any small satellite repurchases associated with randomly generated catastrophic launch failures.

In this scenario, a completely risk-adverse decisionmaker who seeks to minimize the worst-case scenario would initially utilize ten different launch vehicles, minimizing the cost under the worst-case scenario.

Clearly, in this example, the chosen launch strategy depends on the risk preferences of the decisionmaker or the program office.

Identifying Optimal Launch Strategies

Real world launch decisions are more complicated than the aforementioned notional example. Heterogeneous payloads, multiple classes of available launch vehicles, and performance constraints on the maximum allowable mass and capacity all increase the size and complexity of these decisions. The exponential growth in the number of possible launch strategies means that it becomes infeasible to enumerate and calculate

the desired cost percentile for all possible launch configurations for relatively large problems.¹⁰ To provide insight into these large problems, I developed a two part framework for describing the optimal launch strategy across different risk preferences.

First, I used an optimization algorithm to prune all possible launch strategies into an efficient set of launch strategies with respect to the expected cost and the spread in worse-than-expected realizations.¹¹ The downside semivariance of the total cost is used to measure the spread in worse-than-expected realizations.¹² The downside semivariance is defined as the mean squared distance above the expected cost and is similar to the variance of a distribution. A launch strategy is efficient with respect to expected cost and the downside semivariance if it is impossible to decrease the expected cost of a launch strategy without simultaneously increasing the downside semivariance of the launch strategy.

The downside semivariance is an adequate initial surrogate for launch risk. A consistent risk measure must take into account the probability associated with unfavorable events, as well as the repercussions of these events. When selecting launch strategies for small satellites, the downside semivariance can be reduced in two ways: The probability of worse-than-expected scenarios occurring can be reduced, or the severity of the repercussions associated with worse-than-expected scenarios can be reduced. Figure 1.3 displays a set of

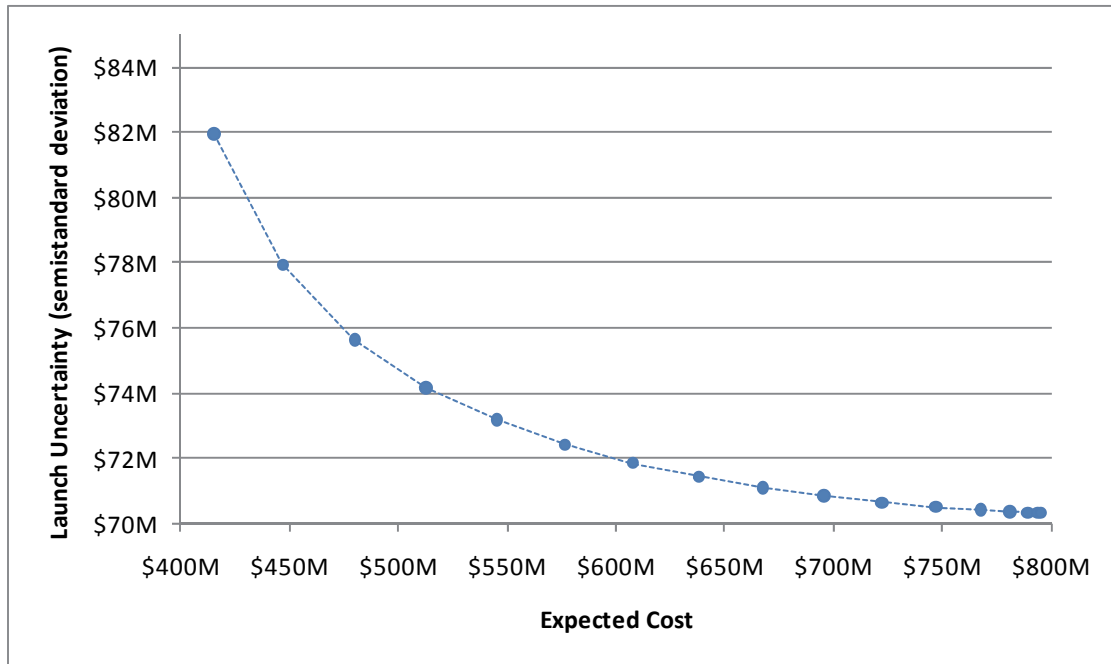
¹⁰ Appendix A discusses the growth in the number of launch strategies.

¹¹ Appendix B provides a thorough overview of this optimization model.

¹² The mathematical formula for the downside semivariance is $SemiVar(X) = E[\max(0, X - E[X])^2]$, where X is a random variable measuring cost. Whereas variance is a measure of the amount of spread in a distribution, downside semivariance is a measure of the amount of spread across those realizations that are worse-than-expected. Markowitz suggested the use of downside semivariance as a risk measure for skewed distributions (Markowitz, 1959). The square root of downside semivariance is referred to as the semistandard deviation and is used for plotting purposes so that all axes are in the \$M and not \$M².

launch strategies that are efficient with respect to cost and uncertainty (downside semivariance).

Figure 1.3
Efficient Set of Launch Strategies with Respect to Cost and Uncertainty
(Downside Semivariance)

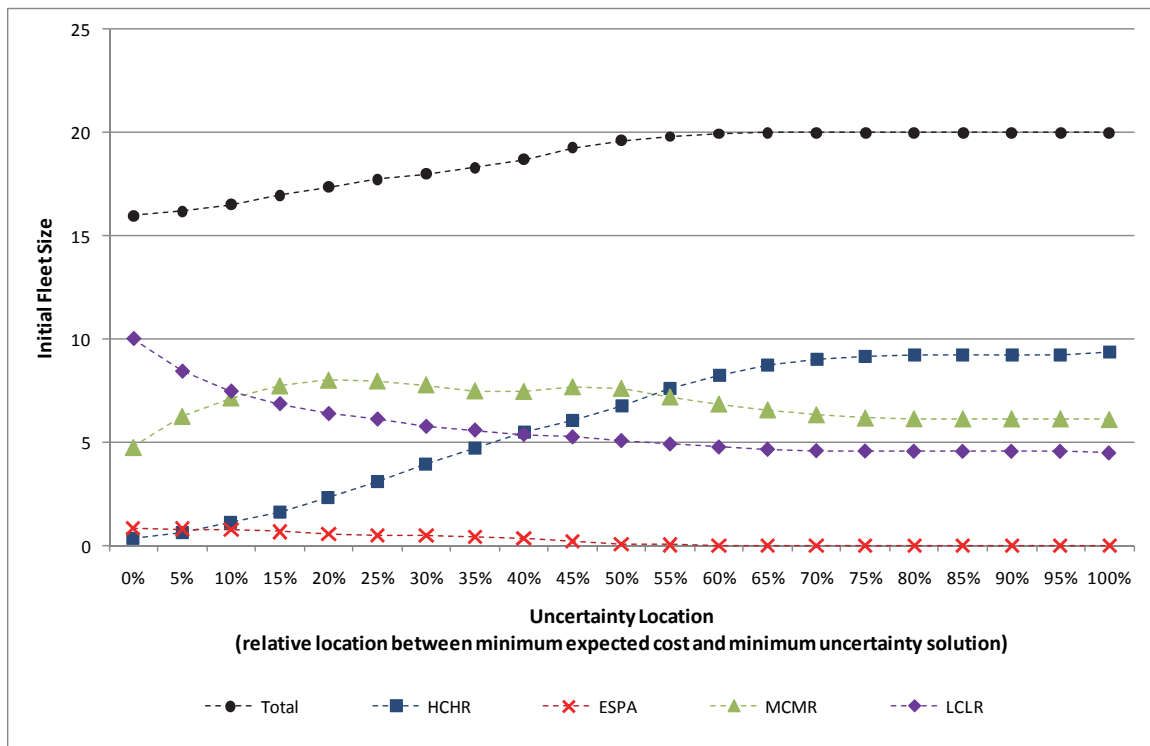


NOTES: This figure traces out an efficient frontier of launch strategies. Each discrete point represents an efficient launch strategy. To obtain this figure, ten randomly generated sets of 20 payloads were drawn, and an optimization algorithm was used to minimize the downside uncertainty across a spectrum of constraints on the expected costs. Table 1.3 contains the set of considered launch vehicles. In addition, when generating this figure, MCMR LV capacity was held at one. The reliability of the LCLR LV was held at 90 percent with a cost of \$12 million. The HCHR LV classification was similar to the Delta II. The provided frontier is the average result from ten sets of 20 randomly generated payloads with a constraint on the expected cost incremented in steps of 2 percent.

Each point in Figure 1.3 represents a specific launch strategy. A launch strategy includes a set of initial launch vehicles and an assignment of payloads to launch vehicles.

In the notional example shown in Figure 1.1 and Figure 1.2, the number of launch vehicles used to service the set of payloads uniquely defined the level of risk exposure. With multiple classes of launch vehicles that have different costs and reliabilities, the number of initial launch vehicles no longer uniquely identifies the risk exposure of a strategy. Instead, I index the risk exposure of a launch strategy based on the relative distance of the expected cost between the minimum expected cost solution and the minimum uncertainty solution. Hereafter, this measure is referred to as the *uncertainty location* of an efficient launch strategy. For example, a launch strategy with an uncertainty location of 30 percent has an expected cost that is 30 percent of the way between the minimum expected cost solution and the expected cost of the minimum uncertainty solution. Figure 1.4 uses this terminology to display how the structure of the small satellite launch fleet changes across different levels of exposure to uncertainty.

Figure 1.4
Optimal Small Satellite Launch Vehicle Fleet Structure across
Uncertainty Locations



NOTES: This figure corresponds to the efficient frontier in Figure 1.3.

Figure 1.4 demonstrates that the class of HCHR LV is utilized very little under the solution that minimizes expected cost (0 percent), and utilized heavily under the uncertainty minimizing solution (100 percent). Therefore, the HCHR class of launch vehicles is used sparingly on the cost-minimizing side of the spectrum and heavily on the uncertainty minimizing side of the spectrum, while the opposite pattern holds for the class of LCLR LV. Also, at an uncertainty location of 60 percent, each payload is assigned to its own launch vehicle. This strategy increases the expected cost but decreases the amount of uncertainty in the cost distribution.

From a theoretical standpoint, the downside semivariance is an attractive risk measure (Zenios, 2007); however, it does not provide an intuitive description of the implications of different risk postures. As such, the second step of this framework uses Monte Carlo simulation to estimate the upper percentiles of the total cost of each efficient launch strategy. These percentiles provide a more intuitive description of risk implications associated with launch decisions. An 85th percentile of \$800 million implies that 85 percent of all possible realizations will result in a total cost that is less than \$800 million. Tracing out an efficient set of launch strategies reduces the set of possible launch strategies into a tractable set of strategies that can be investigated thoroughly through the use of Monte Carlo simulation, providing insight into the distribution of total cost in a way that captures varying risk preferences. The distribution curves produced in this step are similar to those found in Figure 1.1 and Figure 1.2.

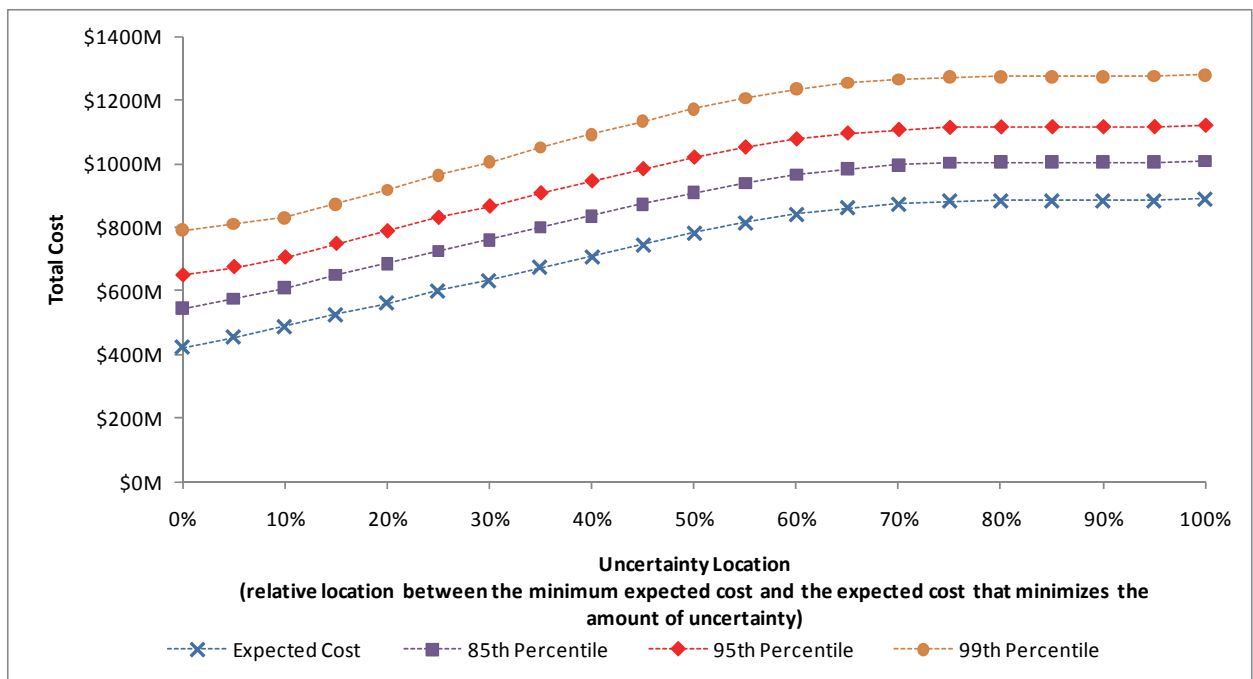
RESULTS

Small Satellite Launch Strategies and Risk Preferences

So far in this research, I have not made any objective judgments concerning risk posturing for small satellite launch programs. Relying on targeted small satellite launch demand and the performance attributes of available launch vehicles, this section evaluates how real world small satellite launch decisions change with risk preferences. The framework presented above was applied to 500 randomly generated sets of

payloads consisting of 20 small satellites each. On average, each satellite costs \$40 million. For each set of payloads, the optimal launch strategy was traced out across a spectrum of risk preferences. Figure 1.5 traces out the cost distribution as the risk preferences of the decisionmaker vary from risk-neutral (0 percent) to extremely risk-averse (100 percent).

Figure 1.5
Distribution of Total Cost across Launch Strategies (20 Small Satellites with an Average Cost of \$40M per Satellite)



NOTES: Vertical columns of points represent the cost distribution for an optimal launch strategy. *Uncertainty location* is defined as the relative location between the expected cost-minimizing launch strategy and the uncertainty minimizing launch strategy. For example, an uncertainty location of 0 percent corresponds to the launch strategy that minimizes expected cost; 100 percent corresponds to the solution that minimizes uncertainty, and 30 percent corresponds to the launch strategy with an expected cost 30 percent of the way between the minimum expected cost and maximum expected cost.

Unlike the notional example in Figure 1.1 and Figure 1.2, the results in Figure 1.5 suggest that given real world performance parameters and constraints, decisionmakers of varying risk preferences

should all make the same decision when choosing how to launch a set of 20 small satellites. Here, the risk-neutral decisionmaker operates based on minimizing the expected cost. The completely risk-adverse decisionmaker would make the same decision minimizing the worst-case scenario. The plot lines in Figure 1.5 are averaged across 500 randomly drawn sets of payloads. On average, the optimal launch strategy across all considered risk preferences is always at the cost-minimizing solution; however, some of the replications resulted in optimal launch strategies that were not at this location.

Table 1.5
Frequency That the Optimal Launch Strategy Occurred at Uncertainty
Locations 0%, 5%, and 10%

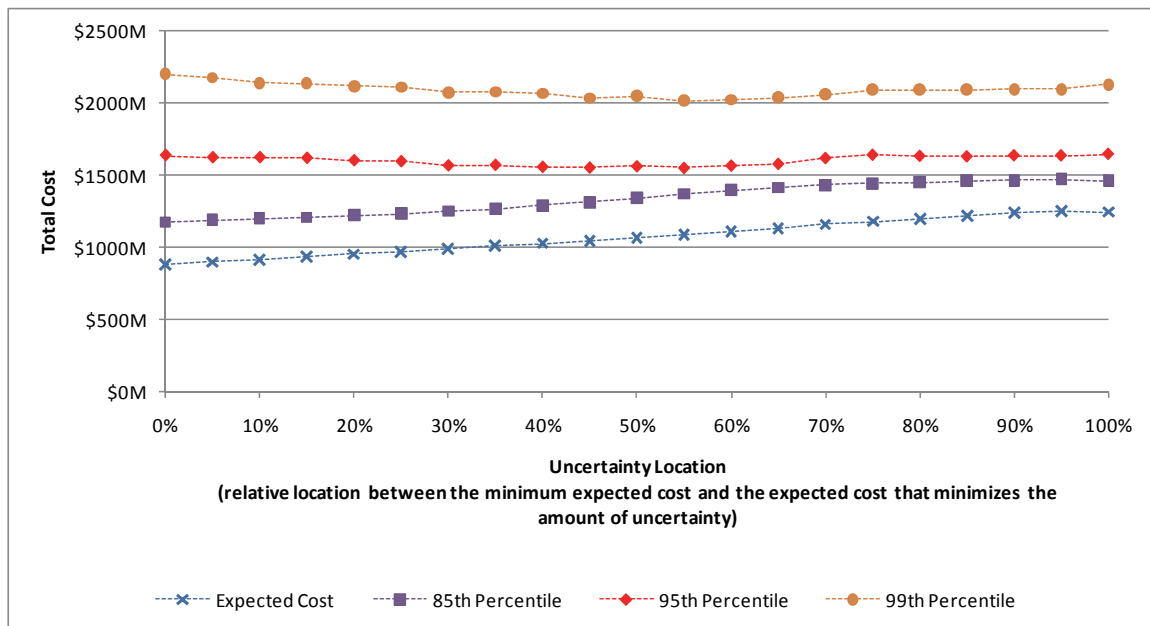
Uncertainty Location	75th Percentile	80th Percentile	85th Percentile	95th Percentile	99th Percentile
0%	99%	98%	98%	90%	66%
5%	1%	2%	1%	9%	25%
10%	0%	0%	1%	1%	9%

Table 1.5 contains the probability that the optimal solution exists at a given uncertainty location for five different levels of risk-aversion. For example, the column labeled "75th Percentile" demonstrates that if it is assumed that the decisionmaker selects the launch strategy that minimizes the 75th percentile, then 99 percent of the replicated payload sets result in an optimal uncertainty location of 0 percent (i.e., the solution that minimizes the expected cost), 1 percent occur at the 5 percent uncertainty location (i.e., the solution with an expected cost that is 5 percent of the way between the minimum expected cost and the expected cost that minimizes the amount of uncertainty), and 0 percent of the replications result in an optimal uncertainty location of 10 percent or greater.

While the expected cost-minimizing strategy is not always the optimal decision across all levels of risk aversion, it is the correct

decision the vast majority of the time for a reasonable set of risk preferences (75th percentile to 95th percentile). Nearly all optimal small satellite launch decisions exist within 5 percent of the cost-minimizing solution. To determine whether these results are robust to changes in targeted demand and the average cost of small satellites, I performed this same analysis for payloads sets that contained five and ten small satellites, respectively, and small satellites with an average cost of \$100 million and \$200 million, respectively. No statistically significant deviations from the above results were observed in the case of \$100 million payloads. As the average price per small satellite increases to \$200 million, there is no longer a launch strategy that is optimal across all risk preferences. Figure 1.6 shows the distribution of total cost changes across different levels of uncertainty exposure for 20 payloads with an average cost of \$200 million.

Figure 1.6
Distribution of Total Cost across Launch Strategies (20 Small Satellites with an Average Cost of \$200M per Satellite)



When dealing with payloads with an average cost of \$200 million or more, different risk preferences will result in different launch

decisions. The risk-adverse posture of the USAF when launching exquisite space systems supports this result. On the other hand, when dealing with satellites that cost between \$40 million and \$100 million, risk preferences have little to no impact on the optimal launch strategy. This suggests the USAF can, and should, pursue risk-tolerant launch strategies for small satellite launches and focus more on minimizing expected cost versus minimizing the spread of the upper percentiles of the cost distribution.

Improving Small Satellite Launch Capabilities

Since I have established that the USAF should pursue more risk-tolerant launch strategies for small satellite launch support, this section analyzes the cost and risk impact of different policy levers designed to improve small satellite space launch capabilities. Four policy scenarios were considered, along with a baseline scenario:

1. **Baseline:** This scenario was constructed to reflect the current set of small satellite launch capabilities. The baseline policy scenario assumes that the EELV is the only available HCHR LV. The baseline scenario also includes the 180-kilogram constraint placed on payloads that are launched on an ESPA ring. In this scenario, the MCMR LV could not dual manifest additional payloads. Finally, the baseline scenario does not include an LCLR LV.
2. **Continued Use of the Delta II for Small Satellite Launch:** This policy option would use the Delta II as a HCHR LV for small satellite launch. Despite the approaching retirement of the Delta II from the NSS launch vehicle inventory, the Delta II still garners interest in the civilian sector where "the rocket is an inviting option for launching a new class of lighter, simpler satellite" (Pasztor, 2007). This is the same satellite niche envisioned by the AF SAB and proponents of NSS small satellites. Because it could potentially support small satellite launches, the AF SAB has recommended that the decision to retire the Delta II be carefully

reconsidered (AF SAB, 2007). This scenario assumes that any continuation of the Delta II program would provide launch vehicles at current cost and performance levels.

3. **Merging ESPA Ring Slots:** The ESPA ring contains six slots for additional payloads. These slots can support a payload of up to 180 kilograms. This policy lever looked at the impact of providing the capability to merge two adjacent ports on the ESPA ring, supporting payloads of up to 360 kilograms. This would allow larger small satellites to be grouped together on ESPA-fitted vehicles. This modification has also been suggested in prior research (AF SAB, 2007; Chavez, Barrera, and Kanter, 2007).
4. **Dual Manifest Capabilities on the MCMR LV:** Bundling small satellites is an important dimension of the small satellite launch strategy decision framework. Based on research interviews conducted with rideshare launch experts, it is currently difficult to bundle small satellites larger than 180 kilograms on medium-cost launch vehicles without considerable increases to the amount of required integration and testing. As such, this policy option would include technological modifications to the MCMR LV class of launch vehicles (e.g., Minotaur IV) that would allow the launch vehicle to easily manifest two payloads simultaneously without lengthy integration and testing.
5. **Fielding a Low-Cost, Low-Reliability Launch Vehicle:** A low-cost, low-reliability launch vehicle may be suitable for small satellites. These launch vehicles would trade reliability for reduced costs, with the gains in cost-effectiveness offsetting the increased probability of a launch failure. Such a launch vehicle would be a drastic departure from the current risk-adverse launch framework. For this portion of the analysis, the LCLR was assumed to

operate at a reliability of 89 percent with a cost of \$12 million per launch.¹³

To determine the relative impact of each policy lever, the above framework was used to select a portfolio of launch vehicles for 20 small satellites under these five scenarios. The cost and risk associated with each scenario were then compared to get an understanding of the impact each policy lever had on small satellite launch capabilities. A full design of experiments was run on the five considered policy levers using ten randomly generated sets of 20 payloads for each scenario.

Similar to earlier findings, across the vast majority of the replications, the launch strategy that minimized expected cost was the same strategy that minimized the worst-case scenario. Therefore, the earlier finding that the expected cost-minimizing solution is usually the optimal decision point across varying risk preferences is likely robust to multiple policy levers and available sets of capabilities. Thus, moving forward in the analysis, all decisions regarding the optimal launch strategy minimize expected cost.

Table 1.6
Cost and Risk Implications of Considered Policy Levers

	Expected Cost	Total Cost			Average Fleet Size			
		85% Cost	95% Cost	99% Cost	HCHR LV	ESPA LV	MCMR LV	LCLR LV
Baseline	\$1143M	\$1222M	\$1293M	\$1383M	0.0	0.0	19.8	0.0
Delta II	\$1015M	\$1106M	\$1182M	\$1303M	0.6	1.2	13.2	0.0
ESPA LV 360-kg payloads	\$976M	\$875M	\$1042M	\$1173M	0.0	2.6	4.9	0.0
MCMR LV dual manifest	\$800M	\$860M	\$070M	\$1082M	0.0	0.0	10.0	0.0
LCLR LV	\$792M	\$1052M	\$1137M	\$1245M	0.0	0.0	1.3	18.7

¹³ Because a mature low-cost, low-reliability launch vehicle does not currently exist, these numbers are difficult to verify. A reliability of 89 percent and a cost of \$12 million were chosen in order to provide some differentiation when compared with the MCMR LV. Later, I address the sensitivity of the utilization of the LCLR LV to these parameters.

Table 1.6 summarizes the cost and risk impacts of these different policy levers. The development of an LCLR LV has the largest impact on the expected cost, while the ability to dual manifest on the MCMR LV has the largest impact on the risk associated with supporting a small satellite program that consists of 20 payloads per year. Even though the LCLR LV is the riskiest of the four considered policy options, the 95-percent cost percentile for this option is still less than the expected cost under the baseline scenario.

This research did not attempt to price these policy levers. The ESPA ring modifications and the MCMR LV modifications appear to be the most attractive, assuming that they could be accomplished with a reasonable amount of effort. These options offer large reductions in cost and risk and require only modifications to existing systems. On the other hand, resurrecting the Delta II or developing a new launch vehicle would require significant investments while providing less of an impact on cost and risk.

These results also inform discussions on the optimal structure of the small satellite launch vehicle fleet. Both the Delta II and the EELV (alone and without an ESPA attachment) are not optimally positioned to support small satellite space launches. Under the baseline scenario, neither the HCHR LV nor the ESPA is utilized optimally (see the "Average Fleet Size" columns of Table 1.6). Table 1.6 also demonstrates that policymakers should consider extending the use of the Delta II for small satellite launches only if it can be fitted with an ESPA-like attachment. The utility of the ESPA ring would increase dramatically if it could be easily modified to allow two adjacent slots to be merged in support of payloads with a mass of 360 kilograms. In the absence of an LCLR LV, the MCMR LV would perform the majority of small satellite space launches.

While the framework used to make these recommendations does not proactively consider and manage mission risk, the Monte Carlo simulations can be used to gauge the mission risk implications of different launch strategies retroactively. One important statistic is the number of launch iterations required to orbit the entire set of payloads (see Table 1.7). The "number of iterations" is defined as the

maximum number of launch attempts required to successfully orbit all satellites in a payload set. For example, if, after the first round of launches, three launch packages failed to reach orbit, the decisionmaker would have to relaunch these three launch packages. If all three remaining packages are placed in orbit the second time, two iterations were required.

Table 1.7
Number of Iterations Until All Payloads Are Orbited

	1 Iteration	2 Iterations	3 Iterations
Baseline	37%	95%	100%
Delta II	50%	97%	100%
ESPA LV 360-kg payloads	73%	99%	100%
MCMR LV dual manifest	60%	98%	100%
LCLR LV	14%	83%	98%

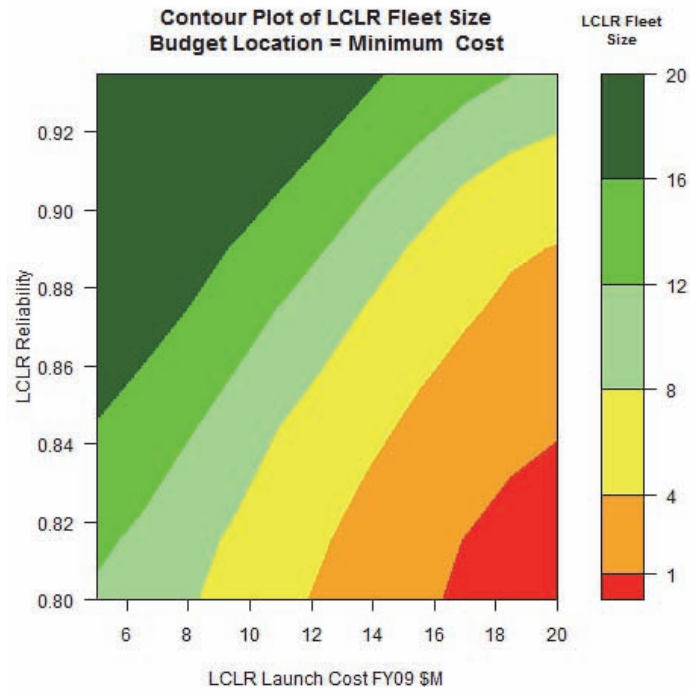
While the addition of the LCLR LV performs relatively well with respect to cost, these financial savings come at the cost of availability. Under the baseline scenario, there is only a 37 percent chance that all 20 payloads will be orbited and operational after the first iteration of launches. For the LCLR LV scenario, this number drops to 14 percent. Modifying the ESPA ring to support payloads with a mass of 360 kilograms not only provides significant cost-savings, it also doubles the probability that all 20 payloads will be orbited and operational after the first iteration of launches, making it the most attractive policy lever.

The Role of a Low-Cost, Low-Reliability Launch Vehicle

The addition of a LCLR LV to the small satellite launch fleet was shown to significantly reduce the expected required cost to launch 20 small satellites. The earlier portion of this analysis assumed that this LCLR LV would cost \$12 million per launch and have a reliability of 89 percent. These numbers cannot be verified because a mature LCLR LV does not currently exist. This section examines how the utilization of a LCLR LV would change based on its cost and reliability. Figure 1.7

displays the initial number of LCLR LV launch vehicles used per year (or per 20 small satellite payloads) across the cost and reliability space.

Figure 1.7
Utilization of LCLR LV Based on Cost and Reliability



Even for less than optimistic realizations of the cost and the reliability of an LCLR LV, if the decisionmaker is willing to accept the increased mission risk documented in Table 1.7, there exists a defined role for such a launch vehicle in support of small satellite space launches.

SUMMARY OF FINDINGS AND CONCLUSIONS

- ***The ability to bundle many satellites on the same launch vehicle provides an additional cost-risk tradeoff that is unique to small satellites.*** There are two significant drivers of financial risk in the context of small satellite space launch: the reliability of the launch vehicles and the aggregation of multiple payloads onto the same launch

vehicle. The reliability of the selected launch vehicle impacts the probability of catastrophic launch failures. Bundling multiple payloads together increases the severity associated with catastrophic launch failures. While all satellite programs face decisions regarding launch vehicle reliability, the option to bundle multiple payloads together is a unique aspect of small satellite space launch and has important cost and risk implications. Aggregating payloads together on the same launch vehicle decreases expected cost by spreading out launch costs across multiple payloads, but it can also increase risk.

- ***In the context of small satellite launches and the current set of obtainable capabilities, the risk-neutral decision is the same as all risk-adverse decisions.*** This fact reduces the difficulty of the decision problem since the same launch strategy is optimal for all rational risk preferences (excluding risk-seeking preferences). This supports the claim that the USAF should be more risk-tolerant when making small satellite launch decisions. This conclusion holds across different sizes of payload sets (5 payloads per year, 10 payloads per year, and 20 payloads per year) as well as different distributions for the cost of a small satellite (\$40 million per satellite and \$100 million per satellite). For payloads that cost \$200 million or more, the risk preferences of the decisionmaker start to have an impact on the launch decision.
- ***Given the current set of launch capabilities, the MCMR class of launch vehicles would provide most of the support for small satellite space launches. The current set of launch capabilities is ill positioned to support a large-scale small satellite program.*** The EELV and ESPA fitted EELV would contribute little to small satellite space launches at optimality, giving the USAF little flexibility in how it

supports a large-scale small satellite launch program. These findings align with previous AF SAB findings.

- ***Adding dual manifest capabilities to the MCMR LV and creating an ESPA attachment that can support payloads of 360 kilograms both result in larger risk reductions than extending the life of the Delta II in support of small satellite space launches.***

While using the Delta II to bolster small satellite launch capabilities would provide an improvement over the baseline set of capabilities, it is inferior to others that involve only modifications to existing launch vehicle systems. The ability to easily dual manifest on the MCMR class of launch vehicles would reduce the expected total cost by \$343 million per 20 payloads and the 85th percentile by \$362 million. Modifying the ESPA ring to support 360-kilogram payloads would reduce the expected cost by \$167 million per 20 payloads and reduce the 85th percentile by \$347 million.

- ***Based on financial risk alone, there is a compelling case for developing an LCLR LV; however, the significant increase in mission risk warrants additional research to ensure that such a strategy is in the best interest of the USAF.*** The development of an LCLR LV would provide significant cost savings while reducing financial risk; however, it would also increase the mission risk associated with fielding a set of small satellites. The option to use an LCLR LV would decrease the expected cost by \$351 million per 20 small satellite payloads, but it would decrease the 85th percentile cost by only \$170 million. In addition, while the other three policy options considered would decrease both financial risk and mission risk, the LCLR LV would increase the mission risk associated with launching 20 small satellites. By incorporating the LCLR LV at the minimum expected cost solution, the probability of fielding all 20 small satellites after a single round of launches is only 14 percent, whereas

the baseline probability is 37 percent. Three or more iterations would be required 17 percent of the time when using an LCLR LV at the expected cost-minimizing solution, while three or more iterations are required only 5 percent of the time under the baseline set of capabilities. The other three policy options would reduce both financial risk and mission risk, and should be considered further if the USAF wishes to support an ambitious small satellite launch program.

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ESSAY TWO: CHALLENGES ASSOCIATED WITH EXPANDED NATIONAL SECURITY SPACE RIDESHARING

INTRODUCTION AND BACKGROUND

Reliable and affordable access to space is an important enabler of National Security Space (NSS) capabilities (National Space Policy of the United States of America, 2010). The reliability of the U.S. domestic launch infrastructure for large satellites is unrivaled; however, one significant shortcoming is the limited number of cost-effective launch options for small satellites (AF SAB, 2007). Ridesharing small satellites on launch missions purchased in support of larger payloads could help make access to space more affordable for small satellites. The U.S. Air Force (USAF) has recently placed an increased emphasis on expanding the number of rideshare opportunities for auxiliary payloads (APLs). In a 2008 memorandum, the Secretary of the Air Force (SecAF) instituted the policy goal of making ridesharing on the Evolved Expendable Launch Vehicle (EELV) commonplace by 2012. The memorandum noted that this policy "is an important milestone in [USAF] efforts to provide routine and affordable access to space for scientific, research, development and Operationally Responsive Space¹⁴ (ORS) missions" (Wynne, 2008, pp. 1).

While the expanded use of these secondary payload adaptors could make access to space more affordable for small satellites, there are also potential drawbacks. Launch missions do not always successfully place their payloads in the correct orbit, and adding additional payloads could increase the risk of this negative outcome.¹⁵ Small satellites cost tens of millions of dollars (AF SAB, 2007). Traditional NSS satellites cost hundreds of millions of dollars, can spend upwards of ten years in development, and will be the foundation of NSS

¹⁴ Operationally Responsive Space is defined as "assured space power focused on timely satisfaction of Joint Forces Commander's needs" (DoD, 2007).

¹⁵ Bundling secondary payloads on a launch mission increases the complexity of the launch integration process.

capabilities for the foreseeable future (AF SAB, 2007; GAO, 2008). Because losing one of these systems has severe financial and operational consequences that are much larger than potential savings that result from ridesharing, the existence and magnitude of any changes in launch vehicle reliability associated with ridesharing auxiliary payloads must be keenly understood in order to make informed rideshare launch decisions.

This research aims to inform NSS rideshare policy by addressing the following questions: What secondary payload adaptors are available for ridesharing small satellites? Can rideshare launch missions improve rapid reaction space launch capabilities? What impact do the various stakeholders and the launch manifest process have on the number and potential utilization of rideshare opportunities? Do rideshare launch missions result in any increased risks to the primary payload, and if so, is ridesharing auxiliary payloads still a cost-effective launch option for small satellites?

EELV AND SECONDARY PAYLOAD ADAPTORS

This section provides an overview of available secondary payload adaptors. Most DoD-compatible secondary payload adaptors are designed to interface with an Evolved Expendable Launch Vehicle (EELV).¹⁶ This overview is based on interviews I conducted with DoD launch professionals and commercial launch providers.

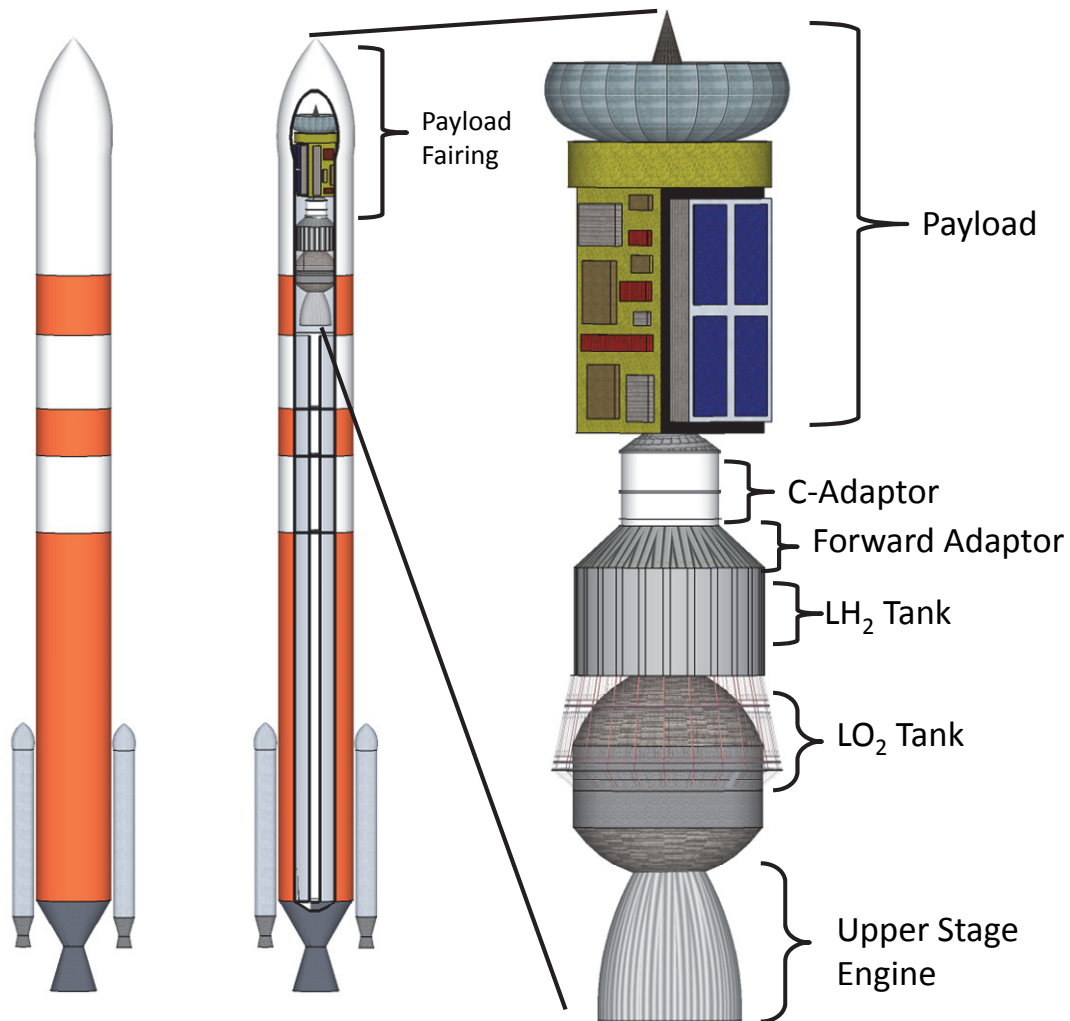
EELV Launch System

The EELV program was designed to make DoD space launch more affordable and reliable by replacing the existing fleet of DoD launch vehicles with two launch systems (the Delta IV and the Atlas V) that use

¹⁶ Secondary payload adaptors exist for other launch vehicles. The Launch Vehicle Rideshare Adapter is designed to integrate with the Falcon 1, Minotaur I, and the Minotaur IV. The Multi-Payload Adapter is designed to integrate on the Minotaur IV. I chose to focus on EELV secondary payload adaptors because the vast majority of NSS launch missions and future rideshare opportunities utilize the EELV.

interchangeable components and launch infrastructure.¹⁷ United Launch Alliance (ULA) manufactures and supports both the Delta IV and the Atlas V launch vehicles. While there are multiple variants of the Delta IV and the Atlas V, they share a similar overall structure (see Figure 2.1).

Figure 2.1
EELV Design and Terminology



¹⁷ See the USAF EELV Factsheet for a survey of the EELV program history. Publicly available at <http://www.vandenberg.af.mil/library/factsheets/factsheet.asp?id=5207> as of February 14, 2011.

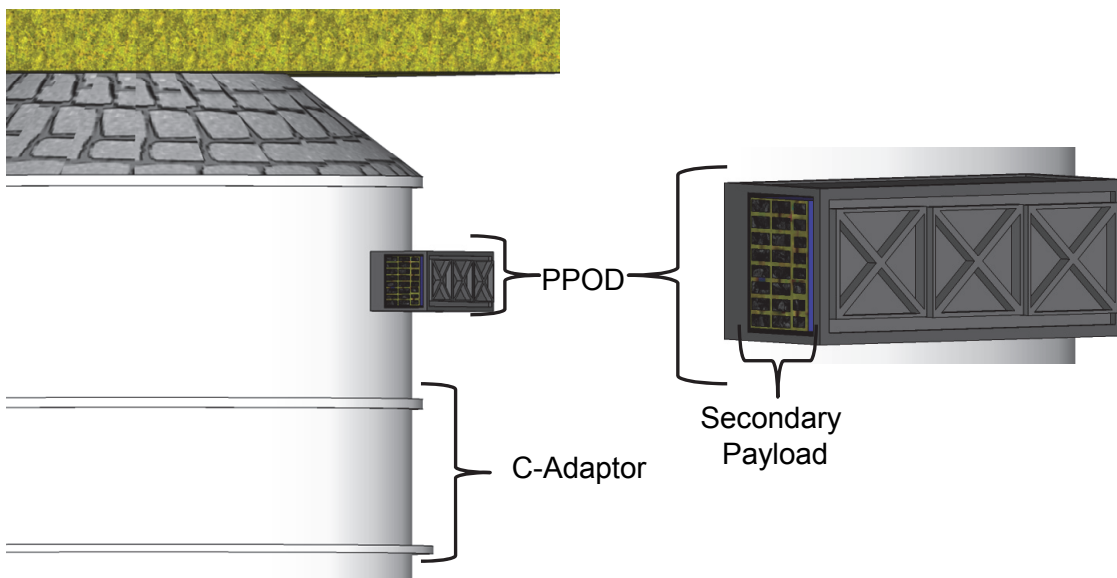
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The height of the EELV ranges from 63 to 70 meters, with a diameter between 4 and 5 meters (Isakowitz, Hopkins, and Hopkins, 2004). Most auxiliary payload adaptors interface with the launch system above the upper stage rocket engine. A forward adaptor (also referred to as a payload attach fitting) is used to mount the primary payload on top of the upper stage rocket. C-adaptors of varying heights can be used to accommodate different sized payloads. The payload fairing is an encasing for the payload. The dimensions of the payload fairing vary, depending on the size of the primary payload.

Secondary Payload Adaptors

The *Poly Picosat Orbital Deployer (PPOD)* is a secondary payload adaptor designed to rideshare very small payloads (see Figure 2.2).

Figure 2.2
PPOD with Integrated Secondary Payload



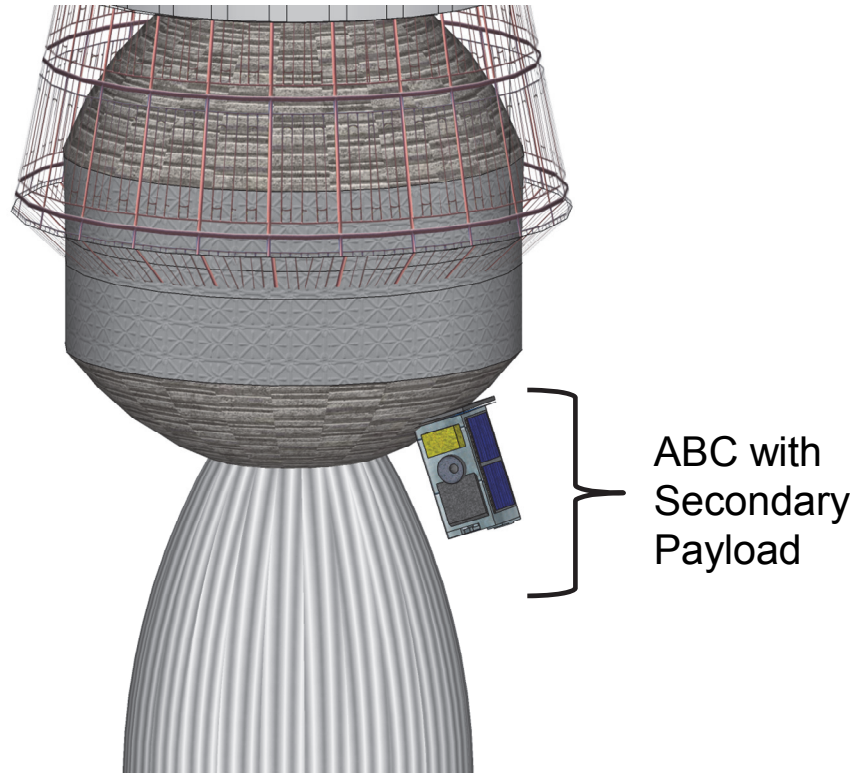
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The original PPOD was designed to support three CubeSats,¹⁸ with a maximum total volume of 34cm x 10cm x 10cm. PPODs come in many different shapes and sizes, but all of them are based on the CubeSat dimensions. The traditional three-satellite PPOD container has a mass of 2.5 kilograms when empty and can accommodate up to 10 kilograms of payload hardware, provided the volume constraints are not violated. PPODs can be mounted on multiple surfaces including c-adaptors, the aft bulkhead of the upper stage rocket, and other secondary payload adaptors.

The **Aft Bulkhead Carrier (ABC)** is designed to support payloads up to 80 kilograms. This secondary payload adaptor attaches on the aft bulkhead in a location normally reserved for a hydrazine canister. The payload can be released in low earth orbit (LEO). Unlike other secondary payload adaptors, the ABC is isolated from the primary spacecraft (see Figure 2.3).

¹⁸ A CubeSat is a common satellite interface that measures 10cm X 10cm X 10cm. A picosatellite is a satellite with a mass between 0.1 kilograms and 10 kilograms. The *CubeSat Design Specification Revision 12* (California Polytechnic State University, not dated) provides an overview of the CubeSat standard bus.

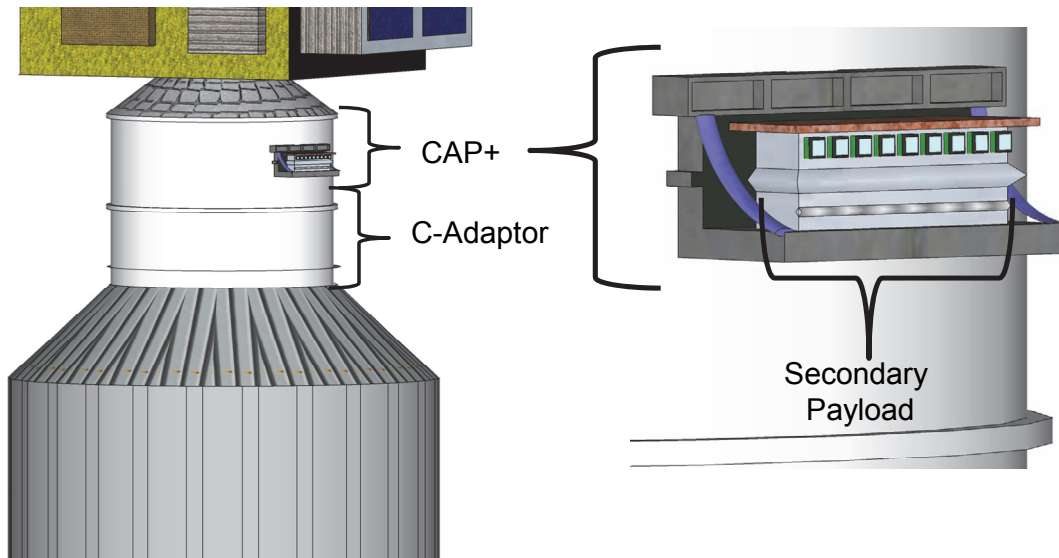
Figure 2.3
ABC with Integrated Secondary Payload



NOTE: This figure was rendered by the author.

The *C-Adaptor Platform Plus (CAP+)* is a secondary payload adaptor that is bolted to a c-adaptor and can support payloads up to 100 kilograms. Because the CAP+ does not jettison its payload, the final orbit of the upper stage components must be compatible with the mission profile of the secondary payload. One potential use of the CAP+ is to demonstrate new space system components in their operational environment. The typical EELV launch configuration can accommodate between two and four CAP+ packages (see Figure 2.4).

Figure 2.4
CAP+ with Integrated Secondary Payload

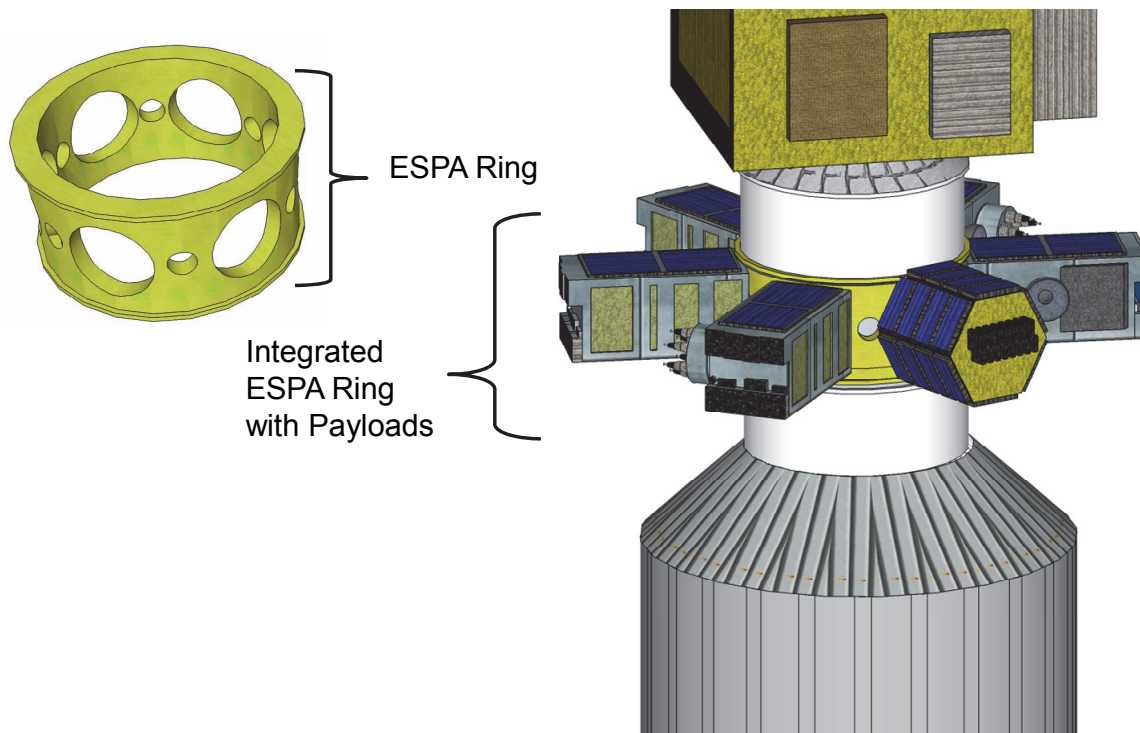


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The **EELV Secondary Payload Adaptor (ESPA) ring** is a modified c-adaptor that can accommodate six additional payloads (see Figure 2.5). Each payload must be less than 180 kilograms and fit within a 61cm x 71cm x 89cm volume. Several modifications to the ESPA ring have been proposed, including a dual-port concept that would accommodate three payloads up to 360 kilograms (AF SAB, 2007). Another concept would facilitate the propagation of large constellations of small satellites by stacking multiple ESPA rings on top of each other on the same launch (Chavez, Barrera, and Kanter, 2007).¹⁹

¹⁹ As of 2011, the ESPA ring has been launched twice and is the most mature DoD secondary payload adaptor. A DoD Space Test Program launch mission (STP-1) in 2007 was the first launch to include an ESPA ring. A modified ESPA ring, known as the Lunar Crater Observation and Sensing Satellite was also included on the Lunar Reconnaissance Orbiter launch in 2009.

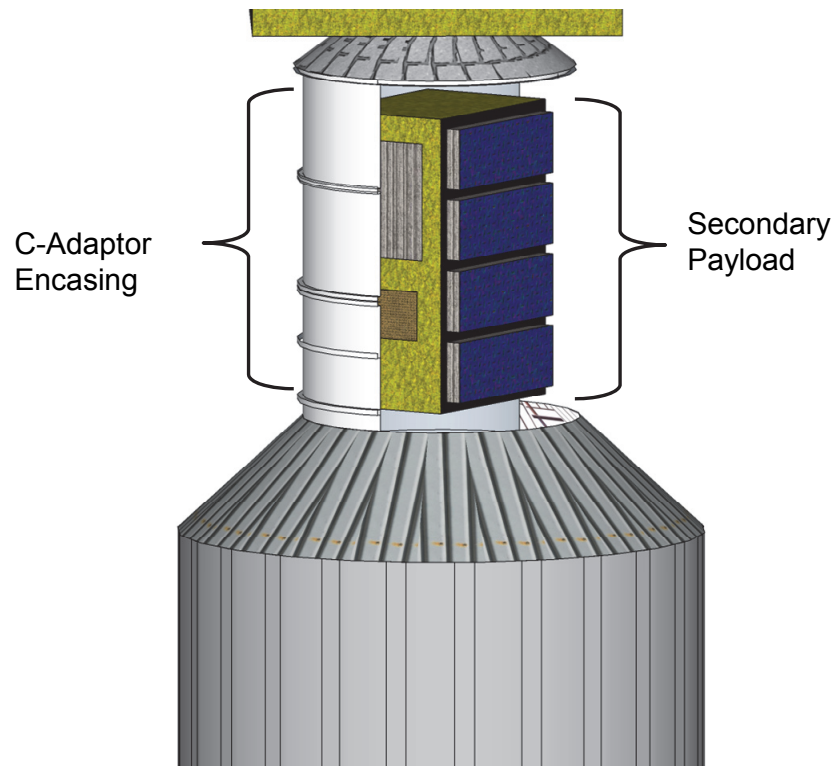
Figure 2.5
ESPA Ring with Integrated Secondary Payloads



NOTE: This figure was rendered by the author.

The *Integrated Payload Carrier (IPC)* takes advantage of the fact that stacked c-adaptors enclose a hollow space (see Figure 2.6). The IPC uses this empty volume to hold an additional payload with a mass that is less than 500 kilograms. Each c-adaptor has a diameter of just over 1.5 meters. The number of c-adaptors that the primary payload will accommodate constrains the maximum allowable height of the auxiliary payload. The IPC encasing can be c-adaptors or ESPA rings.

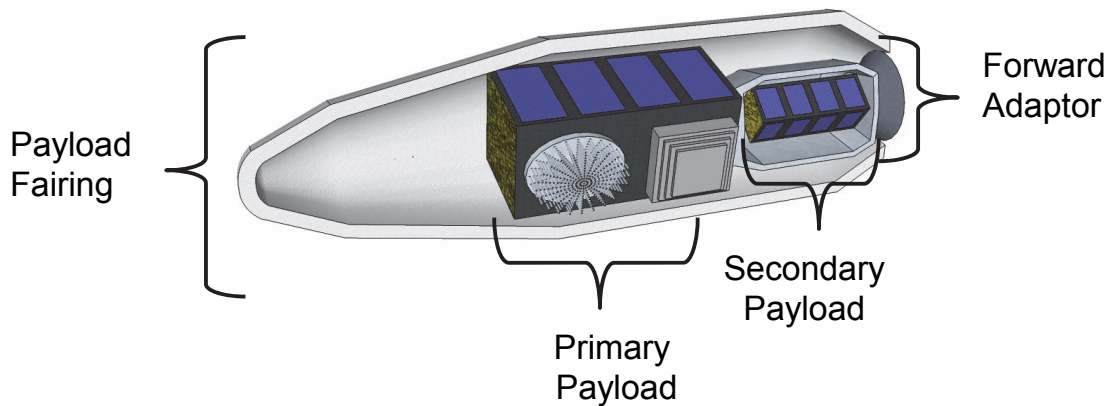
Figure 2.6
IPC and Integrated Secondary Payload (Cross-Section of C-Adaptors)



NOTE: This figure was rendered by the author.

The **Dual Satellite System (DSS)** is designed to support secondary payloads that are less than 2,000 kilograms. In this configuration, two payloads are stacked on top of each other within the payload fairing (see Figure 2.7). Different sized payload fairings and DSSs can accommodate a range of primary and secondary payloads.

Figure 2.7
DSS with Integrated Secondary Payload (Cross-Section of Payload Fairing)



NOTE: This figure was rendered by the author.

DOD RIDESHARE PROCESS AND FUTURE OPPORTUNITIES

Below I discuss the manifest process, operational considerations, and future opportunities for DoD rideshare launch missions. Because of its advanced technical maturity, I choose to focus on the ESPA ring. The USAF has developed a standardized process for manifesting and integrating additional payloads on an EELV via the ESPA ring. These procedures are contained in the *Evolved Expendable Launch Vehicle Secondary Payload Adapter Rideshare Users Guide* (ESPA RUG, 2010). The use of other secondary payload adaptors is currently considered nonstandard and handled on a case-by-case basis; however, the processes, stakeholders, and operational considerations are similar for other secondary payload adaptors.

DoD Rideshare Manifest Process

The Launch and Range Systems Directorate (SMC/LR), a subordinate unit of the Space and Missile Systems Center (SMC), is responsible for maintaining a database of available excess performance margins for upcoming DoD EELV launch missions. Potential rideshare opportunities are identified 36 months prior to the launch date. The Space Development and Test Directorate (SMC/SD) is responsible for developing and testing new space systems and space capabilities. As part of this effort, SMC/SD manages the DoD Space Test Program (STP), which is the

designated "front door" for all DoD APLs. After a potential rideshare launch opportunity is identified, STP works with SMC/LR to identify secondary payloads compatible with the mission profile and performance margins of the launch mission. If the APL organization and STP agree that the rideshare opportunity is favorable, SMC/LR conducts a detailed study with the commercial launch provider to evaluate technical feasibility. If the identified APL is compatible with the overall launch mission, STP and the APL organization put together an APL ESPA Space Flight Plan (ESFP). This package documents roles, responsibilities, funding, projected launch date, top-level mission elements or constraints, and the APL interface plan. In order for an APL to be officially manifested on a launch opportunity, SMC/LR, the primary spacecraft system program office (SPO),²⁰ SMC, and Air Force Space Command (AFSPC) must all approve the ESFP. Approval must be granted no later than 27 months prior to launch in order for the APL to be manifested on a launch opportunity.

Launch Integration and Quality Assurance

Once an APL has been manifested on a launch mission, the APL organization and the launch provider begin the launch integration process. SMC/LR and United Launch Alliance (ULA) have developed an ESPA standard service for integrating APLs on the EELV via the ESPA ring. This process starts 24 months before the launch date, after AFSPC has approved and manifested all APLs on a rideshare opportunity. The launch provider carries out a series of verification analyses to ensure that all launch vehicle systems will perform correctly during the launch and that the launch environment (i.e., the shock, thermal, and vibration loads during the flight) will not damage the onboard systems. This process cumulates with the physical integration of the primary and

²⁰ While this is the first official engagement of the primary spacecraft SPO per the ESPA Rideshare Users Guide, in practice, the primary spacecraft SPO is engaged repeatedly throughout the entirety of the rideshare manifest process.

auxiliary payloads with the launch vehicle at the launch site approximately one month before the launch date.

In addition to these analyses, there are a series of quality assurance requirements that ensure that the APLs do not adversely affect the launch mission. APLs must pass compliance reviews 18 months, 12 months, and 7 months before launch. These reviews assess whether the APL will be ready on schedule and be in compliance with all documented rideshare requirements. In addition, all APL organizations must build, validate, and provide a mass simulator that has the same mass, center of gravity, structural, and dynamic characteristics as the APL. If the APL fails to meet the compliance reviews, the mass simulator is used to ensure that the launch mission integration timeline will not be adversely affected. The decision to use a mass simulator in place of an APL must be made 12 months prior to launch. Because APL organizations are not the primary owner of the launch vehicle, they do not have the same authority over the launch integration process as the primary spacecraft SPO. For example, once integrated at the launch site, the primary spacecraft SPO has the authority to postpone a launch because of spacecraft anomalies. APL organizations do not have this authority. Finally, current rideshare procedures require that the primary spacecraft will separate from the launch vehicle before any additional payloads. This further reduces any risk to the primary spacecraft.

Rideshare Identification and Future Opportunities

An important step in the rideshare manifest process is the identification of potential rideshare opportunities. There are many factors that go into identifying a candidate rideshare opportunity, including available performance margins, mission profile, and schedule compatibility. These constraints limit the number of rideshare opportunities.

In order for a launch mission to be a rideshare candidate, it must have available performance margins to support additional payloads. All launch vehicles must be acquired with excess performance margins (Space

and Missile Systems Center EELV Program Office, 2005). These margins²¹ ensure that changes can be made to the launch vehicle to meet unforeseen mission needs. Only launch missions with performance in excess of these margins are considered for rideshare opportunities. The primary spacecraft SPO acquires and owns the launch vehicle for a given mission and is responsible for ensuring that the acquired launch vehicle can accommodate the primary space system within the required performance margins. Because additional performance increases the cost of a launch system, SPOs have little incentive to acquire launch systems with performance margins that exceed the stated regulations.²² The recent DoD emphasis on reducing the amount of space debris (see *National Security Space Strategy*, 2011) has further limited the number of available launch missions with excess performance margins. There is now a greater emphasis within the NSS community to deorbit upper stage rocket motors following a launch mission. These maneuvers require additional performance and currently take priority over launching additional payloads.

Even if a launch mission has excess performance margins available, any additional payloads must be compatible with the mission profile of the launch vehicle. Current rideshare procedures require all APLs to occupy the separation orbit of the primary spacecraft. While it is

²¹ Medium payload class vehicles must maintain a 7-percent performance margin above a three-sigma assured performance capability. Intermediate and heavy payload class vehicles are required to carry a 2-percent performance margin above a three-sigma assured performance capability. In addition, individual launch vehicles must also carry a fixed amount of performance margin for special instrumentation. For example, in addition to the 2 percent listed above, the Delta IV Medium must have an additional 115 pounds in reserve for special instrumentation. SMC/LR holds authority over these performance margins.

²² One space system program with performance margins available for additional payloads is the current refresh of the Defense Meteorological Satellite Program (DMSP). These satellites were originally designed to be launched on the Delta II. The USAF has since decided to discontinue the use of the Delta II, replacing it with the larger EELV. This change has produced performance margins for additional payloads. DMSP-19 and DMSP-20 are currently scheduled to use an ESPA ring to rideshare additional payloads.

possible to use any remaining upper stage rocket performance to reposition the secondary payload adaptor after the primary spacecraft has separated, in practice, these maneuvers are not considered because of the potential risk to the primary spacecraft, secondary payloads, and other payloads in orbit. Another factor that limits the secondary payloads to the separation orbit of the primary spacecraft is that most APLs are not large enough to support the propulsion required to change orbits. Thus, even if a launch mission has performance margins to support additional payloads, there is no guarantee that its mission profile will align with those payloads looking to rideshare into orbit.

Any secondary payload must also be compatible with the schedule of the overall launch mission. Even though the development and integration of the primary spacecraft and all auxiliary payloads proceed in parallel, the manifest process places specific requirements on the development of auxiliary payloads. Throughout the integration process, all auxiliary payloads must be able to accommodate the testing and verification milestones that start 24 months prior to launch. Even if a payload has been officially manifested on a launch opportunity, it will be dropped from the launch mission if it fails to meet the integration schedule.

The USAF aims to support one ESPA fitted EELV per year. In 2012, a modified ESPA ring will be rideshared on a Defense Meteorological Satellite Program (DMSP) launch mission (Scherbarth, Adler, and Ginet 2009). STP has arranged a series of ESPA standard service rideshare opportunities (Welden, 2011). In 2013, the first ESPA standard service launch mission will be rideshared on the AFSPC-4 launch mission. In 2014, an ESPA standard service will be hosted on an STP dedicated EELV. In 2015, another ESPA ring will be included on a DMSP launch mission. As of this writing, rideshare opportunities after this date have not been solidified, but STP is currently exploring the possibility of ridesharing an ESPA ring on National Reconnaissance Organization (NRO) launches in 2016 and 2017.

EMPIRICAL EVIDENCE OF RIDESHARING IMPACTS ON RELIABILITY AND LAUNCH DELAYS

Ridesharing Impacts on Reliability

The potential impact that ridesharing auxiliary payloads could have on launch vehicle reliability is a primary concern for those who oppose expanding DoD rideshare opportunities. Ridesharing efforts increase the complexity of the launch vehicle integration process. If this increased complexity has a detrimental impact on launch vehicle reliability, then these cost-saving efforts would expose the primary payload and its associated mission to an increased risk. Because the primary spacecraft SPO must approve any additional payloads, estimates of the magnitude and direction of any changes in reliability could improve the rideshare decision process. Despite this need, little to no empirical work has been dedicated to quantifying the change in launch vehicle reliability associated with ridesharing auxiliary payloads.

A dataset on historical space launches was compiled to test the hypothesis that ridesharing auxiliary payloads has a detrimental impact on launch vehicle reliability.²³ This dataset has catalogued every historical space launch attempt from 1957 through the present, along with the date, launch vehicle, assigned payloads, launch location, and launch outcome. To simplify the analysis, payloads were classified into one of five possible categories based on the owner of the primary spacecraft: NSS, Civil/Government, Commercial, International, and Other. The "NSS" category contains all domestic launches for which the mission of the primary space system was closely associated with national defense. The "Civil/Government" category contains all domestic launches that do not support national security efforts or a commercial effort (e.g., NASA launches). The "Commercial" category contains all foreign and domestic launches where the primary spacecraft was a commercial payload, while the "International" category contains all defense, civil,

²³ This dataset was based on the data found in Isakowitz, Hopkins, and Hopkins, 2004 and supplemented with data from the Space Report Launch Log maintained by Jonathon McDowell of the Harvard-Smithsonian Center for Astrophysics.

and government payloads outside of the United States. The "Other" category contains a small sample of payloads developed by academia, usually housed on test flights for new launch vehicles. This category makes up less than 2 percent of the overall dataset. Each launch is classified based on the apogee altitude of the primary spacecraft separation orbit. The category "Low" is assigned to altitudes less than 2,000 kilometers, "Medium" to altitudes between 2,000 and 35,000 kilometers, and "High" to altitudes above 35,000 kilometers. These categories reflect the altitudes of a low earth orbit (LEO), medium earth orbit (MEO), and geosynchronous earth orbit (GEO). Finally, a launch attempt is classified as an "infant" launch attempt if it is one of the first five launch attempts of a new launch vehicle class. This definition reflects launch vehicle reliability terminology (Guikema and Paté-Cornell, 2004).

Figure 2.8
Time Series of Launches with Multiple Payloads

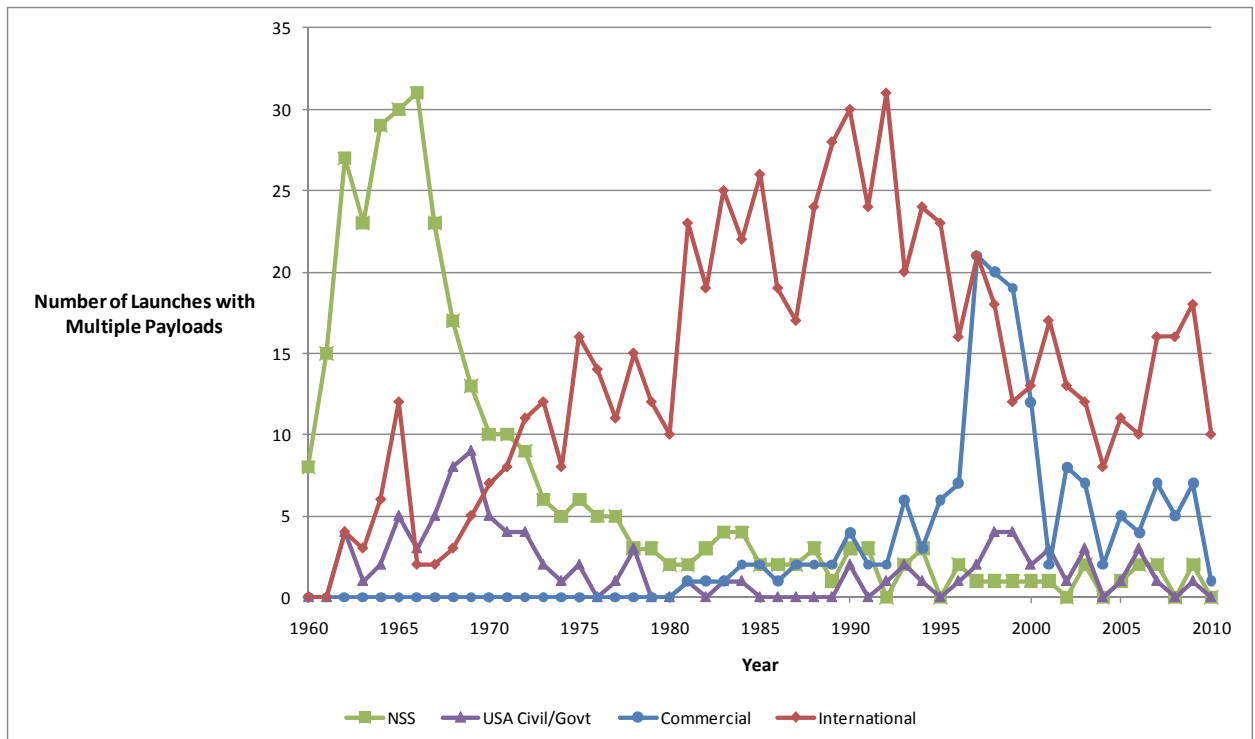


Figure 2.8 demonstrates that the U.S. NSS community has moved away from launch missions with multiple payloads and that the commercial and international launch communities have more recent experience with rideshare launch missions. To attempt to capture the reliability impacts for relatively modern launch vehicles, the analysis was restricted to the sample of launches occurring between 1980 and 2010. Reusable launch vehicles were excluded from the sample. Finally, only launch vehicle classes with more than ten rideshare launch attempts were considered. Table 2.1 summarizes the remaining data.

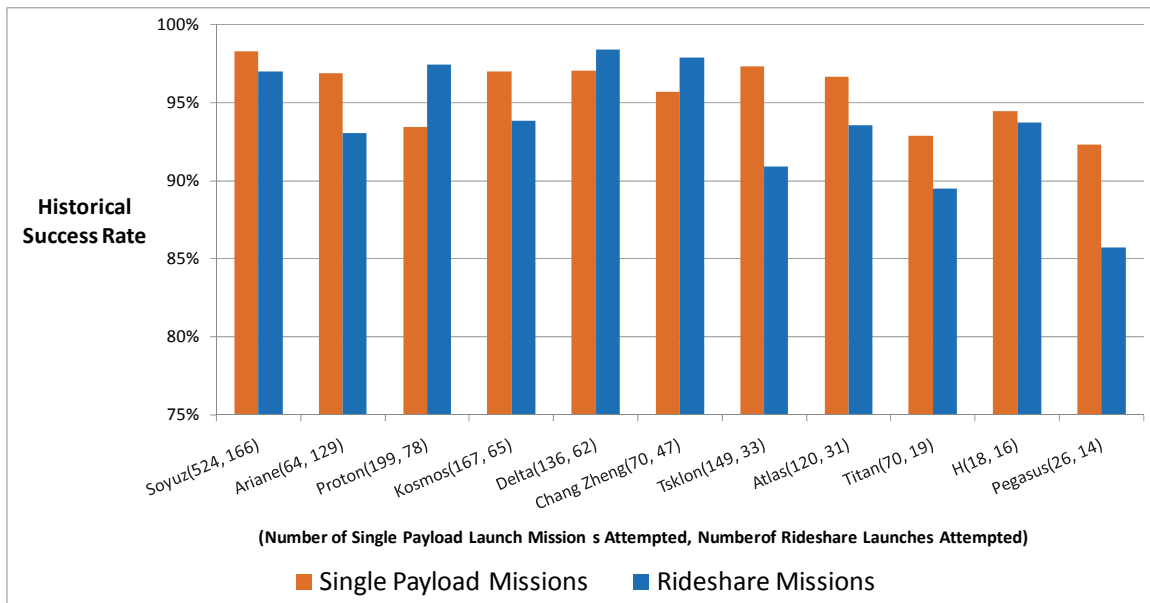
Table 2.1
Summary of Launch Reliability

	Single Payload Missions	Rideshare Missions	All Missions
Total			
Success Rate	96.63%	95.15%	96.19%
Count	1,543	660	2,203
Civil/Government			
Success Rate	96.47%	96.67%	96.52%
Count	85	30	115
Commercial			
Success Rate	91.07%	95.60%	93.27%
Count	168	159	327
International			
Success Rate	97.86%	95.55%	97.22%
Count	1,119	427	1,546
NSS			
Success Rate	94.15%	88.64%	93.02%
Count	171	44	215

While these unadjusted numbers suggest a change in reliability associated with rideshare missions, there are many variables that could confound these estimates. For example, Figure 2.9 identifies the historical differences in reliability between rideshare and single payload launch attempts, broken down by launch vehicle class. If a disproportionate number of rideshare attempts utilized "low-quality"

launch vehicles, then the raw estimates of the change in reliability associated with ridesharing additional payloads would be downwardly biased. The relatively low success rate for the NSS community is partially a result of the large number of NSS launches in the 1980s, when launch vehicle reliability was poor. Thus, the presence of any time trends presents another potential mechanism for biased estimates. Guikema and Paté-Cornell (2004) investigate infancy reliability issues in launch systems and demonstrate that the first five launch attempts of a new launch vehicle carry an additional probability of failure. The target orbit plays a role in determining the complexity of the launch attempt and must also be controlled for in order to identify unbiased results. Finally, the launch procedures and the risk postures of the different satellite users that own and operate the spacecraft and launch facilities could be correlated with both rideshare missions and launch outcomes, biasing the estimates.

Figure 2.9
Rideshare Reliability Comparison by Launch Vehicle Family between 1980 and 2010



A regression model was developed to estimate the rideshare reliability effect while controlling for the other variables that could confound the estimates. The rideshare reliability effect is defined as the incremental change in reliability associated with manifesting any additional payloads on a launch attempt. I used a Bayesian logistic regression model to estimate the effect on launch reliability associated with ridesharing auxiliary payloads.²⁴ After controlling for launch vehicle family fixed effects, any nonlinear time trends in reliability, target orbit, launch vehicle maturity, and the entity responsible for the primary spacecraft, on average, there is a 1.25 percentage point decrease in the probability of a successful launch associated with ridesharing auxiliary payloads. In addition, the implied posterior probability that this incremental effect is less than zero is 82.66 percent. While this result is not statistically significant at the 95 percent threshold commonly used for policy analysis, it is significant enough (and the consequences severe enough) to justify incorporating a decrease in reliability into the rideshare decision process.

Ridesharing Impacts on Launch Delays

A separate concern is that by increasing the complexity of the launch integration process, ridesharing could increase the likelihood and severity of unanticipated launch delays. I was able to supplement the dataset used for the reliability analysis with data on launch delays for all Delta family launches from 1989 to 2008.²⁵ While this subset of 165 observations is limited in comparison to the original dataset, it does allow for anecdotal estimates of the impact that ridesharing auxiliary payloads has on schedule delays.

For each attempted launch, the total launch delay was disaggregated into four categories based on the cause of the delay: launch range infrastructure, launch vehicle, spacecraft, and weather (see Table 2.2).

²⁴ Appendix D provides the development of and justification for this model.

²⁵ These data were provided by the 4th Space Launch Squadron at Vandenberg Air Force Base, California.

While the total launch delay for each observation was reported as the sum of these four components, for this analysis, weather delays were subtracted from the total delay. This ensured that only delays that result from the integration process were considered.

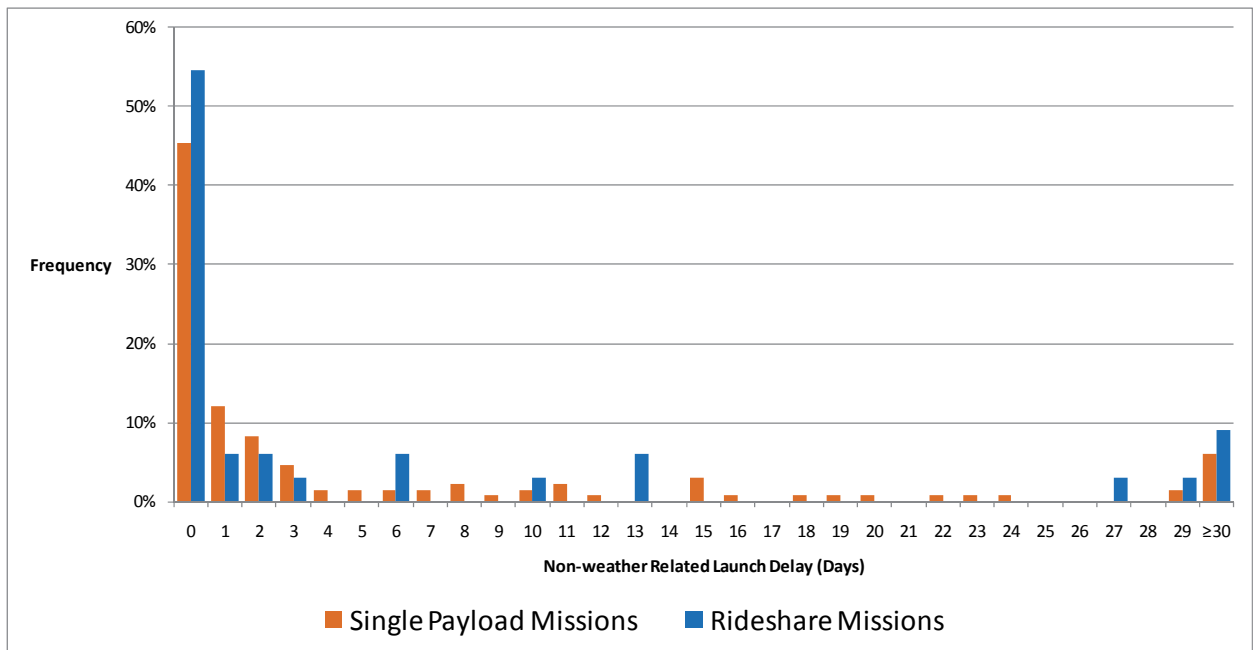
Table 2.2
Summary of Launch Delays

	Single Payload Missions	Rideshare Missions	All Missions
Total			
Average non-weather delay	9.92	17.00	11.33
St. dev. non-weather delay	31.92	50.26	36.26
Percent delayed	54.55%	45.45%	52.73%
Sample size	132	33	165
 Civil/government			
Average non-weather delay	11.69	27.38	14.36
St. dev. non-weather delay	27.26	42.80	30.46
Percent delayed	64.10%	62.50%	63.83%
Sample size	39	8	47
 Commercial			
Average non-weather delay	12.51	2.00	8.95
St. dev. non-weather delay	48.38	4.14	39.53
Percent delayed	45.95%	36.84%	42.86%
Sample size	37	19	56
 NSS			
Average non-weather delay	6.96	50.67	11.19
St. dev. non-weather delay	19.12	105.61	37.59
Percent delayed	53.57%	50.00%	53.23%
Sample size	56	6	62

The sample size of Delta rideshare missions since 1989 is relatively small. Across NSS, commercial, and international launches, rideshare missions were less likely to be delayed but, on average, experienced a much larger delay than the single payload missions. The

average delay for NSS rideshare launch attempts was 50.67 days, though three of the six attempts in the sample launched without experiencing any non-weather delays. Figure 2.10 provides a side-by-side comparison of the distribution of the launch delays for rideshare launch attempts and single payload launch attempts. In general, while the probability of a non-weather delay appears to be lower for rideshare launch attempts, the repercussions of a delay are much larger. Similar to the data in Table 2.1, these are unadjusted numbers that could be confounded by multiple variables.

Figure 2.10
Histogram of Non-Weather Related Launch Delays for Delta Family Launches Since 1989



To get a better understanding of the impact that ridesharing additional payloads has on launch delays, I estimated a negative binomial regression model²⁶ that fits the average length of a launch

²⁶ A *negative binomial regression model* is a nonlinear statistical tool used to estimate the expected value of a count variable as a function of several covariates. A negative binomial model was selected over a Poisson model because the negative binomial model allows for

delay as a function of the presence of any auxiliary payloads, the launch vehicle type, and the usage category of the primary payload. This sample of data contains three Delta family launch vehicles: the Delta II, the Delta III, and the Delta IV. Unlike the reliability analysis, this sample does not include any international launches, only NSS, commercial, and U.S. civil/government launch packages. The relatively small sample makes it difficult to control for the existence of any nonlinear time trends and other factors that influence launch reliability.

After controlling for the launch vehicle type and primary spacecraft usage category, rideshare launch missions are associated with a launch delay that is, on average, 13.64 days longer than single payload launch missions. While the direction of this estimate suggests that rideshare missions do increase the average launch delay, this estimate is statistically insignificant for all commonly accepted significance levels (i.e., $p\text{-value} > 20\%$). A 13-day delay is a relatively small change when the payload itself takes 7 to 12 years to acquire and field, which means the measured effect is also practically insignificant. Because of the relatively small sample size and the inability to detect a statistically significant effect, this estimate should be interpreted only as anecdotal evidence of the effect on launch delays associated with ridesharing auxiliary payloads.

ENTERPRISE ASSESSMENT OF RIDESHARING COSTS

Current arguments regarding the merits of ridesharing auxiliary payloads on existing launch capacity all address the issue from the perspective of individual stakeholders. For example, those within the NSS community who develop and demonstrate small satellite technologies favor ridesharing because it makes access to space for their systems more affordable while also increasing the number of launch opportunities. On

overdispersion in the response variable (see Table 2.2 for evidence of this property), though fitting a Poisson model produces qualitatively similar results. For a more in-depth discussion of nonlinear regression models for count data, see McCullagh and Nelder, 1989).

the other hand, those who develop and field large satellite systems would prefer not to rideshare additional payloads on their launch vehicles because of the potential increase in the probability of a catastrophic launch failure. These isolated arguments do not take into account the additional costs and benefits to the entire NSS enterprise. For example, if a rideshare launch attempt fails, the owner of the small satellite does not absorb the costs of replacing the primary space system. Because the interests of the different stakeholders are not perfectly aligned, a complete assessment of a rideshare opportunity requires an enterprise-level perspective of the aggregate costs and benefits. To better understand the merits of rideshare launch missions, this section provides an enterprise-level estimate of the expected cost savings associated with ridesharing additional payloads on a launch mission²⁷.

With this goal in mind, two possible launch strategies were considered. The "rideshare" scenario assumed that four secondary payloads are manifested on the primary space system's launch vehicle. This adds an additional integration cost and also has an effect on the reliability of the launch vehicle. In the "non-rideshare" scenario, the four secondary payloads are launched on a separate launch vehicle. If a launch is successful, the only incurred costs are the launch vehicle costs and any additional integration costs that are required to integrate the secondary payloads onto the primary space system's launch vehicle. If a launch attempt is a failure, the incurred costs include the costs for the launch system, all integration costs, the cost to replace the lost primary space system, and some cost associated with losing the onboard capabilities. Using the probabilities of each event

²⁷ This section provides a methodology for analyzing a representative DoD rideshare opportunity. One significant difference between DoD and commercial launch risk mitigation is the use of insurance. Launch insurance is available and commonly used for commercial launch attempts to insure against catastrophic launch failures. Thus, the presented methodology would need to be modified to accommodate the availability of insurances before being applied to the commercial launch decision environment.

to calculate the weighted cost gives the expected launch costs for a given strategy. Subtracting the expected rideshare costs from the expected non-rideshare costs gives the expected savings associated with ridesharing the auxiliary payloads with the primary satellite system.

This analysis was built upon a series of assumptions. First, I assumed that the primary space system and all secondary systems have already been purchased. When calculating the cost to replace the lost primary satellite system, I assumed that 60 percent of the original cost was nonrecurring (Wertz and Larson, 1999). The replacement cost for the primary space system is distributed over the amount of time required to acquire a replacement and then discounted into the present. The time spread of the replacement costs is based on the funding profiles for space systems given in Wertz and Larson (1999) and assumes that 60 percent of the non-launch replacement costs have been incurred at the midpoint of the program. The cost to launch the replacement is incurred at the beginning of the last year of the replacement program. A 7-percent discount rate was used based on Office of Management and Budget (OMB, 1992; Kohyama, 2006) guidelines for benefit-costs analysis. When discounting costs to the present, I assumed that all costs are incurred at the beginning of the year. Further, I assumed that the secondary payloads would not be replaced.

When a primary satellite is lost, there is also some cost associated with not having its capabilities available to the user. In the commercial sector, this cost is unrealized revenue. To estimate this cost within the DoD environment, I assumed a fixed cost per year of lost capabilities such that the total net present cost of lost capabilities over the planned lifespan of the system is equal to the original unit cost of the system (i.e., original space system cost plus launch costs). Assuming that the DoD would not acquire a system whose net present lost capabilities cost is less than the system's unit cost implies that this method of quantifying the cost of lost capabilities is a lower bound of the true lost capabilities cost. When calculating the lost capabilities cost for the secondary payloads, I assumed that all secondary payloads have a one-year lifespan, so the cost of lost

capabilities is equal to the cost of the payload. Table 2.3 provides a complete list and description of the parameters.

Table 2.3
Values Used to Estimate Rideshare Cost Savings

Variable	Description	Nominal Value	Justification
$C_{Launch}^{(P)}$	Launch cost for primary space system launch vehicle	\$116M	EELV (DARPA F6 Launch Option Data)
$C_{Integration}$	Cost to integrate secondary payloads on primary system launch vehicle	\$15M	ESPA standard service, research interviews
$C_{Launch}^{(S)}$	Launch cost (including integration costs for additional payloads) for the secondary launch option	\$30M	Minotaur IV (DARPA F6 Launch Option Data) also varied at \$20M, \$30M, \$40M
$p_{Primary}$	Probability of a successful launch for the primary satellite system's launch vehicle	98%	Kimhan et al., 1999
$p_{Secondary}$	Probability of a successful launch for the secondary launch option	95%	Varied (92%, 95%, 98%)
$e_{Rideshare}$	Change in reliability associated with manifesting additional payloads on a launch vehicle	-1.25%	Estimated from historical data, also varied at 0.00%, -0.5%, -1.25%, -2.50%
$C_{System}^{(P)}$	System cost for the primary satellite system	\$800M	Varied from \$200M to \$3,000M
T	Number of years to reacquire primary satellite system	7 years	Research interviews
N	Intended lifespan of primary satellite system	15 years	Research interviews
$C_{Lost}^{(P)}$	Lost capabilities cost per year associated with not having access to the primary space system	\$94M	Varies based on $C_{System}^{(P)}$, assumes net present cost of $C_{Lost}^{(P)}$ over N years is equal to $C_{Launch}^{(P)} + C_{System}^{(P)}$
$C_{Replace,t}^{(P)}$	Cost to replace the primary space system incurred in year t of the reacquisition timeframe	(\$21M, \$56M, \$76M, \$76M, \$57M, \$29M, \$5M)	Varies based on $C_{System}^{(P)}$ and η using cost schedule in Wertz and Larson, 1999
$C_{System}^{(S)}$	Total cost for all auxiliary payloads	4 x \$25M = \$100M	Varied at 4x\$10M, 4x\$25M, 4x\$40M
η	Fraction of $C_{System}^{(P)}$ that is nonrecurring	60%	(Wertz and Larson, 1999)
r	Rate of return used to discount future costs into the present	7%	(OMB, 1992)
$E[C_{Rideshare}]$	Expected net present cost of ridesharing the auxiliary payloads with the primary satellite system		Calculated below
$E[C_{Non-rideshare}]$	Expected net present cost of launching auxiliary payloads on secondary payload launch option		Calculated below
$E[S_{Rideshare}]$	Expected net present savings of ridesharing the auxiliary payloads with the primary space system		Calculated below

NOTES: The DARPA F6 Launch Options Data is a set of validated performance metrics released to the DARPA System F6 program analysis teams.

$$E[C_{Rideshare}] = (p_{Primary} + e_{Rideshare}) (C_{Launch}^{(P)} + C_{Integration}) + (1 - p_{Primary} - e_{Rideshare}) \left(C_{Launch}^{(P)} + C_{Integration} + C_{System}^{(S)} + \frac{C_{Launch}^{(P)}}{(1+r)^{T-1}} + \sum_{t=0}^{T-1} \frac{C_{Lost}^{(P)} + C_{Replace,t}^{(P)}}{(1+r)^t} \right)$$

Equation 2.1

$$E[C_{Non-rideshare}] = (p_{Primary} + e_{Rideshare}) C_{Launch}^{(P)} + (1 - p_{Primary} - e_{Rideshare}) \left(C_{Launch}^{(P)} + \frac{C_{Launch}^{(P)}}{(1+r)^{T-1}} + \sum_{t=0}^{T-1} \frac{C_{Lost}^{(P)} + C_{Replace,t}^{(P)}}{(1+r)^t} \right) + (p_{Secondary} + e_{Rideshare}) C_{Launch}^{(S)} + (1 - p_{Secondary} - e_{Rideshare}) (C_{Launch}^{(S)} + C_{System}^{(S)})$$

Equation 2.2

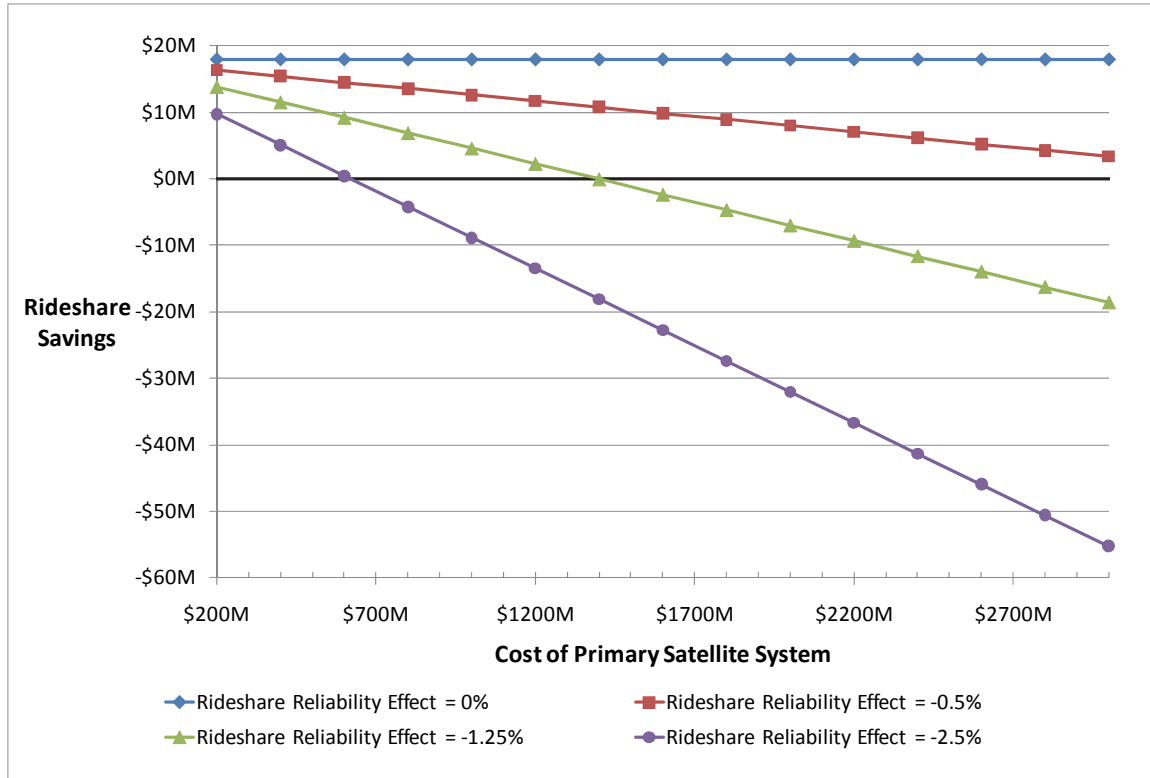
$$E[S_{Rideshare}] = E[C_{Non-rideshare}] - E[C_{Rideshare}]$$

Equation 2.3

The nominal parameters in Table 2.3 imply that ridesharing four \$25 million secondary payloads with an \$800 million satellite system would result in \$6.89 million of expected savings.

The cost of the primary space system and the rideshare reliability effect both play an important role in determining the advisability of a rideshare opportunity. The cost of the primary satellite system has a large impact on the severity of a launch failure. The rideshare reliability effect changes the likelihood of a launch failure when auxiliary payloads are manifested on a launch mission. Figure 2.11 traces out the expected savings associated with ridesharing auxiliary payloads for a range of plausible values for the cost of the primary satellite system and the rideshare reliability effect.

Figure 2.11
Net Present Expected Savings Associated with Ridesharing Auxiliary Payloads



NOTES: Unless otherwise specified, all parameters are fixed at the nominal values listed in Table 2.3 and assume four auxiliary payloads with a cost of \$25 million each. The phrase "rideshare savings" is defined as the expected cost of launching the primary satellite system and the auxiliary payloads on different launch vehicles minus the expected cost of ridesharing the auxiliary payloads with the primary satellite system. Thus, a positive rideshare savings suggests that, in expectation, it is cost-effective to rideshare the auxiliary payloads with the primary satellite system.

Figure 2.11 demonstrates several important facts. First, if ridesharing auxiliary payloads does not reduce launch vehicle reliability, then the cost of the primary satellite system does not affect the advisability of ridesharing. As was discussed earlier, rideshare launch attempts have historically been associated with a decrease in reliability. Assuming the estimates derived in Appendix C (i.e., ridesharing auxiliary payloads reduces reliability by 1.25 percentage points), it is only cost-effective to rideshare the four

additional payloads if the primary satellite system costs less than \$1,400 million. If ridesharing auxiliary payloads reduces launch mission reliability by 2.50 percentage points, then it is cost-effective to rideshare the auxiliary payloads only with primary satellite systems that cost less than \$600M.

While the cost of the primary satellite system and the rideshare reliability effect both play a large role in determining the cost-effectiveness of a rideshare opportunity, the other parameters in Table 2.3 also impact the decision framework. To assess how the input parameters impact the expected rideshare savings, inputs that were difficult to identify or that vary across launch missions and rideshare opportunities were studied further. Specifically, I varied the cost and reliability of the secondary launch option, the rideshare reliability effect, the cost of the primary satellite system, and the costs of the auxiliary payloads. Table 2.4 gives the set of considered inputs.

Table 2.4
Factors Examined to Understand the Sensitivity of Rideshare Savings

Variable	Description	Range
$C_{Launch}^{(S)}$	The cost of the secondary launch option	\$20M, \$30M, \$40M
$p_{Secondary}$	The reliability of the secondary launch option	92%, 95%, 98%
$e_{Rideshare}$	The rideshare reliability effect	0.00%, -0.5%, -1.25%, -2.5%
$C_{System}^{(S)}$	The total cost of all secondary payloads	4x\$10M, 4x\$25M, 4x\$40M
$C_{System}^{(P)}$	The total cost of the primary satellite system	\$500M, \$1,500M, \$2,500M

All 320 possible combinations of the inputs in Table 2.4 were considered. Table 2.5 gives the results of this assessment.

Table 2.5
Rideshare Savings for Different Input Scenarios

				Rideshare Reliability Effect = 0.00%	Rideshare Reliability Effect = -0.50%	Rideshare Reliability Effect = -1.25%	Rideshare Reliability Effect = -2.50%
Secondary Launch Option	Secondary Launch Option \$20M						
	Secondary Launch Option Reliability 92%	Secondary Payload 4x\$10M	Primary Payload Cost \$500M	\$7.40M	\$4.35M	-\$0.23M	-\$7.85M
			Primary Payload Cost \$1,500M	\$7.40M	-\$0.29M	-\$11.83M	-\$31.05M
			Primary Payload Cost \$2,500M	\$7.40M	-\$4.93M	-\$23.43M	-\$54.26M
			Primary Payload Cost \$500M	\$11.00M	\$7.95M	\$3.37M	-\$4.25M
			Primary Payload Cost \$1,500M	\$11.00M	\$3.31M	-\$8.23M	-\$27.45M
			Primary Payload Cost \$2,500M	\$11.00M	-\$1.33M	-\$19.83M	-\$50.66M
			Primary Payload Cost \$500M	\$14.60M	\$11.55M	\$6.97M	-\$0.65M
			Primary Payload Cost \$1,500M	\$14.60M	\$6.91M	-\$4.63M	-\$23.85M
			Primary Payload Cost \$2,500M	\$14.60M	\$2.27M	-\$16.23M	-\$47.06M
			Primary Payload Cost \$500M	\$6.20M	\$3.15M	-\$1.43M	-\$9.05M
	Secondary Launch Option Reliability 95%	Secondary Payload 4x\$10M	Primary Payload Cost \$1,500M	\$6.20M	-\$1.49M	-\$13.03M	-\$32.25M
			Primary Payload Cost \$2,500M	\$6.20M	-\$6.13M	-\$24.63M	-\$55.46M
			Primary Payload Cost \$500M	\$8.00M	\$4.95M	\$0.37M	-\$7.25M
			Primary Payload Cost \$1,500M	\$8.00M	\$0.31M	-\$11.23M	-\$30.45M
			Primary Payload Cost \$2,500M	\$8.00M	-\$4.33M	-\$22.83M	-\$53.66M
			Primary Payload Cost \$500M	\$9.80M	\$6.75M	\$2.17M	-\$5.45M
			Primary Payload Cost \$1,500M	\$9.80M	\$2.11M	-\$9.43M	-\$28.65M
			Primary Payload Cost \$2,500M	\$9.80M	-\$2.53M	-\$21.03M	-\$51.86M
			Primary Payload Cost \$500M	\$5.00M	\$1.95M	-\$2.63M	-\$10.25M
			Primary Payload Cost \$1,500M	\$5.00M	-\$2.69M	-\$14.23M	-\$33.45M
	Secondary Launch Option Reliability 98%	Secondary Payload 4x\$10M	Primary Payload Cost \$2,500M	\$5.00M	-\$7.33M	-\$25.83M	-\$56.66M
			Primary Payload Cost \$500M	\$5.00M	\$1.95M	-\$2.63M	-\$10.25M
			Primary Payload Cost \$1,500M	\$5.00M	-\$2.69M	-\$14.23M	-\$33.45M
			Primary Payload Cost \$2,500M	\$5.00M	-\$7.33M	-\$25.83M	-\$56.66M
			Primary Payload Cost \$500M	\$5.00M	\$1.95M	-\$2.63M	-\$10.25M
			Primary Payload Cost \$1,500M	\$5.00M	-\$2.69M	-\$14.23M	-\$33.45M
			Primary Payload Cost \$2,500M	\$5.00M	-\$7.33M	-\$25.83M	-\$56.66M
			Primary Payload Cost \$500M	\$17.40M	\$14.35M	\$9.77M	\$2.15M
			Primary Payload Cost \$1,500M	\$17.40M	\$9.71M	-\$1.83M	-\$21.05M
			Primary Payload Cost \$2,500M	\$17.40M	\$5.07M	-\$13.43M	-\$44.26M
Secondary Launch Option \$30M	Secondary Launch Option Reliability 92%	Secondary Payload 4x\$10M	Primary Payload Cost \$500M	\$21.00M	\$17.95M	\$13.37M	\$5.75M
			Primary Payload Cost \$1,500M	\$21.00M	\$13.31M	\$7.77M	-\$17.45M
			Primary Payload Cost \$2,500M	\$21.00M	\$8.67M	-\$9.83M	-\$40.66M
			Primary Payload Cost \$500M	\$24.60M	\$21.55M	\$16.97M	\$9.35M
			Primary Payload Cost \$1,500M	\$24.60M	\$16.91M	\$5.37M	-\$13.85M
			Primary Payload Cost \$2,500M	\$24.60M	\$12.27M	-\$6.23M	-\$37.06M
	Secondary Launch Option Reliability 95%	Secondary Payload 4x\$10M	Primary Payload Cost \$500M	\$16.20M	\$13.15M	\$8.57M	\$0.95M
			Primary Payload Cost \$1,500M	\$16.20M	\$8.51M	-\$3.03M	-\$22.25M
			Primary Payload Cost \$2,500M	\$16.20M	\$3.87M	-\$14.63M	-\$45.46M
			Primary Payload Cost \$500M	\$18.00M	\$14.95M	\$10.37M	\$2.75M
			Primary Payload Cost \$1,500M	\$18.00M	\$10.31M	-\$1.23M	-\$20.45M
			Primary Payload Cost \$2,500M	\$18.00M	\$5.67M	-\$12.83M	-\$43.66M
			Primary Payload Cost \$500M	\$19.80M	\$16.75M	\$12.17M	\$4.55M
			Primary Payload Cost \$1,500M	\$19.80M	\$12.11M	\$0.57M	-\$18.65M
			Primary Payload Cost \$2,500M	\$19.80M	\$7.47M	-\$11.03M	-\$41.86M
			Primary Payload Cost \$500M	\$15.00M	\$11.95M	\$7.37M	-\$0.25M
	Secondary Launch Option Reliability 98%	Secondary Payload 4x\$10M	Primary Payload Cost \$1,500M	\$15.00M	\$7.31M	-\$4.23M	-\$23.45M
			Primary Payload Cost \$2,500M	\$15.00M	\$2.67M	-\$15.83M	-\$46.66M
			Primary Payload Cost \$500M	\$15.00M	\$11.95M	\$7.37M	-\$0.25M
			Primary Payload Cost \$1,500M	\$15.00M	\$7.31M	-\$4.23M	-\$23.45M
			Primary Payload Cost \$2,500M	\$15.00M	\$2.67M	-\$15.83M	-\$46.66M
			Primary Payload Cost \$500M	\$15.00M	\$11.95M	\$7.37M	-\$0.25M
			Primary Payload Cost \$1,500M	\$15.00M	\$7.31M	-\$4.23M	-\$23.45M
			Primary Payload Cost \$2,500M	\$15.00M	\$2.67M	-\$15.83M	-\$46.66M
			Primary Payload Cost \$500M	\$15.00M	\$11.95M	\$7.37M	-\$0.25M
			Primary Payload Cost \$1,500M	\$15.00M	\$7.31M	-\$4.23M	-\$23.45M

				Rideshare Reliability Effect = 0.00%	Rideshare Reliability Effect = -0.50%	Rideshare Reliability Effect = -1.25%	Rideshare Reliability Effect = -2.50%
Secondary Launch Option \$40M	Secondary Launch Option Reliability 92%	Secondary Payload 4x\$10M	Primary Payload Cost \$500M	\$27.40M	\$24.35M	\$19.77M	\$12.15M
			Primary Payload Cost \$1,500M	\$27.40M	\$19.71M	\$8.17M	-\$11.05M
			Primary Payload Cost \$2,500M	\$27.40M	\$15.07M	-\$3.43M	-\$34.26M
		Secondary Payload 4x\$25M	Primary Payload Cost \$500M	\$31.00M	\$27.95M	\$23.37M	\$15.75M
			Primary Payload Cost \$1,500M	\$31.00M	\$23.31M	\$11.77M	-\$7.45M
			Primary Payload Cost \$2,500M	\$31.00M	\$18.67M	\$0.17M	-\$30.66M
		Secondary Payload 4x\$40M	Primary Payload Cost \$500M	\$34.60M	\$31.55M	\$26.97M	\$19.35M
			Primary Payload Cost \$1,500M	\$34.60M	\$26.91M	\$15.37M	-\$3.85M
			Primary Payload Cost \$2,500M	\$34.60M	\$22.27M	\$3.77M	-\$27.06M
	Secondary Launch Option Reliability 95%	Secondary Payload 4x\$10M	Primary Payload Cost \$500M	\$26.20M	\$23.15M	\$18.57M	\$10.95M
			Primary Payload Cost \$1,500M	\$26.20M	\$18.51M	\$6.97M	-\$12.25M
			Primary Payload Cost \$2,500M	\$26.20M	\$13.87M	-\$4.63M	-\$35.46M
		Secondary Payload 4x\$25M	Primary Payload Cost \$500M	\$28.00M	\$24.95M	\$20.37M	\$12.75M
			Primary Payload Cost \$1,500M	\$28.00M	\$20.31M	\$8.77M	-\$10.45M
			Primary Payload Cost \$2,500M	\$28.00M	\$15.67M	-\$2.83M	-\$33.66M
		Secondary Payload 4x\$40M	Primary Payload Cost \$500M	\$29.80M	\$26.75M	\$22.17M	\$14.55M
			Primary Payload Cost \$1,500M	\$29.80M	\$22.11M	\$10.57M	-\$8.65M
			Primary Payload Cost \$2,500M	\$29.80M	\$17.47M	-\$1.03M	-\$31.86M
	Secondary Launch Option Reliability 98%	Secondary Payload 4x\$10M	Primary Payload Cost \$500M	\$25.00M	\$21.95M	\$17.37M	\$9.75M
			Primary Payload Cost \$1,500M	\$25.00M	\$17.31M	\$5.77M	-\$13.45M
			Primary Payload Cost \$2,500M	\$25.00M	\$12.67M	-\$5.83M	-\$36.66M
		Secondary Payload 4x\$25M	Primary Payload Cost \$500M	\$25.00M	\$21.95M	\$17.37M	\$9.75M
			Primary Payload Cost \$1,500M	\$25.00M	\$17.31M	\$5.77M	-\$13.45M
			Primary Payload Cost \$2,500M	\$25.00M	\$12.67M	-\$5.83M	-\$36.66M
		Secondary Payload 4x\$40M	Primary Payload Cost \$500M	\$25.00M	\$21.95M	\$17.37M	\$9.75M
			Primary Payload Cost \$1,500M	\$25.00M	\$17.31M	\$5.77M	-\$13.45M
			Primary Payload Cost \$2,500M	\$25.00M	\$12.67M	-\$5.83M	-\$36.66M

NOTES: Unless otherwise specified, all parameters are fixed at the nominal values listed in Table 2.3. The phrase "Rideshare savings" is defined as the expected cost of launching the primary satellite system and the auxiliary payloads on different launch vehicles minus the expected cost of ridesharing the auxiliary payloads with the primary satellite system. Thus, a positive rideshare savings suggests that, in expectation, it is cost-effective to rideshare the auxiliary payloads with the primary satellite system.

Table 2.5 suggests that the cost-effectiveness of a rideshare opportunity depends heavily on numerous input parameters that can vary across opportunities. For example, the reliability and the cost of the secondary launch option partially determine the expected cost of launching the auxiliary payloads on a separate launch vehicle and, thus, can greatly impact the advisability of a rideshare opportunity. This trend is evident in Table 2.5. In addition, Table 2.5 also demonstrates that as the total cost of the auxiliary payloads increases, ridesharing becomes more cost-effective. This trend exists because the reliability of the EELV is superior to most secondary launch options. Thus, while ridesharing may increase the risk exposure of the primary satellite system, it decreases the risk exposure for the auxiliary payloads. The magnitude of this benefit increases as the total cost of the auxiliary

payloads increases. In general, there are too many inputs that affect the advisability of ridesharing to suggest a definitive rideshare policy. Instead, the decision to rideshare auxiliary payloads should be made on a case-by-case basis in a way that incorporates the potential costs to the entire NSS enterprise.

SUMMARY OF FINDINGS AND CONCLUSIONS

- **The USAF and its commercial launch partners have developed the technology to support a robust rideshare program.** The suite of potential secondary payload adaptors is flexible enough to support a wide range of auxiliary payloads without directly interfacing with the primary payload.
- **Historically, rideshare launch missions have been associated with a decrease in launch mission reliability.** After launch vehicle quality, target orbit, the organization that owned the primary payload, launch vehicle maturity, and time trends in reliability are controlled for, ridesharing auxiliary payloads has been associated with a 1.25 percent decrease in the probability of a successful launch. In addition, the empirical posterior probability that this incremental effect reduces reliability is 82.66 percent. While these historical trends do not necessarily generalize to future DoD launch attempts, this reduction in reliability is significant enough to warrant consideration in the rideshare decision logic. Because of a limited sample size, it is impossible to discern significant increases in launch delays associated with ridesharing auxiliary payloads; however, any effect is likely to be practically insignificant when compared with the overall development timeline of a large space system.
- **An expanded DoD Rideshare program would require a policy change mandating that, when possible, SPOs acquire launch systems with excess performance margins dedicated for APLs.** Launch vehicles are fitted for the primary spacecraft. Because of the additional

costs associated with increased performance margins and a potential decrease in launch reliability, SPOs have little incentive to consider launch systems with performance margins above the current requirement. In addition, the use of performance margins to deorbit the launch vehicle upper stage currently takes precedent over ridesharing auxiliary payloads, further limiting rideshare opportunities. Going forward, these obstacles must be overcome if the DoD wants to increase the number of rideshare launch opportunities.

- **The decision to rideshare auxiliary payloads should be made on a case-by-case basis in a way that incorporates the potential costs to the entire NSS enterprise.** Given historical estimates of the rideshare reliability effect and nominal small satellite alternative launch options; it is only cost-effective to rideshare auxiliary payloads with primary satellite systems that cost less than \$1,400M. This conclusion is sensitive to many additional parameters, including the cost and reliability of the secondary launch option, the cost of the secondary payloads, the time required to replace a lost space system, the cost to integrate additional payloads on a launch mission, and the rideshare reliability effect. Because of the number of situation-specific parameters that impact the advisability of a rideshare opportunity, it is difficult to recommend a definitive policy.
- **In its current form, the DoD rideshare program would contribute little to rapid reaction space launch capabilities.** This is one of the stated goals of developing and incorporating rideshare technologies within the DoD (Chavez, Barrera, and Kanter, 2007; Wynne, 2008). Because payloads have to wait for a rideshare opportunity to materialize and then be manifested onboard no later than 27 months prior to launch, there is little room to use the rideshare launch process to rapidly field space capabilities.

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ESSAY THREE: SYSTEMS ANALYSIS FRAMEWORKS FOR FLEXIBLE SPACE ARCHITECTURES

INTRODUCTION

The *National Space Policy of the United States of America* (2010, pp. 14) calls on the National Security Space (NSS) community to continue to “develop and apply advanced technologies and capabilities that respond to changes to the threat environment.” This national policy reinforces a trend within the NSS community that places a greater emphasis on the ability of NSS systems to operate in an uncertain future. There are many strategies that could potentially improve the flexibility of future NSS capabilities. Incorporating small satellites that could be quickly acquired and orbited is one strategy that could allow the NSS community to rapidly respond to changing user needs and new technologies. Once placed in orbit around the earth, satellites are mostly inaccessible, preventing any on-orbit hardware modifications, repairs, fuel replenishment, or servicing. On-orbit servicing capabilities could improve the flexibility of NSS systems by providing the NSS community with the ability to respond to uncertainty by directly modifying space systems after they are placed in orbit.²⁸ Another example of a flexible space system architecture is a fractionated satellite system that allows a set of physically separate modules to cooperate and act as a single system. After defining a set of communication and resource-sharing protocols, the individual modules could be designed independently of each other and integrated on-orbit at different times, allowing the NSS

²⁸ The Defense Advanced Research Projects Agency (DARPA) Orbital Express program goal was “to validate the technical feasibility of robotic, autonomous on-orbit refueling and reconfiguration of satellites” (DARPA, 2007, pp. 1). The program developed and successfully demonstrated a servicing satellite (ASTRO) and a prototype next generation serviceable satellite (NEXTSat/CSC). Once placed in orbit, ASTRO refueled NEXTSat/CSC and replaced an onboard computer.

community to offer incremental modifications and upgrades to on-orbit systems.²⁹

As the NSS community looks to develop and field the next generation of space-based capabilities, additional research has been dedicated to officially incorporating flexibility into systems analysis. Some within the community of practice have argued that the cost-centric framework for DoD systems analysis does not adequately allow for flexibility to be considered in the systems analysis decision process and that a value-centric framework might better facilitate the consideration of flexibility (Weigel and Hastings, 2001; Saleh et al., 2003; Brown and Eremenko, 2006a; Nilchiani and Hastings, 2007; Saleh, 2008; and Brown and Eremenko, 2009). Despite this push to change the systems analysis framework for NSS architectures, there is little research that aims to distinguish the comparative advantages (and disadvantages) of each framework.

This research has four objectives: (1) distinguish the respective strengths and weaknesses of both the cost-centric and the value-centric frameworks through a review of the theoretical foundations and practical techniques associated with each, (2) evaluate the applicability of each technique in the context of the DoD decision environment, (3) assess whether a value-centric framework adequately incorporates flexibility into the systems analysis for the next generation of NSS systems, and (4) demonstrate a cost-centric framework for the design and selection of a flexible space system.

This chapter is organized into five sections. The first section provides definitions for terms used throughout the chapter, along with an overview of the theoretical and historical foundations of the cost-centric and value-centric frameworks for systems analysis. The next section assesses the strengths and weaknesses of each framework in order to identify the types of problems and decision environments each framework is situated to address. This is followed by an evaluation of

²⁹ Hereafter, small satellites, fractionated satellites, and on-orbit servicing systems will be collectively referred to as "flexible space systems."

each framework in the context of the defense decision environment. The next section examines the challenges associated with incorporating flexibility into the systems analysis of NSS systems. Included here is a simple example of how the cost-centric framework can be used to provide insight into the flexibility of a fractionated space system. Finally, I provide a summary and discussion of the overall findings.

BACKGROUND AND LITERATURE REVIEW

Definitions

Within this research, the ***cost-centric framework*** describes a decisionmaking process for system design and selection that selects the system of minimum cost that meets all predetermined performance requirements. First, the set of all proposed designs is condensed by eliminating all system designs that do not meet the performance requirements. Of the remaining systems, the one with the lowest associated cost is selected. System performance capabilities above and beyond the specified system requirements have no impact on the decisionmaking process.

The ***value-centric framework*** describes a decisionmaking process for system design and selection that selects the system that provides the most value, subject to meeting a predetermined budget constraint. Here, the performance attributes of each considered system design are aggregated into a measure of value such that systems of higher value are always preferred to systems with lower value. Under the value-centric framework, system selection is not constrained by a set of performance requirements, but instead, the performance capabilities of the system contribute to the overall value. When dealing with decisions that involve uncertainty, the value-centric framework indicates the decision with the largest expected value.

A system attribute is a characteristic or property of a system. A ***derived attribute*** is a system attribute that is relevant only under some subset of uncertain scenarios and is a function of other system attributes. For example, the adaptability of a system is relevant only if the need to adapt the system arises during its lifespan. Examples of

derived attributes include adaptability, upgradability, scalability, maintainability, and survivability. Derived attributes are also referred to as **quality attributes** (Papazoglou et al., 2008).

Academic Foundations of the Value-Centric and Cost-Centric Frameworks

The goal of economic decision theories is to describe how rational decisions are made in the presence of uncertainties and limited resources. Generally, these theories are not aimed at facilitating the decision process but, rather, at providing an analytic framework that models behavior and can predict how entities respond to exogenous change. Nevertheless, they form the academic basis for applied decision theories designed to actively inform the decisionmaking process.

Expected utility theory is the dominant economic decision theory (Hey and Orme, 1994). The expected utility hypothesis states that, when faced with uncertainty, individuals act in a way that maximizes the expected value of a utility function. A utility function translates states of the world into an ordinal measure of preference such that the decisionmaker prefers state A to state B if the utility of state A is greater than the utility of state B. By maximizing expected utility, an individual is acting in a way that maximizes the long-run average of their realized utility. The expected utility hypothesis was first described in Bernoulli (1843). Von Neumann and Morgenstern (1944) provide a set of axioms that imply the existence of a utility function that adheres to the expected utility hypothesis.

While the underpinnings of the value-centric framework are closely related to the development of expected utility theory, the value-centric framework for systems analysis can be traced to Smith et al. (1953). This work describes "value" as a measure of the worth of an outcome. Under this simple model, when confronted with uncertainty, the decisionmaker selects the decision with the largest expected value over a specified time period. In systems analysis, value is a function of the system's performance attributes. The function that translates the multiple performance attributes of a system into a scalar measure of value is called a value function or a value model. Churchman and Ackoff (1954) present a simplified value theory known as multi-attribute

utility theory (MAUT). MAUT uses an additive value model in which each system attribute is associated with a unique utility function and the overall value of the system is the sum of the utility contribution across all attributes.

The cost-centric framework is not as extensively developed within the academic literature as the value-centric framework. Odhnoff (1965) develops a decision model in which the decisionmaker does not attempt to maximize some measure of value but instead attempts to satisfy some set of goals or requirements. Wierzbicki (1982) derives a mathematical formulation of satisficing³⁰ decisionmaking that accurately captures the cost-centric decision process that the DoD employs. In this framework, decisions are made in a two stage process. In the first stage, the decisionmaker specifies a set of goal levels for system attributes (i.e., system requirements). After reaching these aspiration levels, the remaining resources are used to further optimize specific attributes of the system (e.g., reducing cost). Other requirements-based decision frameworks that are similar to the cost-centric framework can be found in Bordley and LiCalzi (2000) and Bordley and Kirkwood (2004).

Historical Context of the Value-Centric and Cost-Centric Frameworks Within the DoD

Brown and Eremenko (2009) provide an account of the role cost-centric and value-centric acquisition frameworks have had within the context of DoD systems design and selection. Quantitative decisionmaking rooted in economic theory was a significant addition to the DoD Planning, Programming, and Budgeting System introduced by Secretary of Defense Robert McNamara in 1960. The goal of these changes was to improve the DoD procurement process, which McNamara believed had become too antiquated to provide meaningful insight into the complex decisions related to the design, selection, and fielding of defense systems and forces (McNamara, 1964). The techniques of systems analysis were

³⁰ The term *satisficing* is a combination of the words *satisfy* and *suffice* and is used to describe a decision heuristic that looks to sufficiently satisfy a set of predefined requirements.

developed as a way to help inform how best to allocate DoD resources to provide the required levels of national security and defense.

DoD systems analysis theory views the cost-centric and value-centric frameworks as different approaches to the same problem. In a lecture at the University of California, Dr. Charles Hitch (McNamara's assistant secretary of defense, comptroller), described the DoD systems analysis problem as identifying, "[which] strategy (or force, or weapon system), offers the greatest amount of military effectiveness for a given outlay? Or looking at the problem from another direction: How can a given level of military effectiveness be achieved at least cost?" (Hitch, 1965, pp. 124). In the context of the DoD decisionmaking process, these two frameworks differ in more than just the description of their objective function. In this same lecture, Hitch argues that when dealing with the value-centric framework, the analyst works in terms of marginal rates of transformation and substitution (e.g., an increase in top speed of 10 knots provides the same increase in value as a 15-percent increase in fuel efficiency), whereas from the cost-centric standpoint, the analyst works in terms of marginal products and marginal costs (e.g., the additional unit cost associated with increasing the maximum required speed by 10 knots is \$5,000).

While Hitch acknowledges that there are two different frameworks that can be used to design and select DoD systems, he also acknowledges that McNamara preferred looking at the systems analysis problem as identifying how to achieve a given level of defense for the least cost. The primary cited reason for this preference is the difficulty associated with placing a meaningful value on national defense: "Since we do not operate in the market place, we cannot usually calculate the point where, in the business world, marginal cost equals marginal revenue. . . . [I]f the measurements of military effectiveness [i.e., value] are wrong, the answers will also be wrong" (Hitch, 1965, pp. 126). Instead of attempting to place a value on different levels of military performance, McNamara and Hitch preferred to set a level of acceptable performance and choose the system that provided that level of performance at the least cost (Brown and Eremenko, 2009).

While the cost-centric ideas and decision frameworks described by McNamara and Hitch continue to influence DoD procurement decisionmaking, recent efforts both within and outside the DoD have suggested that the value-centric framework can improve DoD development and acquisition outcomes. Former Secretary of Defense William Cohen reintroduced the idea that the DoD should be concerned with value, and not cost: "The Department [of Defense] needs to change its focus from trying to figure what something costs to acquire, to focusing on the value a thing has over its useful life" (Cohen, 1998). Lippitz, O'Keefe, and White (2001) introduced their formulation of the value-centric framework for DoD system acquisition, calling it value-based acquisition (VBA). Under this formulation, a value model would be created to map system performance to an overall aggregate measure of value. This value model would then be used as the basis for system design, selection, and contractor considerations. The value-centric viewpoint was also put forth as the ideal framework for a recent acquisition effort, the DARPA System F6 program.³¹ While the primary goal of the System F6 program was to develop and demonstrate a fractionated satellite, a secondary goal was to use value-centric techniques to inform all major development and engineering decisions (Brown and Eremenko, 2009).

COMPARATIVE ADVANTAGES OF THE COST-CENTRIC AND VALUE-CENTRIC FRAMEWORKS

While the majority of economic decision theories utilize a value-centric approach, DoD systems analysis has traditionally utilized a cost-centric approach. Is the decision to use a cost-centric framework or a value-centric framework arbitrary, or are there types of decision problems that lend themselves to one or the other?

As an example to motivate discussion, consider a family that is looking to purchase a new house. This family must select a single house from a set of candidates. There are many housing attributes that are important to the family, such as the cost of the house, size of the house, number of bedrooms, kitchen layout, shopping convenience,

³¹ Future, Flexible, Fast, Fractionated, Free-Flying Spacecraft united by Information Exchange.

proximity to entertainment, neighborhood appeal, and the school district. A value-centric approach to this decision process would derive a model that quantified each of these attributes and then aggregated them into a single measure of value. The family would choose the house with the largest value. In this example, it is not clear how these different attributes would be combined into a single measure of value. For example, how should the family measure neighborhood safety? What is the marginal rate of substitution between shopping convenience and the size of the house? How should the different preferences of the family members be combined? On the other hand, a cost-centric approach to this decision would first derive a set of requirements (e.g., the house must have four bedrooms, an open kitchen, be in a certain school district, etc.). Once these specifications have been set, the family would then choose the house of minimum cost that meets all of these requirements. In this example, the cost-centric approach seems more practical.

My research identified three features of a decision problem that influence the appropriateness of the cost-centric framework and the value-centric framework: the ability to quantify cost and value, decisionmaker characteristics and preferences, and optimality requirements.

Quantifying Cost, Value, and Requirements

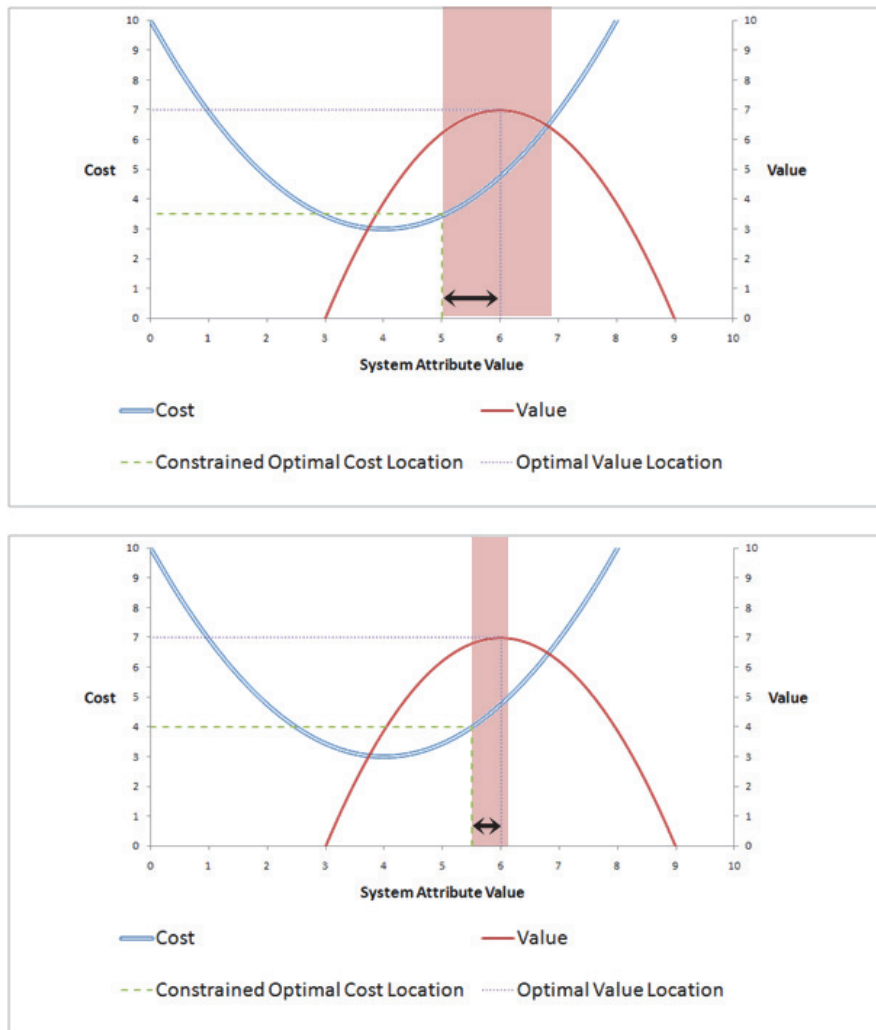
The value-centric and the cost-centric frameworks share similar primary challenges. When conducting a value-centric analysis, the primary challenge is quantifying the value function. This function must translate levels of system performance into a single aggregate value measure that consistently conveys decisionmaker preferences for different systems. For a cost-centric analysis, the primary challenge is in identifying the requirements.

The foundations of a value-centric analysis are degraded if the value model does not accurately reflect decisionmaker preferences. A theoretical requirement of a decision function is that it must consistently and accurately order the preferences of the decisionmaker. If the value model is not consistent or accurate, the analysis becomes

meaningless, since the indicated solution is not necessarily the preferred solution. Another challenge when conducting a value-centric analysis is aggregating multiple performances attributes into a single comprehensive measure of system worth. Consider the design of a new imaging satellite. Cost, reliability, available resolution, and revisit rate can all be quantified using different metrics. A value-centric approach requires that these different metrics be rolled into a single unique value of shared units (e.g., U.S. dollars [USD] or utility) using a viable value model.

Similarly, a cost-centric analysis performed with poorly identified requirements might be considered hollow. Earlier, I argued that the cost-centric framework was similar to mathematical satisficing. Properly specified system requirements should restrict the design such that optimizing only cost will provide a final solution that is close to the theoretically optimal solution. Poorly defined requirements could potentially drive the final solution away from the theoretically optimal solution, indicating a decision that is poorly aligned with the preferences associated with the decision environment. The example in Figure 3.1 graphically presents this idea.

Figure 3.1
Graphical Depiction of Defined Requirements



In this simple example, the system is completely characterized by a single attribute. In the figure, the solid lines graph the cost and the value of the system based on the attribute measure. The two-sided arrows measure the difference between the indicated solution and the optimal solution. In a cost-centric framework, the analyst knows the cost of the system as a function of the attribute but does not take the time to derive a viable value function that correctly maps preferences. Instead, the system is constrained to perform within a specified range (the shaded region), and the minimum cost system within this region is selected. In the first panel of Figure 3.1, the requirements are

"poorly" defined, indicating a system that is qualitatively different from the optimal solution. In the second panel of Figure 3.1, the requirements are improved, and the indicated solution is much closer to the optimal solution. This example demonstrates the satisfying properties of the cost-centric framework and how the quality of the analysis depends on the quality of the requirements.

It is important to note that a cost-centric framework implies that all costs must be aggregated into a single unit to be minimized while system attributes can be constrained on different scales if necessary. Conversely, in a value-centric analysis, value must be aggregated into a single scalar measure that can be optimized while costs are held as constraints. Hitch and McKean (1960, pp. 176) suggest that this difference is the single most significant trait to consider when differentiating between a value-centric approach and a cost-centric approach, noting that "the choice between these two criteria depends largely upon convenience of analysis and upon whether it is gain or cost that can be fixed with the greater degree of 'correctness.'" In the family residence selection problem discussed above, it is easier to fix gains (the attributes of the house) and optimize cost than it is to fix cost and optimize gains. On the other hand, when making corporate investment decisions, it may be more convenient to fix cost and optimize gains.

Decisionmaker Characteristics and Preferences

Group decisionmaking is a difficult process, both in theory and practice. The application of value-centric methodologies to decisions in which the decisionmaking entity is a group of individuals or organizations provides additional practical hurdles that must be overcome. The value-centric methodologies are based on axiomatic decision theories, yet Arrow's theorem states that rational, axiomatic decisionmaking is impossible in a group context unless an individual is appointed as a dictator-like figure and the groups acts like an

individual (Cooke and Bedford, 2001).³² While in some cases, such an approach is possible; in other situations, it is not realistic to expect that a single individual could be appointed to act as a "dictator." In the private sector, the interests of multiple stakeholders associated with a firm's decisions can be aggregated into a single entity that attempts to maximize profit (a measure of value). Elsewhere, it may be difficult to accurately aggregate the preferences of multiple stakeholders into a single value. This aggregation must also be acceptable to all stakeholders. In the housing example, family members may have different preferences that may be hard to aggregate. As another example, consider a system targeted for use by multiple branches of the armed forces. The Air Force, Army, and Navy may have competing objectives that cannot be aggregated into a single value measure. Under such situations, it may be impossible to develop a value function to consistently, transparently, and concurrently capture the preferences of each stakeholder.

Optimality Requirements

The focus on identifying a solution that optimally aligns with the preferences of the decisionmaker is an appealing aspect of the value-centric framework; however, there are scenarios that justify a departure from optimality. First, and maybe most significant, the optimal solution may not be needed or the additional cost and time required to identify the optimal solution may outweigh any additional benefits the optimal solution provides. This idea is reflected in the aphorism "the last ten percent of performance generates one-third the cost and two-thirds of the problems" (Augustine, 1997, pp. 103). Taking the time to accurately elicit decisionmaker preferences and develop a consistent value model may improve the final system; however, the additional value may not justify the additional costs.

Also, significant uncertainties in the problem formulation can play a large role in determining the importance of pursuing an optimal system

³² For more information on Arrow's theorem, the interested reader is directed to Arrow, 1958.

design. All value-centric methodologies are predicated on the idea that, when faced with uncertainty, the system with the highest expected value should be selected. Some uncertainties are relatively easy to include in such an analysis (e.g., failure probabilities). Other uncertainties--such as subjective uncertainties (e.g., the probability country X will develop capability Y in the next 10 years) and deep uncertainties (e.g., the geopolitical environment in 30 years)--are more difficult to quantify and measure. When uncertainties are not easily measured or quantified, an expected value calculation is difficult to perform and defend for accuracy and validity.

Reasons for Using the Cost-Centric Framework

Formulations of the value-centric approach to systems analysis dominate the academic literature. Even the literature dedicated to the cost-centric approach acknowledges that this strategy typically produces less than optimal systems. Despite these observations, the cost-centric framework has been the dominant framework for systems analysis within the DoD for the past 60 years. My research indicates that there are four scenarios that favor the cost-centric framework over the value-centric framework:

1. ***The additional time required to optimize an imperfect value model outweighs any additional benefits.*** It can be easier or more efficient to choose reasonable ranges or scales for objectives than to calculate marginal rates of substitution across different attributes. Value models will always be an imperfect approximation of reality. To produce a meaningful value model, all decisionmakers must be heavily involved in the entire process in order to ensure that the model properly conveys the desired preferences. In many cases, the added benefits that result from accurately describing a system-value model will not outweigh the additional costs required to build, validate, and analyze the accurate models that the processes require.

2. ***It is easier to correctly formulate the problem through the cost-centric framework than the value-centric framework.***

Under the cost-centric framework, system requirements are constraints within an optimization problem. These constraints can be formulated using separate units (e.g., the range must be greater than X; the resolution must be greater than Y). Under the value-centric approach, a value model must be developed that aggregates these measures of performances into a single measure of value (for example, USD) that is consistent and viable with decisionmaker preferences. Not all problems will center on benefits that can be easily quantified.

3. ***The decisionmaker thinks in terms of aspiration levels (system requirements) as opposed to marginal tradeoffs.***

Decisionmakers might not always have consistent, measurable preferences but, instead, want to achieve certain, predetermined goals or capabilities. Requirements and aspiration levels are a natural extension of goal-oriented management practices.

4. ***When making decisions that require the input of multiple decisionmakers, compromise is reached through the agreement on a set of goals (requirements) and not through the aggregation and balancing of individual preferences (value function).*** Aggregating competing preferences of multiple stakeholders into a common value measure poses both theoretical and practical problems. What is the appropriate relative weight of different objectives? Whose preferences are more important? How should these competing preferences be used to translate performance into an ordinal system rank? The cost-centric framework can circumvent these challenges by identifying requirements that are reasonable for all stakeholders involved.

DEFENSE-SYSTEMS-ANALYSIS DECISION ENVIRONMENT

Valuing National Defense and Military Effectiveness

The key challenge in implementing a value-centric analysis is constructing a consistent value function. The assumption that firms maximize profit simplifies this challenge in the private sector, allowing value to be measured in monetary units. For DoD system acquisition decisions, there is no commonly accepted quantitative measure for military effectiveness or national defense. The additional value that a weapon system provides to national defense is difficult to quantify, and it is even more difficult to do so in a way that is transparent enough to accurately frame debate and policy decisions.

Using the commercial value of a DoD system is one proposed method for circumventing the difficulties associated with quantifying the military effectiveness (Brown and Eremenko, 2009). This technique is appealing for systems with clear commercial counterparts; however, there is no reason to believe that the equivalent commercial value of a DoD system correlates with the value that system provides to national defense. Such economic forces as equilibrium supply and demand drive commercial value. The needs of the warfighter, strategic vulnerabilities, threat assessments, and adversary force posturing all drive the value--or, more appropriately, the effectiveness--of a DoD system. It is true that the commercial value of the space capabilities could be used to construct a system value model for DoD systems analysis decisions, but such a model would optimize commercial value, and not necessarily military value.

When using a cost-centric framework, the analyst is not forced to aggregate system performance metrics into a single measure. Those system attributes that can be easily combined into a common measure (monetary units such as USD) are optimized, while the others are characterized by constraints. Measures of system performance do not have to be aggregated into a common measure of military value. When done properly, this local approximation can provide transparent solutions that are nearly optimal. This makes the cost-centric approach a convenient and appealing framework for the DoD decision environment.

The Joint Capabilities Integration and Development System

It is important to note that system analysis decisions are not made independent of the rest of the DoD acquisition process but, instead, are part of a larger process designed to provide the capabilities required to satisfy national security objectives. The Joint Capabilities Integration and Development System (JCIDS) is the set of procedures that ensures acquisition and budgeting decisions are made in a consistent manner across all branches of the military "by identifying and assessing capability needs and associated performance criteria to be used as a basis for acquiring the right capabilities, including the right systems" (CJCS, 2009). The first part of the JCIDS is a capabilities-based assessment (CBA). This assessment identifies the defined mission, required capabilities, and any existing capability gaps. The operational risk of these gaps is then identified and prioritized. Next, the CBA assesses potential nonmaterial solutions and provides recommendations for filling capability gaps. The Joint Requirements Oversight Council (JROC) is then responsible for validating these capability requirements and for determining one of three possible directions for addressing the capability gaps: (1) accept operational risk with no further action, (2) pursue a nonmaterial solution to address or fill capability shortfalls, or (3) recommend a material solution to address or fill the capability shortfalls (CJCS, 2009). When a material solution is recommended, the requirements identified in the CBA drive all subsequent phases in the acquisition process, including the analysis of alternatives (AOA), technology development; engineering and manufacturing development (EMD); production; deployment; and sustainment.

In each of these phases of the acquisition process, systems analysis decisions are addressed using the cost-centric framework and the requirements identified in the CBA. The JCIDS process ensures that new systems are pursued only if there is an operational need to fill an existing capability gap. The requirements derived in the CBA and handed down to the acquisition decision authority ensure that the new system will fill the existing capability gap and mitigate associated preexisting operational risk.

All decisions for potential DoD systems must be made in the context of the JCIDS. The JCIDS is suppose to guide acquisition and budgeting decisions in a systematic way across the entire DoD (CJCS, 2009). Strategic objectives are translated into capability requirements, which are used to derive capability shortfalls. When a new system is pursued to meet these requirements, the system requirements are derived in order to ensure the capability shortfalls are adequately addressed. The cost-centric framework of constraining system performance attributes to a set of requirements is a natural extension of the JCIDS, which produces the requirements used in the cost-centric analysis. The value-centric framework would shift the focus of the acquisition framework from filling capability gaps to maximizing some measure of military effectiveness. To correctly implement the value-centric approach for these decisions, the CBA would have to produce a set of value preferences for the new system. Because capability assessments depend on all other programs and systems across the DoD, this change would require a radical reworking of the JCIDS framework.

SYSTEMS ANALYSIS FRAMEWORKS FOR FLEXIBLE SPACE ARCHITECTURES

Rapid-reaction launch systems, small satellites, on-orbit serving systems, and other flexible space systems have been proposed as potential systems that can improve the flexibility of NSS capabilities. All of these proposed systems share the common goal of increasing the number of cost-effective recourse decisions that are available following an unexpected event. Thus, the systems analysis framework that supports these systems must incorporate uncertainty and a dynamic decision environment. In contrast, these considerations are less important in traditional NSS systems in which the long development cycles, large unit costs, and on-orbit inaccessibility limit the ability to change the mission profile of a system after launch.

The debate between the cost-centric and value-centric framework for systems analysis is of particular interest to the NSS community and its efforts to improve the flexibility of its space-based capabilities. Specifically, it has been hypothesized within the community that the value-centric framework would do a better job of incorporating

flexibility into NSS systems analysis decisions (Weigel and Hastings, 2001; Saleh et al., 2003; Brown and Eremenko, 2006a; Nilchiani and Hastings, 2007; Saleh, 2008; and Brown and Eremenko, 2009). Here, I address these questions in the context of fractionated space systems; however, the arguments and techniques would be similar for other flexible space systems.

Overview of Fractionated Space Systems

The Air Force Chief Scientist (AF/ST) has identified fractionated architectures as a potential capability area for future Air Force space systems (United States AF/ST, 2010). The AF/ST defines a fractionated space satellite as a set of physically separate, functionally different on-orbit modules that can act independently or cooperate to act as a single system. After defining a set of communication protocols, the individual modules could be designed independently of each other and integrated on-orbit. In contrast, an integrated satellite system³³ is one in which all subsystems are housed on the same satellite bus and integration occurs prior to launch.

There are many purported benefits associated with fractionated space architectures. The majority of these benefits address the ability of NSS systems to respond to uncertainty. A properly designed fractionated space system could accommodate additional modules with new or expanded capabilities, even after the initial system has been placed into orbit around the earth.³⁴ This mechanism would allow fractionated architectures to be scaled to meet unforeseen growth in demand (scalability), modified to provide a new capability (adaptability), maintained at a low cost (maintainability), and upgraded to improve the performance of the existing capability (upgradeability). In addition, properly taking advantage of fractionated redundancy could improve the

³³ The fractionated space system literature uses the terms *integrated satellite system* and *monolithic satellite system* interchangeably.

³⁴ In contrast, the performance characteristics and delivered products of an integrated satellite are severely constrained once it is placed in orbit.

survivability of NSS systems, since it is conceivable that the system may survive and sustain some operations following the loss of any single module. Other purported benefits of fractionated systems include the ability to assemble systems on-orbit that are larger and more capable at a lower overall launch cost and the ability to lower the cost per mission type by sharing common on-orbit resources across systems. In the extreme, a space-based network of shared resources and distributed computing would allow developers to orbit very simple payloads that rely on this network for computing support, communication, and power, potentially reducing barriers to entry in the commercial space industry (Shah and Brown, 2008).

The ability to fractionate space systems introduces many additional decisions into the design process. How many separate modules should the DoD orbit? How should the subsystems be distributed across these modules? How should the modules be deployed? Throughout this research, I refer to these questions as *fractionation decisions*. Fractionation decisions need to be made in the context of potential uncertainties and the additional recourse decisions fractionation affords.

Fractionation and the Value-Centric Framework

The primary goal of current fractionation research is to produce a space system that is more flexible and robust than the traditional monolithic NSS systems (Mathieu and Weigel, 2006). Pursuing this goal, some, such as Shah and Brown (2008) and Brown and Eremenko (2009), have argued that the cost-centric framework for system selection and design limits the ability of the NSS community to acquire flexible architectures that can adequately respond to uncertainty. Instead, because the cost-centric approach fixates on cost, they argue it does not adequately consider architectures that contribute value by creating greater flexibility to leverage future opportunities or minimize risk:

Flexibility is not an inherent part of a system--it must be designed into it. Adding flexibility comes at some cost, while doing little to ensure basic requirements are met. When focusing on meeting the requirements at hand and minimizing the risks, opportunity rarely receives a thought--particularly since it comes at a cost (Shah and Brown, 2008, pp. 31-32).

These arguments imply that because a fractionated system will increase the size, weight, and power of a design, and these attributes strongly correlate with cost, the cost-centric framework will provide inadequate comparisons between fractionated and monolithic architectures.

Real Options Analysis

While many different analytic techniques for value-centric decisionmaking can be found in the literature, the incorporation of Real Options Analysis (ROA) into the system design of potential fractionated architectures has gained traction within the community of practice. ROA is a suite of mathematical decision models designed to inform managerial decisions in a way that accounts for the added value of flexibility. A real option is the right, but not the obligation, to pursue a particular action at a date in the future (Trigeorgis, 1996). A real option implies flexibility, since the option carries no obligation to act, and will be exercised only if future uncertainties unfold in a way that favors exercising the option. The emphasis on valuing flexibility is a primary driver in the push to incorporate these ROA techniques into the fractionation decision process. It can be argued that upgradeability, adaptability, and scalability can all be formulated as real options.

The mathematics behind ROA is rooted in the valuation of financial options. A financial option is the right, but not the obligation, to buy or sell some underlying asset at a later date for a predetermined price (Guthrie, 2009). A ROA assigns value to each potential decision by constructing a replicating portfolio of financial assets that match the cash flows of the decision (to the greatest degree possible) across all future scenarios and uncertainties, taking into account the fact that managers will exercise real options only in favorable conditions. The replicating portfolio consists entirely of financial assets, and a value can be assigned using market mechanisms. Because the replicating portfolio and the managerial decision have identical (or very similar) cash flows, they must also have the same value (Guthrie, 2009). Mathematical techniques for carrying out this valuation process include

partial differential equations, binomial approximations, and Monte Carlo simulations (Lander and Pinches, 1998).

Recent literature provides numerous examples of ROA techniques being used to inform space system design and employment. ROA techniques have been used to evaluate the benefits of on-orbit servicing systems (Saleh, Lamassoure, and Hastings, 2002; Lamassoure et al., 2002), to manage NASA research and development expenditures (Shishko, Ebbeler, and Fox, 2003), and to assess the value of different satellite communication systems (Dahlgren, 2007). The optimal replacement of a set of low-earth orbit satellites is considered in Gavish and Kalvenes (1997). A dynamic approach is used that allows launch decisions to be readdressed following launch failures and on-orbit infant mortality failures.³⁵ This approach captures the essence of Real Options Analysis. Here, the analysis considers the option to expand future launch manifests in response to launch failures, along with the option to abandon future launches that are not required or are not cost-effective. Similar to the use of a binomial approximation of continuously changing asset value, the optimal decision is solved at each possible node of the outcome tree.

de Weck, de Neufville, and Chaize (2004) provide another application of ROA to space policy. The article proposes a business model for planning the deployment of a satellite constellation that comprises a large number of satellites whose demand is highly uncertain. Without knowing future demand patterns, the decisionmaker runs the risk of deploying too many or too few satellites. Deploying too many satellites results in excessive cost and reduced profit margins, while deploying too few satellites results in lost opportunities. The presented model is based on the ROA framework. Demand for the satellite service is modeled as geometric Brownian motion and approximated using a binomial tree. The constellation size and deployment strategy are not determined up front. Instead a deployment strategy that allows the

³⁵ *Infant mortality* is a phrase used to characterize a system with a failure rate that decreases over time. Castet and Saleh (2009) empirically demonstrate significant infant mortality in space systems.

decisionmaker to react to and capitalize on a changing demand pattern at later stages in the program is derived. The article culminates with a case study that demonstrates an average reduction in the life cycle cost of 20 percent for architectures similar to the Iridium telecommunication satellite constellation.

Drawbacks to Applying the Value-Centric Approach to Fractionation Decisions

Earlier it was argued that the structure of the value-centric framework does not easily translate to the defense decision environment. The same concerns exist when considering applications of the value-centric framework to DoD fractionation decisions. The military value of a system is difficult to quantify in a consistent and transparent manner. Some have argued that the existence of commercial equivalents to many DoD space systems makes it reasonable to assume a market-based value for DoD space products. As mentioned earlier, this technique is problematic since there is no guarantee that market value and military value are actually correlated.

The use of ROA within the DoD context could provide even deeper challenges. Many of the assumptions associated with these techniques do not necessarily reflect the defense decision environment. Lander and Pinches (1998) provide a survey of the ROA techniques and models and find that most require that value exists in a complete market with no arbitrage opportunities. This assumption allows the analyst to conclude that the value of the real option is equal to the value of the replicating portfolio. Even if the analyst can produce a consistent value model for a potential defense system, there is no reason to believe that this value will be the equilibrium result of market forces. Bowman and Moskowitz (2001, pp. 776) summarize the consequences of these types of challenges when they conclude:

Options are a theoretically attractive way to think about the flexibility inherent in many investment proposals; however, the use of the [ROA] methodology presents many practical difficulties, which can lead all but the most careful users to make erroneous conclusions.

This is not to say that the value-centric framework and ROA are always ill-positioned to address fractionation decisions. In the commercial space sector, where profit generation drives value and market forces of supply and demand drive profit, these value-based techniques could provide considerable insight into fractionation questions and other flexibility considerations. The structure and assumptions of these techniques, however, reduce the meaningfulness of the conclusions in the context of DoD decisions.

Flexibility and the Cost-Centric Framework

While some within the community of practice have suggested that the cost-centric framework is ill-positioned to address flexibility considerations, the relevant theoretical literature does not provide justification for this claim. It is true that in the private sector, flexibility can be incorporated into the decision process through ROA and other value-based methods; however, the assumptions that go into these mathematical models do not accurately translate to the DoD decisionmaking environment. The DoD should not attempt to assess the flexibility of fractionated space systems by borrowing corporate decision tools that are inadequate for the defense decisionmaking environment. These tools are built upon specific assumptions about the motivations and preferences of the corporate decisionmaker that may not translate to the DoD decision environment. Instead, the DoD should be looking to develop tools that more accurately reflect the assumptions and contextual environment of the DoD decisionmaking process. Such an approach would better capture the benefit of system flexibility for DoD systems.

The claim that "adding flexibility comes at some cost, while doing little to ensure basic requirements are met" (Shah and Brown, 2008, pp. 31-32) is true only if there are no requirements constraining the flexibility of the system. Flexibility, like any other system attribute, can be incorporated into a cost-centric framework through specified requirements. There are many different definitions of flexibility that can be used to construct a quantitative measure. Mandelbaum and Buzacott (1990) develop a definition of flexibility in

the context of decision theory. Given a two-staged decision, the flexibility of a first-stage decision is equal to the conditional number of second-stage decisions available after committing to the first decision. Nilchiani and Hastings (2007) define flexibility as "the ability of a system to respond to potential internal or external changes affecting its value delivery, in a timely and cost-effective manner." Saleh, Mark, and Jordan (2009) provide a complete survey of the flexibility literature in the context of systems engineering.

A simple yet informative measure of system flexibility is the probability that the system will be able to accommodate all future demand fluctuations. At a basic level, a DoD space system fills demand for some set of space-reliant consumers via space-based products. Uncertainty is relevant only if it diminishes the ability of the system to supply the required level of demand. System A is more flexible than System B if it can provide required demand levels across a larger set of future scenarios. In order for the cost-centric framework to adequately take into account the ability of a system to respond to uncertainty, the system requirements must take into account the stochastic nature of the future. When faced with uncertainty, it is difficult, if not impossible, to require that a space-based system meet all future demand possibilities. Instead, requirements should be formulated in a way that acknowledges that the future is uncertain and specifies a required level of responsiveness. Stochastic programming is a set of mathematical tools that can be used to take into account the staged decision structure found in Mandelbaum and Buzacott's definition of flexibility while also incorporating future uncertainties.

A STOCHASTIC PROGRAMMING FRAMEWORK FOR FRACTIONATION

Just as the mathematical tools of ROA might provide a way to account for flexibility under the value-centric framework, I argue that a set of mathematical models known as stochastic programming can be used to incorporate flexibility into the cost-centric framework. This section demonstrates how stochastic programming techniques can be used to develop a cost-centric framework for systems analysis and selection that captures flexibility. First, I provide a brief overview of the

components of a stochastic program. Next, I formulate the fractionation decision as a cost-centric stochastic program. Finally, I use a simple example to demonstrate how this formulation captures and trades the flexibility of a fractionated space system.

Mathematical Programming and Stochastic Programming

The goal of a mathematical program is to find an allocation of resources or set of decisions that optimizes some objective function while simultaneously adhering to a set of constraints. The general form of a mathematical program is:

$$\begin{aligned} & \underset{x}{\text{Minimize}} && f(x) \\ & g(x)_i \leq 0 && i = 1 \dots m \\ & h(x)_j = 0 && j = 1 \dots n. \end{aligned}$$

Equation 3.1

In this formulation, x is a decision vector corresponding to the available decision variables, $f(x)$ is the objective function to be optimized, $g(x)$ is a vector of m inequality constraints, and $h(x)$ is a vector of n equality constraints. The goal is to estimate the values of x that satisfy all of the constraints and optimizes $f(x)$.

Dantzig (1955) provides the foundation of stochastic programming by introducing a static two-stage optimization in which the objective is to minimize the expected cost. The total cost consists of two parts, a deterministic portion and a stochastic portion. The deterministic portion of total cost is known with certainty, while the stochastic portion will be known only after all resources have been allocated. The distribution of the stochastic cost component is realized as a function of the initial resource allocation strategy. These problems are labeled as two-stage problems because the resources are allocated in the first stage before the stochastic parameters are realized in the second stage.

Charnes and Cooper (1959) expand the stochastic program formulation to include chance constraints. Here, resources are still allocated

under uncertainty with the goal of minimizing expected cost; however, there is also uncertainty related to the parameters that describe the constraints. Under this formulation, the constraints do not necessarily have to hold in all scenarios, but rather, the constraints must hold with some probability. For example the constraint $g(x)_i < 0$, becomes $\Pr[g(x)_i < 0] \geq \alpha$, where α is some probability representing a desired level of confidence that the constraint is satisfied.

Walkup and Wets (1967) describe stochastic programming with recourse. In these problems, two types of decisions are made. The first set of decisions is made before information regarding future uncertainties is realized. The second set of decisions is made after a sufficient amount of uncertain information has been realized. Thus, the decisionmaker allocates resources before the uncertainty is resolved then readjusts those allocations after the uncertainty is revealed. The solution to a stochastic program returns an initial set of decisions, along with a set of recourse decisions for every possible future state of the world. Taken together, these decisions minimize expected cost while satisfying program-specific constraints, which can be chance constraints.

Let S be the set of all future scenarios, indexed by s . Let w^s be a vector of realized values of the uncertain parameters under scenario s and π_s be the probability that scenario s is realized. Let x be the decision vector for the deterministic decisions that have to be made before future uncertainties are resolved. Further, let y^s be the decision vector of recourse decisions made if scenario s is realized. In addition let $f(x)$ and $q_s(x, y^s, w^s)$ be the deterministic cost function and stochastic cost functions, respectively. Note that the deterministic cost is only a function of the deterministic decision vector, while the stochastic cost is a function of the deterministic decisions, the recourse decisions, and the realized parameters. Similarly, the inequality and equality constraints can depend on the deterministic decisions, the stochastic decisions, and the uncertain parameters. Finally, let $\alpha \in \mathbb{R}^m$ and $\beta \in \mathbb{R}^n$ be vectors of probabilities corresponding to the desired level of confidence that each constraint is satisfied. Under this notation, the deterministic equivalent of the stochastic

programming with recourse decision variables and chance constraints can be written as:

$$\begin{aligned} \underset{x,y}{\text{Minimize}} \quad & f(x) + \sum_{s \in S} \pi_s q_s(x, y^s, w^s) \\ \text{Pr}[g(x, y, w)_i \leq 0] \geq & \alpha_i \quad i = 1 \dots m \\ \text{Pr}[h(x, y, w)_i = 0] \geq & \beta_i \quad i = 1 \dots n. \end{aligned}$$

Equation 3.2

Modeling Fractionation Decisions

The decision framework in a stochastic program can be leveraged to facilitate fractionation decisions. Deterministic design decisions for a fractionated system candidate must be made before key uncertainties have been realized. For example, the distribution and redundancy of mission critical subsystems across the separate modules must be determined before knowing which module will fail first. After the deterministic design decisions are made, the flexibility of a system incorporates how the system responds after uncertainties are realized. The availability and consequences of these recourse decisions will depend on all previous decisions and the realized uncertainties. For example, a system with built-in redundancy may be able to respond to the failure of one module by simply reallocating on-orbit resources, while a system without the proper redundancy would be forced to build and launch a new module. Correctly applying the stochastic programming framework to fractionation decisions would ensure that these dependencies are incorporated into the decision process.

Table 3.1 provides examples of deterministic decisions and stochastic decisions that are relevant to the design of a fractionated space system.

Table 3.1
Examples of Stochastic and Deterministic Decisions

<u>Examples of Deterministic Decision</u>
-- Should a fractionated architecture or a monolithic architecture be used to provide a new space-based capability?
-- How many modules should the system be fractionated into?
-- How should the subsystems be distributed among the different modules?
-- How much redundancy should be included across the different modules?
<u>Examples of Stochastic Decisions</u>
-- How should the on-orbit resources be allocated to meet changing user needs?
-- Should additional modules be deployed in response to a launch failure, on-orbit failure, spike in demand, or unforeseen change in requirements?

The stochastic programming framework uses scenarios to model uncertainty. A scenario is a set of realized values for the uncertain parameters, along with a corresponding probability of occurrence. For example, consider a decision problem with only two relevant uncertainties: uncertainty related to the launch of the system and uncertainty related to the demand of a system. A specific scenario would convey three things: (1) the outcome of the launch (success or failure), (2) the demand level for the capability, and (3) the probability that the scenario occurs.

In my framework, the probability that the system will be able to meet all future demand fluctuations measures system flexibility. This definition incorporates flexibility into the decision process by replacing requirements with chance constraints. "All constraints must be satisfied in X percent of possible future scenarios" is an example of a chance constraint, where X is a measure of the flexibility of a system. Thus, in addition to the traditional requirements that result from the JCIDS process, my framework would require the determination of a minimum level of acceptable flexibility. Finally, this framework is

cost-centric in that it selects the minimum cost architecture that meets all of the requirements. When dealing with uncertainty, this cost can be a deterministic measure of cost or some probabilistic measure of cost (e.g., expected cost or some percentile of the cost distribution), depending on the context of the problem.

Example Fractionation Problem

Consider a space system that must provide a set of space-based products. Let P be the set of space-based products, indexed by p . The amount of each product that can be supplied depends on the availability of on-orbit resources, (e.g., processor time, storage, communication time, etc.). Let R , be the set of all resources, indexed by r . These resources can be provided by different subsystems. Let F be the set of all subsystems, indexed by f .

I make multiple assumptions to simplify this example. First, it is assumed that resources are combined additively such that the total amount of resource r available on-orbit is equal to the sum of the amount of resource r contributed by all available subsystems. In addition, I assume a linear transformation function that describes how much of resource r is required to produce one unit of product p .³⁶ Finally, on-orbit resources must be allocated across the set of products, and the amount of product p that can be supported is constrained by each resource. For example, if there is enough of resource 1 allotted to support four units of product 1, but only enough of resource 2 to support three units of product 1, the system as a whole can provide only three units of product 1.

For this example, I consider a space system that provides two products.³⁷ There are five different resources, and five potential

³⁶ These two assumptions are a first-order approximation of how a space product is delivered and are based on the mechanics behind the DARPA F6 Phase 1 value models and the system driver identification process found in Wertz and Larson (1999). These simple assumptions are appropriate only for high-level analyses and studies, such as an initial feasibility analysis.

³⁷ It is important to note that the goal of this example is **not** to demonstrate the benefits of a fractionated space system; but rather, to

subsystems. The parameters associated with these resources are given in Table 3.2 and Table 3.3.

Table 3.2
Example: Subsystem Parameters

	Resource 1	Resource 2	Resource 3	Resource 4	Resource 5
Subsystem 1	100	0	0	0	0
Subsystem 2	0	100	50	10	0
Subsystem 3	0	0	100	50	10
Subsystem 4	10	0	0	100	50
Subsystem 5	50	10	0	0	100

Table 3.3
Example: Transformation Rates

	Resource 1	Resource 2	Resource 3	Resource 4	Resource 5
Product 1	1	1	1	1	1
Product 2	2	2	1	1	1

The decisionmaker must determine how to distribute these subsystems across a set of modules, M . In addition, the modules must be distributed across a set of launch vehicles, L . There are costs associated with each decision. The cost of each module is equal to the sum of the costs of all subsystems placed on that module, plus a fixed cost for purchasing the module. There is also a cost associated with each launch vehicle. For this example, I considered up to five identical modules and three identical launch vehicles. All modules are assumed to cost \$40 million before placing subsystems on them, while each launch vehicle is assumed to cost \$20 million. The assumed costs for each subsystem are provided in Table 3.4.

demonstrate how flexibility can be incorporated into a cost-centric analysis of a flexible space system.

Table 3.4
Example: Subsystem Costs

	Cost
Subsystem 1	\$10M
Subsystem 2	\$5M
Subsystem 3	\$10M
Subsystem 4	\$15M
Subsystem 5	\$5M

Finally, this example considers three different uncertainties: launch uncertainties, on-orbit availability uncertainties, and demand uncertainties. Launch uncertainties reflect the uncertainties associated with launching payloads into orbit. I assume that if selected, each launch vehicle has a 90-percent chance of successfully placing all assigned modules into the correct orbit. The availability uncertainties reflect the uncertainties associated with spacecraft infant mortality. Once on-orbit, I assume a 5-percent infant mortality rate. If a module fails its initial checkout, any onboard subsystems and their associated resources are not available to the system. There are three possible demand levels associated with each product. These demand levels and associated probabilities are provided in Table 3.5 and Table 3.6.

Table 3.5
Example: Demand Levels

	Low	Medium	High
Product 1	20	50	100
Product 2	10	20	60

Table 3.6
Example: Demand-Level Probabilities

	Low	Medium	High
Product 1	35%	50%	15%
Product 2	30%	60%	10%

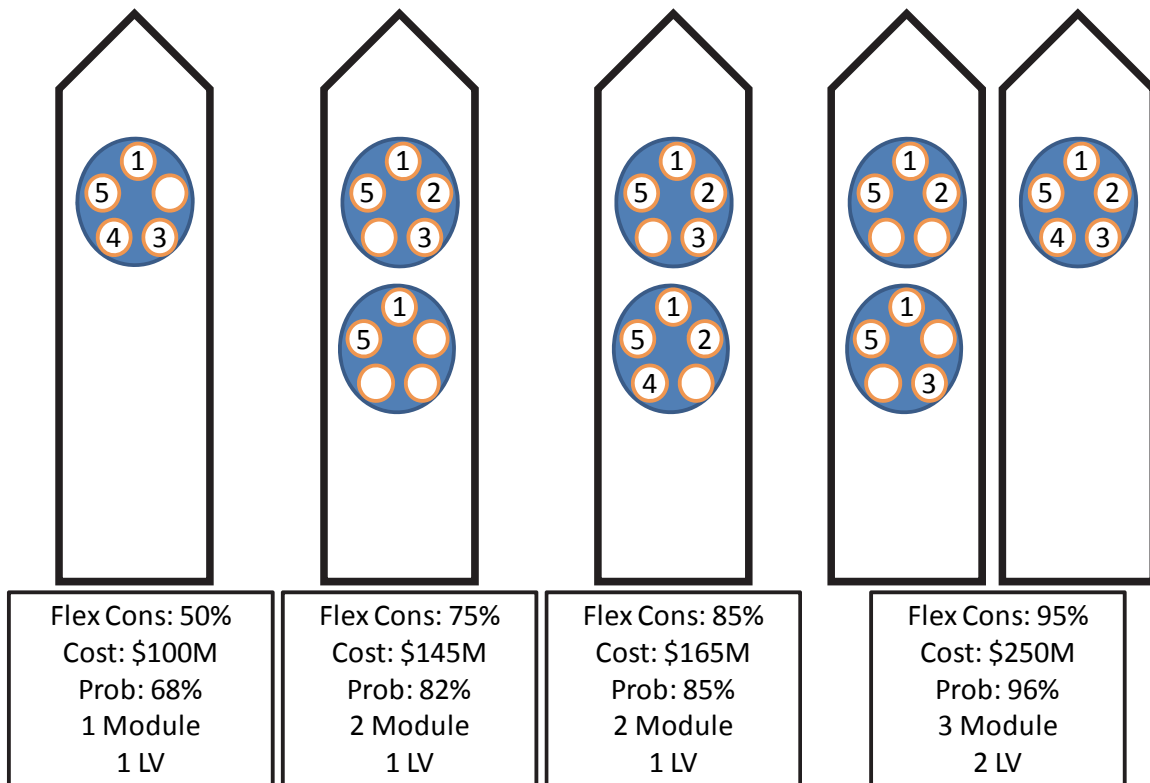
If all these uncertainties are assumed to be independent, there are $3^2 \times 2^5 \times 2^3 = 2,304$ different scenarios that could unfold.

The objective is to select the system design of minimum cost. The probability that the chosen design satisfies all demand must exceed some predetermined threshold, α . The deterministic decisions are the number of modules to purchase, the number and distribution of subsystems across each purchased module, and the distribution of the modules across each launch vehicle. After all the uncertainties are realized (launch, infancy failures, and demand levels), the recourse decisions allow the decisionmaker to reallocate the on-orbit resources across the different space-based products in order to provide for as much demand as possible, given the available on-orbit resource set. Appendix D formulates this problem as a mixed-integer linear program.

Although this is a very simple example, it does capture some of the important decision points of the fractionation decision process. The example captures the basic fractionation decision of how many modules to orbit, along with the distribution of subsystems across those modules and subsystem redundancy. For example, one possible design would place the minimum number of required subsystems on one module. This would be a cheap solution; however, the failure of the launch vehicle or module would leave the decisionmaker with little recourse. Conversely, a design with multiple modules with distributed redundancy would be positioned to respond to a launch failure or some infant mortality, but it would be more expensive. Finally, the example demonstrates an adaptability mechanism, as the recourse decisions allow the decisionmaker to perform on-orbit reallocation based on the demand for the different products.

Using this example, I solved for the cost-minimizing architecture for four different constraints on the overall probability that all demand is met: 50 percent, 75 percent, 85 percent, and 95 percent. Figure 3.2 is a pictorial representation of the progression of the optimal architecture as the lower limit associated with the flexibility constraint is increased.

Figure 3.2
Example: Progression of Optimal Fractionated Architecture



NOTES: "Flex Cons" equals "flexibility constraint" and is the lower bound on system flexibility. "Prob" equals "probability" and is the probability that the system design will be able to support all future demand levels.

In Figure 3.2, each large circle represents a module, with the inner circles representing fractionated subsystems. The first architecture is designed assuming that the probability that all demand is met must exceed 50 percent. The minimum cost solution that attains this constraint includes only one module and one launch vehicle. When the lower limit on the flexibility constraint is increased to 75 percent and 85 percent, the cost-minimizing solution includes two modules with distributed redundancy in the subsystems. For example, when the flexibility of the system is required to be greater than 75 percent, subsystem 1 and subsystem 5 are included in both modules, adding a layer of redundancy for these two subsystems. This redundancy is added without having to field completely redundant modules and reduces the

consequences of losing one module to an on-orbit infancy failure. Increasing the number of subsystems also gives the system the ability to successfully respond to the high demand scenarios. Finally, when the lower limit on the flexibility constraint is increased to 95 percent, the optimal architecture utilizes three modules. Distributing these three modules across two launch vehicles reduces the consequences of a launch failure.

SUMMARY OF FINDINGS AND CONCLUSIONS

- *The value-centric framework aims to identify a solution that is optimally aligned with the preferences of the decisionmaker, while the cost-centric framework is a convenient method for identifying a solution that satisfactorily addresses the preferences of the decisionmaker.* While the value-centric framework is more prevalent in the theoretical literature, there are problem attributes that favor a cost-centric approach. Some problems are more conveniently formulated using the cost-centric framework. Other times, the additional time required to optimize an imperfect value model outweighs any additional benefits. In addition, some decisionmakers may not have consistent preferences but, instead, have a set of tangible goals or aspiration levels. Finally, it may be difficult to formulate consistent value functions for problems that involve multiple stakeholders with different preferences.
- *The promise of identifying an optimal solution is appealing; however, practical challenges dampen the usefulness of these frameworks in the context of the DoD decision environment.* Specifically, the incommensurable nature of military effectiveness and marginal improvements to national defense make it very hard to identify a consistent value model for DoD systems. In most DoD applications of system analysis, cost is readily quantified into a common unit, such as USD.

Military value is much harder to measure and to quantify with a single metric. Unlike financial obligations, there is no commonly accepted measure for military effectiveness or national security. Thus, for many DoD applications, it is easier to aggregate and then minimize costs while enforcing constraints on system requirements (which can exist on different scales) than it is to aggregate the values of all system performance attributes into a common unit to be subsequently maximized. While there is no guarantee that an optimal solution is identified, the cost-centric framework provides a transparent approach to systems analysis that provides meaningful and consistent insight into DoD acquisition decisions. This tradeoff between optimality and consistency is reinforced by Bowman (1963), who concludes that consistent managerial decision frameworks are more valuable than approaches purporting to give "optimal" solutions.

- ***The fact that DoD acquisition decisions are made in the context of a larger enterprise makes it difficult to apply the value-centric framework to only flexible space systems.*** All decisions for potential DoD systems must be made in the context of the JCIDS. The strength of JCIDS is that it guides acquisition and budgeting decisions in a systematic way across the entire DoD. Strategic objectives are translated into capability requirements, which are used to derive capability shortfalls. The cost-centric framework is a natural extension of this process, as the requirements that are produced as a result of the JCIDS guide subsequent phases of the acquisition process. Applying the value-centric approach to just the design of and selection of flexible space architectures would be impractical. The JCIDS is designed to provide a unified approach to system procurement, and any significant program-level changes would potentially

disrupt the entire enterprise, unless these changes were adopted across the entire enterprise.

- ***Flexibility can be incorporated into the cost-centric framework.*** Flexibility is a system attribute. Just like any other system attribute, a set of requirements can be used to incorporate flexibility into the cost-centric decision problem. Here, flexibility is measured as the probability that all future demand will be satisfied. This measure is then incorporated into the decision problem by requiring that the flexibility of the system surpass some lower bound.
- ***The decision logic that supports flexible space systems is different than the logic that informs traditional NSS system decisions.*** This decision logic must take into account uncertainties and additional recourse decisions that traditional NSS systems do not afford. The mathematical structure of stochastic programming provides one methodology for formulating these problems. These decision models are specifically designed to take into account uncertainty and interrelated recourse decisions.

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CONCLUSIONS AND FUTURE RESEARCH

INTRODUCTION

My research investigated three separate policy challenges. While the resulting observations and conclusions from each essay are independent of each other, there are some broad themes that encompass the conclusions from each research effort. In this chapter, I summarize these themes and provide suggestions for future research.

GENERAL THEMES

As I compiled the results from each essay, I noted the following key themes:

- *The technology required to field flexible space systems is actively being developed and demonstrated; however, the decision logic that supports these systems must also be developed in order for the NSS community to realize the true benefit of these systems.* The USAF, DARPA, and the industrial base have conceptualized, developed, or demonstrated small satellites that offer military value, on-orbit servicing, and fractionated space systems. These systems will not reach their true potential without the development of a decision logic that dictates how they will be used to respond to uncertainty. For example, the cost-effectiveness and timeliness of small satellites is diminished if they are launched using the same risk-adverse launch paradigm that supports traditional NSS systems.
- *Acquiring, employing, and sustaining a portfolio of flexible NSS systems require a decision logic that is systematically different from the decision logic that supports traditional NSS systems.* The attributes of the traditional NSS system leave the decisionmaker with little recourse following some unexpected realizations: Repositioning a satellite system can be difficult and reduces useable lifespan; reacquiring a new system is a long, expensive process; and most systems cannot be physically modified

once placed in orbit. Making these decisions available affects how NSS systems should be acquired, employed, and sustained.

- ***The ability to respond to uncertainties allows decisionmakers to mitigate potential risks and capitalize on potential opportunities.*** Because of the risk-adverse nature of traditional NSS programs, managing uncertainty and managing risk are typically viewed as being equivalent. This does not need to be the case. In addition to reducing any risks, properly employing flexible space systems can allow the NSS community to capitalize on unforeseen opportunities. For example, a fractionated space system could be used to quickly field an unanticipated new technology.
- ***The decision logic that supports these flexible space systems should provide an enterprise-level assessment of potential courses of action.*** Space systems operate in a net-centric environment, and system-level decisions can impact an interconnected set of stakeholders and systems. For example, evaluating the advisability of a rideshare opportunity requires an understanding of the launch savings afforded to the auxiliary payloads and any additional risks to the primary satellite system. Ignoring this interconnectedness can result in suboptimal decisions.
- ***Any flexible space system decision logic should incorporate cost risk and mission risk.*** Cost risk and mission risk are two important dimensions of any DoD decision problem. Neglecting either one can result in an incomplete analysis. For example, based on cost-risk alone, a low-cost, low-reliability launch option would offer a significant improvement to USAF small satellite launch capabilities. Once mission risk is incorporated, the utility of this potential launch option diminishes. Incorporating mission risk has a similar result on the advisability of a rideshare opportunity.

- *The DoD should not attempt to assess the flexibility of fractionated space systems by borrowing corporate decision tools that are inadequate for the defense decisionmaking environment.*

These tools are built upon specific assumptions about the motivations and preferences of the corporate decisionmaker that may not translate to the DoD decision environment. Instead, the DoD should be looking to develop tools that more accurately reflect the assumptions and contextual environment of the DoD decisionmaking process. Such an approach would better capture the benefit of system flexibility for DoD systems.

FUTURE RESEARCH

If the NSS community decides to supplement its portfolio of NSS systems with the flexible space system discussed above, there is a unique set of challenges that must be overcome. My primary objective with this research was to provide analytical insight into some of these challenges by examining how a portfolio of flexible space systems would be acquired, employed, and sustained. I did not intend to address whether these systems *should* become part of the NSS portfolio. In general, future research should continue to explore the benefits of (and alternatives to) these flexible space systems. Specific attention should be committed to describing the military utility and quantifying the cost-effectiveness of these systems. Furthermore, these flexible space systems could adversely affect the space environment. For example, proliferating large constellations of small satellites that are constantly being repositioned could increase the frequency of orbital collisions and, thus, increase the growth of space debris. Additional attention should be committed to understanding these risks.

More specifically, an in-depth analysis of mission risk should be used to expand upon the results and conclusions in essay one. Another natural extension of essay one is to explore how launch vehicle production rates, launch facility volume constraints, and small satellite mission sets affect optimal small satellite launch strategies. The NSS ridesharing literature would benefit from an analysis of the cost, benefits, and contractual mechanics of ridesharing NSS payloads on

domestic commercial launches. In addition, an engineering-based "bottom-up" probabilistic risk assessment of secondary payload adaptors could refine the estimates of the rideshare reliability effect found in essay two. In essay three, I argue that flexibility should be incorporated into DoD systems analysis by placing a requirement on some quantifiable measure of system flexibility. While my measure of flexibility is based on the theoretical literature, future research should examine other measures of flexibility for DoD systems.

APPENDIX A: EXPONENTIAL GROWTH IN THE NUMBER OF LAUNCH STRATEGIES

INTRODUCTION

Essay one makes the claim that the number of launch strategies quickly increases as the number of payloads and launch vehicles increase, making it difficult to simulate the cost distribution for every strategy. This claim is demonstrated below.

PROBLEM SETUP AND RESULTS

Consider a set of four payloads, all of which are different, and four types of launch vehicles. The goal is to calculate the total number of possible launch strategies. To simplify the calculation, it is at first assumed that there are no mass constraints.

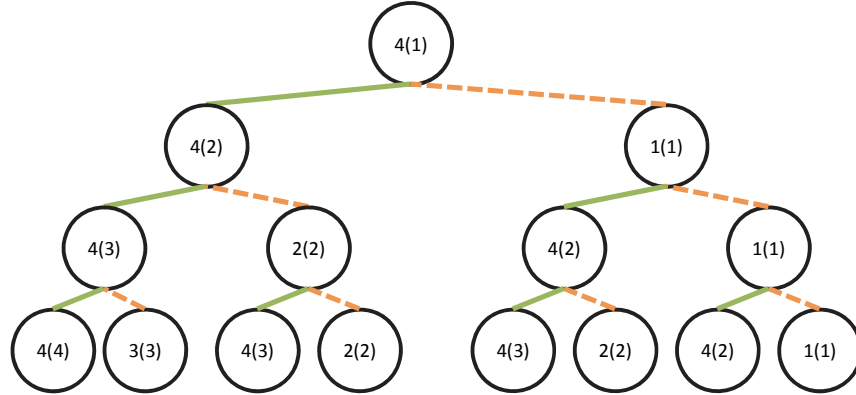
When assigning the first payload to a launch vehicle, the decisionmaker has four possible choices, one choice for each type of launch vehicle. When assigning the second payload, the decisionmaker must first decide whether to bundle this payload on an existing launch vehicle (i.e., place the payload on the launch vehicle to which payload one was assigned) or to place payload two on a new launch vehicle. If it is decided to bundle payload one with payload two, the decisionmaker has $4 \times 1 = 4$ decisions. If, on the other hand, it is decided that two separate launch vehicles will be used, the decisionmaker has $4 \times 4 = 16$ decisions. This process repeats itself until all four payloads have been assigned.

Figure A.1
Assigning Four Payloads to Four Types of Launch Vehicles

----- Existing LV
—— New LV

Node Terminology

Number of Options at Node(Number LVs After Decision)



$$4^4 + 3 \times 4^3 + 2 \times 4^3 + 2^2 \times 4^2 + 1 \times 4^3 + 1 \times 2 \times 4^2 + 1^2 \times 4^2 + 1^3 \times 4 = 756$$

The example with four payloads and four types of launch vehicles is displayed in Figure A.1. Each node represents a decision point, with the first number being the number of options available at that point, and the second number, in parentheses, representing the number of launch vehicles being used up to that point. For this example, there are 756 possible launch strategies.

Notice that the first term in the summation will always take the form L^P , where L is the number of launch vehicles and P is the number of payloads. This term represents the decision to place every payload on its own launch vehicle. Because there are L possible launch vehicles for each payload, there are L^P strategies associated with assigning a unique launch vehicle for each payload. Because all the other terms are positive, L^P is a lower bound on the total number of strategies (and will dominate for large P). The addition of mass constraints and capacity constraints does not change this fact, provided all individual payloads

are compatible with all types of launch vehicles (a reasonable assumption for small satellites).

In the analysis performed in essay one, if the decisionmaker decides to place each payload on its own launch vehicle, the ESPA class would never be chosen, since it costs more than the HCHR class, but it has the same reliability and performance constraints. Thus, with the three remaining launch vehicle classes and 20 payloads, a lower bound for the number of launch strategies is $3^{20} \approx 3.5$ billion. The large number of launch strategies makes it difficult, if not impossible, to simulate the cost distribution for each launch strategy.

APPENDIX B: LAUNCH VEHICLE ASSIGNMENT PROGRAM DERIVATION

LAUNCH VEHICLE ASSIGNMENT PROGRAM

This appendix provides an overview of the first step of the framework presented in essay one for constructing small satellite launch strategies. This optimization problem prunes the set of possible launch strategies into a manageable set of strategies that is efficient with respect to expected cost and the spread in worse-than-expected outcomes (i.e., downside semivariance). Hereafter, this optimization problem will be referred to as the launch vehicle assignment program (LVAP).

Similar to the Markowitz portfolio selection problem, the LVAP selects a launch strategy that minimizes the downside semivariance in the cost distribution, subject to a constraint on the expected cost, as well as other performance and assignment constraints. Minimizing semivariance across a range of budget constraints on the expected cost traces out an efficient set of launch strategies.

RELEVANT LITERATURE

Risk Measures for Portfolio Selection

Markowitz's (1952) portfolio optimization is one of the first analytic asset allocation strategies that balances the tradeoffs between risk and reward. Markowitz's (1952, pp. 77) portfolio selection is built on the assumption that "the investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing." Under this formulation, an efficient frontier of allocation strategies is produced such that no efficient portfolio can increase expected returns without also increasing the variance in those returns or vice versa. Markowitz used the variance in portfolio returns as his risk measure and showed how minimizing risk for a spectrum of required expected returns produces an efficient frontier of diversified portfolio holdings.

As a measure of risk, variance penalizes both upward deviations from the mean and downward deviations from the mean. When dealing with expected returns, deviations above the mean are positive outcomes and should not be penalized. Thus, Markowitz also considered semivariance

as a measure of risk (Markowitz, 1959). For a random variable, X , measuring total cost (as opposed to profit or return), the downside semivariance is defined as:

$$SemiVar(X) = E[\max(0, X - E[X])^2].$$

Equation B.4

This metric captures only the variance associated with realizations that have a total cost that is greater than expected. According to Markowitz (1959), the advantages of using the variances metric instead of the semivariance metric are computational cost, convenience, and familiarity. Calculating the variance is an easier calculation, and variance and standard deviation are well understood. Given the available computing power of the time, semivariance calculations were much harder to formulate and solve to optimality. Markowitz did acknowledge, however, that using the semivariance metric produced better portfolios, since the variance metric reduced extreme gains and losses while the semivariance metric sought to reduce only losses. For symmetric distributions, the two formulations are equivalent. For a more in-depth survey of the mathematics of portfolio analysis, the interested reader is directed to Steinbach (2001).

Fishburn (1977) introduces a more general framework for risk measures, known as the α - t risk model. The α - t measure of risk can be written as:

$$R(\alpha, t, X) = E[\max(0, X - t)^\alpha].$$

Equation B.5

When $t = E[X]$ and $\alpha = 2$, this measure reduces to Markowitz's semivariance measure. These α - t risk measures are sometimes referred to as lower partial moment risk measures. Other general risk measure formulations include Stone's three-parameter risk measures (1973), Bell's one-switch risk rule (1988), and Jia and Dyer's risk-value models (1996).

Risk Analysis of Space Launch Decisions

Baeker, Collins and Haber (1996) provide one of the first risk analysis of a space launch system. This analysis focuses on the repercussions of earth-bound debris fragments following a launch failure. In the literature, traditional launch vehicle reliability is measured as the probability of a successful launch based on historical figures (Isakowitz et al., 1996). Guikema and Paté-Cornell (2004a) improve on this by estimating launch vehicle reliability using Bayesian statistical methods. This Bayesian approach is then applied to quantify the increased risk associated with utilizing new launch vehicles (Guikema and Paté-Cornell, 2004b). Krevor and Wilhite (2007) provide a methodology for estimating the cost associated with an increase in reliability during the conceptual design phase of a launch vehicle. For a detailed survey of catastrophic launch failures and their causes, the interested reader is directed to Chang (1996).

The intersection of launch vehicle portfolio construction and launch vehicle reliability is less developed. Doherty (1989) examines launch risk in order to determine the optimal structure for satellite insurance contracts. The analysis of launch vehicle risk found in Parkinson (1998) identifies five sources of financial risk associated with launch failures: cost of insurance, cost of a replacement launch, cost of failure investigation, cost to maintain the system through a period of downtime, and unrealized profit from lost business.

Gavish and Kalvenes (1997) derive a dynamic program that addresses optimal replenishment strategies for low earth orbit satellite constellations. In this model, all satellites are assumed identical and launch events are modeled as independent Bernoulli random variables. Risk is modeled as a nonlinear backorder cost associated with a shortfall of available satellites in orbit. The objective of the optimization problem is to address the satellite shortfall at minimum cost.

Weigel and Hastings (2004) present a formulation of the launch vehicle selection problem that identifies three risk managing strategies: minimum cost strategies, minimum risk strategies, and strategies that balance cost and risk. In their model, risk is equated

to the expected replacement cost of the launch vehicle and assigned payloads. For example, a launch vehicle with a 5-percent failure rate that cost \$20 million carrying a \$50 million payload would have a measured risk of $0.05(\$50 \text{ million} + \$20 \text{ million}) = \$3.5 \text{ million}$. The minimum cost strategy selects the lowest cost launch vehicle that meets all performance constraints. The minimum risk strategy selects the launch vehicle that minimizes the risk measure, subject to launch and feasibility constraints. The third strategy minimizes a weighted sum of cost and risk. These decisions are formulated as mixed-integer optimization problems that assign launch vehicles to payloads.

Gralla et al. (2005) address launch vehicle selection in the context of a Human Lunar and Mars Exploration (HLE/HME) program. The size of a HLE/HME transportation vehicle could be too large to launch on a single launch vehicle and would need to be launched as modules that are assembled on-orbit. This model is a mixed-integer linear program that assigns modules to launch vehicles in a way that minimizes total cost. A risk analysis is performed after assigning payloads and launch vehicles by calculating the number of spares required to meet some overall probability of orbiting all required modules of the transportation system. When considering launch failures, the first launch of each selected launch vehicle is modeled as a Bernoulli random variable, while the launch of a spare, if needed, is assumed to always result in a success.

The model presented here is similar to the ones found in Weigel and Hastings (2004) with a few important differences. In addition to selecting launch vehicles, I also assign payloads to launch vehicles in a way that is similar to the assignment of modules to launches found in Gralla et al. (2005). This allows the optimization scheme to take into account the ability to bundle multiple small satellites on the same launch vehicle. The model presented here incorporates a risk measure similar to Markowitz's semivariance. Aligning with most existing literature, the outcome of a launch attempt is modeled as an independent Bernoulli trial.

MODEL FORMULATION

There are two problems that need to be accounted for when constructing a launch strategy for a set of payloads. The first problem involves selecting which launch vehicles to use to launch a set of payloads. The second problem involves assigning payloads to launch vehicles. The goal is to create a mathematical program that performs both of these tasks in a way that captures the tradeoffs between financial risk and reward. Specifically, consider the risk associated with catastrophic launch failures. Using less expensive launch vehicles may reduce the initial costs, but this strategy also increases the probability of a catastrophic launch failure. Similarly, bundling payloads on the same launch vehicle decreases initial costs by spreading out launch costs across multiple payloads, but this strategy also increases the repercussions associated with a catastrophic launch failure.

Similar to the theoretical foundations of Markowitz portfolio selection theory, the formulation presented here looks to select launch strategies (i.e., a suite of launch vehicles and payload-launch assignments) that minimize risk subject to budget and performance constraints.

Preliminaries

Let I be a set of independent launch packages in a launch portfolio, indexed by i . Let ψ denote the total cost of the launch strategy and ψ_i be the total cost associated with launch package i . Each launch package consists of a launch vehicle of cost μ_i and reliability π_i . Further, let ϖ_i denote the total cost of all payloads assigned to launch vehicle i . Let Z_i denote the number of launches up to and including the first success. It is assumed that all launch failures are catastrophic and result in the loss of all payloads and the launch vehicle. If launch packages are launched and relaunched until the first successful launch, the total cost associated with launch package i is expressed by:

$$\psi_i = Z_i(\mu_i + \varpi_i).$$

Equation B.6

Assuming all launch packages are independent, the total cost associated with the launch portfolio is:

$$\psi = \sum_{i \in I} \psi_i = \sum_{i \in I} Z_i (\mu_i + \varpi_i).$$

Equation B.7

Assume that each attempted launch of a launch vehicle is an independent Bernoulli trial with probability π_i . Under these assumptions, Z_i follows a geometric distribution with $E[Z_i] = 1/\pi_i$ and $\text{Var}[Z_i] = (1 - \pi_i) / \pi_i^2$. The expected cost of the entire portfolio and the variance of that cost can be written as:

$$E[\psi] = \sum_{i \in I} \frac{(\mu_i + \varpi_i)}{\pi_i},$$

Equation B.8

$$\text{Var}[\psi] = \sum_{i \in I} \frac{(\mu_i + \varpi_i)^2 (1 - \pi_i)}{\pi_i^2}.$$

Equation B.9

Define the downside semivariance of an individual launch package as:

$$\text{SemiVar}[\psi_i] = E[\max(0, \psi_i - E[\psi_i])^2].$$

Equation B.10

If it is assumed that $1/2 < \pi_i \leq 1$, the expected number of launches will be between one and two. Thus, when $Z_i = 1$, $\psi_i \leq E[\psi_i]$, and when $Z_i \geq 2$, $\psi_i \geq E[\psi_i]$. This implies that the downside semivariance for an

individual launch will be the variance associated with two or more attempted launches, and it can be derived analytically as:

$$SemiVar[\psi_i] = \sum_{k=2}^{\infty} \left[\left(\frac{1}{\pi_i} (\mu_i + \varphi_i) - k(\mu_i + \varpi_i) \right) \pi_i (1 - \pi_i)^{k-1} \right],$$

$$SemiVar[\psi_i] = \frac{(1 - \pi_i)(1 - \pi_i + \pi_i^2)}{\pi_i^2} (\mu_i + \varpi_i)^2.$$

Equation B.11

These analytically convenient expressions allow the launch vehicle portfolio assignment problem to be formulated as a mixed-integer optimization problem. The goal of the optimization is to assign a predefined set of payloads to a set of launch vehicles in a way that minimizes risk while conforming to a budget constraint on the expected cost.

Classical portfolio optimization looks to assign asset allocation weights in a way that minimizes the downside semivariance in returns subject to achieving a minimum expected return. The assumption of symmetric returns means that downside semivariance is equal to upside semivariance, so minimizing the overall variance is equivalent to minimizing the downside semivariance. Given the assumptions above, the distribution of total costs will be skewed because of the relatively low number of launch packages that are included in a launch portfolio, the relatively high reliabilities of the launch vehicles, and the large replacement costs associated with catastrophic failures. The downside semivariance of a launch portfolio consisting of multiple launch packages is difficult to calculate in a way that could be easily implemented in an optimization algorithm; however, summing the downside semivariance for each individual launch (Equation B.11) can serve as an approximation of the overall downside semivariance. Thus, the sum of the downside semivariance from each individual launch will be the

objective function for our optimization problem.³⁸ Approximating the downside semivariance of the portfolio cost with the sum of the individual downside semivariances will hereafter be referred to as the SIDV estimator.

A budget constraint on the expected cost constrains the assignment of payloads to launch vehicles. In addition, launch vehicles are constrained by the total mass they can carry into orbit and the number of payloads they can hold. The size of a payload that can be placed into orbit depends on the altitude of the orbit. For this problem, each orbit was assumed to be a low earth orbit (LEO), a common operational restriction placed on small satellites.

Mathematical Formulation of the LVAP

Indices and Sets

Y -- Set of all launch vehicles types, indexed by y

M -- Set of all payloads, indexed by m

N -- Set of all possible number of launches of a given launch vehicle, indexed by n

Decision Variables

$X_{m,y,n}$ -- The binary decision to launch payload m on the n^{th} launch vehicle of type y

S_y -- The number of launch vehicle type y to purchase

$L_{y,n}$ -- The binary decision to purchase the n^{th} occurrence of launch vehicle type y

Payload Attributes

³⁸ This assumption is later shown to perform reasonably well in scenarios that involve small satellites.

γ_m -- Cost of payload m

θ_m -- Mass of payload m

Launch Vehicle Attributes

μ_y -- Cost of launch vehicle y

π_y -- Reliability of launch vehicle y

σ_y -- Mass constraint on launch vehicle y

ϕ_y -- Individual payload mass constraint on launch vehicle y

χ_y -- Maximum number of payloads that can be placed on launch vehicle y

Program Attributes

β -- Maximum allowable expected cost for all launches, payloads, and launch vehicles

The goal of the optimization is to assign each payload to a launch vehicle in a way that minimizes an approximation of the downside semivariance of the total cost while adhering to all program and performance constraints.

$$\underset{X_{m,n}, S_y, L_{y,n}}{\text{Minimize}} \sum_{y \in Y} \sum_{n \in N} \left[\frac{\left(\mu_y L_{y,n} + \sum_{m \in M} \gamma_m X_{m,y,n} \right)^2 (1 - \pi_y)(1 - \pi_y + \pi_y^2)}{\pi_y^2} \right]$$

Equation B.12

$$\sum_{y \in Y} \frac{S_y}{\pi_y} + \sum_{y \in Y} \sum_{n \in N} \left(\frac{\sum_{m \in M} \gamma_m X_{m,y,n}}{\pi_y} \right) \leq \beta$$

Equation B.13

$$L_{y,n} \leq L_{y,n-1} \leq L_{y,n-2} \leq \dots \leq L_{y,1}, y \in Y$$

Equation B.14

$$\sum_{n \in N} L_{y,n} \leq S_y, \forall y \in Y$$

Equation B.15

$$0 \leq L_{y,n} \leq 1, \forall y \in Y, n \in N$$

Equation B.16

$$0 \leq S_y, \forall y \in Y$$

Equation B.17

$$X_{m,y,n} \leq L_{y,n}, \forall m \in M, n \in N, y \in Y$$

Equation B.18

$$\sum_{m \in M} \theta_m X_{m,y,n} \leq \sigma_y, \forall n \in N, y \in Y$$

Equation B.19

$$\theta_m X_{m,y,n} \leq \phi_y, \forall m \in M, n \in N, y \in Y$$

Equation B.20

$$\sum_{m \in M} X_{m,y,n} \leq \chi_n, \forall y \in Y, n \in N$$

Equation B.21

$$\sum_{y \in Y} \sum_{n \in N} X_{m,y,n} = 1, \forall m \in M$$

Equation B.22

$$X_{m,y,n} \in \{0,1\}, \forall m \in M, y \in Y, n \in N$$

Equation B.23

The objective function is the sum of the downside semivariances from each individual payload set. Equation B.13 enforces the budget constraint on the expected cost. Equation B.14 ensures that the n^{th} occurrence of launch vehicle y is not purchased if the $n-1$ occurrence was not purchased. Equation B.15 ensures that the total number of launch vehicles of class y that are purchased is equal to the sum of the individual purchases. Equation B.18 ensures that payloads are placed only on launch vehicles that are purchased.

Equation B.19 through Equation B.21 deal with the capacity constraints on each launch vehicle. Equation B.19 ensures that the total mass placed on each launch vehicle is less than a specified mass constraint. Equation B.21 ensures that the number of payloads assigned to an individual launch vehicle is less than or equal to the total number of payloads that the launch vehicle can support. Some launch vehicles that can be fitted with multiple payloads have constraints on

how large an individual payload can be. Equation B.20 ensures that these individual mass constraints are not violated. Equation B.22 ensures that all payloads are orbited, while Equation B.23 enforces the binary constraint on the decision variables $X_{m,y,n}$. The structure constraints (Equation B.15- through Equation B.18) ensure that $L_{y,n} \in \{0,1\}$ and $S_y \in \mathbf{N}_0$, provided $X_{m,y,n} \in \{0,1\}$.

Reducing Computation Time for the LVAP

Because $X_{m,y,n}$ is discrete, the objective function and many of the constraints in the LVAP are non-convex. This makes problems that involve a large number of payloads and launch vehicles difficult to solve. Recasting the optimization as a mixed-integer linear program can reduce the required computation time by allowing the use of more efficient branch and bound algorithms. To do this, Equation B.12 will be recast as a linear function of the decision variables. First, the squared quantity in Equation B.12 is expanded to give:

$$\sum_{y \in Y} \sum_{n \in N} \left[\left(2\mu_y \sum_{m \in M} \gamma_m L_{y,n} X_{m,y,n} + \mu_y \mu_y L_{y,n} L_{y,n} + \sum_{m' \in M} \sum_{m \in M} \gamma_m \gamma_{m'} X_{m',y,n} X_{m,y,n} \right) \left(\frac{(1-\pi_y)(1-\pi_y+\pi_y^2)}{\pi_y^2} \right) \right].$$

Equation B.24

Equation B.24 has three nonlinearities in the decision variables, $X_{m',y,n} X_{m,y,n}$, $L_{y,n} L_{y,n}$ and $L_{y,n} X_{m,y,n}$. The nonlinearity $L_{y,n} L_{y,n}$ can be replaced with $L_{y,n}$ since $L_{y,n} \in \{0,1\}$ at a feasible solution. In addition, the nonlinear term $L_{y,n} X_{m,y,n}$ can be replaced with $X_{m,y,n}$, since $X_{m,y,n} \in \{0,1\}$, $L_{y,n} \in \{0,1\}$ and $X_{m,y,n} \leq L_{y,n}, \forall m \in M, n \in N, y \in Y$ at a feasible solution. These constraints ensure that the term $L_{y,n} X_{m,y,n}$ always takes on the value of $X_{m,y,n}$, since if $X_{m,y,n} = 1$, Equation B.18 ensures that $L_{y,n} = 1$, and if $X_{m,y,n} = 0$ the product $L_{y,n} X_{m,y,n} = 0$. Thus, the objective function can be rewritten as:

$$\sum_{y \in Y} \sum_{n \in N} \left[\left(2\mu_y \sum_{m \in M} \gamma_m X_{m,y,n} + \mu_y \mu_y L_{y,n} + \sum_{m' \in M} \sum_{m \in M} \gamma_m \gamma_{m'} X_{m',y,n} X_{m,y,n} \right) \left(\frac{(1-\pi_y)(1-\pi_y+\pi_y^2)}{\pi_y^2} \right) \right].$$

Equation B.25

To deal with the last nonlinearity, $X_{m',y,n}X_{m,y,n}$, I introduce an additional variable. Let $G_{m,m',y,n}$ be the binary decision to place payload m and payload m' on the n^{th} occurrence of launch vehicle y . Because both payloads have to be on the same individual launch vehicle, the expression $G_{m,m',y,n} = X_{m',y,n}X_{m,y,n}$ must hold. It can be shown that $G_{m,m',y,n} = X_{m',y,n}X_{m,y,n}$ will hold if $G_{m,m',y,n}$ is constrained such that:

$$0 \leq G_{m,m',y,n} \leq 1 \forall m \in M, m' \in M, n \in N, y \in Y,$$

Equation B.26

$$G_{m,m',y,n} \leq X_{m,y,n} \forall m \in M, m' \in M, n \in N, y \in Y,$$

Equation B.27

$$G_{m,m',y,n} \leq X_{m',y,n} \forall m \in M, m' \in M, n \in N, y \in Y,$$

Equation B.28

$$G_{m,m',y,n} \geq X_{m,y,n} + X_{m',y,n} - 1 \forall m \in M, m' \in M, n \in N, y \in Y,$$

Equation B.29

Introducing these additional decision variables and constraints removes all nonlinear terms. Thus, the equivalent, linear objective function becomes:

$$\sum_{y \in Y} \sum_{n \in N} \left[\left(2\mu_y \sum_{m \in M} \gamma_m X_{m,y,n} + \mu_y \mu_y L_{y,n} + \sum_{m' \in M} \sum_{m \in M} \gamma_m \gamma_{m'} G_{m,m',y,n} \right) \left(\frac{(1 - \pi_y)(1 - \pi_y + \pi_y^2)}{\pi_y^2} \right) \right]$$

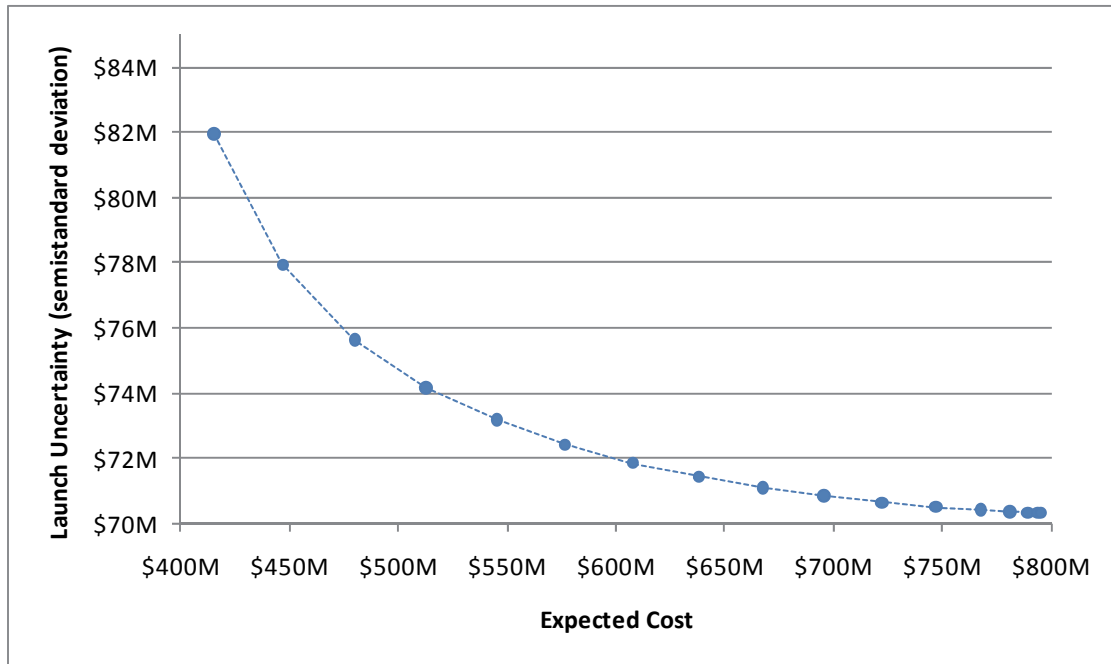
Equation B.30

Constructing Efficient Frontiers

The LVAP is used to prune the set of all possible launch strategies into a set that is efficient with respect to expected cost and the downside semivariance. This is done by incrementing the expected budget constraint between two extremes. On one extreme, the budget constraint can be set at the lowest feasible expected cost, giving the optimal minimum cost solution. At the other extreme, the expected budget constraint can be set at the minimum value that achieves the minimum semivariance solution. Incrementing the budget constraint between the

minimum expected cost budget and the minimum expected semivariance budget produces an efficient set of launch strategies.

Figure B.1
Efficient Set of Launch Strategies with Respect
to Cost and Uncertainty (Downside Semivariance)



NOTES: This figure traces out an efficient frontier of launch strategies for a notional example. To obtain this figure, ten randomly generated sets of 20 payloads were drawn, and the LVAP was used to minimize the downside uncertainty across the spectrum of possible expected costs. The provided frontier is the average result from ten sets of 20 randomly generated payloads with the expected budget constraint incremented in 50 equally spaced steps between the minimum cost and minimum semivariance solution.

Figure B.1 is a graphical representation of this process. Each point represents the expected cost and the root of the downside semivariance for a solution to the LVAP. The point on the far left is the solution with the minimum expected cost. As the budget constraint is loosened, it becomes possible to reduce additional uncertainty from the launch strategy.

ASSESSING THE VALIDITY OF LVAP ASSUMPTIONS

Multiple assumptions went into the formulation of the LVAP. Potential deviations from these assumptions could lead to reduced performance of derived launch portfolios. This section assesses the validity of these assumptions in the context of constructing small satellite launch strategies.

Technological and Practical LVAP Assumptions

The launch packages that make up a launch portfolio were assumed to be independent events. Specifically, the probability of success was assumed to be constant across all relaunches of an individual package and for all launches of a particular launch vehicle class. This assumption is reasonable in a mature launch fleet, when multiple launches have allowed engineers to eliminate any systematic risk that could lead to correlated launch failures. This also assumes that the reliability does not improve with additional launches.

It was also assumed that a failed launch always results in a relaunch. Thus, there is a nonzero probability that an individual package of payloads will require 2, 10, or 100 launches. In practice, the time relevance of the payloads coupled with ballooning costs would result in the package being scrubbed or dispersed, and not continually relaunched until a success is achieved. The high reliabilities, however, reduce the importance of these extreme events. A launch vehicle with a reliability of 90 percent has a 0.1-percent chance of requiring four or more launches. Thus, the contributions to the expected cost and the variance from the unlikely scenarios involving many relaunches (three or more) will have a small additional impact on the estimated moments.

Launch pad availability was assumed. If further research indicates that this was an important factor, this could be included in the form of volume constraints. Calculating the downside semivariance of individual launch costs was based on the assumption that the launch vehicle specific reliability is greater than 50 percent. All classes of launch vehicles in the NSS launch inventory have a demonstrated reliability

that is much greater than 50 percent, suggesting this is a valid assumption.

Estimating Downside Semivariance with SIDV Approximation

An analytically efficient estimate of the downside semivariance was used as a measure of risk. This estimate was based on the assumption that the loss of any single launch vehicle would result in a total cost that was greater than the expected cost. For a single launch with reliability greater than 50 percent, this assumption leads to the exact downside semivariance of the cost. As the number of launch vehicles increases, the precision of this estimator decreases.

Evaluating the efficiency of this approximation requires a way to generate launch strategies so that the SIDV approximation of the semivariance could be compared to the actual semivariance. To this end, I considered four classes of launch vehicles that roughly capture the tradeoffs between cost and reliability in the current NSS launch fleet. Table B.1 contains these launch vehicle classes and their performance attributes.

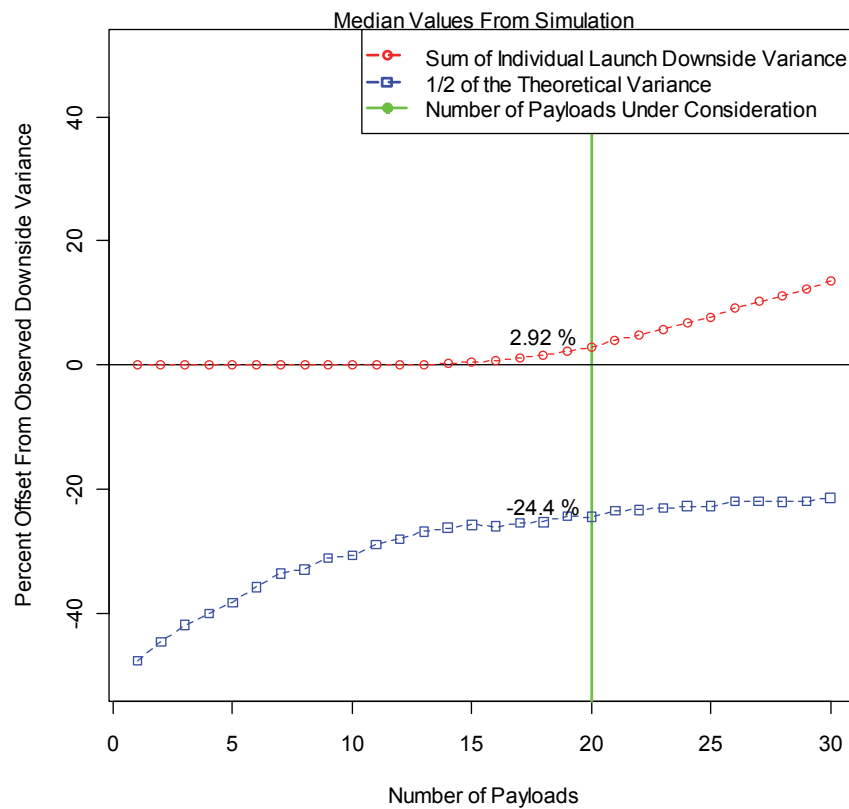
Table B.1
Four Classes of Considered Launch Vehicles

Launch Vehicle Class	Cost	Reliability	Total Mass Constraint	Individual Mass Constraint	Capacity
High-Cost, High-Reliability LV (HCHR LV)	\$54M	98%	3,899 kg	None	1
High-Cost, High-Reliability LV with ESPA ring (ESPA LV)	\$69M	98%	3,899 kg	180 kg	7
Medium-Cost, Medium-Reliability LV (MCMR LV)	\$30M	95%	1,735 kg	None	1
Low-Cost, Low-Reliability (LCLR LV)	\$12M	90%	700 kg	None	1

NOTE: Because most conceivable small satellite missions would take place in LEO (AF SAB, 2007), the total mass constraint assumes that the launch vehicle is placing its payload in LEO.

Because the LVAP is designed to facilitate the construction of small satellite launch strategies, random sets of payloads were generated based on parametric relationships between cost and mass for small satellites (Bearden, 2001).

Figure B.2
Relative Percentage Offset of Downside Semivariance Estimation



NOTES: This figure demonstrates the relative offset between the empirically observed semivariance and two methods of estimating semivariance. The SIDV estimator estimates the semivariance of the launch cost by aggregating the semivariance across each individual launch. The other method assumes a symmetric distribution and estimates the semivariance by dividing the overall variance in half. For each considered number of payloads, the offset for each estimator was estimated using 10,000 randomly generated launch strategies using the launch vehicle classifications found in Table B.1. Estimator offset is measured as (Estimated Semivariance - Empirically Observed Semivariance); therefore, a positive offset implies that the estimated semivariance is greater than the observed semivariance (i.e., the estimator overestimates the risk associated with a launch strategy).

A simulation was used to gauge estimation error of the SIDV estimator as the number of payloads under consideration increases. The true downside semivariance was empirically estimated for 10,000 random launch portfolios for 30 different portfolio sizes. The empirically estimated downside semivariance was then compared to the SIDV estimate of the downside semivariance. In addition, I recorded the relative performance of approximating semivariance as half of the overall variance. The results are found in Figure B.2. For launch portfolios of less than 13 small satellites, the SIDV estimate produces a statistically insignificant offset. In the same range, assuming that the downside semivariance is equal to half of the total variance produces an offset of between 20 percent and 40 percent. When dealing with launch portfolios that consist of 20 small satellites (the nominal parameters used in my analysis), the SIDV estimate was within 2.92 percent of the empirically estimated downside semivariance, while using one-half of the variance as an estimate of downside semivariance was off by an average of 24 percent. As the number of payloads increases, the accuracy of the SIDV estimate diminishes while the accuracy of the symmetrical assumption improves.

The number of payloads is not the only factor that determines the accuracy of the SIDV estimate. The SIDV estimate is accurate in the range of 1-20 payloads, in part, because the reliabilities of the launch vehicles in the NSS inventory are relatively high. As the reliability of the launch vehicles decreases, the expected number of launches until the first success increases. A higher number of expected failures weakens the assumption that the failure of any single launch vehicle will result in a scenario cost that is worse than the expected cost. Because this assumption forms the basis of the SIDV estimator, a full experiment was used to determine whether the performance of the SIDV estimator is sensitive to the nominal reliability and cost assumptions. This experiment considered portfolios of 10, 20, 50, 100, and 200 payloads. Launch vehicle and payload costs were offset by a factor of 90 percent and 110 percent, while the launch vehicle reliabilities were offset by factors of 95 percent, 97.5 percent, and 105 percent.

Table B.2
Assumed Launch Vehicle Reliabilities for the Full SIDV Accuracy
Experiment

Reliability Offset	LCLR Reliability	MCMR Reliability	ESPA Reliability	HCHR Reliability
95%	85.50%	90.25%	92.34%	92.34%
97.5%	87.75%	92.63%	94.77%	94.77%
100%	90.00%	95.00%	97.20%	97.20%
105%	94.50%	99.75%	100.00%	100.00%

Table B.2 provides the reliabilities that were assumed for each launch vehicle class under each scenario. For each combination of the different factors, the accuracy of the SIDV estimate was calculated by evaluating the relative offset for 10,000 randomly generated sets of payloads.

Table B.3
SIDV Accuracy Experiment Results

Number of Payloads		10		20		50		100		200	
Cost Offset	Reliability Offset	Observed SIDV Offset	Observed 1/2 Variance Offset	Observed SIDV Offset	Observed 1/2 Variance Offset	Observed SIDV Offset	Observed 1/2 Variance Offset	Observed SIDV Offset	Observed 1/2 Variance Offset	Observed SIDV Offset	Observed 1/2 Variance Offset
90%* Cost	90.0%* Rel.	12.32% ±0.06%	-21.32% ±0.04%	32.56% ±0.06%	-16.34% ±0.04%	43.57% ±0.01%	-11.11% ±0.03%	45.56% ±0.01%	-8.12% ±0.03%	46.84% ±0.01%	-5.90% ±0.03%
	95.0%* Rel.	3.44% ±0.04%	-23.91% ±0.04%	21.55% ±0.08%	-18.48% ±0.04%	41.35% ±0.03%	-12.67% ±0.03%	44.83% ±0.01%	-9.32% ±0.03%	46.35% ±0.01%	-6.78% ±0.03%
	97.5%* Rel.	1.05% ±0.02%	-25.84% ±0.05%	13.27% ±0.08%	-20.15% ±0.04%	38.13% ±0.04%	-13.90% ±0.04%	44.13% ±0.01%	-10.23% ±0.03%	45.94% ±0.01%	-7.49% ±0.03%
	100.0%* Rel.	0.21% ±0.01%	-29.44% ±0.06%	4.72% ±0.06%	-22.74% ±0.04%	30.61% ±0.07%	-15.83% ±0.04%	42.32% ±0.02%	-11.75% ±0.03%	45.27% ±0.01%	-8.61% ±0.03%
	105.0%* Rel.	0.01% ±0.00%	-41.77% ±0.08%	0.04% ±0.00%	-35.21% ±0.08%	1.96% ±0.04%	-24.60% ±0.06%	16.09% ±0.11%	-18.87% ±0.04%	35.96% ±0.07%	-14.09% ±0.04%
100%* Cost	90.0%* Rel.	12.28% ±0.06%	-21.28% ±0.04%	32.61% ±0.05%	-16.32% ±0.04%	43.58% ±0.01%	-11.10% ±0.03%	45.56% ±0.01%	-8.10% ±0.03%	46.85% ±0.01%	-5.91% ±0.03%
	95.0%* Rel.	3.37% ±0.04%	-23.89% ±0.04%	21.55% ±0.07%	-18.41% ±0.04%	41.37% ±0.03%	-12.61% ±0.03%	44.84% ±0.01%	-9.31% ±0.03%	46.36% ±0.01%	-6.75% ±0.03%
	97.5%* Rel.	1.01% ±0.02%	-25.82% ±0.05%	13.27% ±0.08%	-20.12% ±0.04%	38.14% ±0.04%	-13.88% ±0.04%	44.15% ±0.01%	-10.22% ±0.03%	45.96% ±0.01%	-7.44% ±0.03%
	100.0%* Rel.	0.18% ±0.01%	-29.50% ±0.06%	2.92% ±0.05%	-22.74% ±0.04%	30.63% ±0.07%	-15.80% ±0.04%	42.34% ±0.02%	-11.72% ±0.03%	45.28% ±0.01%	-8.59% ±0.03%
	105.0%* Rel.	0.00% ±0.00%	-41.81% ±0.08%	0.04% ±0.00%	-35.23% ±0.09%	1.89% ±0.04%	-24.49% ±0.05%	16.06% ±0.11%	-18.78% ±0.04%	35.97% ±0.07%	-14.02% ±0.04%
110%* Cost	90.0%* Rel.	12.31% ±0.06%	-21.31% ±0.04%	32.57% ±0.06%	-16.33% ±0.04%	43.59% ±0.01%	-11.08% ±0.03%	45.58% ±0.01%	-8.07% ±0.03%	46.85% ±0.01%	-5.92% ±0.03%
	95.0%* Rel.	3.40% ±0.04%	-23.85% ±0.04%	21.53% ±0.07%	-18.38% ±0.04%	41.37% ±0.03%	-12.62% ±0.03%	44.84% ±0.01%	-9.31% ±0.03%	46.36% ±0.01%	-6.77% ±0.03%
	97.5%* Rel.	0.98% ±0.02%	-25.81% ±0.05%	13.28% ±0.07%	-20.08% ±0.04%	38.16% ±0.04%	-13.82% ±0.04%	44.14% ±0.01%	-10.23% ±0.03%	45.95% ±0.01%	-7.46% ±0.03%
	100.0%* Rel.	0.16% ±0.01%	-29.42% ±0.06%	4.69% ±0.05%	-22.69% ±0.04%	30.61% ±0.07%	-15.76% ±0.04%	42.35% ±0.02%	-11.69% ±0.03%	45.29% ±0.01%	-8.56% ±0.03%
	105.0%* Rel.	0.00% ±0.00%	-41.80% ±0.08%	0.03% ±0.00%	-35.14% ±0.09%	1.85% ±0.04%	-24.42% ±0.06%	16.05% ±0.11%	-18.69% ±0.04%	36.00% ±0.07%	-13.97% ±0.04%

NOTES: The red box highlights the assumed conditions for my research on small satellite launch strategies.

Table B.3 demonstrates that the SIDV estimator is sensitive to the number of payloads, their costs, and the reliabilities of the launch vehicles. Increasing the number of payloads under consideration reduces the accuracy of the SIDV estimator. For 50 payloads, assuming that the distribution in expected costs is symmetric produces more accurate estimates of the downside semivariance than the SIDV estimator. The SIDV performs well within the range of nominal parameters for small satellites. Another important attribute of the SIDV estimator is that it will always be an overestimate of the downside semivariance of the launch portfolio cost, since it assumes the single failure of any launch vehicle drives the total cost beyond expectation.

This analysis indicates that for moderately sized payload sets and relatively high reliabilities, the SIDV approximation is an adequate estimate of the downside semivariance in the launch costs. An important caveat to this conclusion is that this analysis looked only at launch vehicle and payload attributes that would be expected in the context of small satellite launch strategies. The efficiency of the SIDV estimator may change as the launch vehicles and payload sets are modified to reflect different types of satellite designs.

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APPENDIX C: BAYESIAN ESTIMATES OF THE RIDESHARE RELIABILITY EFFECT

RELEVANT BACKGROUND AND LITERATURE

Launch Vehicle Reliability Estimation

The Federal Aviation Administration and the USAF have established a set of guidelines and principles for valid launch vehicle probability of failure estimation (FAA, 2005). These guidelines define launch vehicle reliability as the probability of a successful launch and establish four principles that all estimation methodologies must adhere to: (1) account for launch vehicle failure probability in a consistent manner; (2) incorporate accurate data, scientific principles, and valid methodologies; (3) account for the outcomes of all previous flights; and (4) account for changes to the vehicle configuration and other factors.

Within the launch reliability literature, the commonly accepted reliability estimation technique is an application of the binomial distribution estimation problem developed in Raiffa and Schlaifer (1961). This technique uses a Bayesian approach to statistical modeling and was first applied to launch vehicle reliability in Guikema and Paté-Cornell (2004a). Consider a launch vehicle with m demonstrated successful launches after n attempts. Assume that all launch attempts are independent with reliability p . The Bayesian approach to parameter estimation treats p as a random variable. Thus, the goal is to derive the probability density function (pdf) of p , conditional on observing m successes after n trials. This pdf is known as the posterior distribution and can be expressed using Bayes' rule as:

$$f_{P|M,N}(p|m,n) \propto f_{M,N|P}(m,n|p)f_P(p).$$

Equation C.1

The constant of proportionality in Equation C.1 is uniquely determined by the fact that $f_{P|M,N}(p|m,n)$ is a probability density function and must integrate to one. The term $f_{M,N|P}(m,n|p)$ is the traditional likelihood function. Because launches are assumed to be

independent with constant reliability, the likelihood, conditional on some value of p , can be expressed as:

$$f_{M,N|P}(m, n | p) = \binom{n}{m} p^m (1-p)^{n-m}.$$

Equation C.2

The prior distribution, $f_p(p)$, can be selected based on expert opinion or similar launch attempts. One common technique is to assume that, a priori, p is distributed uniformly over the interval $[0,1]$. This gives the prior distribution $f_p(p)=1$. Substituting the likelihood function and prior distribution into Equation C.1 gives:

$$f_{P|M,N}(p | m, n) \propto \binom{n}{m} p^m (1-p)^{n-m}.$$

Equation C.3

Raiffa and Schlaifer (1961) show that Equation C.3 implies that the posterior distribution follows a Beta distribution and is given by:

$$p | m, n \sim \text{Beta}(m+1, n-m+1).$$

Equation C.4

The Bayesian approach to launch vehicle reliability estimation has many attractive attributes. Whereas classical approaches to parameter estimation would produce a point estimate of launch vehicle reliability, the Bayesian approach provides the entire distribution of the reliability of the launch vehicle. This distribution is based on the available data and prior beliefs about the system. The Bayesian approach also performs well under relatively small sample sizes, provides a mechanism for incorporating expert opinion, and, in many cases, produces tighter confidence intervals (Guikema and Paté-Cornell, 2004a). Because it is ideally situated to handle problems with relatively small sample sizes, the FAA cites the Bayesian approach to launch vehicle reliability modeling with an uninformative prior as an acceptable approach to estimating the reliability of a launch vehicle (FAA, 2005).

Bayesian reliability estimation techniques extend beyond the launch vehicle reliability literature. Similar techniques have been used to estimate the ability of command, control, communication, and intelligence systems to detect nuclear attacks (P             and Fischbeck, 1995) and to assess the probability of terrorist threats (P             and Guikema, 2002). A recent application uses similar methods to calculate the stockpile reliability of U.S. Armed Forces supply depots (Anderson-Cook et al., 2007). Non-defense related applications include commercial marketing forecasts (Rossi and Allenby, 2003), measures of traffic safety (Lord and Park, 2008), and assessing the performance of power systems after hurricane events (Winkler et al., 2010).

Parametric Regression Models for Binary Outcomes

Parametric regression models are commonly used to estimate effects after controlling for other confounding variables. For example, Moore and White (2005) and Hoetker (2007) use parametric regression techniques to estimate DoD acquisition outcomes. The simplest regression framework is the linear regression model, which assumes that the expected value of some outcome is a linear combination of the explanatory variables. Zellner (1971) provides the first Bayesian formulation of this problem. Let $Y \in \mathbb{R}^J$ be a vector of J independent outcomes, which are individually labeled as $y_1, \dots, y_J$. Further, let $x_j \in \mathbb{R}^K$ be a vector of known covariates associated with y_j and $X \in \mathbb{R}^{J \times K}$ be a matrix with rows x_j^T . Finally, let $\beta \in \mathbb{R}^K$ be a vector of unknown coefficients and σ^2 be some unknown variance. The classical linear regression model assumes that:

$$y_j | x_j, \beta, \sigma^2 \sim N(x_j^T \beta, \sigma^2)$$

Equation C.5

When y_j is a binary outcome, Equation C.5 is known as the linear probability model. The posterior joint distribution of β and σ^2 can be expressed as:

$$f_{\mathbb{B}, \Sigma^2 | Y, X}(\beta, \sigma^2 | Y, X) \propto \prod_{j=1}^J \phi(y_j; x_j^T \beta, \sigma^2) f_{\mathbb{B}, \Sigma^2}(\beta, \sigma^2)$$

Equation C.6

In Equation C.6, $\phi(\bullet; \mu, \sigma^2)$ is the $N(\mu, \sigma^2)$ pdf. In practice, the linear probability model has many drawbacks. First, the values of β can range across $\pm\infty$, potentially predicting probabilities outside the interval $[0, 1]$. Another drawback is that the linear probability model assumes a constant variance structure that is independent of p_j ; however, the variance of an independent Bernoulli trial is $p_j(1 - p_j)$.

Despite these limitations, the linear probability model is commonly used because of its simplicity and interpretability (Aldrich and Nelson, 1984). Equation C.5 implies that $p_j = x_j^T \beta$, where $\Pr(y_j = 1) = p_j$. Another attractive feature is that coefficient β_k can be interpreted as the marginal change in the probability p_j associated with a unit change in the k^{th} covariate.

Albert and Chib (1993) develop a nonlinear Bayesian regression model that does not have the same limitations as the linear probability model. This model assumes that a cumulative density function (cdf), $H(\bullet)$, links the probabilities p_j and the linear structure $x_j^T \beta$.

This model can be expressed as:

$$p_j = H(x_j^T \beta)$$

Equation C.7

Because the link function is a cumulative density function, predicted values of p_j are guaranteed to exist on the interval $[0, 1]$. The posterior joint distribution of β is given by:

$$f_{B|X,Y}(\beta | X, Y) \propto \prod_{j=1}^J H(x_j^T \beta)^{y_j} (1 - H(x_j^T \beta))^{1-y_j} f_B(\beta).$$

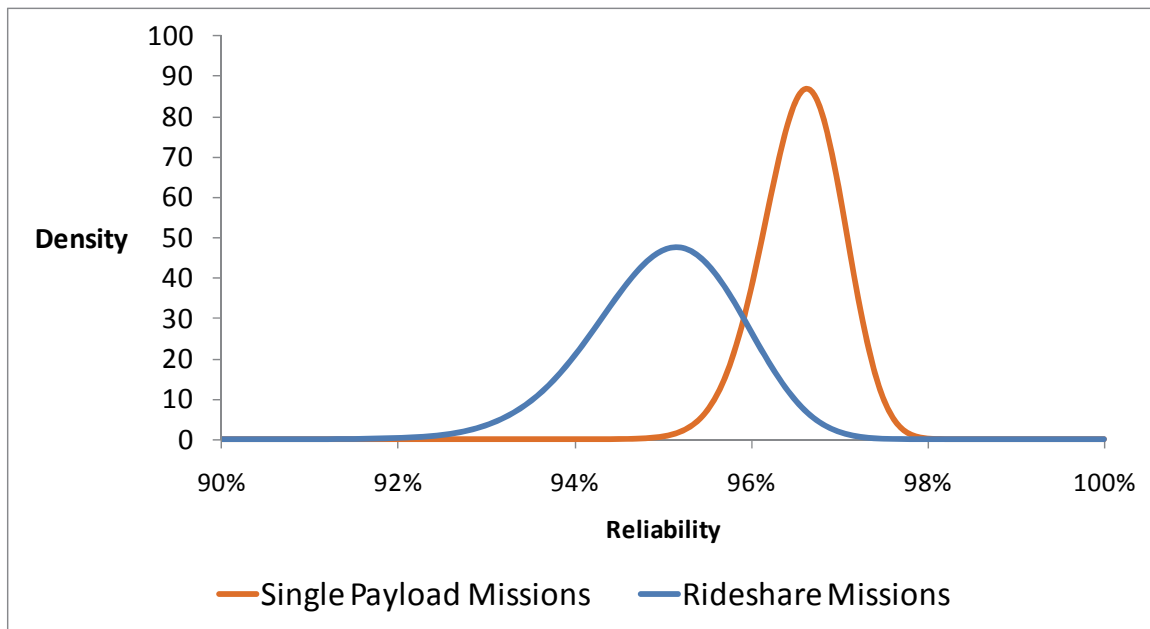
Equation C.8

The two most common choices for $H(\bullet)$ are the standard normal cdf, $\Phi(\bullet)$, which gives the probit regression model, and the logistic cdf, $\Psi(\bullet)$, which gives the logistic regression model. While Equation C.7 and Equation C.8 overcome the theoretical shortfalls of the linear probability model, the model coefficients are no longer directly interpretable.

METHODOLOGY

First, the traditional launch vehicle reliability techniques were used to attempt to understand the change in reliability associated with ridesharing additional payloads. All considered launch missions were categorized into one of two possible cells. One cell contained all launch missions with one payload, while the second cell contained all launch missions with multiple assigned payloads. Equation C.4 was used to derive the posterior distribution of the launch reliability for each cell. Figure C.1 gives these distributions.

Figure C.1
Unadjusted Posterior Reliability Distributions



These distributions imply that there is a 1.55 percentage point decrease in reliability associated with ridesharing additional payloads. In addition, the empirical posterior probability that rideshare launch attempts have a lower reliability than their single payload counterparts is 95.67 percent.

There are many variables that could systematically bias these unadjusted estimates of the rideshare reliability effect. For example, if launch vehicles of "low quality" are disproportionately used for rideshare launch missions, unadjusted estimates of the rideshare

reliability effect would exaggerate any differences in reliability. One possible strategy that would control for launch vehicle quality would be to further disaggregate the cells based on both the launch vehicle used and whether multiple payloads were manifested; however, launch vehicles are not the only factor that could potentially confound the estimates. The target orbit is a significant driver of launch mission complexity and may have some impact on reliability. Also, previous research has shown that the first five launch attempts of a new launch vehicle are more likely to experience a launch failure (Guikema and Pate-Cornell, 2004b). Finally, the launch procedures and risk postures of the different satellite users that own and operate the spacecraft and launch facilities could be correlated both with rideshare missions and launch outcomes, potentially introducing a systematic bias in the estimates. Each level of disaggregation multiplicatively increases the number of unique combinations that need to be considered. Because of the relatively small sample size, it quickly becomes impractical to use this matching strategy to control for all of the known explanatory variables. This phenomenon is called the "curse of dimensionality" (Bellman, 1957).

It is important to use an estimation technique that controls for these confounding variables. To this end, three regression models were used to estimate the relationship between ridesharing additional payloads and launch vehicle reliability while controlling for variables that could systematically bias the results:

$$p_j = w_j \alpha + x_j^T \beta,$$

Equation C.9

$$p_j = \Phi(w_j \alpha + x_j^T \beta),$$

Equation C.10

$$p_n = \Psi(w_j \alpha + x_j^T \beta)$$

Equation C.11

In each model, w_j is a binary variable equal to one if launch attempt j contains more than one payload. The vector x_j^T is a vector of covariates that includes binary variables for the target orbit, launch

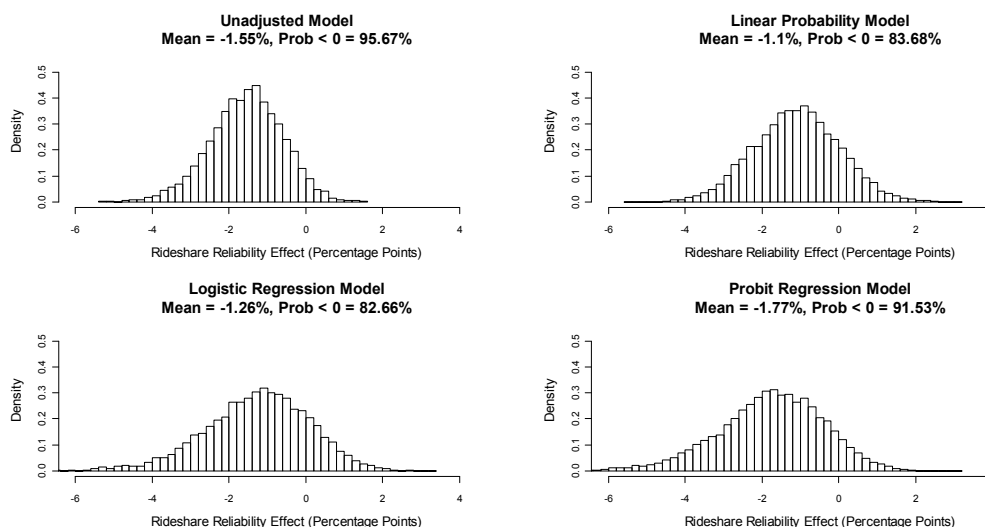
vehicle family, primary payload owner, whether a launch attempt was one of the first five launches of a new launch vehicle, and year fixed effects. These covariates help control for systematic biases in the estimates. Equation C.9 is a linear probability model, Equation C.10 is a probit regression model, and Equation C.11 is a logistic regression model. For each model, the marginal distribution of α was estimated by randomly sampling from the posterior distribution 10,000 times. In the linear probability model, α can be interpreted as the average incremental effect on reliability associated with ridesharing additional payloads. While the nonlinear regression techniques do not afford direct interpretations, they were transformed into estimates of the average incremental effect using the techniques in Bartus (2005).

The typical launch vehicle reliability calculation assumes an uninformative prior (FAA, 2005; Guikema and Paté-Cornell, 2004a). Such an assumption cannot be properly implemented in a regression context since the parameters can range across $\pm\infty$. Instead, I used a weakly informative prior, as described in Gelman, Jakulin, and Grazia (2008). Such a prior is nearly uninformative for a plausible range of coefficient values. All calculations were carried out in the R environment for statistical computing (R Development Core Team, 2010) using the "arm" package (Gelman et al., 2011).

RESULTS

For each regression model, I simulated the distribution of the average incremental effect associated with ridesharing additional payloads. The change in reliability was calculated such that negative average marginal effects imply that ridesharing additional payloads decreases reliability. Figure C.2 includes the distribution for each regression model. For comparison, the estimated distribution of the unadjusted rideshare reliability effect (which corresponds to Figure C.2) is also included.

Figure C.2
Distribution of the Rideshare Reliability Effect



All four estimates suggest that rideshare launch attempts have historically been associated with a decrease in launch vehicle reliability. This negative association persists after controlling for launch vehicle, target orbit, payload ownership, decreased reliability of relatively new launch vehicles, and any nonlinear trends in reliability over time. For all four statistical models, on average, ridesharing additional payloads reduces reliability by over 1.0 percentage points. In addition, in all four cases, the probability that this effect is negative is greater than 80 percent. Based on out-of-sample cross validation, the logistic regression model is the preferred model.

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APPENDIX D: COST-CENTRIC FRAMEWORK FOR A NOTIONAL FRACTIONATED SPACE SYSTEM

This appendix translates the example fractionated satellite decision problems found in Essay 3 into a mixed-integer optimization problem.

The deterministic fractionation design decisions and system cost are modeled first. Under a cost-centric framework, this expression of cost serves as the objective function to be minimized. Let L be the set of all launch vehicles, indexed by l , M be the set of all modules, indexed by m , and F be the set of all subsystems that can be fractionated, indexed by f . Further, let $w_l^{(L)}$ denote the binary decision to utilize launch vehicle l , $w_m^{(M)}$ denote the binary decision to utilize module m , and $x_{m,f,l}$ denote the binary decision to use launch vehicle l to launch module m , which houses subsystem f . If $c_l^{(L)}$ is the cost of launch vehicle l , $c_m^{(M)}$ is the baseline cost of module m , and $c_f^{(F)}$ is the cost of subsystem f , then the overall cost of a system architecture can be expressed as:

$$\sum_{\forall l \in L} c_l^{(L)} w_l^{(L)} + \sum_{\forall m \in M} c_m^{(M)} w_m^{(M)} + \sum_{\forall l \in L} \sum_{\forall m \in M} \sum_{\forall f \in F} c_f^{(F)} x_{m,f,l}.$$

Equation D.1

To ensure that subsystems are placed only on purchased modules and purchased launch vehicles, the following constraints must be included:

$$0 \leq w_l^{(L)} \leq x_{m,f,l} \quad \forall f \in F, l \in L, m \in M,$$

Equation D.2

$$0 \leq w_m^{(M)} \leq x_{m,f,l} \quad \forall f \in F, l \in L, m \in M.$$

Equation D.3

Also, to prevent a module from being placed on multiple launch vehicles, define the decision variable $w_{m,l}^{(M,L)}$ as the decision to place module m on launch vehicle l , along with the constraints:

$$0 \leq w_{m,l}^{(M,L)} \leq x_{m,f,l} \quad \forall f \in F, l \in L, m \in M,$$

Equation D.4

$$0 \leq \sum_{\forall l \in L} w_{m,l}^{(M,L)} \leq 1 \quad \forall m \in M.$$

Equation D.5

The variables $x_{m,f,l}$, $w_{m,l}^{(M,L)}$, $w_m^{(M)}$, and $w_l^{(L)}$ must all be binary variables; however, at a feasible solution, $w_{m,l}^{(M,L)}$, $w_m^{(M)}$, and $w_l^{(L)}$ will be binary variables if $x_{m,f,l} \in \{0,1\}$.

The second part of this formulation involves modeling the resource-sharing decisions that are made after the system has been placed into orbit and the relevant uncertainties have been revealed. A recourse decision must be made under each scenario under consideration. Let P be the set of products or capabilities that the system can provide, indexed by p . Further, let S be the set of scenarios, indexed by s .

Assume that the demand for each product is uncertain and varies across the scenarios. Let $d_{p,s}$ be the demand for product p under scenario s .

The goal of the stochastic portion of the problem is to allocate the on-orbit resources to meet demand, with $z_{p,s}$ denoting the volume of product p that the system supports under scenario s . The supply of product p in scenario s cannot exceed the demand for product p in scenario s :

$$0 \leq z_{p,s} \leq d_{p,s} \quad \forall p \in P, s \in S.$$

Equation D.6

Also, the system must have enough resources available on-orbit to support the chosen level of supplied products. To model this, let R be the set of resources that are shared on-orbit. Assume that resources are transformed into products, with $e_{r,p}$ being the linear rate of exchange from resource r into product p . Said differently, $e_{r,p}$ is the number of units of product p that a single unit of resource r can support. In addition, assume that $g_{r,f}$ measures the number of units of resource r available on subsystem f . This formulation is general enough to accommodate subsystems that supply multiple types of resources

to the overall system. Let $h_{r,p,s}$ determine the amount of each resource dedicated to each product under each scenario. This decision variable is constrained by the total available set of on-orbit resources, which is a function of the fractionated components that are selected in the deterministic portion of the decision, as well as any uncertainties that may impact the availability of the modules. Let $b_{s,l}^{(L)}$ be a binary parameter equal to 1 if the launch of launch vehicle l is a success in scenario s and 0 otherwise. Similarly, let $b_{s,m}^{(M)}$ be a binary parameter indicating the availability of module m under scenario s . Using this notation, the constraint that the sum of all committed resources must be less than or equal to the sum of all resources that are available in orbit can be expressed as:

$$0 \leq \sum_{\forall p \in P} h_{r,p,s} \leq \sum_{\forall l \in L} \sum_{\forall m \in M} \sum_{\forall f \in F} g_{r,f} x_{m,f,l} b_{s,m}^{(M)} b_{s,l}^{(L)} \quad \forall r \in R, s \in S.$$

Equation D.7

The volume of p supplied in scenario s cannot exceed the minimum supportable volume of p across all resources. This constraint is expressed as:

$$z_{p,s} \leq e_{r,p} h_{r,p,s} \quad \forall p \in P, r \in R, s \in S$$

Equation D.8

Finally, chance constraints are used to force the optimization to settle on a system that can satisfy all demand in a specified proportion of the scenarios. Let π_s be the probability that scenario s is realized. Further, let I_s be an indicator variable that is equal to 1 if all demand is met in scenario s and zero otherwise. Because I_s can be equal to 1 only if all demand is met, the following constraint must hold:

$$d_{p,s} I_s \leq z_{p,s} \quad \forall p \in P, s \in S.$$

Equation D.9

Let α be the minimum acceptable probability that all demand is met. The chance constraint on the overall system flexibility can be expressed as:

$$\alpha \leq \sum_{\forall s \in S} \pi_s I_s.$$

Equation D.10

The optimization involves two stages. First, Equation D.1 is minimized subject to all constraints associated with on-orbit resource sharing, the chance constraint, and all auxiliary constraints. While the solution to this problem will be a feasible architecture of minimum cost, the variables I_s are only guaranteed to satisfy $\alpha \leq \sum_{\forall s \in S} \pi_s I_s$, and not to be at their "true" maximum value. Let $x_{m,f,l}^*$ be the solution to the first optimization problem. The second optimization algorithm selects the variable I_s that maximizes

$$\sum_{\forall s \in S} \pi_s I_s$$

Equation D.11

subject to the constraint $x_{m,f,l} = x_{m,f,l}^*$ and all on-orbit resource sharing constraints (Equation D.6 through Equation D.9).

The entire problem is expressed below.

Step 1: Cost Minimization

$$\underset{x_{m,f,l}, w_l^{(L)}, w_m^{(M)}, z_{p,s}, h_{r,p,s}, I_s}{\text{Minimize}} \quad \sum_{\forall l \in L} c_l^{(L)} w_l^{(L)} + \sum_{\forall m \in M} c_m^{(M)} w_m^{(M)} + \sum_{\forall l \in L} \sum_{\forall m \in M} \sum_{\forall f \in F} c_f^{(F)} x_{m,f,l}$$

Subject to:

$$0 \leq w_l^{(L)} \leq x_{m,f,l} \quad \forall f \in F, l \in L, m \in M$$

$$0 \leq w_m^{(M)} \leq x_{m,f,l} \quad \forall f \in F, l \in L, m \in M$$

$$0 \leq w_{m,l}^{(M,L)} \leq x_{m,f,l} \quad \forall f \in F, l \in L, m \in M$$

$$\sum_{\forall l \in L} w_{m,l}^{(M,L)} \leq 1 \quad \forall m \in M$$

$$0 \leq z_{p,s} \leq d_{p,s} \quad \forall p \in P, s \in S$$

$$0 \leq \sum_{\forall p \in P} h_{r,p,s} \leq \sum_{\forall l \in L} \sum_{\forall m \in M} \sum_{\forall f \in F} g_{r,f} x_{m,f,l} b_{s,m}^{(M)} b_{s,l}^{(L)} \quad \forall r \in R, s \in S$$

$$z_{p,s} \leq e_{r,p} h_{r,p,s} \quad \forall p \in P, r \in R, s \in S$$

$$d_{p,s} I_s \leq z_{p,s} \quad \forall p \in P, s \in S$$

$$\alpha \leq \sum_{\forall s \in S} \pi_s I_s$$

$$x_{m,f,l} \in \{0,1\}$$

$$I_s \in \{0,1\}$$

Step 2: Resource Sharing Optimization

$$\underset{z_{p,s}, h_{r,p,s}, I_s}{\text{Maximize}} \quad \sum_{\forall s \in S} \pi_s I_s$$

Subject to:

$$0 \leq z_{p,s} \leq d_{p,s} \quad \forall p \in P, s \in S$$

$$0 \leq \sum_{\forall p \in P} h_{r,p,s} \leq \sum_{\forall l \in L} \sum_{\forall m \in M} \sum_{\forall f \in F} g_{r,f} x_{m,f,l} b_{s,m}^{(M)} b_{s,l}^{(L)} \quad \forall r \in R, s \in S$$

$$z_{p,s} \leq e_{r,p} h_{r,p,s} \quad \forall p \in P, r \in R, s \in S$$

$$d_{p,s} I_s \leq z_{p,s} \quad \forall p \in P, s \in S$$

$$I_s \in \{0,1\}.$$

APPENDIX E: LAUNCH SYSTEM TECHNICAL SUMMARIES

LAUNCH SYSTEMS

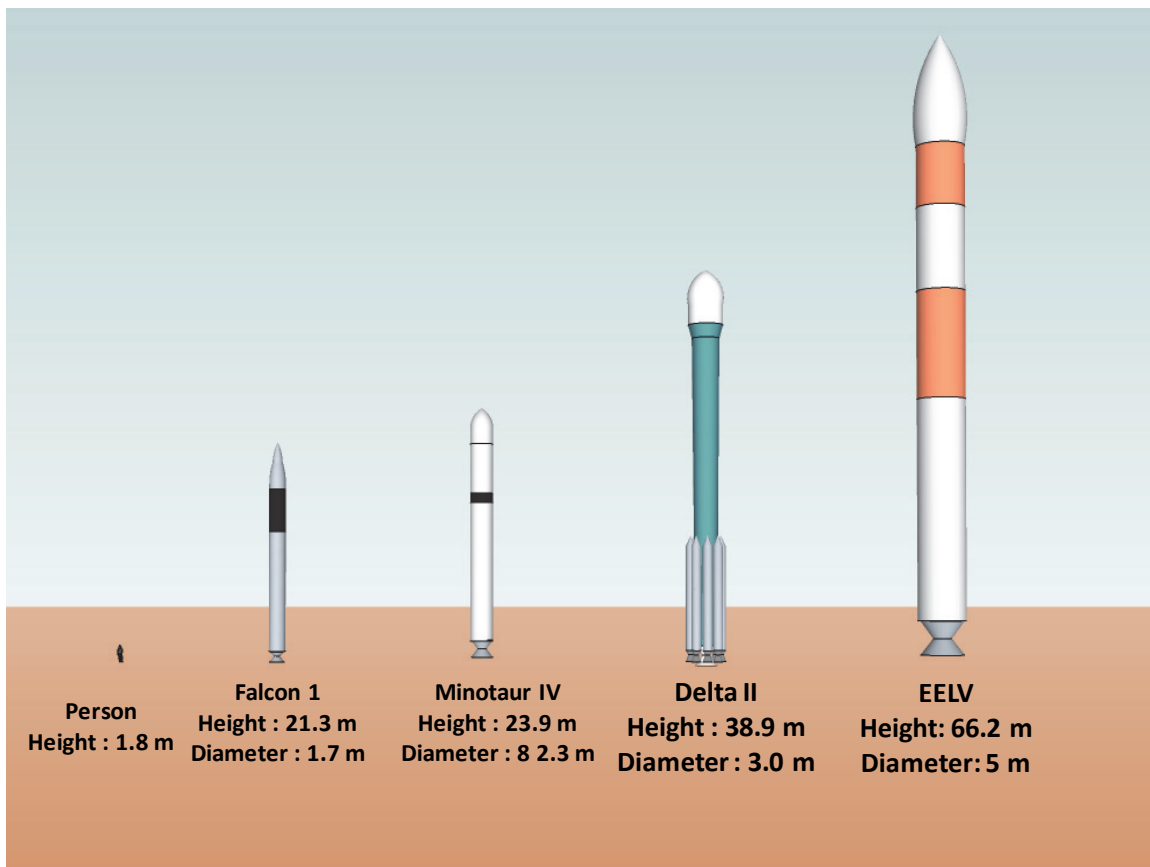
This appendix provides an overview of the five launch systems referenced in the three essays: Falcon 1, Minotaur IV, Delta II, Delta IV, and Atlas V. For a more detailed discussion of the technical attributes of these and other launch systems, the interested reader is directed to Isakowitz et al., 2004.

Table E.1
Launch System Technical Summaries

	Falcon 1	Minotaur IV	Delta II	Delta IV	Atlas IV
Height	21.3 m	23.9 m	38.9 m	66.2 m	65.2 m
Diameter	1.7 m	2.3 m	3.0 m	5 m	5.4 m
First Stage	Merlin 1C	Peacekeeper boosters	RS-27A	RS-68	RD-180
Upper Stage	Kestrel	Orion-38	AJ-10-118K	RL10B-2	Single-engine Centaur
Maximum Performance to LEO	670 kg	1,735 kg	5,058 kg	13,701 kg	20,520 kg
Maximum Performance to GTO	No capability	No capability	No capability	6,822 kg	8,670 kg
Maximum Performance to GEO	No capability	No capability	No capability	2,786 kg	3,810 kg
Launch Service Provider	Space Exploration Technologies	Orbital Sciences Corporation	United Launch Alliance	United Launch Alliance	United Launch Alliance

NOTES: LEO performance was calculated assuming 185 km at 28°. Delta II assumes the 7920 variant, Delta IV assumes the Medium+ (5,4) variant, and the Atlas IV assumes the 551 variant. The Minotaur IV is actually a four-stage rocket. A converted Peacekeeper Booster houses the first three stages (SR118, SR119, and SR120). While Delta II 7920 cannot place payloads in GTO, the Delta II 7925 includes a Star 48B third-stage motor and can place 1,832 kilograms into GTO.

Figure E.1
Launch System Renderings



NOTE: This figure was rendered by the author.

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