Competition, Procurement and Learning-by-Doing in the Space Launch Industry

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Abstract

We estimate a dynamic model of the U.S. space launch industry. The model allows past launches to improve rocket reliability and lower launch costs. It also allows the government to make forward-looking procurement choices. We use the model to analyze policy-relevant issues in the recent history of the industry: the 2006 United Launch Alliance "merger-to-monopoly"; innovation in the form of SpaceX's Falcon 9 and ULA's recent introduction of Vulcan; the costs and benefits of forward-looking procurements; and the trade-offs between the advantages of centralized control and possible inefficiencies. We identify large benefits to merger synergies and innovation but also significant inefficiencies from market competition.

Keywords: dynamic competition, learning-by-doing, procurement, forward-looking buyers, mergers, antitrust, space launch.

JEL codes: C73, D21, D43, L13, L41.

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1 Introduction

> "*It is the policy of the United States to enhance American greatness in space by enabling a competitive launch marketplace and substantially increasing commercial space launch cadence and novel space activities by 2030.*" [Presidential Executive Order "Enabling Competition in the Space Launch Industry", August 2025]

> "*A space revolution is coming. The 21st century will be the century of space. Europe needs to be at the forefront.*" [EU Commissioner for Defense and Space, June 2025]

Industries of strategic national importance, such as aerospace, defense, nuclear power and aircraft manufacturing, often share common features. On the supply-side, one or two sellers, who can benefit from large economies of scale or learning-by-doing (LBD) economies, have to make large investments to develop better products. On the demand-side, a government buyer knows that it will be in the market repeatedly and cares about not only procurement costs, but also the reliability of the products being purchased. Having a domestic industry that matches or outperforms the industries of rival countries can also be vital to the country's national interests. We study the space launch industry, which is critical to intensifying international competition in space, and, in some readings, the future of humanity (Rees (2003), Vance (2015), Guthrie (2017), Troutman (2020)).

We assemble a dataset of unmanned medium-to-heavy-rocket launches which place objects into stable orbits and beyond.[1] We combine this with a new dataset that we assemble on the prices paid by the U.S. government for launches. We use these data to estimate a model of dynamic competition and procurement under three different market structures that have characterized the U.S. space launch industry since 2002. The model allows for accumulated know-how to lower the seller's production costs, and to increase the valuation of the launch to a buyer. We interpret the latter as a reliability effect in light of the space launch literature and patterns that we find in our own data. Our model therefore has LBD on the demand-side as well as the cost-reducing LBD that appears in the previous literature (e.g. Benkard (2000), Benkard (2004)). Our model also assumes a forward-looking government buyer that accounts for how its procurement choices affect the evolution of know-how and

[1] Stable orbits generally require altitudes above 160 km to avoid significant atmospheric drag.

future competition, so that we allow for interactions between dynamically optimizing agents on both sides of the market (Sweeting et al. (2022)).

We use our estimated model to perform counterfactuals that address several questions relevant to policy in the space launch industry, and, potentially, other strategic industries with similar characteristics. First, we compare the performance of alternative market structures. In particular, we seek to understand the effects of the United Launch Alliance (ULA) "merger-to-monopoly" joint venture (JV) between Boeing and Lockheed Martin in 2006. The Federal Trade Commission (FTC) allowed the JV to proceed based on its understanding that the consolidation would lead to the Atlas V and Delta IV rocket families having enhanced reliability (Kovacic (2019)), a particular form of merger synergy. Our analysis can be viewed as a model-based retrospective (Miller and Weinberg (2017), An and Zhao (2019)) on a high-profile and, at the time, controversial enforcement decision. Our model predicts that, in the presence of the synergy, which takes the form of learning benefiting both of ULA's rockets, the decision to allow the JV was the right one, in the sense that the JV raised both buyer (i.e., government) and total surplus.[2]

Second, we compare market outcomes with those under a social planner. This comparison is relevant in our setting, as space industries in other parts of the world, and the U.S. space industry historically, have been subject to much tighter government (and therefore buyer) control. Weinzierl (2018) provides an overview of the growing role of commercial companies in providing launch services in the U.S., and argues that "[t]he vulnerabilities of centralized control will be familiar to any economist: weak incentives for the efficient allocation of resources, poor aggregation of dispersed information, and resistance to innovation due to reduced competition."[3] We assess this argument by quantifying how much inefficiency, in increased production costs, would be required to make the planner and market outcomes equivalent. Absent innovation, we find that a 36% production cost inefficiency offsets the benefits of planner control.

[2]Kovacic (2019) argues that the experience of the 15 years after the approval has been "astonishingly positive." Our approach allows us to come to a similar conclusion based on counterfactual predictions about what would have happened if the JV had been blocked.

[3]Of course, in reality, there is significant government involvement in investment decisions in the launch industry. For example, up to 2018, the U.S. government had committed approximately $1.2 billion to the development of Vulcan Centaur, out of total development costs of around $8 billion (Albon (2024) and `https://en.wikipedia.org/wiki/Vulcan_Centaur`).

Third, we compare the performance of the government's forward-looking procurement rule, which we assume for estimation, with a static procurement rule. Lewis and Yildirim (2002) and Sweeting et al. (2022) have shown that, when a buyer faces duopoly suppliers, benefiting from cost-side LBD, and has, at most, a fairly unattractive outside option, a static procurement rule can be buyer-optimal because it intensifies supplier competition. In our model, where we consider alternative market structures and reliability-enhancing LBD, and the buyer frequently chooses not to launch, we find more nuanced results. Duopolists tend to underinvest in winning launches to increase their experience or know-how, and a forward-looking buyer can offset this underinvestment, so that future buyer surplus increases. On the other hand, we find a static procurement rule is optimal for the buyer when it faces a ULA monopolist benefiting from a learning efficiency, because a static rule causes the monopolist, which has to compete with the outside good, to lower prices.

Fourth, we study the effects of SpaceX (SPX) on welfare and on the incentives of ULA to innovate. SPX's Falcon 9 rockets introduced a lower launch cost technology, which was also able to benefit from an unprecedented number of commercial launches that were used to roll out SPX's Starlink satellite communication system. Once SPX entered, ULA committed to developing Vulcan Centaur, a rocket designed to be less expensive than ULA's older Atlas V and Delta IV systems. We show substantial benefits to the government buyer of SPX's availability. The presence of SPX more than doubles the probability that ULA innovates. We also find that, when innovation is possible, buyer control can be even more valuable.

We view our substantive results concerning policy questions in the space industry as our primary contribution. The space industry is currently a focus of international competition and U.S. litigation concerning procurement policies, including the weight placed on future supply (Erwin (2019)), and we believe that we are the first to take a model-based approach to understanding these issues. More broadly, the U.S. government is currently considering potentially "revolutionary" reforms to its procurement policies (Office of Federal Procurement Policy (2025)). The second Trump administration is also looking to take ownership stakes or controlling "golden share" interests in strategically important firms (Mishra (2025)).

We are also contributing to the literature on dynamic competition with a new application, and by incorporating features, such as demand-side LBD effects and forward-looking procurement, that have not been included in existing empirical studies, and have not been thoroughly explored theoretically. We are also contributing to the merger retrospective literature with a model-based assessment of a well-known agency choice not to block a merger, which turned on the often controversial question of merger efficiencies.

The structure of the rest of the paper is as follows. After a brief review of the related literature, Section 2 provides institutional background on the industry and Section 3 describes the data. Section 4 details the model, and notes its limitations. Section 5 explains how we fix certain parameters (e.g., know-how depreciation rates) and estimate others, and discusses our parameter estimates and model fit. Section 6 describes our counterfactuals and their policy implications. Section 7 concludes.

Related Literature Our paper builds on the theoretical and empirical literatures that use models of dynamic competition to study questions in antitrust, industrial policy and international trade (for example, theoretical papers by Fudenberg and Tirole (1983), Cabral and Riordan (1994), Besanko et al. (2010) and Besanko et al. (2014), and empirical papers by Baldwin and Krugman (1988), Irwin and Pavcnik (2004), Benkard (2004), An and Zhao (2019) and Barwick et al. (2025)). The models that we use draw directly from this literature, although we will allow for LBD to improve the buyer's valuations of products, as well as reduce the seller's costs. Similar to the analysis of the Boeing/McDonnell Douglas merger in An and Zhao (2019), our work provides a retrospective analysis of a consummated merger. In our case, the JV truly was a merger to monopoly until SPX entered.

Our model differs from the papers considered above in allowing for there to be a monopsonistic and forward-looking buyer, rather than atomistic buyers.[4] Lewis and Yildirim (2002) present a theoretical model where such a buyer spreads purchases between two sellers who benefit from LBD in order to maintain competition, even though this has the effect of raising prices. Sweeting et al. (2022) examine the effects of forward-looking buyer behavior in the context of the Besanko et al. (2010) and Besanko et al. (2014) models, allowing for buyers to internalize some proportion of their effects on future buyer surplus, where the monopsonist

[4]The dynamic demand literature, such as Erdem et al. (2003) and Hendel and Nevo (2006) allows for forward-looking buyers, who ignore any effect that they might have on the evolution of the state. In our model, the buyer takes these effects into account.

case corresponds to full internalization. As well as showing that a forward-looking buyer can soften competition so much that static procurement is optimal, Sweeting et al. (2022) also show that multiple equilibria, which are common in these models when buyers are atomistic, are eliminated when buyers are even moderately forward-looking. While our model is not identical to the model in Sweeting et al. (2022), the results in that paper provide some comfort that our model, which we solve repeatedly in estimation, is likely to have a unique equilibrium.

Our post-2016 counterfactuals also consider the possibility of innovation, and we analyze the effects of competitive pressure on innovation in a dynamic model. Goettler and Gordon (2011), Yang (2020) and Igami and Uetake (2020) provide related analyses in the CPU, smartphone chip and hard disk drive industries respectively, while Gilbert (2022) and Federico et al. (2020) provide conceptual arguments for how innovation should factor into competition analysis. We provide a complementary analysis that looks at innovation incentives under different market structures when there is a forward-looking monopsonistic buyer.

We analyze the effects of a merger that internalizes learning across products within the same firm on market outcomes and welfare. As noted, the FTC allowed the ULA merger to proceed because it recognized enhanced learning economies, including their benefits on reliability, as efficiencies. The extent to which mergers actually generate efficiencies and the extent to which claimed efficiencies should be credited is controversial (Rose and Sallet (2019)). Our evaluation suggests that, in our setting, the efficiencies identified by the Commission were large enough so that the merger benefited the buyer.

Finally, we contribute to an emerging literature studying economics related to human activities in space and transportation to space. Groesbeck (2020) simulates a model of learning-by-doing for the space launch industry but studies how international embargoes affect reliability. As noted above, Weinzierl (2018) provides a survey of recent developments of both space launches and the development of other activities in space, as well as emerging problems such as the externalities caused by space debris, an issue also analyzed in Rao and Rondina (2025). We analyze some of the trade-offs between inefficiency and planner control suggested by Weinzierl. Our paper therefore connects to the non-space empirical literatures that have tried to compare the efficiency of state-owned vs. non-state-owned firms along different dimensions, although our exercises are focused on control rather than ownership, and are model-based predictions rather than descriptive analyses. For example, La Porta and López-de Silanes (1999) examine the effects of privatization of many Mexican firms in the 1980s and 1990s, finding privatization increases productivity. Chen et al. (2021) similarly finds that previously state-owned firms become more productive after privatization in China. Cao et al. (2020) find that the innovative efficiency of firms, measured by the number of patents per dollar spent on R&D, is higher for firms that are partially state-owned than for fully state-owned or non-state-owned firms. In the space context, Kantor and Whalley (2025) study the spillover from publicly-funded R&D to manufacturing productivity and value-added during the Cold War space race between the U.S. and the Soviet Union.

2 Space Launch Industry and Institutional Background

To put our modeling choices and our counterfactuals in context, we now explain some of the recent history and institutional background of the space launch industry.

2.1 Timeline of U.S. Launch Systems After the Space Shuttle

Our focus is on unmanned launches that put payloads, including satellites, into stable Earth orbits, typically at altitudes above 160 kilometers, or outer space. For example, the International Space Station, Starlink and most spy satellites, and the Hubble Space Telescope are all in low Earth orbit (LEO), usually defined as 160 to $2,000$ kilometers above Earth, whereas many weather satellites stay fixed above a particular location and are at much higher altitudes. Examples of suitable U.S. launch systems are Atlas V, Delta IV and Falcon 9, with Ariane 5, Long March 5 and Soyuz 2 as European, Chinese and Russian systems, respectively, which are classified as medium-to-heavy launch vehicles (McConnaughey et al. (2012)), defined as being capable of lifting 2 to 50 tons of payload to LEO.

The Apollo and Space Shuttle systems were developed in a highly centralized way by NASA, with commercial vendors providing important components. However, following slow development, large cost overruns and accidents, President Reagan's February 1988 "Directive on National Space Policy" instructed future US policy "to encourage to the maximum extent feasible, the development and use of United States private sector space transportation capabilities without direct Federal subsidy" with the aim "to reduce the costs of space transportation and related services." As noted by Weinzierl (2018), the President's 2004 Commission on Implementation of United States Space Exploration Policy argued that "NASA's role must be limited to only those areas where there is irrefutable demonstration that only government can perform the proposed activity". This emphasis on commercial launch services has been repeated by subsequent administrations.

In 1994, the U.S. government initiated the "Evolved Expendable Launch Vehicle" (EELV) program to make launches more affordable and reliable through the development of lower cost systems based on older technology.[5] This was followed by a sequence of both innovations and changes in market structure.

In 1995, Lockheed and Martin Marietta merged and developed the Atlas V system as part of the EELV program.[6] The two firms had developed the Atlas II and Titan systems, respectively, which were both based on intercontinental ballistic missile technologies. The following years of 1996 and 1997 saw mergers of Boeing, Rockwell (an engine developer) and McDonnell-Douglas, with Boeing developing the Delta IV as an alternative EELV.[7] The first post-testing and certification EELV launches took place in 2002, with Boeing and Lockheed Martin subsequently competing for government launches. The competition for government contracts was viewed as fierce, with two Boeing (former Lockheed Martin) employees criminally charged with undertaking industrial espionage.

In 2006, Lockheed Martin and Boeing proposed to form the United Launch Alliance joint venture. When it did not challenge the deal, the FTC issued a public document, the "Analysis of Agreement Containing Consent Order to Aid Public Comment", explaining that the Department of Defense "has informed the Commission that the creation of ULA

[5] The EELV program became the National Security Space Launch program in March 2019. Within the Department of Defense, the program was initiated by the Air Force, but transitioned to the Space Force in December 2019.

[6] The Federal Trade Commission agreed a consent order with the parties that was aimed at allowing other launch system developers access to certain technologies `https://www.ftc.gov/sites/default/files/documents/commission_decision_volumes/volume-119/ftc_volume_decision_119_january_-_june_1995pages_618-723.pdf`.

[7] Boeing and McDonnell Douglas had jointly developed earlier versions of Delta.

will advance U.S. national security interests by improving the United States' ability to access space reliably", citing "[f]irst, the single ULA workforce will benefit from a launch tempo [...] greater than could be expected from the two separate Lockheed and Boeing workforces" and "[i]n addition, integrating the two firms' complementary technologies will infuse each firm's launch vehicles with the technical improvements and innovations of its competitor, further enhancing the reliability". The analysis concluded that "[u]nder these unique circumstances, the increase in reliability can be recognized as an efficiency flowing from the joint venture."[8] Then-Commissioner Kovacic later explained that the "FTC's approval rested on two assumptions: that the claimed efficiencies were significant, and that the DoD and [NASA] would use best efforts to facilitate entry into the launch services sector." (Kovacic (2019)).

The connection to possible entry reflected how the ULA JV was proposed around the same time that SPX was undertaking the first test flights of Falcon 1, which was based on new technological choices that might lower launch costs dramatically, but whose success was far from certain.[9] SPX's Falcon 9 rocket was only certified for national security launches in May 2015. Therefore, between 2006 and 2015, the government had to rely on Atlas V and Delta IV rockets provided by a monopolist ULA.

After SPX's certification, the launch market became essentially a duopoly, with anecdotal evidence of fierce price competition. For example, SPX won its first contract by undercutting ULA on an Air Force satellite contract by 40%, leading ULA to lower its Atlas V and Delta IV prices by as much as one-third (Klotz (2016), Klotz (2017)). Simultaneously, ULA announced the development of its Vulcan Centaur system, which was also designed to have reusable first-stage rockets, to lower costs and to replace Atlas and Delta.[10] Atlas V and Delta IV undertook their final government launches in 2025 and 2024, and after various delays, Vulcan was certified in 2025.[11]

[8] `https://www.ftc.gov/sites/default/files/documents/cases/2006/10/0510165analysis.pdf`.

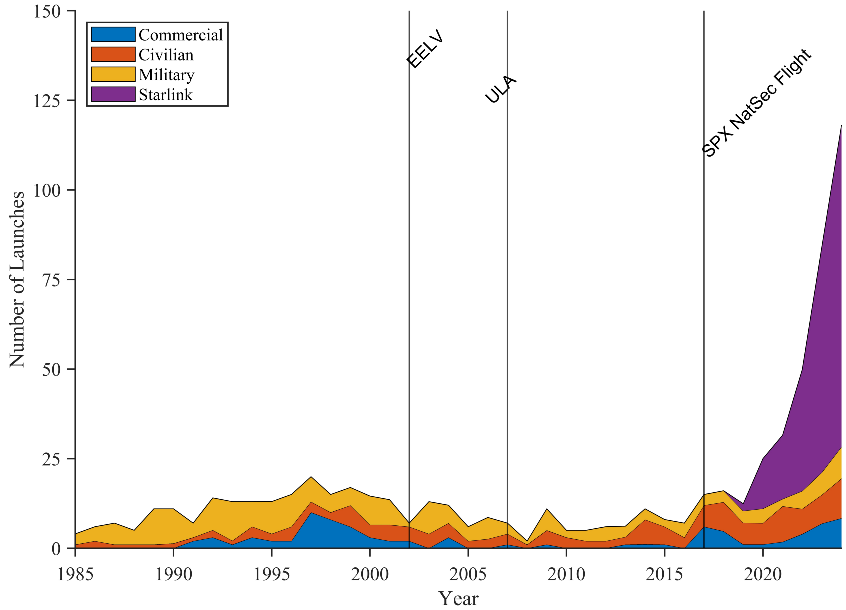
[9] Falcon's initial development was partly funded by $396 million NASA "Commercial Orbital Transportation Services" development contract, but an extra $1.6 billion contract for deliveries to the ISS was only secured in 2008 when the fourth launch of Falcon I was successful. In a 2014 "60 Minutes" interview, Musk described how "[w]e were running on fumes at that point. We had virtually no money... a fourth failure would have been absolutely game over. Done."

[10] As well as competition from SPX, ULA faced the problem that Atlas V used Russian RD-180 engines, which were subject to congressional policy which made them more difficult to use after the Russian invasion of Crimea in 2014 (Smith (2016)).

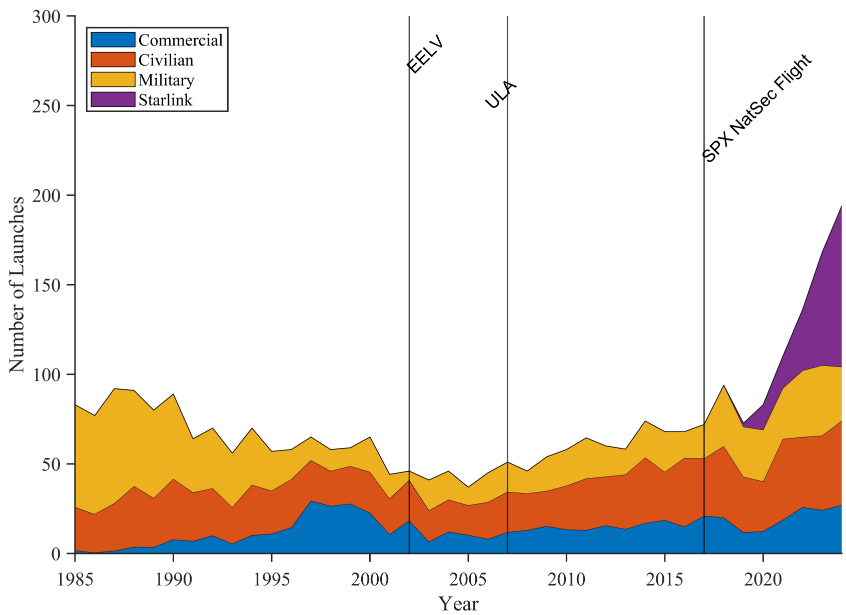
[11] Vulcan began to win future launch contracts in 2022 but did not receive government certification for

Figure 1: US and Global Rocket Launches 1985-2024 by Type of Launch.

(a) US Launches



(b) Global Launches



Note: For each payload, we define its type based on the status of its owner. Payloads owned by defense agencies are classified as "Military", while those owned by other government agencies or academic institutions are classified as "Civilian". When a launch carries multiple payloads with different types, we split the launch count in proportion to payload weights.

Falcon 9 was also heavily used to launch SPX's commercial Starlink satellites, with over 8,811 satellites launched as of Oct. 30, 2025.[12] Figure 1 shows how commercial (with Starlink broken out), civilian (non-military government) and military launches have varied over time, both in the US and globally. Apart from the late 1990s when there were many commercial launches related to the dotcom bubble, civilian and military launches have accounted for the majority of launches until Starlink's development. We will explain how we account for commercial launches when we simulate our model.

2.2 The Role and Conduct of US Government Procurement

Our model will assume that the US government acts as a long-lived forward-looking strategic buyer when procuring launches, and we will consider a static procurement rule as a counterfactual. In practice, agencies procure launches under standard federal procurement rules.[13] These rules require agencies to promote "full and open competition through the use of competitive procedures" (Competition in Contracting Act of 1984), although the Section 6.202 of the Federal Acquisition Rules allows contract actions to "establish or maintain an alternative source or sources for the supplies or services being acquired if the agency head determines that to do so would (1) [i]ncrease or maintain competition and likely result in reduced overall costs for the acquisition, or for any anticipated acquisition" as well as allowing choices that aim to maintain facilities and capabilities that are in the interests of national defense.[14] As we will discuss below, the maintenance of reliable launch systems is important and a function of past procurement choices.

national security payload launches until 2025.

[12]The real time count can be tracked at `https://www.space.com/spacex-starlink-satellites.html`, last accessed on November 5th, 2025. A Falcon 9 launch can put between 24 and 48 Starlink satellites into orbit.

[13]Military and intelligence launches are primarily done through Space Force's Space Systems Command, while NASA conducts procurement for civilian science and space exploration launches. We assume that these separate agencies internalize all of the effects on each other's future surplus.

[14]In response to a challenge from Blue Origin of a multiyear Air Force procurement, the Government Accountability Office ruled that the procurement rules "do not mandate that the government make multiple contract awards in order to incentivize future private investment necessary to satisfy the government's fulfillment of its future requirements" (Erwin (2019)).

3 Data and Descriptive Analysis

In this section, we briefly describe the sources of our data, the construction of our price measure, and present evidence that rocket reliability increases in the number of recent launches, which will motivate us to include a measure of experience, or know-how, in the buyer's expected utility from a launch. Further details of the data are included in Appendix A.

3.1 Launch Data and Reliability

We create a dataset of unmanned orbital rocket launches using medium- to heavy-lift rockets by governments or government agencies in major countries (US, Soviet Union/Russia, China, Japan, India or members of the EU), between 1985 and 2024, using the General Catalog of Artificial Space Objects (GCAT) (McDowell (2025)), with some augmentation from Gunter's Space Page (Krebs (2025)). The dataset includes information on launch and rocket characteristics (e.g., rocket family and variant, payload capacity, success of the launch outcome), but not prices.

Our focus is on rocket families, such as Lockheed Martin or ULA's Atlas V family or SPX's Falcon 9 family. Families usually have several variants that can be used for particular types of missions or payloads, but they share common components such as engines. We refer to the most frequently used variant as the representative variant and use its characteristics to describe the rocket family.

Table 1 presents the summary statistics from this global launch data. We exclude the first launch of each rocket family, as well as any launch conducted by a family that has been inactive for more than two years, since such launches are typically test flights. There are 1,921 launches meeting our criteria from 1985 and 2024. About 64% of these launches target low Earth orbit (LEO), or 160-2,000 km above the Earth's surface, and together these launches account for 70% of the total payload mass in our sample.

In the table, we define a launch as a success if the payload reaches the pre-specified orbit. There are a number of failure scenarios, ranging from serious accidents such as explosions during takeoff and total losses of payload, to potentially correctable failures such as

Table 1: Summary Statistics of Global Governmental Launches, 1985–2024

	Obs	Mean	Std. Dev.	Min	Max
Launch Success	1,921	0.96	0.19	0	1
# Launches in Past 2 Yr	1,921	26.29	30.03	1	219
LEO payload capacity (in tonnes)	1,921	9.22	6.32	1.80	57
$\mathbb{1}\{\#\text{stages}>2\}$	1,921	0.65	0.48	0	1
$\mathbb{1}\{\text{US Launch}\}$	1,921	0.21	0.41	0	1
$\mathbb{1}\{\text{Russia/Soviet Union Launch}\}$	1,921	0.45	0.50	0	1
$\mathbb{1}\{\text{China Launch}\}$	1,921	0.20	0.40	0	1
$\mathbb{1}\{\text{EU Launch}\}$	1,921	0.06	0.24	0	1
$\mathbb{1}\{\text{Japan/India Launch}\}$	1,921	0.08	0.26	0	1

Note: This table presents summary statistics for the global launch data from 1985 to 2024. Each observation corresponds to a governmental orbital launch. For each launch, # Launches in Past 2 Yrs denotes the number of launches of the corresponding rocket family within the preceding two years, including both governmental and commercial launches. For Atlas V and Delta IV, this measure also includes launches by the other rocket family occurring after the formation of the ULA.

malfunctions of upper stage boosters that leave the payload in a lower orbit.[15]

The rockets in our sample have an average carrying capacity of 9 tonnes to a "standard" LEO,[16] though this capacity varies substantially across rocket families.[17] The main U.S. vehicles, such as Atlas V, Delta IV, and Falcon 9, have an average LEO payload capacity of 15 tonnes. We do not observe the weights of many payloads. In particular, the weights of spy satellites are often classified. The average reported payload mass to LEO in our data is 6 tonnes.

The number of stages approximates the complexity of the rocket, where 65% of launches use rockets with more than two stages.[18] Of the 1,921 launches, 21% are from the United States. Approximately half of the Soviet/Russian launches took place before the dissolution of the USSR.

[15]Even if an injection problem can be corrected, this usually diminishes performance or reduces the payload's useful lifespan (NASA Jet Propulsion Laboratory (2002), Carlier (2016)).

[16]The standard LEO is defined here as a 200 km (120 mi) circular orbit at 28.7° inclination.

[17]The capacity can also vary (1) across orbits for a given rocket and (2) across variants within a rocket family. The capacity is lower if the target orbit is higher. Some variants of a rocket family are equipped with additional boosters and can launch a heavier payload for a given orbit.

[18]Multiple stages increase fuel efficiency by discarding deadweight during ascent.

3.1.1 Recent Launch Experience and Reliability

Government-mission payloads are usually far more expensive than the rockets that carry them, so that, from the buyer's perspective, reliability, or the expected success rate, is one of the most important characteristics of a rocket.[19] Although some features of a rocket cannot be changed after the design phase, the industry perceives that reliability can be improved significantly by accumulating experience (Office of Commercial Space Transportation (2002), Moore (2019)) through continuous operations, post-flight performance analysis, and iterative design refinements. The FTC's "Analysis of Agreement" document in the ULA case also emphasized how a high launch tempo is critical for operational safety.

We measure a rocket family's experience by its recent launch cadence, defined as the number of launches of the rocket family within the preceding two years. This experience measure includes both governmental and non-government commercial launches based on the GCAT data. We choose the two-year window to reflect the fact that, because of organizational forgetting (Benkard (2000)), experience is likely to depreciate.[20] We will explain, in the model and estimation sections, how this measure serves as a proxy for intangible know-how. We also assume that after the ULA joint venture, Atlas V and Delta IV share learning: each family's experience equals its own launches in the preceding two years plus the other family's post-ULA launches in that window. Table 1 shows that the average rocket family experience across launches in our data is 26, reaching a maximum of 219 for SPX at the end of our sample.

We merge the experience of the two ULA rocket families for two reasons. First, Kovacic (2019) explains that the ULA JV was expected to generate learning synergies between the two rocket families.[21] Second, Appendix A.3.2 presents additional regression results that are consistent with additional launches of one ULA rocket family increasing the reliability of the

[19] Walter Lauderdale, Chief of the Falcon Division and former Technical Director of the EELV Program at the U.S. Air Force, quoted in Hitchens (2021), stated that earlier GPS III satellites had a price tag of about $500 million, while a Falcon 9 launch costs around $65 million.

[20] Office of Commercial Space Transportation (2002) notes that constant monitoring of vehicle performance is necessary to maintain high reliability; even proven systems may lose reliability due to changes in manufacturing or operating procedures.

[21] Our launch records show that after ULA's formation, nearly all launches were successful. There is only one partial failure of an Atlas V launch on June 15, 2007, at a time when Delta IV had not yet conducted any launches under ULA. After that, both rocket families rapidly accumulated launches. All of these launches were successful.

other.

We find a robust positive relationship between the number of past launches and mission success. Appendix A.3.1 presents graphical reliability curves illustrating the relationships between accumulated success rates and the number of launches that we see for both the US and non-US launches in our data. We also note that this relationship is similar for all major launch systems from different countries. Here, we take a regression approach, and explore whether selection could affect the reliability relationship. We use global launches for this analysis because launch failures are rare.

Our first model is the simple probit model shown in equation (1). The dependent variable, l_{ijt}, is the success of a launch of rocket family j for mission i at time t. e_{jt} denotes family j's experience at time t, measured as the number of launches of family j within the preceding two years. X_{ijt} is a set of control variables, including rocket carrying capacity, number of stages, and country/region fixed effects.

$$l_{ijt} = \mathbb{1}\left\{\alpha_0 + \alpha_e \ln e_{jt} + \alpha_X X_{ijt} + \psi_{ijt} > 0\right\}, \quad \psi_{ijt} \sim N(0,1) \tag{1}$$

Columns (1)–(4) of Table 2 report the marginal effects for the estimated probit models with different control variables. The coefficient on ln (# Launches in Past 2 Yrs) in Column (4) is 0.018, which implies that a doubling of experience increases the probability of success by approximately 1.25 percentage points, which is sizable given that the average probability of success is 0.96. For the 120 ULA Atlas V and Delta IV launches, the model predicts 3.71 failures, which would decline to 2.57 expected failures, if the experience level at the time of each launch was doubled.

There are several possible selection issues with this specification. We would be especially concerned about a false positive result, where, for example, governments choose rocket families with low experience for more complex missions, which are more likely to fail, because these families have unusual characteristics tailored for these missions.

We address this issue by augmenting the probit model with a selection stage modeled as a multinomial logit model. The model captures the choice of a government with a potential launch opportunity to use one of the rocket families available to it, which we restrict to

Table 2: Rocket Reliability Estimation Results

	Probit Model				Probit Model and Selection Equation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$
Rocket Reliability												
ln (# Launches in Past 2 Yrs)	0.012***	0.012***	0.014***	0.018***	0.011***	0.011***	0.013***	0.019***	0.009***	0.009***	0.011***	0.016***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)
ln (LEO capacity)		-0.011	-0.012*	-0.007		-0.011	-0.012*	-0.007		-0.009*	-0.010**	-0.006
		(0.007)	(0.007)	(0.007)		(0.007)	(0.007)	(0.008)		(0.005)	(0.005)	(0.006)
$\mathbb{1}\{\#\text{stages} > 2\}$			-0.016	0.003			-0.015*	0.003			-0.013	0.002
			(0.010)	(0.012)			(0.009)	(0.013)			(0.008)	(0.011)
Error Term Distribution												
σ_ξ					0.696***	0.715***	0.716***	0.740***	0.707***	0.726***	0.726***	0.719***
					(0.158)	(0.159)	(0.159)	(0.159)	(0.155)	(0.157)	(0.157)	(0.158)
ρ					-0.063	-0.010	-0.008	0.011	-0.210	-0.159	-0.155	-0.112
					(0.846)	(0.852)	(0.856)	(0.899)	(0.809)	(0.816)	(0.823)	(0.871)
Region FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Demand Shifter	-	-	-	-	Casualties	Casualties	Casualties	Casualties	GDP	GDP	GDP	GDP
Observed Launches	1,921											

Note: *,** ,*** denote significance at the 10%, 5% and 1% levels. Standard errors in parentheses. Results in the Rocket Reliability section are reported as average marginal effects. Columns (1)–(4) correspond to the probit model specified in Equation (1); Columns (5)–(12) correspond to the joint model of rocket selection and rocket reliability specified in Equations (1) and (2). Columns (5)–(8) use interactions between the two-year-lagged global total of war-related fatalities and rocket-family fixed effects as demand shifters, while Columns (9)–(12) use interactions between the two-year-lagged GDP of the mission country and rocket-family fixed effects.

families that have been active in its country in the current or any of the past four quarters.[22]

For the logit model, we define the "indirect utility" of assigning family j to opportunity i at time t as

$$u_{ijt} = \beta_0 + \beta_e \ln e_{jt} + \beta_X X_{ijt} + \beta_z Z_{ijt} + \xi_{ijt} + \epsilon_{ijt} \tag{2}$$

$$\begin{bmatrix} \psi_{ijt} \\ \xi_{ijt} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_\xi \\ \rho\sigma_\xi & \sigma_\xi^2 \end{bmatrix} \right) \tag{3}$$

where Z_{ijt} denotes a set of rocket-family-specific demand shifters, which do not appear in the reliability equation. For these shifters, we use interactions between the two-year-lagged world casualties from wars and rocket family fixed effects, or interactions between the two-year-lagged GDP of the mission country and rocket-family fixed effects.[23] ξ_{ijt} represents an unobserved demand shock, which we allow to be correlated with the reliability equation unobservable, while ϵ_{ijt} follows a standard type I extreme value distribution. The utility from the outside option is $u_{i0t} = \epsilon_{i0t}$. We estimate the models jointly by maximizing likelihood.

Columns (5)–(8) of Table 2 report the estimates of the reliability equation using the fatalities interactions as the Zs, and columns (9)-(12) report the results using the GDP interactions. The estimated recent launch coefficients are similar to those in columns (1)-(4), and the ρ correlation coefficients vary in sign and are not statistically significant. These results are consistent with the space launch engineering literature's evidence that launch experience improves reliability.

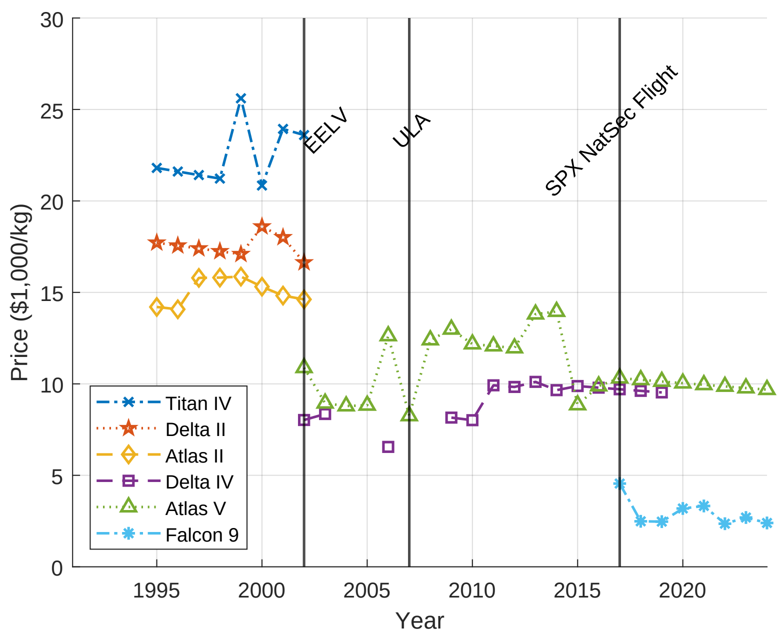
[22]To construct the set of potential launches, we first determine the highest observed number of launches separately by quarter, sector (civil or military), orbit, and country. We then define the number of potential launches for each category as 1.1 times this maximum observed number of launches, thus giving the government an outside option of no launch. In our sample of 1,921 launches, only 4% of government launches use foreign rockets, and 92% of these launches belong to the EU, India, or Japan. The remainder are joint missions involving the US, which account for 2% of US launches. China and Russia government launches never use foreign rockets. Overall, international trade in government launches is very limited.

[23]The world casualties from wars are constructed using data from the Polynational War Memorial (`https://www.war-memorial.net/wars_all.asp`). For each conflict, we observe its duration and total number of battle deaths. We assume that battle deaths are distributed evenly across the years of the conflict. The GDP data are obtained from the National Accounts Estimates of Main Aggregates published by the United Nations Statistics Division (`https://data.un.org/Data.aspx?d=SNAAMA&f=grID%3a102%3bcurrID%3aUSD%3bpcFlag%3a0`). When computing the GDP of the European Union, we include all countries that are ever part of the EU. For Russia, we use the GDP of the Soviet Union before 1991 and the GDP of Russia thereafter. The logic of these demand shifters is that international tensions, for example, might both increase demand for spy satellite launches in general, and rocket families that are particularly suited for launching spy satellites.

3.2 Price Data

GCAT does not record either bids or transaction prices. Appendix A describes how we construct a new dataset of launch transaction prices from FAA launch reports, government contract records, and public news reports, and how we use these data and hedonic regressions, to construct a measure for the average launch price in each year for the representative variant of each US rocket family.

Figure 2: Rocket Family Prices (2010 dollars)



Note: see Appendix A for details of the sources and construction. Each rocket family's price corresponds to the representative variant and is expressed in $1,000 per kilogram of payload capacity to standard LEO in 2010 dollars.

Figure 2 presents the resulting rocket family–level prices in \$1,000 per kilogram units in 2010 dollars. We calculate the price as the launch price divided by the LEO payload capacity of the representative variant. Our price measure follows a standard, widely used convention in the space launch industry (Mathieu et al. (2022)). Within each rocket family, variants differ in carrying capacities and therefore can have substantially different prices when measured per launch. However, these variants typically exhibit similar prices per kilogram to LEO. As shown in Figure A.1, this pattern holds for the Delta IV, Atlas V, and Falcon 9. Our analysis is at the rocket family level, so using price per kilogram to LEO provides an appropriate and consistent measure for comparing the cost-effectiveness of rocket families. Three vertical lines mark key events in the US launch market. The first line indicates the initial launch of the EELV program rockets (Atlas V and Delta IV). The second line marks the merger of Boeing (owner of the Delta series) and Lockheed Martin (owner of the Atlas series) to form ULA. The third line marks the entry of Falcon 9 rockets into national security launches. For comparison, Space Shuttle launches cost \$54,500/kg.

Average prices have fallen with each new generation. Vulcan is not shown, but, in 2023, ULA was awarded 11 future national security missions on Vulcan rockets, which, given its payload capacity, implied prices of \$3,290 per kilogram (Sheetz (2023)), similar to Falcon 9's \$3,420/kg price in 2023. Finally, the figure shows that EELV rocket prices, especially Atlas V, increased after the ULA JV and fell around the time of SPX's entry.[24]

[24] Due to lead times in contracting over actual launches, it is not surprising that we may see some disciplining effect of SPX on ULA prices before ULA launches begin.

4 Model

This section describes our model. After a brief overview, we describe the simplest version of our model of competition and procurement. We detail the equations that characterize the equilibrium with a forward-looking buyer, and note what would change with a static buyer or a social planner. We then outline our extension to consider innovation, and the state transition processes that we assume when solving the model and taking it to data. We briefly acknowledge some real world factors that even the adjusted model does not capture.

4.1 Overview

We solve distinct stationary, infinite horizon, discrete state dynamic games for three eras since 2002. The eras are (1) Boeing/Lockheed Martin single product duopoly from 2002 to 2006; (2) ULA multi-product monopoly from 2007 to 2016; and (3) ULA-SPX duopoly from 2017 to 2023. We assume that each transition to the next era is an unanticipated and exogenous shock.

In the simplest ("no innovation") version of the model, there is no product entry or exit, so that the state space is defined by the know-how (depreciated launch experience) of each product. There is a potential US government launch procurement in each period. A product's know-how will affect the government's valuation of using that product, and it may also affect the seller's costs. Both the government's preferences and the seller's production costs will also depend on private information shocks. Sellers will simultaneously submit bids for each product, and the government buyer will choose one of the products, or the outside good, to maximize either its value, if it is forward-looking, or its current flow payoff, if it is static. Conditional on the procurement outcome and the ownership of the products, know-how will evolve stochastically. When we consider innovation, ULA will stochastically receive opportunities to replace Atlas V and Delta IV with a new product, Vulcan Centaur, which has a lower production cost given the same know-how.

4.2 Model without Innovation

We detail the model for "era 3" where there are two competing sellers, denoted by $i \in \{\text{ULA,SPX}\}$. Products are denoted by $j \in \{\text{Atlas (A), Delta (D), Falcon (F)}\}$. Atlas and Delta are owned by ULA. Time periods are denoted by t, and we assume $t = 1, ..., \infty$. We will assume 20 time periods each year, an assumption which will matter when we account for commercial launches, and a discount factor of δ. The industry state is $\mathbf{e} = (e_A, e_D, e_F)$, where the know-how states (e_j) will be discrete. The players (sellers and buyer) are assumed to observe the current know-how state.

4.2.1 Seller Costs

If product j is chosen in a procurement at time t, the production cost of launch will be

$$c_{jt} = c_j(e_{jt}, \zeta_{jt}) = \exp\left(\gamma_j - \gamma^e \ln e_{jt} + \sigma_\zeta \zeta_{jt}\right) \tag{4}$$

where γ_j is a rocket family intercept term (we will assume $\gamma_A = \gamma_D \neq \gamma_F$), and ζ_{jt} is an i.i.d. normally distributed private cost shock, with probability density function $g(\zeta)$, observed by the owner of product j. Therefore, ULA observes two cost shocks and SPX observes one. As know-how will tend to increase with past launches, $\gamma^e > 0$ implies the existence of "learning-by-doing" economies in production.

4.2.2 Procurement and Buyer Payoffs.

In each period, there is a procurement for a single government/national security launch (US government civilian and defense launches are not distinguished). The sellers simultaneously submit bids, b_{jt}, for each product. The chosen product will be paid its bid. If product j is chosen for the launch, the flow indirect utility of the buyer is

$$u_{jt}^B = \beta_{\text{era}} + \beta_j + \beta^e \ln e_{jt} - \alpha b_{jt} + \varepsilon_{jt}, \tag{5}$$

where for the β_js, we assume $\beta_A = \beta_D \neq \beta_F$. If the outside good (no launch) is chosen, the indirect utility is

$$u_{0t}^{B} = \varepsilon_{0t}. \tag{6}$$

The εs are type I extreme value i.i.d. payoff shocks that are private information to the buyer when bids are made.

4.2.3 State Transitions

We assume that production takes place immediately after the procurement. Conditional on the buyer's choice k, the state will transition before the next period with probabilities $\Pr(\mathbf{e}_{t+1}|\mathbf{e}_t, k)$. We describe these transition probabilities in Section 4.4.

4.2.4 Equilibrium

We assume that the firms play a stationary, symmetric Markov Perfect Nash Equilibrium (MPNE, Maskin and Tirole (2001)). The Markovian restriction is that strategies can depend only on payoff relevant state variables. In the no-innovation game, the equilibrium will be defined by seller values (in vector form, $\mathbf{V_i^S}(\mathbf{e})$) and optimal (expected value-maximizing) bidding strategies ($\mathbf{b_{ij}^*}(\mathbf{e}, \boldsymbol{\zeta}_i)$) for the sellers for each product, given their cost shocks ($\boldsymbol{\zeta}_i$), and the value ($\mathbf{V^B}(\mathbf{e})$) and optimal procurement strategies for the buyer, where expectations are consistent with the processes generated by the state transition processes and other players' strategies.

Values are defined at the start of each period, before buyer preference shocks or seller cost shocks are known. We also define intermediate value functions, which define values after the buyer's procurement choice has been made, but before know-how transitions are realized. For a particular state $\mathbf{e}$ and a winning rocket k,

$$V_i^{S,INT}(\mathbf{e}, k) = \delta \sum_{e'} \Pr(\mathbf{e}'|\mathbf{e}, k) V_i^S(\mathbf{e}') \tag{7}$$

$$V^{B,INT}(\mathbf{e}, k) = \delta \sum_{e'} \Pr(\mathbf{e}'|\mathbf{e}, k) V^B(\mathbf{e}'). \tag{8}$$

Given a vector of bids $\mathbf{b}$ and the logit assumption on the preference shocks, the optimal choice probability of a forward-looking buyer for one of the inside products k is

$$D_k(\mathbf{b}, \mathbf{e}) = \frac{\exp\begin{pmatrix} V^{B,INT}(\mathbf{e}, k) + \beta_{\text{era}} + \beta_k \\ + \beta \ln e_{kt} - \alpha b_{kt} \end{pmatrix}}{\exp\left(V^{B,INT}(\mathbf{e}, 0)\right) + \sum_{n=A,D,F} \exp\begin{pmatrix} V^{B,INT}(\mathbf{e}, n) + \beta_{\text{era}} + \beta_n \\ + \beta \ln e_{nt} - \alpha b_{nt} \end{pmatrix}}. \tag{9}$$

and, before the realization of the payoff shocks, the buyer's value will be

$$V^B(\mathbf{e}) = \iiint \log\Bigg(\exp\left(V^{B,INT}(\mathbf{e}, 0)\right) + \sum_{n=A,D,F} \exp\begin{pmatrix} V^{B,INT}(\mathbf{e}, n) + \beta_{\text{era}} + \beta_n \\ + \beta \ln e_{nt} - \alpha b^*_{nt}(\zeta_n, \mathbf{e}) \end{pmatrix} \Bigg) g\left(\zeta_{Ft}\right) g\left(\zeta_{Dt}\right) g\left(\zeta_{At}\right) d\zeta_{Ft} d\zeta_{Dt} d\zeta_{At}. \tag{10}$$

SPX's value is

$$\begin{aligned} V^S_{SPX}(\mathbf{e}) = \iiint \Bigg\{ & D_F(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})[V^{S,INT}_{SPX}(\mathbf{e}, F) + b^*_F\left(\zeta_{Ft}, \mathbf{e}\right) - c_F(e_{Ft}, \zeta_{Ft})] \\ & + \sum_{n=0,A,D} D_n(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e}) V^{S,INT}_{SPX}(\mathbf{e}, n) \Bigg\} g\left(\zeta_{Ft}\right) g\left(\zeta_{Dt}\right) g\left(\zeta_{At}\right) d\zeta_{Ft} d\zeta_{Dt} d\zeta_{At} \end{aligned} \tag{11}$$

In the case of ULA, with rockets (A)tlas and (D)elta,

$$\begin{aligned} V^S_{ULA}(\mathbf{e}) = \iiint \Bigg\{ & D_A(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})[V^{S,INT}_{ULA}(\mathbf{e}, A) + b^*_A(\zeta_{At}, \zeta_{Dt}, \mathbf{e}) - c_A(e_{At}, \zeta_{At})] \\ & + D_D(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})[V^{S,INT}_{ULA}(\mathbf{e}, D) + b^*_D(\zeta_{At}, \zeta_{Dt}, \mathbf{e}) - c_D(e_{Dt}, \zeta_{Dt})] \\ & + \sum_{n=0,F} D_n\left(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e}\right) V^{S,INT}_{ULA}(\mathbf{e}, n) \Bigg\} g\left(\zeta_{Ft}\right) g\left(\zeta_{Dt}\right) g\left(\zeta_{At}\right) d\zeta_{Ft} d\zeta_{Dt} d\zeta_{At} \end{aligned} \tag{12}$$

The optimal bids will be characterized by first-order conditions where a seller's costs are appropriately adjusted to reflect future values and diversion to commonly-owned products, as well as production costs. For Falcon, $b_F^*(\zeta_{Ft}, \mathbf{e})$ will satisfy

$$\iint \Bigg\{ D_F(b_F, \mathbf{b^*}_{-F}(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e}) + \frac{\partial D_F(b_F, \mathbf{b^*}_{-F}(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})}{\partial b_F} \left[b_F - c_F(e_{Ft}, \zeta_{Ft}) + V_{SPX}^{S,INT}(\mathbf{e}, F) \right]$$
$$+ \sum_{n=0,A,D} \frac{\partial D_n(b_F, \mathbf{b^*}_{-F}(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})}{\partial b_F} V_{SPX}^{S,INT}(\mathbf{e}, n) \Bigg\} g(\zeta_{Dt})\, g(\zeta_{At})\, d\zeta_{Dt} d\zeta_{At} = 0. \tag{13}$$

For ULA, the first-order condition for Atlas will be conditional on ζ_{At} and ζ_{Dt}. For $b_A^\star$,

$$\int \Bigg\{ D_A(b_A, b_D, b^*{}_F(\zeta_{Ft}, \mathbf{e}), \mathbf{e}) + \frac{\partial D_A(b_A, b_D, b^*{}_F(\zeta_{Ft}, \mathbf{e}), \mathbf{e})}{\partial b_A} \left[b_A - c_A(e_{At}, \zeta_{At}) + V_{ULA}^{S,INT}(\mathbf{e}, A) \right]$$
$$+ \frac{\partial D_D(b_A, b_D, b^*{}_F(\zeta_{Ft}, \mathbf{e}), \mathbf{e})}{\partial b_A} \left[b_D - c_D(e_{Dt}, \zeta_{Dt}) + V_{ULA}^{S,INT}(\mathbf{e}, D) \right]$$
$$+ \sum_{n=0,F} \frac{\partial D_n(b_A, b_D, b^*{}_F(\zeta_{Ft}, \mathbf{e}), \mathbf{e}), \mathbf{e})}{\partial b_A} V_{ULA}^{S,INT}(\mathbf{e}, n) \Bigg\} g(\zeta_{Ft})\, d\zeta_{Ft} = 0. \tag{14}$$

The first order condition with respect to b_D is similarly defined. Given logit demand,

$$\frac{\partial D_j(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})}{\partial b_j} = -\alpha D_j(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})(1 - D_j(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})) \tag{15}$$

and

$$\frac{\partial D_j(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e})}{\partial b_k} = \alpha D_j(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e}) D_k(\mathbf{b}^*(\boldsymbol{\zeta}_t, \mathbf{e}), \mathbf{e}) \text{ if } j \neq k. \tag{16}$$

Existence and Uniqueness. Given the buyer's logit preferences, there will exist a unique equilibrium to the bidding game given the buyer-seller continuation values if firm costs and bids are bounded (Caplin and Nalebuff (1991), Nocke and Schutz (2018)).[25] Existence of an equilibrium in the dynamic game then follows from an application of the logic of Proposition

[25] When we solve the model, we assume that the private cost shocks are between the 2.5% and 97.5% quantiles of the normal distribution, and bids are restricted to be from 50% of the production cost (when the cost shock corresponds with 2.5% quantile) and 3 times the highest cost (when the cost shock corresponds with 97.5% quantile), and, for computational reasons, we will approximate the continuous distribution assumption by using 10 discrete values of the possible cost shocks and 10 discrete possible bid levels. Our computational method follows Bichler et al. (2025), extended to a dynamic game, and is described in detail in Appendix B.

2 in Doraszelski and Satterthwaite (2010), although in the context of the model where there is no entry and exit (see also Besanko et al. (2010) and Sweeting et al. (2022)).

Uniqueness of the dynamic MPNE would require additional assumptions (e.g., no know-how depreciation, so the game is directional (Iskhakov et al. (2016))). Besanko et al. (2010) shows that multiplicity exists for many parameters in a duopoly game where there is LBD and stochastic know-how forgetting on the cost-side, and buyers are short-lived. We assume that the buyer is long-lived, so that the buyer fully internalizes how its purchase choices affect future buyer surplus. Sweeting et al. (2022) demonstrate that multiplicity is removed in the Besanko et al. (2010) and Besanko et al. (2014) models when buyers internalize even a small fraction of these effects. Consistent with this finding, we have not encountered examples of multiplicity when solving our model for any era.[26]

Static Buyer We will estimate the model assuming a long-lived buyer. However, we will investigate what would happen if the government was either prohibited from considering future surplus by procurement rules or, for strategic reasons, committed not to do so. The equilibrium in this model is characterized by the same equations, if we set the δ in equation (8) equal to zero (the δ in equation (7) would be unaffected).

Social Planner We find the social planner solution as a benchmark. We follow Deng et al. (2025) in thinking of the planner as a long-lived buyer who faces sellers whose bids are equal to their production costs. The planner's purchase probabilities can then be found by solving equations (8), (9) and (10).

4.2.5 Connecting Eras

As already noted, we solve distinct games for the three different market structure eras in our data. The transitions between eras are therefore treated as exogenous surprises to both the government buyer and the sellers. However, we run simulations across eras, so that the new era begins with the distribution of know-how at the end of the previous era.

[26] We also note that our model allows for an outside good, and that the existence of this option, which essentially has a fixed price, may also tend to eliminate multiplicity.

4.3 Innovation

So far we have described a model where the set of products is fixed within an era. However, during era 3, ULA committed to replacing Atlas V and Delta IV with Vulcan. In our counterfactuals, we therefore also consider a variant of the model where, during era 3, ULA will stochastically receive opportunities to replace both of its existing rockets with Vulcan. If ULA chooses to pay a cost and innovate when given such an opportunity, Vulcan will compete indefinitely with Falcon 9 starting from the next period, when Vulcan will start with the lowest level of know-how.

As Vulcan was only certified in 2025, we cannot estimate separate demand and cost parameters. We therefore assume that Vulcan will have the same cost intercept as Falcon 9, but have the same demand intercepts as Atlas V and Delta IV.[27]

We assume that the probability that ULA gets to make an innovation choice is $\frac{1}{60}$ each period during era 3. We will assume 20 periods per year, so that ULA will have at least one opportunity in a year with probability $1 - \left(\frac{59}{60}\right)^{20} = 0.29$. We assume that ULA's cost of innovation is $C + \sigma_C \nu_{nt}$, where ν_{nt} is an i.i.d. extreme value type 1 random variable. The parameters we set for C and σ_C are described in Section 5.[28]

4.4 Know-How States and Transitions: Model and Simulations

We now discuss our definition of the know-how state space and the transition process. We explain how, when we simulate the model, we adapt the transition process so that it can capture more variation in know-how and commercial launches. The details of solution and estimation are given in Section 5 and Appendix B.

As we are solving three distinct dynamic games, and we calibrate several demand and cost parameters of the model using a nested fixed point method, we have to limit the size

[27]The new Vulcan rocket may be equipped with new technologies that improve the government buyer's utility for choosing the rocket. Our model does not capture this dimension of improvement. Nonetheless, we believe that demonstrated know-how is still the first-order issue in the government decision. For example, delays in the certification flights of Vulcan led the government to shift missions from Vulcan to Falcon rockets (Erwin (2025)).

[28]We would note that ULA, or Boeing and Lockheed Martin, might have considered introducing a new rocket in earlier eras, as the know-how of the Space Shuttle and SPX's development efforts made the theoretical possibility of lowering costs through reusability widely known. We can assess how different market structures would have affected incentives to innovate during era 3 using counterfactuals.

of the state space to make the computation tractable. The burden is highest in era 3 when ULA has two products and competes with SPX's Falcon 9 rockets. We consider four levels of know-how for each product, corresponding to $e_{jt} \in \{1, 5, 10, 15\}$.[29] Following Benkard (2004), who aggregates know-how, we will use a stochastic process to model transitions between these aggregated states.

We assume that the transition will occur in two parts. First, if the product is sold and the state is e_{jt}, the know-how state will increase to the next level with probability $\frac{1}{e_{jt}^U - e_{jt}}$ where e_{jt}^U is the know-how of the next bin. If know-how does not increase, it will remain at e_{jt}. For the learning synergy, we assume that both Atlas V's and Delta IV's know-how may increase to the next level independently if either rocket is chosen. The post-learning know-how is denoted by e'_{jt}. Second, know-how depreciation may occur. Specifically, the know-how state after the learning event will drop down to the next level below e'_{jt}, e_{jt}^L, with probability $\lambda \dfrac{e'_{jt}}{e'_{jt} - e_{jt}^L}$, and otherwise stay the same. The value of λ is chosen to be 0.0341. If know-how were continuous, a fraction λ of know-how would depreciate at every procurement, and a value of $\lambda = 0.0341$ would imply that one-half of know-how would be lost every year without a sale.

4.4.1 Simulations

When we simulate the model, for estimation and for counterfactual, we slightly modify our approach to know-how to be more fine-grained and to account for commercial launches. Specifically, we allow know-how to take any integer value between 1 and 15. We use the values of e_{jt} =1, 5, 10 and 15 to calculate buyer preferences and firm costs when the integer know-how falls into the bins {1-4,5-9,10-14,15+}. The state transition still occurs in two parts. First, we add 1 to the know-how when a rocket is chosen for a government launch. Second, each rocket's know-how independently drops to the next lower level with probability $\lambda \dfrac{[e'_{jt}]}{[e'_{jt}] - e_{jt}^L}$, where $[e'_{jt}] \in \{1, 5, 10, 15\}$ is the level of know-how corresponding to the bin of post-learning know-how e'_{jt}.

After the last procurement of each year, we add the observed number of commercial

[29] Benkard (2004) uses a significantly larger state space reflecting the fact that Benkard can estimate the cost and demand functions without solving the model, whereas we use a nested fixed point procedure for estimating a number of parameters.

launches during the year to the rocket's know-how before the depreciation stage. Between 2002 and 2023, there are 11 years in which Atlas V launched one commercial mission, and 3 years in which it launched two commercial missions. Delta IV launched two commercial missions in two separate years. SPX's Falcon has many commercial and Starlink missions, with 15 such missions before 2017 and then an average of 31 missions per year in 2017–2023. As Falcon would therefore almost certainly have had the highest know-how whatever the realizations of depreciation could have been, we fix SPX's know-how at 15 throughout the game.[30]

As noted, we assume a learning synergy across the Atlas and Delta rockets under ULA. The only difference to the process described above when we allow for the synergy is that we add the government and commercial sales of either rocket to both of their know-how counts before the depreciation stage.

4.5 Limitations

We recognize that our modeling has several limitations, reflecting the need for tractability and the limited data available. For example, although some missions can be shifted between different rockets, many scientific missions are planned many years ahead of the launch, whereas our model assumes that procurement takes place at the time of launch. We do not account for the time taken to customize launches, especially for payloads that are extra heavy or which need to be placed into higher orbits, as well as the considerable time, sometimes measured in decades, that it can take to develop new rockets. We use a standardized measure of cost to put an average payload into standard LEO for simplicity. We also do not account for block buy purchases where the government procures several purchases in a single contract. These contracts are motivated by trying to allow firms to realize some economies of scale through planning out a series of rocket builds. In particular, ULA has argued that it can offer launches at lower prices when the government provides quantity guarantees through purchases in a block buy contract (Gruss (2014)).[31]

[30]We have experimented with alternative treatments and found no significant differences on the results.

[31]The advantage of a block buy contract to the government is that it allows a seller to set prices on the basis of LBD benefits that it can be confident will be realized. Our model, which assumes prices are set procurement-by-procurement, has firms set prices based on the expected future LBD benefits of a sale. In

5 Estimation

In this section, we explain how we choose certain parameters and estimate the remaining ones, and provide some intuition for identification.

5.1 Parameter Selection and Simulated Method of Moments Estimation

We set several parameters at what we regard as sensible values, and estimate the remainder using a Simulated Method of Moments (SMM) approach.

Fixed Parameters. We set the discount factor at $\delta = 0.9974$, implying an annual discount factor of around 0.95, and that there are 20 periods per year. With this discount factor and no direct data on production costs, it is hard to identify cost-side LBD, so we assume that $\gamma^e = 0.234$ in our preferred specification, and consider $\gamma^e = 0$ for as a robustness check. $\gamma^e = 0.234$ implies a progress ratio of 0.85, or that costs decrease by 15% if know-how doubles, and is consistent with NASA's reported estimates of progress ratios for aerospace industries.[32] As mentioned in Section 4, the depreciation parameter, λ, is set to 0.0341.

We also set the innovation cost parameters (C, σ_C). We assume a mean innovation cost of $16.5 billion with a standard deviation of $15.8 billion. These are consistent with the average of reported development costs of ULA's Vulcan ($6 billion, Gruss (2016)), and projected costs of SPX's Starship ($10 billion, Smith (2024); Space Investments (2024)), Blue Origin's New Glenn ($10 billion, Bogaisky (2025)) and NASA's Space Launch System ($40 billion, Spaceflight News (2025)). Given our price units of $1,000 per kilogram capacity to standard LEO in the model, we assume an average EELV rocket capacity of 15 tonnes to LEO and convert the mean and the standard deviation to $C = 1,100$ and $\sigma_C = 540$ respectively.[33]

practice, we find that a rocket's simulated prices in our model do not vary much over time (e.g., by less than 5%) so that they look fairly consistent with the relatively flat prices that would emerge in a block buy contract.

[32] `https://web.archive.org/web/20120830021941/http://cost.jsc.nasa.gov/learn.html`, accessed October 14, 2025.

[33] We calculate $C = 1,100$ by dividing $15.8 billion by 15 tonnes and changing the price units to $1,000 per kilogram. We calculate σ_C in the same way. In practice, the government conducts numerous launch missions carrying payloads of varying masses and targeting different orbits. As discussed in Section 3, even

Simulated Method of Moments. To find the remaining parameters (era intercepts in the utility of the buyer, price coefficient, the reliability coefficient on know-how, and intercepts of production costs of Atlas V/Delta IV, and SpaceX/Vulcan, and the cost shock scaling parameter), we match average simulated values of several outcomes from the solved model (given the parameters) to similar observed outcomes in the data. For the purpose of defining moments in the data for estimating the model, we treat rocket know-how as variables that we can observe, defining know-how as equal to the number of government and commercial launches in the previous two calendar years.[34] In the case of Atlas V and Delta IV after the ULA JV, we use the total count of the launches of either rocket. Consistent with Section 4.4, we group the observed know-how into the levels used in the model (1, 5, 10 and 15).[35] We also assume that the buyer purchases at most 20 launches a year.

We use the following two groups of moments, matching buyer choice probabilities and transaction prices in the data and those predicted in the model.

1. firm-specific market shares are matched with model-predicted winning probabilities, where we average across years within an era and 100 sets of simulations. In addition, we match the probability that the highest know-how rocket wins,[36] and the probability that a rival rocket has the highest know-how and that rocket wins.

2. Average transaction prices.

    (a) yearly average prices from the data are matched with averages of winning prices in the simulations, where we draw from the estimated cost distributions to simulate the bids in each procurement opportunity, and use the buyer's choice probabilities to determine the expected price of the winning launch rocket.

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for orbits with similar altitudes but different inclinations, a rocket's carrying capacity can vary substantially, and we measure rocket family prices using price per kilogram capacity to LEO. To simplify the analysis, we abstract from payload variation across missions and orbits and assume a representative mission payload of 15 tonnes to the standard LEO. This value closely matches the average LEO carrying capacity of the rockets used in US government LEO missions (14.57 tonnes) and in all US government missions (15.61 tonnes).

[34] Therefore, the know-how level is the same for a rocket within a year.

[35] We take 1, 5, 10 and 15 to represent 1-4, 5-9, 10-14 and 15+ respectively.

[36] The data moment would be the number of wins by the highest know-how rocket in each year, divided by the total number of procurements, which is the number of years times 20. For the model moment, the equilibrium strategy predicts the winning probability of the highest know-how rocket for an observed know-how state in each procurement, and we sum these probabilities across years and then divide the sum by the total number of procurements.

(b) standard deviation of prices: for each time series of simulated prices in (a), we compute the standard deviation of prices and compute the average standard deviation across the simulations. This is matched with the observed standard deviation across years in the data.

The objective function is minimized by searching across a wide parameter space using a combination of the genetic algorithm and surrogate optimization. We weigh each moment by the inverse of the corresponding data moment's standard deviation.

We note that our treatment of know-how as measurable when calculating the moments does not exactly match the stochastic transitions assumed in the model. There are advantages to explicitly constructing know-how from data. Our approach explicitly accounts for the know-how that includes both the government and commercial launches, and it enables us to specify conditional moments, such as the choice probability given know-how, which are helpful in pinning down how much the government values know-how.

5.2 Identification

We only observe 267 U.S. government launches between 2002 and 2023 so our model is necessarily parametric. However, we can discuss the intuitions for the identification of the demand and cost parameters. The intuitions assume that the model has a unique equilibrium for all parameters.

The key sources of variation are the changes in rocket know-how (number of past launches), the changes in ownership structure, and the changes in the available products across eras. We are assuming the process for know-how evolution and that rockets start at the lowest level of know-how (i.e., initial conditions are observed).[37] If we observed every bid, as well as the buyer's choices, and we assumed that the buyer and the sellers made static payoff-maximizing choices, then standard arguments (for example, based on the inversion of the choice probabilities) would imply that these three types of variation would be sufficient to identify the price, know-how and intercept coefficients in the demand system, once we normalize the value of the outside good to zero, and the cost intercepts. The variation in bids

[37]Even if we assumed that we cannot measure know-how directly from data, we would still be able to assume that each new rocket family begins with the lowest level of know-how.

across procurements where the sellers have the same know-how would identify the scaling of the cost shocks. We are assuming that the buyer makes forward-looking choices, but, given the assumed know-how transitions and the assumed discount factor (Chow (1994), Abbring (2010)), the buyer's value (V^B) and the seller values are simply the discounted sums of the components of static flow payoffs so that the same identification arguments apply.

A practical challenge is that we only observe, at best, transaction prices, and more precisely, given how we construct prices of a representative variant of each rocket family (see Appendix A), the average winning bid across all transactions for a given rocket in a given year, rather than all bids. This is, of course, a common phenomenon in auction, or auction-like, settings where only winning prices are observed, or can be treated as informative about values (e.g., Athey and Haile (2002), Cosconati et al. (2025)). Critically, we are assuming that there is no common heterogeneity, observed by the bidders, but not the researcher, on the demand-side or the supply-side which we would need to account for.

5.3 Estimation Results

Table 3 lists the estimated parameters. The "baseline" column provides the estimates when we assume $\gamma^e = 0.234$, and the second column gives the estimates when $\gamma^e = 0$.

The baseline price and know-how coefficients imply that, for a typical 15 tonne LEO capacity, a doubling of know-how causes the buyer's willingness to pay for the launch to increase by $\left(\ln 2 \times \frac{1.551}{0.631} \times 15 =\right)$ \$25 million. We estimate that, all else equal, era 3 demand was lower than demand in eras 1 and 2, and that ULA's rockets are preferred to SPX's. Therefore, the higher rate of launches in era 3, and SPX's higher market share, are explained by lower costs and higher levels of reliability. When we assume that there is no cost LBD, we also estimate a smaller demand-side preference for know-how, and smaller cost intercepts.

Table 4 shows the fit of the moments used in estimation. The overall choice probability moment represents the average probability that a launch is procured from one of the products across all 440 (= 20 per year × 22 years) procurement opportunities. The models fit most of the moments closely, although the baseline model underpredicts ULA's era 3 prices, and the no LBD model underpredicts Boeing and Lockheed Martin's era 1 prices.

Table 5 reports the own-price elasticities of Atlas V (which is symmetric to Delta IV up

Table 3: Model Parameter Estimates

	Baseline (LBD in Costs)	No LBD in Costs
Price ($1,000 per kg)	0.631***	0.650***
	(0.021)	(0.089)
Know-How	1.551***	0.907***
	(0.052)	(0.212)
SPX	-3.018***	-4.153***
	(0.655)	(0.742)
Era 2	-0.002	1.069***
	(0.065)	(0.316)
Era 3	-1.156***	0.631***
	(0.181)	(0.153)
Constant	2.181***	3.004***
	(0.489)	(0.813)
Atlas/Delta Cost Intercepts	2.786***	2.293***
	(0.175)	(0.228)
New Generation Cost Intercept	0.372**	0.255***
Falcon 9 / Vulcan	(0.154)	(0.054)
Cost LBD	0.234	0
	-	-
Cost Shock Scale Parameter σ	0.221**	0.269**
	(0.098)	(0.123)

Note: *,**,*** denote significance at the 10%, 5% and 1% levels. Standard errors are in parentheses. The cost LBD coefficients, the discount factor, and the parameters that determine the evolution of know-how are assumed. Standard errors are calculated using a bootstrap with 200 repetitions.

to know-how states), the cross-price elasticities of Delta IV choice probability with respect to a change in Atlas V prices, and the diversion ratio between Atlas V and the outside good in era 1, as functions of the know-how states. The statistics are averages across the cost realizations in each state (for average prices see Table 7), and they are calculated as "short-run" changes: i.e., how demand would change when a price changes but buyer and seller continuation values are held fixed.[38] We report the statistics both under duopoly and under ULA monopoly, where the firms realize the learning synergy.

The estimates imply an Atlas V own-price elasticity of between -4.6 to -4.8. The cross-price elasticity varies much more across states, and is consistent with Delta IV being much more of a substitute to Atlas V when Delta IV has considerable know-how (i.e., it is reli-

[38]Table 7 reports state-specific prices for era 2, but because the era 2 demand dummy coefficient is almost equal to zero, era 1 prices and choice probabilities are almost identical.

Table 4: Fit of the Moments Used in Estimation

	Data	Baseline (Cost LBD)	No Cost LBD
Choice Probability			
Overall	0.389	0.397	0.374
Era 2	0.186	0.188	0.171
Era 3, ULA	0.080	0.070	0.083
Era 3, SPX	0.107	0.122	0.094
Highest Know-How	0.339	0.348	0.314
Highest Know-How Rival	0.152	0.159	0.143
Price			
Era 1	9.124	9.416	8.370
Era 2	10.650	10.687	10.498
Era 3, ULA	9.914	9.191	10.000
Era 3, SPX	3.515	3.504	3.554
Standard Deviation	0.864	0.860	0.893

Table 5: Elasticities and Diversion Ratios with Respect to Atlas V Price Change

	Duopoly				Monopoly				
	Atlas V Own-Price Elasticity								
Atlas V \ Delta IV	1	5	10	15		1	5	10	15
1	-4.825	-4.830	-4.834	-4.838	1	-4.782	-4.845	-4.862	-4.867
5	-4.689	-4.711	-4.710	-4.708	5	-4.653	-4.720	-4.760	-4.780
10	-4.620	-4.653	-4.658	-4.657	10	-4.604	-4.647	-4.679	-4.708
15	-4.631	-4.654	-4.661	-4.661	15	-4.568	-4.594	-4.633	-4.661
	Cross-Price Elasticity								
Atlas V \ Delta IV	1	5	10	15		1	5	10	15
1	0.339	0.309	0.281	0.259	1	0.606	0.218	0.112	0.078
5	1.178	1.041	1.051	1.062	5	1.399	0.984	0.738	0.620
10	1.603	1.400	1.368	1.374	10	1.703	1.440	1.239	1.062
15	1.538	1.391	1.350	1.352	15	1.926	1.762	1.524	1.352
	Diversion Ratio to No Purchase								
Atlas V \ Delta IV	1	5	10	15		1	5	10	15
1	0.901	0.808	0.776	0.781	1	0.861	0.792	0.772	0.758
5	0.900	0.811	0.780	0.781	5	0.918	0.817	0.781	0.759
10	0.903	0.807	0.779	0.781	10	0.946	0.838	0.791	0.770
15	0.908	0.806	0.779	0.781	15	0.959	0.850	0.804	0.781

Note: Know-how of Atlas V in rows, know-how of Delta IV in columns. The diversion ratio measures the proportion of lost Atlas V demand which goes to the outside good when Atlas V price increases. Statistics calculated for era 1, and are averages across realized cost shocks.

Table 6: Long-Run Elasticities with Respect to Atlas V Price Change

	Duopoly					Monopoly			
Atlas V \ Delta IV	1	5	10	15		1	5	10	15
1	-1.094	-1.033	-0.967	-0.956	1	-0.389	-0.290	-0.219	-0.194
5	-0.701	-0.693	-0.684	-0.675	5	-0.348	-0.359	-0.363	-0.385
10	-0.516	-0.502	-0.486	-0.474	10	-0.329	-0.340	-0.361	-0.396
15	-0.405	-0.393	-0.369	-0.356	15	-0.302	-0.299	-0.313	-0.356

Note: Know-how of Atlas V in rows, know-how of Delta IV in columns. The long run elasticities are calculated as the relative decrease in Atlas V demand at each state when firm bids are reduced by 5% for each realized cost shock and the buyer re-solves the optimal forward-looking procurement problem. Statistics calculated for era 1, and are averages across realized cost shocks.

able). This is also reflected in the reported diversion ratios to the outside good. Cross-price elasticities are also higher under monopoly when know-how is low, which is consistent with the monopolist setting lower prices in low know-how states in order to invest in building know-how, a feature that will play an important role in the counterfactuals.

Table 6 reports "long-run" own-price elasticities for Atlas V. These long-run elasticities are calculated allowing buyer's continuation values to change in response to a permanent change in Atlas V's prices in all states. As Hendel and Nevo (2006) found in the storable goods setting, long-run own-price elasticities are much smaller in magnitudes than the short-run demand elasticities. In our setting, the reduced price sensitivity reflects how a buyer attempts to avoid the loss of know-how in the long run by limiting the decrease in demand.

6 Counterfactuals

We now discuss our counterfactuals. We first consider the period 2002–2016, where we assume no innovation, and then the period 2017–2023 period, when SPX entered and ULA chose to develop Vulcan. We will primarily be interested in buyer and total surplus, but will discuss changes in average transaction prices, the number of government launches, the average Lerner indices $\left(\frac{p-c}{p}\right)$, and average know-how to explain what takes place. All counterfactuals assume the baseline estimates (i.e., with LBD in costs as well as reliability).

6.1 No Innovation Counterfactuals: 2002-2016

We begin by considering the effects of market structure, before considering the organization of supply (private versus government ownership) and the effects of forward-looking vs. static procurement rules.

6.1.1 Industry Structure

We compare the simulated equilibrium outcomes under the observed, "factual", market structure (duopoly in 2002-2006, monopoly in 2007-2016, therefore "duopoly-then-monopoly") with two alternatives: (1) no JV, so that Boeing and Lockheed Martin remain separate ("always duopoly"); (2) ULA is formed at the start of 2002 ("always monopoly"). In all three cases, we allow for the small change in the "era" demand intercept in 2007. In each case, we simulate the model forward 1,000 times.

To understand the comparisons we make below, it is useful to review the average equilibrium prices and buyer choice probabilities in each state during the two eras under each market structure. The era 2 values are shown in Table 7, although, because the difference in the demand intercepts is very small, the era 1 values are almost identical. The first point to notice is that, even in the highest know-how state, the probability that the buyer purchases one of the products is no more than 0.53, so that the outside good is often chosen. As we will note below, this leads to some differences from the existing literature on theoretical/computational models of dynamic competition.

Second, a monopolist charges higher prices, and margins, than the duopolist when both

Table 7: Average Bid Prices, Costs and Winning Probabilities: Era 2

	Duopoly					Monopoly			
	Average Bid Prices								
Atlas V\Delta IV	1	5	10	15		1	5	10	15
1	14.841, 14.841	14.887, 11.342	15.456, 11.330	15.602, 11.323	1	12.583, 12.583	16.146, 10.656	18.014, 10.911	19.366, 11.604
5	11.342, 14.887	11.116, 11.116	11.618, 11.045	11.620, 11.323	5	10.656, 16.146	11.625, 11.625	12.928, 11.174	14.218, 11.610
10	11.330, 15.456	11.045, 11.618	11.043, 11.043	11.049, 11.323	10	10.911, 18.014	11.174, 12.928	11.928, 11.928	12.620, 11.753
15	11.323, 15.602	11.323, 11.620	11.323, 11.049	11.323, 11.323	15	11.604, 19.366	11.610, 14.218	11.753, 12.620	12.333, 12.333
	Average Costs								
Atlas V\Delta IV	1	5	10	15		1	5	10	15
1	16.681, 16.681	16.681, 11.437	16.681, 9.721	16.681, 8.839	1	16.681, 16.681	16.681, 11.437	16.681, 9.721	16.681, 8.839
5	11.437, 16.681	11.437, 11.437	11.437, 9.721	11.437, 8.839	5	11.437, 16.681	11.437, 11.437	11.437, 9.721	11.437, 8.839
10	9.721, 16.681	9.721, 11.437	9.721, 9.721	9.721, 8.839	10	9.721, 16.681	9.721, 11.437	9.721, 9.721	9.721, 8.839
15	8.839, 16.681	8.839, 11.437	8.839, 9.721	8.839, 8.839	15	8.839, 16.681	8.839, 11.437	8.839, 9.721	8.839, 8.839
	Winning Probability								
Atlas V\Delta IV	1	5	10	15		1	5	10	15
1	0.036, 0.036	0.028, 0.285	0.020, 0.358	0.013, 0.342	1	0.135, 0.135	0.011, 0.397	0.001, 0.426	0.000, 0.392
5	0.285, 0.028	0.251, 0.251	0.202, 0.322	0.215, 0.279	5	0.397, 0.011	0.219, 0.219	0.094, 0.347	0.042, 0.377
10	0.358, 0.020	0.322, 0.202	0.293, 0.293	0.311, 0.249	10	0.426, 0.001	0.347, 0.094	0.227, 0.227	0.142, 0.309
15	0.342, 0.013	0.279, 0.215	0.249, 0.311	0.264, 0.264	15	0.392, 0.000	0.377, 0.042	0.309, 0.142	0.212, 0.212

Note: We report the average prices bid in each procurement, the average costs and buyer's choice probabilities for Atlas V and Delta IV rockets in each state. The demand intercept is based on the era 2 estimate, which is nearly identical to era 1 estimate.

products are in the highest know-how state. As a consequence, when both products have the lowest know-how, the monopolist has stronger incentives to accumulate know-how, which explains why (1,1) prices are lower under monopoly than duopoly (both are below cost), and the probability that the monopolist makes a sale is several times higher than under duopoly.

Third, in some asymmetric states, such as (1,10), the monopoly price of the leading product is also lower than the duopoly price. This is explained by the fact that, given the assumed learning synergy, the most profitable way for the monopolist to improve the laggard product is to make a sale of the leading one (for example, in (1,10) the laggard product is only sold with probability 0.001). This synergy also leads to the rockets' know-how being fairly symmetric under duopoly.

Panels (a) and (b) of Figure 3 show the changes in average prices and the number of launches each year under "always monopoly" and "always duopoly", relative to the averages of the factual simulations. These figures capture how the differences in strategies across states detailed in Table 7 translate into differences in outcomes over time, as states evolve. Panels (c) and (d) present the average levels of know-how (unweighted averages across the products) and Lerner indices under the three different scenarios. While the different era 1 market structures create large differences between the actual and "always monopoly" outcomes in 2007 and 2008, these differences are almost eliminated after 2010.

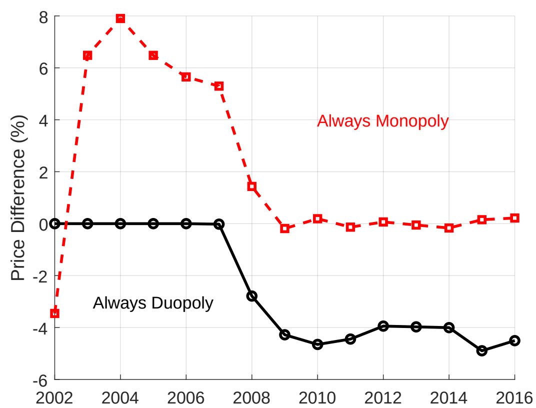
Know-how starts at the lowest level in 2002. A monopoly would have lowered prices so that know-how would have accumulated more quickly, with 4 more government launches per year in 2002 and 2003, an increase of more than 100%. Between 2007–2009, "always monopoly" is associated with higher prices than "duopoly-then-monopoly" not because of any differences in strategies (the monopoly strategies apply in both cases) but because the existence of monopoly in earlier years has led to higher know-how on both products, increasing buyer valuations and seller margins.

We predict that if the joint venture had been blocked, prices would have been lower. The buyer's valuation of launches would have been lower because of reduced reliability and lower duopoly markups. Despite the lower prices, the number of launches is also lower.

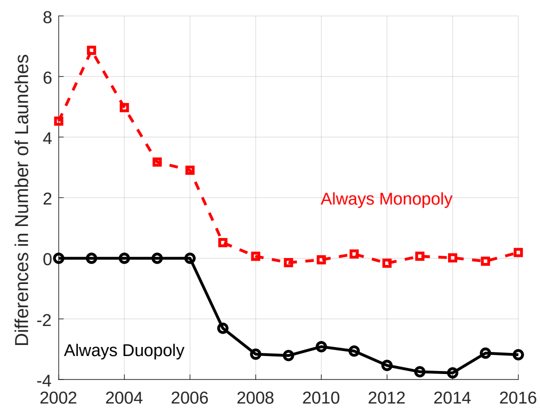
We can compare welfare effects over different time frames. For the alternative market structures, Table 8 compares (i) average outcomes in 2016 (the last year of era 2) and (ii)

Figure 3: Effects of Alternative Market Structures on Expected Market Outcomes 2002–2016

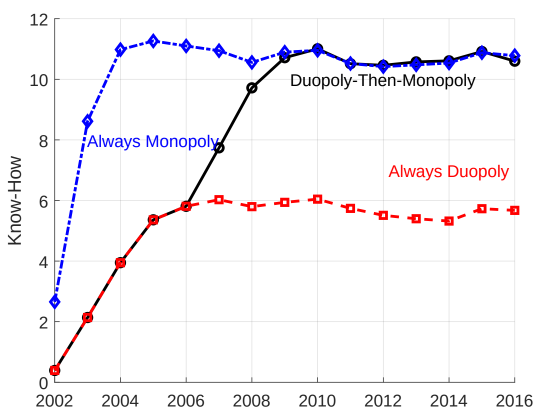
(a) % Price Difference



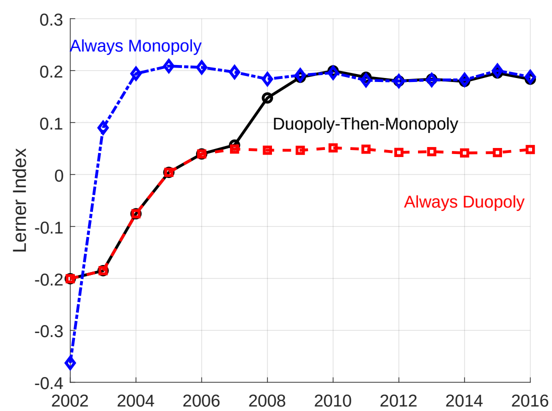
(b) Quantity Difference



(c) Average Know-How



(d) Lerner Index



Note: "Always monopoly" assumes that ULA was formed as a multiproduct monopoly in 2002. "Always duopoly" assumes that the ULA JV was never consummated. Panel (a) shows the % difference in average transaction prices for each year in 2002–2016 between simulations of "always monopoly" and "always duopoly" relative to the factual "duopoly then monopoly" market structure. Panel (b) shows changes in the average number of launches in each year. Panel (c) shows the evolution of average know-how of the sellers in each market structure, and panel (d) shows the average evolution of the Lerner index. We simulate and average 1,000 equilibrium paths in each case.

Table 8: Market Outcomes With No Innovation: Eras 1 and 2

	Factual	Always Monopoly		Always Duopoly		Planner		Down-Select Atlas V		Always Monopoly No Synergy	
			Δ		Δ		Δ		Δ		Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Price ($1,000/kg)											
2016	10.46	10.46	0.00	9.99	-0.47			10.18	-0.27	10.10	-0.35
2002-2016	10.28	10.38	0.09	9.95	-0.33			10.14	-0.14	10.10	-0.19
Number of Launches/Year											
2016	8.53	8.68	0.14	5.31	-3.22	16.71	8.18	3.85	-4.68	4.33	-4.21
2002-2016	6.94	8.49	1.55	4.84	-2.10	16.54	9.59	3.68	-3.27	3.84	-3.10
Know-How											
2016	10.60	10.78	0.18	5.67	-4.92	12.94	2.34	6.94	-3.66	5.13	-5.47
2002-2016	8.03	10.11	2.07	4.99	-3.04	12.46	4.42	6.27	-1.76	4.51	-3.52
Lerner Index											
2016	0.18	0.19	0.00	0.05	-0.13			0.07	-0.12	0.06	-0.12
2002-2016	0.14	0.16	0.02	0.03	-0.11			0.05	-0.09	0.05	-0.09
Product-Level HHI											
2016	6,509	6,438	-72	8,453	1,944	5,628	-881	10,000	3,491	9,391	2,882
2002-2016	5,257	5,132	-126	6,106	849	5,054	-204	10,000	4,743	6,959	1,701
Buyer Surplus ($bn/Year)											
2016	0.45	0.45	0.00	0.33	-0.12	0.97	0.52	0.31	-0.14	0.31	-0.13
2002-2016	0.39	0.43	0.04	0.31	-0.07	0.87	0.49	0.30	-0.08	0.30	-0.08
Variable Profits ($bn/Year)											
2016	0.24	0.25	0.00	0.05	-0.19			0.05	-0.19	0.05	-0.19
2002-2016	0.15	0.21	0.06	0.03	-0.11			0.04	-0.11	0.04	-0.11
Avg PDV (2016 States, $bn)											
Buyer	8.92	8.92	0.00	6.33	-2.58	19.11	10.19	5.98	-2.94	6.12	-2.80
Seller	4.91	4.92	0.00	0.87	-4.04			0.74	-4.17	0.85	-4.06
Total	13.83	13.84	0.01	7.20	-6.63	19.11	5.28	6.71	-7.12	6.98	-6.86

Note: The price panel reports the average winning prices. The quantity panel reports the average number of launches per year. The know-how panel reports the unweighted average know-how that takes into launches and stochastic depreciation. The Lerner index is defined as the difference in winning price and production cost relative to the winning price. The product-level HHI is defined as the sum of the square of each product's number of launches divided by the total number of launches times 10,000. The buyer surplus is the buyer annual flow surplus, which is the expected surplus given the potential bids from firms in each procurement aggregated to a year. The variable profit is the firm expected flow surplus similarly aggregated from each procurement to a year. The PDV is the present discounted values from the equilibrium model solution averaged across the states reached in 2016 across simulation paths.

average annual outcomes across all years in era 1 and era 2 (2002–2016). We also report the average present discounted values (PDV) in our model based on the states reached in 2016 across on the simulation paths.[39]

Comparing the "always monopoly" (column 2) and "always duopoly" (4) outcomes to the factual (1) outcomes, we see that continued duopoly would have lowered both buyer and total surplus. The product-level HHI is lower under monopoly than under duopoly, reflecting how the learning synergy tends to keep Delta IV and Atlas V fairly symmetric even when Atlas V has more commercial launches. Under duopoly, commercial launches tend to lead Atlas V to secure more government sales.

6.1.2 Social Planner Comparison

Although monopoly market outcomes are preferred to duopoly outcomes in our setting, monopoly outcomes can still be inefficient. We therefore also simulate outcomes under the social planner solution with two products. The differences between the planner outcome and the always monopoly with a long-lived buyer equilibrium outcome come from how the social planner purchases at production cost, whereas the long-lived buyer faces prices set by a strategic monopolist. We assume that the social planner enjoys the same learning synergy as the monopolist, and that, when we simulate outcomes, the pattern of commercial launches is unaffected.

Column (6) of Table 8 reports the average annual outcomes for our three different time horizons under the planner. Appendix Table D.1 lists costs and the planner's choice probabilities in each state. The planner purchases almost twice as many launches as the monopolist, so that both rocket families are likely to reach the highest know-how quickly. The resulting increases in the present discounted values of buyer and total surpluses are substantial (over \$10 billion and \$5 billion respectively). In Section 6.1.4, we will evaluate how much production inefficiency a government would be willing to tolerate when production is state-controlled.

[39] The know-how states reached in 2016 reflect commercial launches in prior years, but the PDVs are based on the buyer and firm strategies and the state transitions in the model that assumes no future commercial launches.

6.1.3 The Down-Select Option and the Role of Know-How Synergy.

So far, we have assumed that both Atlas V and Delta IV are available in era 2. Kovacic (2019) notes that, when the ULA joint venture was being evaluated, the FTC believed that, if the JV was not consummated, the procuring government agencies might commit to buying from only one of the companies in order to speed up the chosen system's accumulation of know-how, a policy known as a permanent "down-select" (where the down-selected firm is the one that is chosen).

Column (8) of Table 8 shows outcomes if Atlas V, which has more commercial sales, is down-selected.[40] Compared to continued duopoly, the down-select increases know-how, but slightly reduces buyer and total surplus. However, the factual (two-product monopoly after 2007) outcomes are significantly better than the down-select outcomes, so we continue to interpret the FTC's decision not to challenge the JV as the correct one.[41]

One reason why monopoly is preferred to duopoly or the down-select is that the learning synergy works to speed the accumulation of know-how. Column (10) of Table 8 shows average simulated outcomes under the two-product monopoly when there is no synergy. Relative to the monopoly with learning synergy, know-how and the average number of launches are lower, prices are higher, and the product-level market structure tends to be much more asymmetric. Buyer and total surpluses are slightly higher than under the down-select, but they are lower than under duopoly. Therefore, our results also support the FTC's stated view that the existence of the learning synergy was critical to its enforcement decision. It is noticeable that the no synergy monopoly and duopoly welfare outcomes are quite similar, showing that, in this context, and absent the synergy, the market power of the monopolist would have been roughly offset, from the buyer's perspective, by the greater incentive of the monopolist to lower its future costs, a type of efficiency that our dynamic model of

[40] We assume the commercial launches on Atlas V are the same as observed in the data, i.e., it does not take additional commercial launches from Delta IV.

[41] The reductions in buyer surplus under the down-select partly reflect the standard "loss-of-variety" effect when a product is removed in a demand system with logit preference shocks (Ackerberg and Rysman (2005)). In this setting, maintaining alternative rocket families may be especially important as, if a system is rendered inoperative after a failed launch, the government might be left without the ability to undertake critical missions. Our surplus calculations do not account for the fixed costs of maintaining a rocket family which might be significant in practice.

competition can quantify.[42]

6.1.4 Planner with Cost Inefficiency

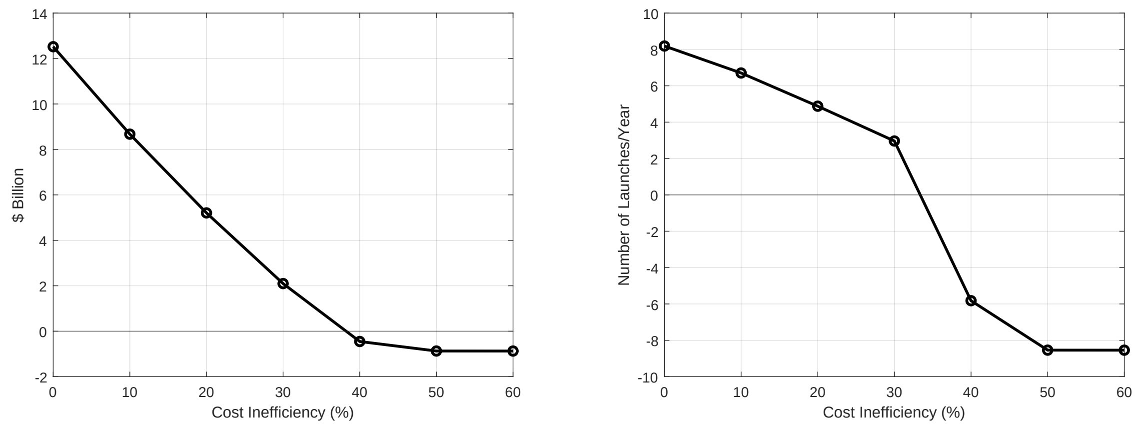
As noted in Section 2, launch providers are more tightly state-controlled outside the US. One might assume that the benefit of state control is that planner outcomes can be implemented. On the other hand, as noted by Weinzierl (2018), state control could lead to various types of inefficiencies. We therefore evaluate the level of cost inefficiency that would offset the gains from the social planner's outcome.

Specifically, we assume that, under state control, the buyer pays the costs of the launches as in the planner scenario, but the costs would be multiplied by a scalar $\mu \geq 1$.[43] We resolve the planner problem for μ values between 1 and 1.60 (1.60 corresponding to 60% cost inefficiency). We assume that, given know-how, rocket reliability is unchanged and that the planner still enjoys the learning synergy from managing both families.[44]

Panel (a) of Figure 4 shows the changes in planner/buyer and firm surpluses between the planner and market outcomes, while panel (b) shows the change in the average number of launches in 2016 from the market solution. For cost inefficiencies of 30% or less (based on interpolation the threshold would be 36%), total surplus is higher under the planner. However, cost inefficiencies of 50% or more would lead to the planner choosing to undertake almost no launches, and almost all surplus being eliminated.

Figure 4: Differences Between Planner and Factual Outcomes: Production Cost Inefficiency

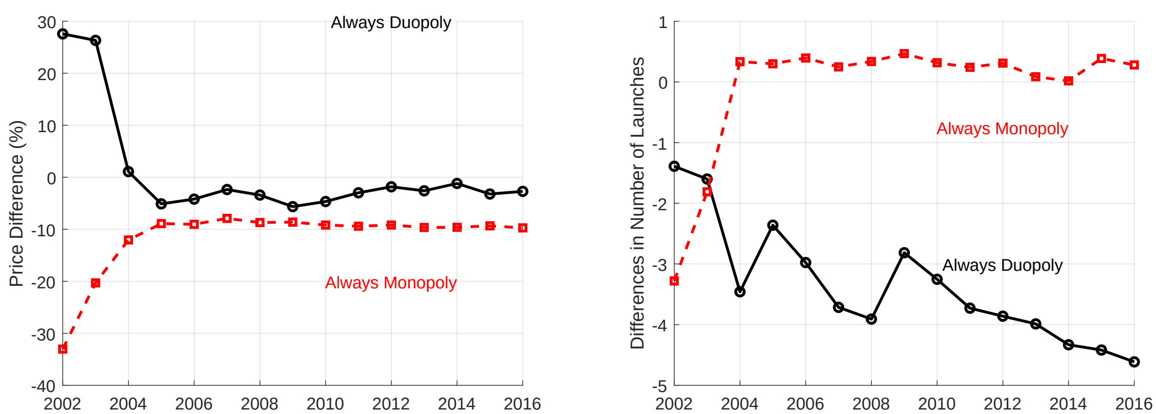
(a) Buyer Surplus Difference (b) Quantity Difference



Note: Figure (a) plots the planner surplus minus the buyer surplus in the market equilibrium at different levels of cost inefficiencies. The right figure (b) plots the planner number of launches minus that in the market equilibrium. We use era 2 demand intercept.

Figure 5: Difference Between Static Buyer and Dynamic Buyer

(a) Price (b) Quantity



Note: The red line in panel (a) shows the % difference in average transaction prices for each year in 2002–2016 between simulations of "always monopoly" under a dynamic and static buyer. The red line in panel (b) shows changes in the average number of launches in each year. The black lines compare a static and a dynamic buyer under the "always duopoly" market structure. We simulate and average 1,000 equilibrium paths in each case.

Table 9: Market Outcomes With No Innovation: Static Buyer

	Always Duopoly			Always Monopoly		
	Dynamic Buyer	Static Buyer	Δ	Dynamic Buyer	Static Buyer	Δ
	(1)	(2)	(3)	(4)	(5)	(6)
Price ($1,000/kg)						
2016	9.99	9.64	-0.35	10.46	9.45	-1.00
2002-2016	9.95	9.61	-0.34	10.38	9.35	-1.03
Number of Launches/Year						
2016	5.31	0.70	-4.61	8.68	8.87	0.20
2002-2016	4.84	1.43	-3.41	8.49	8.40	-0.09
Know-How						
2016	5.67	3.82	-1.85	10.78	10.73	-0.05
2002-2016	4.99	3.92	-1.06	10.11	9.93	-0.18
Lerner Index						
2016	0.05	0.09	0.04	0.19	0.12	-0.07
2002-2016	0.03	0.08	0.05	0.16	0.09	-0.07
Product-Level HHI						
2016	8,453	9,781	1,327	6,438	6,381	-57
2002-2016	6,106	6,962	856	5,132	5,130	-2
Buyer Surplus ($bn/Year)						
2016	0.33	0.29	-0.04	0.45	0.57	0.12
2002-2016	0.31	0.31	-0.00	0.43	0.55	0.13
Variable Profits ($bn/Year)						
2016	0.05	0.01	-0.04	0.25	0.14	-0.11
2002-2016	0.03	0.02	-0.02	0.21	0.10	-0.11
Avg PDV (2016 States, $bn)						
Buyer	6.33	5.48	-0.85	8.92	11.38	2.46
Seller	0.87	0.06	-0.81	4.92	2.75	-2.17
Total	7.20	5.54	-1.67	13.84	14.13	0.29

Note: The price panel reports the average winning prices. The quantity panel reports the average number of launches per year. The know-how panel reports the unweighted average know-how that takes into launches and stochastic depreciation. The Lerner index is defined as the difference in winning price and production cost relative to the winning price. The product-level HHI is defined as the sum of the square of each product's number of launches divided by the total number of launches times 10,000. The buyer surplus is the buyer annual flow surplus, which is the expected surplus given the potential bids from firms in each procurement aggregated to a year. The variable profit is the firm expected flow surplus similarly aggregated from each procurement to a year. The firm PDV is the average present discounted values from the equilibrium model solution averaged across the states reached in 2016 across simulation paths. The PDV of a static buyer is the present value of its future flow surpluses based on equilibrium strategies and state transitions.

6.1.5 Static vs. Dynamic Procurement Strategy

Figure 5 shows the differences, over time, in prices and quantities when the buyer uses a static rule (i.e., makes choices with zero weight on future buyer surplus) under the "always monopoly" and "always duopoly" market structures. Table 9 report the average market outcomes. The detailed buyer choice probabilities, bids, costs and winning probabilities at each state are given in Appendix Table D.2.

Under "always duopoly", static procurement causes prices to rise initially but then fall below the level under a dynamic buyer. The number of launches is significantly lower. By 2016, both products are likely to be in the lowest know-how state, and buyer and firm surpluses both fall.[45] The result that a forward-looking procurement policy is better is different from the findings emphasized by Lewis and Yildirim (2002) and Sweeting et al. (2022). Those studies, also considering dynamic duopoly, show that a static policy can benefit the buyer by promoting supplier competition to gain a cost advantage. The main difference to the current setting is that those articles also assume that the buyer always, or almost always, makes a purchase so that the difference between the static and dynamic buyer is in the degree of seller asymmetry along the equilibrium path. In our setting, and especially under duopoly, the buyer often chooses not to purchase, which can result in little know-how accumulation by either firm. A forward-looking buyer recognizes that purchasing

[42] The discussion above based on Table 8 compares the values of different market structures in 2016. Of separate interest is how a merger or down-select affects welfare at the time the ULA merger was proposed. We therefore compute the 2007 buyer PDV under the alternative market structures using the states reached in the factual simulations at the end of era 1, taking into account the synergy from the merger. We find that the present discounted buyer value under ULA monopoly with the learning synergy is still the highest, \$2.48 billion higher than under a duopoly market, and \$2.80 billion higher than when the buyer down-selects Lockheed Martin's Atlas 5.

[43] One might view inefficiencies as resulting from the use of less suitable technologies rather than inefficient management of the production process for a given rocket. As an extreme example, NASA's Space Shuttle cost about \$450 million per launch (Adler (2020)), almost 4 times the price of an Atlas V launch for comparable lift capacity.

[44] We note that Europe's Ariane 5 and Russia's Soyuz-2 rockets are similar to ULA's rockets in terms of reliability.

[45] The Lerner index is higher with a static buyer, even though we also predict lower average transaction prices and higher mean costs (lower average know-how). The explanation for this combination of facts is that, compared to the case with a dynamic buyer, the firms have weaker incentives accumulate know-how in low know-how states, so that they tend to set higher bids and markups (Table D.2 shows that the average bid in state (1,1) is 17.165 with a static buyer, compared to 14.481 with a dynamic buyer (Table 7)) . However, with a static buyer there is only likely to be a transaction when the realized bid is very low, reflecting an especially low cost draw for the winning firm.

less increases costs and lowers reliability in the future, so that a forward-looking procurement leads to more efficient outcomes.

On the other hand, under "always monopoly", which is not a case considered by the literature, the buyer does better with a static policy because the monopolist, with stronger incentives to accumulate know-how, and a better learning technology due to the synergy, lowers its prices, especially in low know-how states, to offset the static buyer's reduced propensity to purchase. Relative to the dynamic buyer case, the loss in firm surplus is offset by the gains in buyer surplus, resulting in a net increase in total surplus.

6.2 Era of Innovation: 2017-2023

We now study the role of SPX entry and ULA innovation over the period of 2017-2023. We explore (i) how SPX's entry affected outcomes; (ii) how SPX's entry affected ULA's innovation incentives; (iii) whether ULA's innovation incentives are efficient.[46]

6.2.1 Entry and Innovation

Column (1) of Table 10 shows simulated market outcomes under the factual multiproduct ULA and SPX duopoly. Column (4) shows outcomes if SPX had not entered and ULA did not innovate, with the differences in column (5). SPX's entry creates significant gains to the buyer, and reductions in ULA's surplus and the know-how of ULA's rockets. Even though the government prefers ULA launches, all else equal, recall that we are assuming that Falcon 9 has the highest level of know-how, because of its many commercial launches, so that Falcon 9 wins two-thirds of government launches even in 2017.

Column (2) summarizes outcomes if EELV rockets (Atlas V and Delta IV) are replaced by Vulcan at the start of era 3 (although, of course, this ignores the time required to develop and test Vulcan). Recall that Vulcan has the same cost intercept as Falcon 9, and that the government prefers Vulcan to Falcon 9 when they have equal know-how, but that Vulcan begins with the lowest level of know-how, while Falcon 9 has the highest. In PDV terms, the government is $2.5 billion better off when its options are Vulcan and Falcon 9, compared

[46] We also investigate whether a static procurement strategy would change ULA's innovation incentives in Appendix C.2.

Table 10: Market Outcomes With Innovation: Era 3

	Duopoly EELV, Falcon	Duopoly Vulcan, Falcon	Δ	Monopoly EELV	Δ	Monopoly Vulcan	Δ	Duopoly EELV, Falcon No SPX Comm	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Price ($1,000/kg)									
ULA, 2017	9.19	2.54	-6.65	9.35	0.16	4.56	-4.62	9.19	0.00
2017-2023	9.19	4.43	-4.76	9.34	0.15	5.86	-3.33	9.19	-0.00
SPX, 2017	3.39	2.67	-0.72					1.01	-2.39
2017-2023	3.56	2.67	-0.89					2.63	-0.93
Number of Launches/Year									
ULA, 2017	3.25	13.11	9.86	6.06	2.82	14.56	11.32	4.28	1.04
2017-2023	1.81	13.74	11.93	5.40	3.59	15.00	13.20	1.76	-0.05
SPX, 2017	8.67	4.29	-4.38					5.79	-2.88
2017-2023	8.86	3.90	-4.96					8.50	-0.36
Know-How									
ULA, 2017-2023	6.17	11.20	5.03	8.88	2.71	11.57	5.40	5.76	-0.41
SPX, 2017-2023	15.00	15.00	0.00					9.42	-5.58
Lerner Index									
ULA, 2017	0.17	0.50	0.33	0.15	-0.02	0.67	0.50	0.16	-0.01
2017-2023	0.14	0.79	0.66	0.13	-0.01	0.84	0.70	0.14	-0.00
SPX, 2017	0.77	0.72	-0.05					-0.40	-1.17
2017-2023	0.78	0.72	-0.06					0.63	-0.16
Firm-Level HHI									
2017	6,454	6,509	55	10,000	3,546	10,000	3,546	5,805	-649
2017-2023	7,881	6,756	-1,125	10,000	2,119	10,000	2,119	8,044	163
2017 Surplus ($bn/Year)									
Buyer	0.66	0.97	0.32	0.37	-0.29	0.44	-0.22	0.37	-0.29
ULA	0.07	0.25	0.18	0.12	0.05	0.68	0.61	0.08	0.02
SPX	0.33	0.12	-0.21					-0.03	-0.36
2017 PDV ($bn)									
Buyer	17.94	20.54	2.60	11.99	-5.95	15.99	-1.95	17.65	-0.30
ULA	0.16	16.95	16.79	15.61	15.45	20.83	20.68	0.18	0.02
SPX	1.97	1.01	-0.97					1.62	-0.35
Total	20.08	38.50	18.42	27.60	7.53	36.83	16.75	19.45	-0.62

Note: We report the average winning prices, number of launches per year, average rocket know-how, Lerner indices, firm-level HHI, average flow surpluses of buyers and firms, and 2017 present discounted values of the buyer and firms in this table. For EELV (Atlas V and Delta IV) and Falcon rockets, We start the simulation from the know-how levels observed in the data, where the know-how levels are 15, 5 and 15 for Atlas V, Delta IV and Falcon 9. We include commercial launch in the know-how at the end of each year. We fix Falcon 9 know-how at 15. The exception is column (8), where the initial Falcon 9 know-how is 1. We allow this know-how to evolve and do not include its commercial launch know-how. We start at the know-how level of 1 for Vulcan and assume there are no commercial launches.

Table 11: ULA Innovation Probability

	Factual	Monopoly		Duopoly		Planner	
	EELV, Falcon	EELV	Δ	EELV, Falcon*	Δ	EELV	Δ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2017	0.16	0.08	-0.09	0.18	0.02	0.10	-0.06
2017-2023	0.17	0.07	-0.10	0.17	-0.00	0.11	-0.07

*: Falcon 9 initial know-how is set to the lowest level 1 and its commercial launches are not included.
Note: We report the average innovation probability in 2017 and 2017-2023 conditional on no ULA innovation in prior years. For EELV (Atlas V and Delta IV) and Falcon rockets, We start the simulation from the know-how levels observed in the data, where the know-how levels are 15, 5 and 15 for Atlas V, Delta IV and Falcon 9. The exception is column (4), where the initial Falcon 9 know-how is 1 and its commercial launches are excluded.

to Atlas V, Delta IV and Falcon 9, with ULA capturing the vast majority of the producer surplus.[47]

Column (4) of Table 10 shows outcomes if ULA's EELV rockets are the only options for the government (e.g. Falcon 9 fails or is never certified), and column (6) does so in the case where Vulcan is the only option. Because Vulcan has much lower costs and a monopolist ULA has a strong incentive to accumulate know-how for Vulcan, buyer welfare and ULA's surplus is higher when only Vulcan is available than when ULA has an Atlas V and Delta IV monopoly, despite the reduction in variety. From a welfare perspective, and not considering the costs of innovation, both the replacement of EELV rockets by Vulcan, and the entry of SPX, are therefore desirable.

We can also see, from Table 10, that the increase in ULA's value from introducing Vulcan is much higher when SPX is a competitor. This is consistent with the fact that, when SPX is in the market, ULA's EELV rockets struggle to compete so that the extent to which Vulcan cannibalizes the profits of ULA's earlier generation technologies is small.

We can compute the implied probabilities of innovation, and compare them with planner choices, using our assumed arrival rate of innovation opportunities and distribution of innovation costs. These are shown in Table 11. The first row reports the probability of innovation in 2017, assuming that innovation results in the immediate introduction of Vulcan. The second row shows the average annual probabilities over the years 2017-2023 conditional on innovation not occuring in prior years. Consistent with Table 10, the probability of ULA

[47] Our estimate of SPX surplus does not include Starlink.

Table 12: Market Outcomes with Innovation in Era 3: Planner Solution

	Factual	Planner		Planner	
	EELV, Falcon	EELV	Δ	Vulcan	Δ
	(1)	(2)	(3)	(4)	(5)
Number of Launches/Year					
ULA, 2017	3.25	12.88	9.63	19.83	16.58
2017-2023	1.81	12.86	11.05	19.83	18.02
SPX, 2017	8.67				
2017-2023	8.86				
Know-How					
ULA, 2017-2023	6.17	12.13	5.96	12.53	6.36
SPX, 2017-2023	15.00				
2017 Surplus ($bn/Year)					
Buyer	0.66	0.62	-0.04	1.37	0.72
ULA	0.07				
SPX	0.33				
2017 PDV ($bn)					
Buyer	17.94	34.34	16.40	44.76	26.81
ULA	0.16				
SPX	1.97				
Total	20.08	34.34	14.27	44.76	24.68

Note: We report the average number of launches per year, average rocket know-how, average buyer flow surpluses, and 2017 present discounted values of the buyer in the planner outcomes. We start the simulation from the know-how levels observed in the data, where the know-how levels are 15 and 5 and 15 for Atlas V and Delta IV. We start the Vulcan know-how at 1.

innovation is higher, by about two-and-a-half times, when its rockets compete with Falcon 9 than when they do not.

One might wonder if these results reflect Falcon 9's assumed high level of know-how. Therefore, in the final columns of Table 10 and column (4) of Table 11 we report outcomes (without ULA innovation) and innovation probabilities if we assume SPX has no commercial launches, and that Falcon 9's know-how starts at the lowest level and evolves as it competes with ULA's EELV for government sales. The effect on the ULA innovation probability is small, because the gain in ULA expected surplus when EELV rockets compete with a weakened Falcon 9 is both small, and almost exactly equal to, its gain when it is Vulcan that faces a weaker competitor.

6.2.2 Planner and Innovation

We can compare market innovation choices with those which might arise under government control. In this context, we think a sensible comparison is with a setting where ULA is state-controlled, and SPX is not used for government missions. This would reflect what happens outside the US, where governments do not use private companies for their launches, and private companies are much smaller than those controlled by the state.

Table 12 compares outcomes when the ULA EELV rockets and Falcon 9 compete for government launches in a market, when the planner uses only the EELV rockets and the planner only uses Vulcan. The planner would launch the EELV rockets nearly 13 times a year, slightly higher than the EELVs and Falcon 9 combined in the market outcome, but the flow surplus is slightly lower without SPX, because of the loss of variety. If the planner introduces Vulcan in 2017, the number of launches is even higher, although the buyer has lower 2017 surplus in the planner solution, because the new rocket starts with higher costs than Falcon 9, and lower know-how than both EELVs and Falcon rockets in the factual market. The PDV of buyer surplus when the planner can buy Vulcan is \$10.1 billion greater than in the EELV case, and \$24.6 billion greater than in the EELV/Falcon 9 market outcome.

Column (6) of Table 11 shows the probabilities of planner innovation. The probabilities are higher than the market ULA monopolist probabilities in column (2), reflecting the fact that the planner internalizes some of the benefits of Vulcan which ULA does not capture. However, the planner is less likely to innovate than ULA would be if it faces competition from SPX, reflecting the fact that the gain in ULA's value from innovation when it faces Falcon (\$16.8-0.23 billion in Table 10) exceeds the (\$44.4-34.3 billion) planner's gain from operating Vulcan rather than the EELVs.[48]

Appendix C.1 examines how much cost inefficiency would be needed to offset the gains from the planner solution when innovation is possible. We find that the required inefficiencies have to be much larger than the production cost inefficiencies identified in our era 1 and era

[48] One might have thought that the difference was driven by ULA, in the market outcome, stealing business from SPX (i.e., a classic excess entry (Mankiw and Whinston (1986)) result). However, as can be seen from the small values of SPX PDV surplus in Table 10, this is not the reason for the difference. Instead, with LBD, the issue is that when the EELV rockets are offered in competition with SPX they tend to have low know-how and high costs.

2 analysis.

7 Conclusion

We have estimated a dynamic model of competition and procurement for the space launch industry in order to try to provide model-based answers to several key policy questions arising in this strategically important industry. We find that, in the presence of learning economies, the FTC's decision not to challenge the United Launch Alliance joint venture was likely the correct one, even though it was, in essence, a merger-to-monopoly. Second, we show that the certification of SpaceX for national security launches and the subsequent development of Vulcan are likely beneficial, and that competition from SpaceX was likely important in ULA deciding to develop the Vulcan system. At a slightly more abstract level, we also find that it may be optimal for the government to follow a static procurement rule when facing a monopolist supplier, but that a forward-looking rule can be important in advancing supplier know-how when there is competition. We also quantify the trade-offs that may exist between the benefits of government control of launch suppliers (marginal cost pricing and the internalization of the benefits that innovation creates for the buyer) and the types of inefficiency that government control is likely to generate (Weinzierl (2018)).

Our results highlight that in industries where learning-by-doing is important, procurement not only adds demand but also acts as industrial policy. Each award is an investment that could reduce procurement cost or improve product quality in the future. Although we focus on competition between firms already in a market, this lesson could apply more broadly to entry. For example, recognizing the catalytic nature of government procurement, NASA financed a significant portion of the development cost of Falcon 9 through contracts to supply the International Space Station, even as NASA had the option to use Russian Soyuz rockets that had already proved themselves to be reliable at the time. Such examples show how a forward-looking government buyer can shape not only the short-run outcomes but also the technological trajectory of an industry.

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A Data Appendix

This appendix provides additional information on the data, and, in particular, on the estimation of the annual transaction prices for different US rocket families, including Atlas V, Delta IV and SpaceX (SPX).

A.1 Launch Records

Our primary data source for launches and rocket characteristics is the General Catalog of Artificial Space Objects (GCAT) (McDowell (2025)). The dataset is organized by launches and records the launch date, payload and its owner, the associated rocket (our focus), and a measure of the launch success ranging from 0 to 100%. For each rocket, GCAT reports the manufacturer, number of stages, and carrying capacity. We validate and, where necessary, augment GCAT with records from Gunter's Space Page (Krebs (2025)).

We construct a dataset with the following coverage:

- Years 1985-2024
- Civil (e.g. scientific) or military launches on behalf of government agencies, although, in our regressions and when constructing moments, we will measure rocket family experience or know-how using counts that will include commercial launches.
- Unmanned launches to put objects into stable Earth orbit using medium- to heavy-lift rockets (LEO payload capacity greater than 2,000 kilograms).
- Launches where the primary payload is owned by United States, Soviet Union/Russia, countries that have ever been in the European Union, China, Japan, and India. These countries account for 95% of government launches between 1985 and 2024.

Our analysis is at the rocket-family or -system level (for example, the Atlas V rocket system that was developed by Lockheed Martin and then operated by ULA). A rocket family typically has a number of variants for use on missions with different payload weights or shapes, or with different orbital heights (for example, `https://www.ulalaunch.com/rockets/atlas-v`, accessed October 17, 2025, lists ten variants of Atlas V), although the variants will share core components such as engines. As detailed below, when we define prices we will try to create a price that tracks the price of the most commonly launched, or "representative" variant, using hedonic regression to control for cross-variant price differences.

A.2 Rocket Prices

GCAT does not report launch prices. We therefore construct a new dataset of launch prices for US launches, drawing on three sources: FAA launch reports, government contract records, and public news reports, which we then use to create a measure of the average government transaction price for the "representative" variant in each rocket family for each year. Here we discuss the data and the steps in constructing the measures. Throughout we deflate prices to 2010 U.S. dollars using the Aerospace Producer Price Index.[49]

A.2.1 Sources

FAA reports: The Federal Aviation Administration's Commercial Space Transportation launch reports cover 1996–2009 (quarterly) and 2010-2017 (annual). From 2000 to 2017 prices are reported at the launch level, but there are a significant proportion of missing values after 2009 and we drop a few values as the prices seem to include some additional services.[50] We use the midpoint if the reported price is a range.

Government contracts: We also use data from government rocket purchase contracts obtained from the U.S. Department of War contract announcements (`https://www.defense.gov/News/Contracts/`). These contracts fall under the Evolved Expendable Launch Vehicle (EELV) program, later renamed the National Security Space Launch (NSSL) program. This program covers the Department of Defense/War national security missions using Atlas V, Delta IV, and Falcon families. We focus on launch services contracts, which correspond directly to rocket purchases, and exclude launch support contracts, which are related to payload integration or launch infrastructure. For each contract, we observe the rockets, the quantity of each rocket purchased, and the total contract amount. The contract data span 2008–2023.

News reports: Finally, we supplement our dataset with prices, where we can find them, from internet news reports between 1995 and 2024. These observations are recorded at the rocket–year level.[51] When prices appear as ranges, we again use the midpoint as the reference value.

A.2.2 Government Contract Decomposition

The government contracts that we observe often report a single contract price for several launches, often using different variants. We use the following procedure to try to decompose the price to the launch-level.

1. For contracts containing only multiple units of the same rocket variant, we calculate an average price by dividing the total contract amount by the number of rockets in the contract.

2. We use information from single-rocket contracts within the same year, or the single variant contracts from Step 1, to decompose bundled contracts. When all rockets in a contract can be matched to observed prices, we allocate the total contract amount

[49] Source: U.S. Bureau of Labor Statistics, Producer Price Index by Industry: Aerospace Product and Parts Manufacturing [PCU33643364], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/PCU33643364, May 20, 2025.

[50] For example, an Atlas V version 401 launch on April 18, 2017 has a price of $150 million, which is greater than ULA's 2017 list price of $109 million for that variant.

[51] The internet reports typically mention the price of a rocket without specifying the associated mission or exact time. Therefore, we record these data at the rocket–year level, using the reported price and the time of the report as the observation.

proportionally based on the relative price ratios. If exactly one rocket cannot be mapped, we assign the residual value to that rocket after deducting the average prices of the mapped ones. If more than one rocket cannot be matched, we proceed to the next step.

3. We estimate price ratios across rocket variants and use these ratios to decompose more complex bundled contracts. For Atlas V, we use data from ULA's RocketBuilder pricing tool to compute variant-level price ratios, assuming these ratios remain stable over time.[52] For Delta IV, we derive their relative price ratios from single-rocket contracts and nearby-year FAA reports. For Falcon rockets (Falcon 9 and Falcon Heavy), we use the list prices published on SPX's official website to estimate their relative price ratio. When a bundle includes rockets from different rocket families (e.g. Atlas V and Delta IV), we adjust the ratios using price information from single-rocket contracts and the preceding steps. These ratios are then applied to impute the rocket-level prices for the bundled contracts that cannot be decomposed in Steps 1 and 2.

A.2.3 Imputation through Hedonic Regression

Based on the data, we do not observe transaction prices for the representative variant of each rocket family in each year that the family is active. To fill these gaps, we estimate a weighted hedonic regression to capture the relationship between rocket prices and observable characteristics, and use the fitted model to impute, where necessary, missing prices for representative variants.

An observation in the regression would ideally be the price for one particular launch, although some of our price data is more aggregated. We weight our observed prices to capture how many launches, possibly happening at different times, they may capture.

- For FAA launch-level prices, the weight is set to one.
- For FAA quarterly-level prices, the weight equals the number of launches of that rocket in the quarter.
- For government contracts, each observation corresponds to a procurement contract. When multiple contracts exist for the same rocket–year, we compute a quantity-weighted mean price based on the number of units purchased. Because government contracts report only the award date and there is generally a two-year lag between contract award and rocket launch (Robinson-Smith (2025)), each aggregated rocket–year price is given a weight equal to the number of government launches of that rocket in the award year and the following two years.
- For online report prices, each observation corresponds to a report. When multiple reports exist for the same rocket–year, we compute the unweighted average price. Following the approach for the contract data, we assign each rocket–year price a weight

[52] ULA released the interactive pricing tool, RocketBuilder, in 2016 and discontinued it in 2017. We accessed the tool via the Wayback Machine and collected prices for all Atlas V variants. The archived version is available at: `https://web.archive.org/web/20161203124622/https:/www.rocketbuilder.com/start/configure`.

equal to the number of commercial launches of that rocket in the report year and the subsequent two years.

Our hedonic regression model is then specified as follows: the price of rocket j from rocket family f at time t, observed in data source s, is specified as:

$$\begin{aligned}\ln\left(p_{jfst}\right) =& \theta_1 \ln\left(\text{LEO Capacity}\right)_{jf} + \theta_2 \ln\left(\text{Rocket Length}\right)_{jf} \\ &+ \theta_3 \mathbb{1}\left\{\text{Heavy}\right\}_{jf} + \theta_4 \mathbb{1}\left\{\text{Reuse}\right\}_{jf} + \theta_5 \#\left\{\text{Yrs Since Initial Launch}\right\}_{ft} \\ &+ FE_f + FE_f \times \mathbb{1}\left\{t \geq \text{ULA Merger}\right\}_t + FE_f \times \mathbb{1}\left\{t \geq \text{SPX Certification}\right\}_t + \omega_{jfst}\end{aligned} \tag{17}$$

where *LEO Capacity* denotes rocket j's payload capacity, in kilograms, to the low Earth orbit (LEO). *Rocket Length* represents the overall length of the rocket in meters. $\mathbb{1}\left\{\text{Heavy}\right\}_{jf}$ is an indicator for heavy-lift variants (e.g., Delta IV Heavy within the Delta IV family). $\mathbb{1}\left\{\text{Reuse}\right\}_{jf}$ is an indicator for reusable rockets.[53] $\#\{\text{Yrs Since Initial Launch}\}$ measures the number of years since the initial launch of rocket family f. $\mathbb{1}\left\{t \geq \text{ULA Merger}\right\}_t$ equals one for years 2006 and onward, after the formation of ULA. $\mathbb{1}\left\{t \geq \text{SPX Certification}\right\}_t$ takes the value one for years 2015 and onward, when SPX was certified for national security launches. By interacting rocket-family fixed effects with the indicator for the period following the ULA JV and with the indicator for the period following SPX's certification, we allow the effects of these two events on rocket prices to vary flexibly across rocket families. In one specification, we extend Equation (17) by including rocket family recent launches, #Launches in Past 2 Yrs, which is defined as the number of launches of the rocket's family in the previous two years.

Table A.1 presents the regression results. Column (1) excludes rocket-variant–specific characteristics. The estimated coefficient on $\#\left\{\text{Yrs Since Initial Launch}\right\}$ indicates that, on average, rocket prices decrease by about 0.5% per year. The overall R^2 is 0.89, and the within rocket family R^2 is 0.05. Column (2) adds rocket characteristics. The estimated coefficients align with expectations: the coefficient on $\ln\left(\text{LEO Capacity}\right)$ is positive, while the coefficient on $\mathbb{1}\left\{\text{Reuse}\right\}$ is negative, suggesting that rockets with greater payload capacity are more expensive, whereas reusable rockets tend to be cheaper. The within rocket family R^2 increases to 0.12, so that variant characteristics explain a non-negligible part of the within-family variation in rocket prices.

Column (3) applies an alternative weighting scheme in which government contract prices and internet report prices are matched only to launches occurring in the report year, excluding launches in the subsequent two years. The estimated coefficients are broadly similar to those in Column (2). In Column (4), we exclude all Starlink missions when constructing the regression weights, and the results remain robust.

Column (5) further includes rocket family recent launches, $\ln\left(\#\text{ Launches in Past 2 Yrs}\right)$,

[53]Not all Falcon 9 and Falcon Heavy rockets are reusable. Early Falcon 9 variants lacked recovery capability, and in some missions, operators use expendable versions to increase payload capacity by not reserving fuel for first-stage recovery. The error term is denoted by ω. We obtain prices for both expendable and reusable configurations from online reports. When computing regression weights, the reusable version counts launches that attempt first-stage recovery, while the expendable version counts launches that do not. Data on recovery attempts are drawn from the Falcon launch history page on Wikipedia (`https://en.wikipedia.org/wiki/List_of_Falcon_9_and_Falcon_Heavy_launches_(2010%E2%80%932019)`).

Table A.1: Hedonic Regression Results for Rocket Prices

VARIABLES	(1) $\ln(p)$	(2) $\ln(p)$	(3) $\ln(p)$	(4) $\ln(p)$	(5) $\ln(p)$	(6) $\ln(p)$
$\#\{\text{Yrs Since Initial Launch}\}$	-0.005***	-0.009***	0.006*	-0.002	-0.006**	
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	
$\ln(\text{LEO Capacity})$		0.204***	0.196***	0.256***	0.208***	0.195***
		(0.027)	(0.038)	(0.032)	(0.027)	(0.026)
$\ln(\text{Rocket Length})$		0.044	-0.084	-0.097	0.052	0.088
		(0.141)	(0.182)	(0.167)	(0.142)	(0.141)
$\mathbb{1}\{\text{Heavy}\}$		0.176***	0.132**	0.153***	0.169***	0.167***
		(0.044)	(0.063)	(0.053)	(0.045)	(0.045)
$\mathbb{1}\{\text{Reuse}\}$		-0.115***	-0.072	-0.044	-0.109***	-0.119***
		(0.033)	(0.044)	(0.040)	(0.034)	(0.033)
$\ln(\#\text{ Launches in Past 2 Yrs})$					-0.014	-0.030***
					(0.010)	(0.007)
R^2	0.887	0.894	0.900	0.878	0.895	0.895
Within R^2	0.054	0.120	0.157	0.162	0.120	0.117
Observations	448	448	419	448	438	438
Weight	Launch-Adjusted	Launch-Adjusted	Current-Year	Non-Starlink	Launch-Adjusted	Launch-Adjusted
Rocket Family FE	Yes	Yes	Yes	Yes	Yes	Yes
Rocket Family FE $\times \mathbb{1}\{t \geq \text{ULA Merger}\}$	Yes	Yes	Yes	Yes	Yes	Yes
Rocket Family FE $\times \mathbb{1}\{t \geq \text{SpaceX Certification}\}$	Yes	Yes	Yes	Yes	Yes	Yes

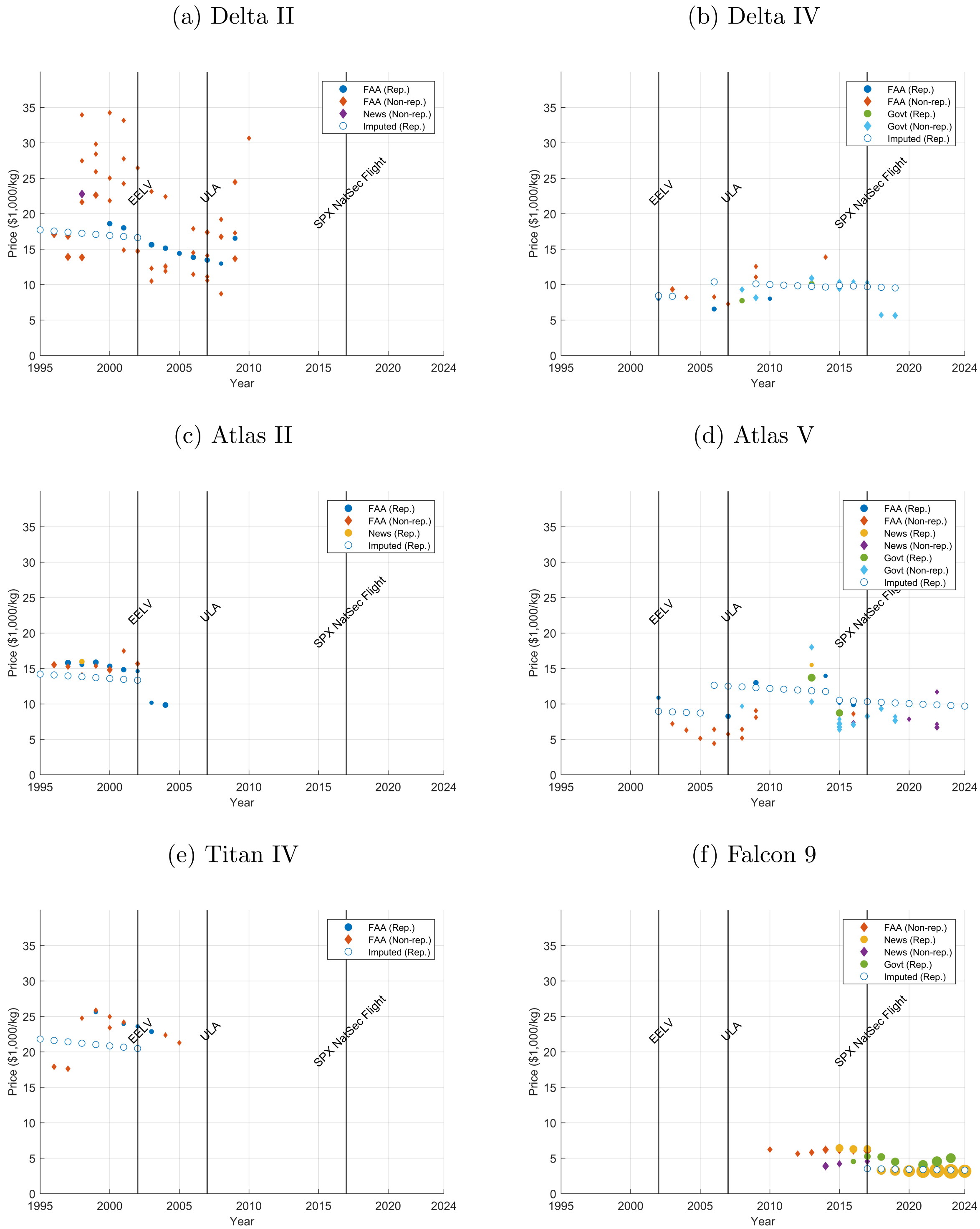
Note: *,**,*** denote significance at the 10%, 5% and 1% levels. Standard errors in parentheses. Because some price observations are aggregated, we assign regression weights to reflect the number of launches each observation may represent. FAA launch-level prices receive a weight of one. FAA quarterly-level prices are weighted by the number of launches of that rocket in the corresponding quarter. Annual-level government contract prices and online report prices are weighted by the number of government and commercial launches of that rocket in the award/report year and the following two years, respectively. Column (3) applies an alternative weighting scheme in which annual-level prices are matched only to launches occurring in the award/report year. Column (4) excludes all Starlink missions when constructing the regression weights.

and excludes observations for rocket families with no launches in the preceding two years. The coefficient on ln (# Launches in Past 2 Yrs) is negative but not statistically significant. Column (6) removes #Yrs Since Initial Launch, and the coefficient on ln (# Launches in Past 2 Yrs) becomes negative and statistically significant. Given that we find that rocket family recent launches increase reliability and the buyer's value of a launch, this finding is consistent with rocket family recent launches also lowering launch costs (Benkard (2000), Benkard (2004)). On the other hand, in the data it is somewhat difficult to disentangle the effects of time and accumulating launches.

Among the five specifications presented in Table A.1, we select the specification in Column (2) as our preferred model for imputing representative rocket variant prices. Although the inclusion of ln (# Launches in Past 2 Yrs) in Columns (5) and (6) shows the negative relationship between rocket prices and family recent launches, we choose not to embed this relationship directly into the imputed prices. Moreover, the inclusion of ln (# Launches in Past 2 Yrs) does not improve R^2 or within R^2. For these reasons, we adopt the specification in Column (2) as our preferred model.

To help the reader to understand how the imputed representative prices relate to the underlying price observations, Figure A.1 shows both series for the major U.S. rocket families. For the observed price, each marker represents a rocket-year level weighted average of prices from the indicated data source, with weights defined in the hedonic regression. "Rep." refers to representative variants; "Non-rep." refers to non-representative variants. Imputed prices are predicted using the preferred hedonic regression model. For the observed prices, marker size is proportional to the square root of the weight defined in the hedonic regression, which reflects the number of launches associated with that price observation. Vertical lines mark the initial launch of the EELV program rockets, the merger of Boeing and Lockheed Martin to form ULA, and the entry of Falcon 9 rockets into national security launches. Prices are deflated to 2010 U.S. dollars and expressed per kilogram of LEO payload capacity.

Figure A.1: Observed and Imputed Rocket Prices for Major U.S. Rocket Families



Note: Each marker represents a weighted average of rocket–year prices derived from the indicated data source, with weights defined in the hedonic regression. "Rep." refers to representative variants; "Non-rep." refers to non-representative variants. Imputed prices are predicted from the hedonic regression model (Column (2) of Table A.1). For the observed prices, marker size is proportional to the square root of the weight defined in the hedonic regression, which reflects the number of launches associated with that price observation. Vertical lines mark the initial launch of the EELV program rockets, the 2006 merger of Boeing and Lockheed Martin to form ULA, and the entry of Falcon 9 rockets into national security launches. Prices are deflated to 2010 U.S. dollars and expressed per kilogram of LEO payload capacity.

Based on the data sources and the hedonic model described above, we construct the rocket family–year prices used in the estimation of the structural model. For each family–year, when the representative variant's price is observed, we compute a weighted average price based on the regression weights defined earlier; when it is not observed, we impute the representative-variant price using the preferred hedonic specification. All prices are expressed in 2010 U.S. dollars per kilogram of LEO payload capacity.

A.3 Recent Launch Experience and Reliability

In the text, we briefly explain the evidence for accumulated launches being associated with increasing reliability, explaining why we include experience, measured as the number of launches within the last two years, in the buyer's indirect utility function. Here we provide some more detail on the analysis.

A.3.1 Reliability Curve

The existing academic and industry literatures (e.g. Moore (2019), Wagenblast and Bettinger (2024)) discuss the role of reliability and its relation to accumulated launches.[54] A common way to represent these relationships is by using "reliability curve" figures that plot, on the y-axis, the cumulated probability of success based on launches up to the x value, against the cumulative number of launches, and to show that the relationship is upward sloping.

Figure A.2 shows these plots for major rocket families in the US (panel (a)) and the rest of the world (panel (b)). The GCAT data defines a % success of each launch, reflecting how some launches may have partial success (e.g. a satellite was not launched into exactly the correct orbit, but the operator was able to maneuver it into the correct position, at the cost of using fuel which may reduce the satellite's useful life). However, for our purposes, we define a launch as a failure whenever it does not have 100% success. Panel (a) presents the accumulated reliability of U.S. rocket families. As shown in the figure, the reliability of Atlas V, Delta IV, and Falcon increases with the number of launches. Panel (b) displays the accumulated reliability of non-U.S. rocket families, showing that Russian, Chinese, and European rockets also exhibit higher reliability as they accumulate launches.

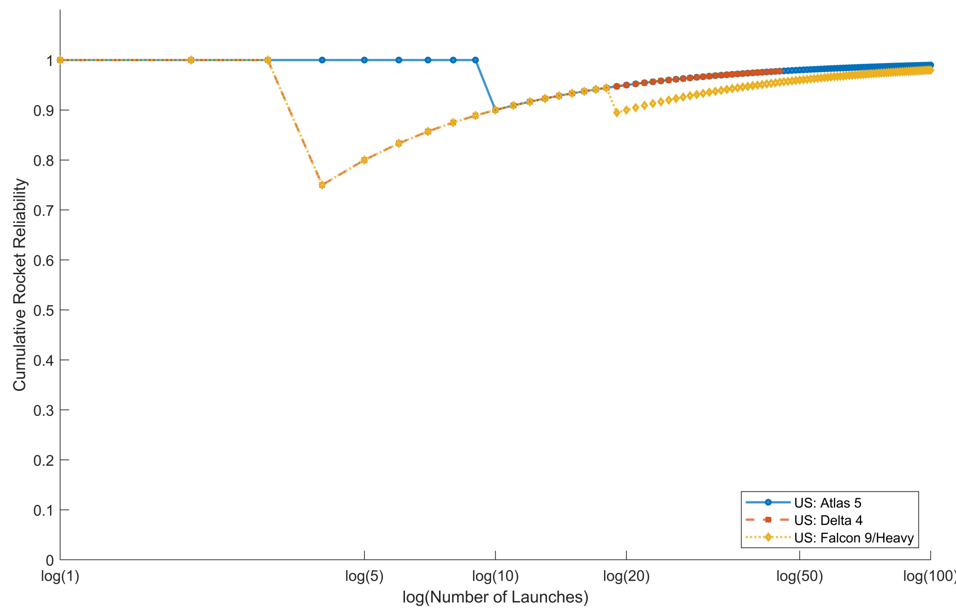
A.3.2 Learning Synergy

Kovacic (2019) argues that the formation of ULA would strengthen learning processes by increasing launch tempo and enabling technical improvements from each rocket family to

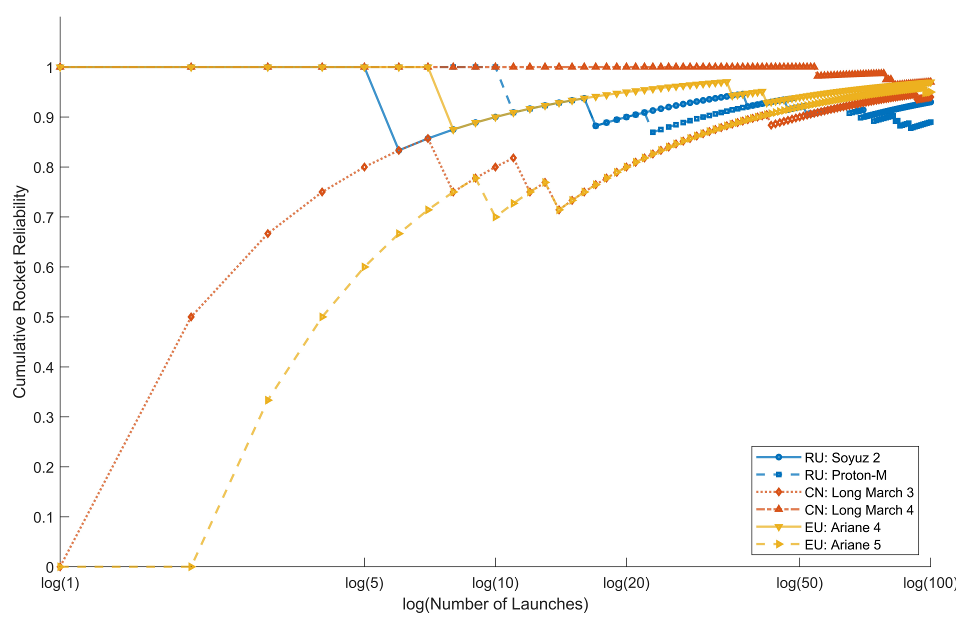
[54] For example, from Moore (2019), "The Aerospace Corporation (Aerospace) periodically generates predictions of the probability of mission success (aka reliability) for upcoming national security space launches, using reliability models based on the success and failure history of over 800 U.S. European launch missions. These predictions are a vital input to forward-looking studies such as functional availability analyses and constellation risk assessments, tools that mission planners utilize to ensure high confidence in enduring constellation success. The predictions are based on the reliability growth principle, which is the continuous improvement in reliability as a system is operated or tested and as/or process defects are discovered and corrected. Analysis of historical launch data ... shows that reliability growth is one of the most significant factors affecting launch reliability—the more experience behind a launch vehicle family, the more reliable future launches are expected to be."

Figure A.2: Accumulated Reliability of Major Rocket Families

(a) US Rocket Families



(b) Non-US Rocket Families



Note: Accumulated reliability is defined as the total number of successful launches of a rocket family divided by its total number of launches. Both governmental and commercial launches are included in the calculation.

diffuse to the other, thereby enhancing overall reliability. We use a regression approach to examine whether we can see evidence for the synergy in the data.

Table A.2 reports the regression results, where each observation corresponds to a launch. # Own Launches in Past 2 Yrs denotes the number of launches by the rocket family in the preceding two years.[55] # Partner Launches in Past 2 Yrs applies only to ULA rocket families. For each ULA rocket family, it counts launches that (i) were conducted by the other family, (ii) occurred after the formation of ULA, and (iii) took place within the preceding two years. We set ln (# Partner Launches in Past 2 Yrs) to zero for all other rocket families and for launches that occurred before ULA's formation. Because all ULA launches with positive # Partner Launches in Past 2 Yrs are successful, this variable cannot be identified in the probit specification, so we estimate linear probability models instead. Columns (1)–(4) include alternative sets of control variables. Across specifications, the regression results are consistent with the presence of learning synergy: launches of one ULA rocket family appear to enhance the reliability of the other.

Table A.2: Learning Synergy Estimation Results

	(1)	(2)	(3)	(4)
Dependent Variable	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$	$\mathbb{1}\{\text{Succ.}\}$
ln (# Partner Launches in Past 2 Yrs)	0.025**	0.028**	0.025**	0.025*
	(0.012)	(0.012)	(0.012)	(0.013)
ln (# Own Launches in Past 2 Yrs)	0.012***	0.013***	0.014***	0.019***
	(0.004)	(0.004)	(0.004)	(0.004)
ln (LEO capacity)		-0.014**	-0.014**	-0.009
		(0.007)	(0.007)	(0.007)
$\mathbb{1}\{\#\text{stages} > 2\}$			-0.010	0.013
			(0.010)	(0.012)
Region FE	No	No	No	Yes
Observed Launches	1,920			

Note: *,**,*** denote significance at the 10%, 5% and 1% levels. Standard errors in parentheses. # Own Launches in Past 2 Yrs denotes the number of launches by the rocket family in the preceding two years. # Partner Launches in Past 2 Yrs applies only to ULA rocket families. For each ULA rocket family, it counts launches that (i) were conducted by the other family, (ii) occurred after the formation of ULA, and (iii) took place within the preceding two years. We set ln (# Partner Launches in Past 2 Yrs) to zero for all other rocket families and for launches that occurred before ULA's formation.

[55] One launch has # Own Launches in Past 2 Yrs equal to zero. This observation is omitted when taking logarithms, leaving 1,920 launches in the estimation sample.

B Solving and Simulating the Dynamic Model

In this appendix, we describe the methods used to solve the dynamic games, and how, given a solution, we simulate data to provide moments that can be compared to moments in the data, and for counterfactuals.

B.1 Numerical Solution of Dynamic Game

As described in the text, we solve distinct games for each era, based on the assumption that the transitions between eras are unanticipated surprises, so that strategies are computed assuming that players believe their games has an infinite horizon.

The state variables of the game are discrete (levels of know-how for the available rocket families), but in each period, the sellers receive i.i.d. private shocks to their launch costs for each rocket, while the buyer receives private preference shocks for procuring a launch from one of the rockets and the outside good.

B.1.1 Continuation Game with Innovation

The most complicated game follows SpaceX's entry where we allow for ULA to innovate by replacing Atlas V and Delta IV with Vulcan. In this case, we first solve the dynamic game which follows after the innovation, where no further innovation is possible, and then use the computed values from this game as continuation values for ULA's innovation option in the pre-innovation game. For other eras, or when no innovation is allowed, there is a single dynamic game to solve.

B.1.2 Solution Method

We use an iterative method to solve the game. Given a vector of continuation values, we solve the bidding strategies of firms and procurement strategy of the buyer. Given the strategies, we update the value functions.

The solution of bidding strategies is based on discretizing costs and bids. Bichler et al. (2025) proposes a method to efficiently approximate the solution to an incomplete information auction with continuous cost/valuations and continuous bids using discrete costs and discrete possible bids. The method then solves for best-response distributions over the possible bids for each bidder. The updating rule uses simultaneous online dual averaging. Bichler et al. (2025) show that the method has significant speed advantages (i.e. quick convergence to a solution), and, in cases where an analytical Bayesian Nash equilibrium can be computed, that the approximation errors are small.

To apply this method, we discretize a rocket's costs into $K^c = 10$ levels, $c_1 < c_2 < \ldots < c_{K^c}$, based on the quantiles of the normally distributed ν_{it} from the 2.5% quantile to 97.5% quantile. We also discretize possible bids into $K^a = 10$ levels. We start the algorithm using a possible bid set of equally spaced K^a points, $a_1 < \ldots < a_{K^a}$ between $0.5c_1$ and $2.5c_{K^c}$. However, if when we run the algorithm, we predict that firms would bid at the upper bound, a_{K^a}, we extend the upper bound of the support.[56] We use $\pi_n\left(k^a, k^c, \boldsymbol{e}\right)$ to denote the

[56]Specifically we increase the upper bound by 10% and re-space the bid levels.

Algorithm 1 Solve for the No-Innovation Dynamic Optimal Pricing Strategy

Input: initial pricing strategy $\pi_{n,1}$

1. Initialize $t \leftarrow 1$, difference$\leftarrow \infty$, a_{K^a} binding$\leftarrow$true
2. **while** a_{K^a} binding
3. **while** difference$>10^{-5}$ and
4. new buyer choice prob $d_{t+1}(\boldsymbol{e}) \leftarrow$ buyer problem
5. buyer updates value function taking into account know-how depreciation
6. given $d_{t+1}(\boldsymbol{e})$ and $\pi_{n,1}$, each firm simultaneously computes the best response $\tilde{\pi}_{n,t}$
7. update $\pi_{n,t+1} \leftarrow \eta_t \tilde{\pi}_{n,t} + (1-\eta_t)\,\pi_{n,t}$
8. firms update value function taking into account know-how depreciation
9. difference$\leftarrow \max\{\|d_t - d_{t+1}\|, \sum_n \|\pi_{n,t} - \pi_{n,t+1}\|\}, t \leftarrow t+1$
10. **end while**
11. a_{K^a} binding$\leftarrow \sum_{k^c} 1\left(\pi_n\left(k^{K^a}, k^c, \boldsymbol{e}\right) > 0.1\right) \geq 2$ for any n, k^c and $\boldsymbol{e}$
12. **if** a_{K^a} binding
13. $a_{K^a} \leftarrow 1.1 \times a_{K^a}$
14. $a_k \leftarrow \dfrac{k}{10}(a_{K^a} - a_1) + a_1$
15. **end if**
16. **end while**

Note: $\eta_t = \dfrac{2}{t+1}$ is the Frank-Wolfe step size.

probability that the bid of rocket n is at level k^a given a cost level k^c and the current state of know-how $\boldsymbol{e}$. When ULA has two rockets, it is setting bids for both of them, as a function of both of their cost shocks. While the method allows for equilibrium strategies to be pure or mixed, our solutions are almost always approximations to a pure strategy, with over 99% of the probability weight concentrated at one bid level for every possible cost realization.

The algorithm is summarized in Algorithm 1 for the case when there is no innovation. The extension to the algorithm when innovation is possible is given in Algorithm 2, where we are also solving for the probability of innovation in each state. Our method extends the static case in Bichler et al. (2025) to a dynamic game with both LBD and innovation. Although Bichler et al. (2025) establishes convergence only in static cases, we do not encounter non-convergence in the estimation process (where we search across a large parameter space using a combination of genetic algorithm and surrogate optimization).

Algorithm 2 Solve for the Dynamic Optimal Innovation and Pricing Strategy

Input: initial pricing strategy $\pi_{ULA,1}, \pi_{SPX,1}$, initial innovation probability o_1, post-ULA innovation buyer value V^{inv}, ULA value W^{inv}_{ULA}, SpaceX value W^{inv}_{SPX}.

1. Initialize $t \leftarrow 1$, difference$\leftarrow \infty$, inv difference$\leftarrow \infty$,
2. **while** inv difference$> 10^{-2}$
3. $\quad a_{K^a}$ binding$\leftarrow$true.
4. $\quad$Run Algorithm 1 given the post innovation value functions, π and o_t
5. $\quad$Solve for optimal innovation prob $\tilde{o}_t$
6. $\quad o_{t+1} = \eta_t \tilde{o}_t + (1 - \eta_t)\, o_t$
7. $\quad$inv difference$\leftarrow \|o_t - o_{t+1}\|$.
8. **end while**

Note: $\eta_t = \dfrac{2}{t+1}$ is the Frank-Wolfe step size.

B.2 Simulation

We now describe how we simulate the model. Simulation is used to generate model predicted moments for estimation and the assessment of model fit, and to generate counterfactual predictions. All of our simulations will use 1,000 simulated paths.

Era 1 Atlas V and Delta IV are owned by separate firms, and there is no innovation. We first solve for the optimal pricing strategies and buyer choice probabilities using Algorithm 1.

All simulations begin in the year 2002, the start of the EELV era, with know-how levels$= 1$ for both rockets. In each procurement, given the current levels of rocket know-how, we simulate cost realizations for each procurement opportunity and, use the equilibrium bid strategies and buyer choice probabilities, to simulate the outcome (i.e., whether any rocket is procured, and if so which).

We then simulate the evolution of know-how. To calculate the new know-how stock for the next procurement, we first add 1 to the know-how stock of the rocket chosen for launch up to the level of 15. Next, each rocket's know-how independently drops to the next lower level with probability $\lambda \frac{[e'_{jt}]}{[e'_{jt}] - e^L_{jt}}$, where $[e'_{jt}] \in \{1, 5, 10, 15\}$ is the level of know-how corresponding with the bin of post-learning know-how e'_{jt}. We repeat this for the $N = 20$ procurement opportunities we assume for each year.

At the end of the year, if a rocket undertakes commercial launches, we add the number of launches to the know-how stock in the last procurement before the depreciation stage.

As a result of these calculations, the know-how levels in the next period may not take on the exact values of {1,5,10,15} which we use when solving the dynamic game. We will assume that the strategy at a know-how level is the strategy corresponding with the bin {1-4,5-9,10-14,15+} in simulation.

Era 2 Atlas V and Delta IV are owned by the same firm. We modify the simulation procedure to account for the synergy in know-how accumulation. We re-solve the equilibrium pricing strategies that account for (1) the era 2 demand intercept and (2) buyer and firm expectations that a new launch adds to the know-how of both rockets. In the latter, the know-how increase is probabilistic and independent: for example, if either rocket is chosen at state $\boldsymbol{e} = (1, 1)$, the know-how moves to $(1, 5)$ or $(5, 1)$ with probability $1/4 \left(1 - \frac{1}{4}\right)$, and it moves to $(5, 5)$ with probability $\frac{1}{16}$. Given these strategies, we repeat the procedure above to simulate new launches 1,000 times, starting at the know-how level at the end of era 1. We still assume the know-hows of both rockets depreciate independently, but we add the new launches to both rockets' know-how.

Era 3 SpaceX and ULA compete. We solve for their strategies using Algorithm 2. The know-how accumulation for ULA is the same as in Era 2 for pre-innovation simulations. Post-innovation simulations are similar to the procedure in Era 1 based on solutions using Algorithm 1 and the low production cost parameter.

C Extension to Analysis with Innovation

C.1 Planner Solution: Innovation and Cost Inefficiency

We consider two potential cost inefficiencies: (1) an innovation cost inefficiency where the mean innovation cost is $\left(1 + \mu^I\right) \cdot C$, and (2) a production cost inefficiency where the cost of the new rocket post-innovation is $(1 + \mu)\, c\,(e_t)$. We graph indifference curves of planner surplus net of the the monopoly buyer and total surplus in (3) in Figure C.1. The government should still prefer a planner takeover if this increases production costs by 450% (innovation costs held fixed) or if it increases innovation costs by 150% (production costs held fixed),

(a) Planner-Buyer Surplus (b) Planner-Total Surplus

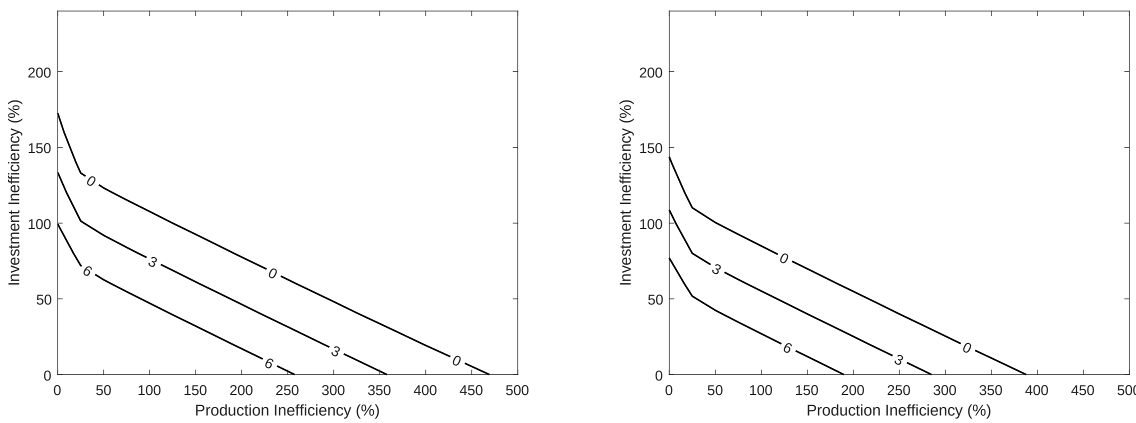


Figure C.1: Planner Indifference Curves

Note: The numbers indicate the planner surplus gains over the buyer surplus or total surplus in the ULA-SpaceX duopoly market based on era 2 demand.

but the total surplus might be lower. We also see that the planner surplus would still see significant gains (over 6 billion dollars) even if the production costs are 100% higher and the mean innovation costs are 50% higher. The high tolerances of production cost inefficiency is consistent with the high markup post innovation charged by a monopoly ULA (column (6) of Table 10)

C.2 Static Procurement Strategy and Innovation

Static-buying strategy can have also affect innovation. In particular, a static buyer would favor the current lowest-cost provider, thus further reducing ULA's pre-innovation surplus. In Table C.1, we compute the market outcomes with a static buyer, pre- and post- innovation, and with and without SPX.

Consistent with the intuition above, we indeed find a larger difference in the pre- and post- ULA surplus when SPX is absent from the market. In other words, the difference of ULA 2017 PDV in columns (2) and (4) is larger than the difference between (6) and (8). The greater surplus difference implies a greater probability of innovation of 0.18, higher than 0.16 with the dynamic buyer in Table 11.

Table C.1: Market Outcomes with Innovation: Static Buyer

	Duopoly		Monopoly	
	EELV, Falcon	Vulcan, Falcon	EELV	Vulcan
	(1)	(2)	(3)	(4)
Price ($1,000/kg)				
ULA, 2017	9.11	1.66	9.16	2.57
2017-2023	9.22	4.19	9.18	5.27
SPX, 2017	3.50	2.79		
2017-2023	3.72	2.79		
Number of Launches/Year				
ULA, 2017	2.22	10.63	4.15	14.22
2017-2023	0.76	12.94	1.94	14.56
SPX, 2017	8.85	5.73		
2017-2023	8.93	4.30		
Know-How				
ULA, 2017-2023	5.29	10.89	6.23	11.46
SPX, 2017-2023	15.00	15.00		
Lerner Index				
ULA, 2017	0.18	0.13	0.15	0.51
2017-2023	0.17	0.78	0.13	0.83
SPX, 2017	0.78	0.72		
2017-2023	0.79	0.72		
Firm-Level HHI				
2017	7,178	5,873	10,000	10,000
2017-2023	8,963	6,525	10,000	10,000
2017 Surplus ($bn/Year)				
Buyer	0.65	1.08	0.39	0.85
ULA	0.05	0.06	0.08	0.28
SPX	0.35	0.17		
PDV (2017 States, $bn)				
Buyer	17.09	19.05	12.82	17.59
ULA	0.08	19.22	14.92	20.29
SPX	0.96	0.26		
Total	18.13	38.53	27.75	37.88

Note: We report the average winning prices, number of launches per year, average rocket know-how, Lerner indices, firm-level HHI, average flow surpluses of buyers and firms, and 2017 present discounted values of the buyer and firms in this table. For EELV (Atlas V and Delta IV) and Falcon rockets, We start the simulation from the know-how levels observed in the data, where the know-how levels are 15, 5 and 15 for Atlas V, Delta IV and Falcon 9. We fix Falcon 9 know-how at 15.

D Additional Tables

Table D.1: Planner Costs and Winning Probabilities: Era 2

	Average Costs			
Atlas V \Delta IV	1	5	10	15
1	16.681, 16.681	16.681, 14.178	16.681, 12.892	16.681, 12.051
5	14.178, 16.681	14.178, 14.178	14.178, 12.892	14.178, 12.051
10	12.892, 16.681	12.892, 14.178	12.892, 12.892	12.892, 12.051
15	12.051, 16.681	12.051, 14.178	12.051, 12.892	12.051, 12.051

	Planner Choice Probabilities			
Atlas V \Delta IV	1	5	10	15
1	0.310, 0.310	0.023, 0.751	0.003, 0.807	0.001, 0.791
5	0.751, 0.023	0.411, 0.411	0.177, 0.661	0.081, 0.735
10	0.807, 0.003	0.661, 0.177	0.426, 0.426	0.266, 0.572
15	0.791, 0.001	0.735, 0.081	0.572, 0.266	0.415, 0.415

Note: We report the average costs and buyer's choice probabilities for Atlas V and Delta IV rockets in each state. The demand intercept is based on the era 2 estimate, which is nearly identical to era 1 estimate.

Table D.2: Average Bid Prices, Costs and Winning Probabilities: Static Buyer, Era 2

	Duopoly					Monopoly			
	Average Bid Prices								
Atlas V \Delta IV	1	5	10	15		1	5	10	15
1	17.165, 17.165	17.560, 11.624	17.674, 10.768	17.675, 11.323	1	10.316, 10.316	14.114, 8.735	16.781, 9.649	18.728, 10.772
5	11.624, 17.560	11.626, 11.626	11.635, 10.760	11.652, 11.323	5	8.735, 14.114	9.959, 9.959	11.837, 9.970	13.539, 10.798
10	10.768, 17.674	10.760, 11.635	10.757, 10.757	10.760, 11.323	10	9.649, 16.781	9.970, 11.837	11.007, 11.007	12.260, 11.418
15	11.323, 17.675	11.323, 11.652	11.323, 10.760	11.323, 11.323	15	10.772, 18.728	10.798, 13.539	11.418, 12.260	12.333, 12.333
	Average Costs								
Atlas V \Delta IV	1	5	10	15		1	5	10	15
1	16.681, 16.681	16.681, 14.178	16.681, 12.892	16.681, 12.051	1	16.681, 16.681	16.681, 14.178	16.681, 12.892	16.681, 12.051
5	14.178, 16.681	14.178, 14.178	14.178, 12.892	14.178, 12.051	5	14.178, 16.681	14.178, 14.178	14.178, 12.892	14.178, 12.051
10	12.892, 16.681	12.892, 14.178	12.892, 12.892	12.892, 12.051	10	12.892, 16.681	12.892, 14.178	12.892, 12.892	12.892, 12.051
15	12.051, 16.681	12.051, 14.178	12.051, 12.892	12.051, 12.051	15	12.051, 16.681	12.051, 14.178	12.051, 12.892	12.051, 12.051
	Winning Probability								
Atlas V \Delta IV	1	5	10	15		1	5	10	15
1	0.001, 0.001	0.001, 0.127	0.001, 0.316	0.001, 0.346	1	0.066, 0.066	0.008, 0.368	0.002, 0.455	0.000, 0.412
5	0.127, 0.001	0.114, 0.114	0.093, 0.294	0.090, 0.319	5	0.368, 0.008	0.214, 0.214	0.095, 0.387	0.042, 0.397
10	0.316, 0.001	0.294, 0.093	0.251, 0.251	0.247, 0.269	10	0.455, 0.002	0.387, 0.095	0.251, 0.251	0.147, 0.304
15	0.346, 0.001	0.319, 0.090	0.269, 0.247	0.264, 0.264	15	0.412, 0.000	0.397, 0.042	0.304, 0.147	0.212, 0.212

Note: We report the average prices bid in each procurement, the average costs and buyer's choice probabilities for Atlas V and Delta IV rockets in each state. The demand intercept is based on the era 2 estimate, which is nearly identical to era 1 estimate.