Beyond Learning-by-Doing: Cost Efficiency in the Commercial Space Launch Industry

Abstract

The rapid expansion of the commercial space industry has generated growing interest in understanding the economic mechanisms underlying declining launch costs. Although previous research provides substantial evidence that accumulated production experience reduces launch costs, it is unknown about whether launch providers achieve greater cost efficiency for a given level of cumulative experience. This study addresses this gap by extending Wright's Law within a stochastic frontier framework. A one-sided error component is introduced into the learning curve to measure cost inefficiency as the deviation from the minimum attainable cost conditional on cumulative production experience. The model further distinguishes firm-specific learning from potential learning spillovers generated by rivals' cumulative experience. Heterogeneity in cost inefficiency is examined using patent activity, market share, the post-2015 New Space era, and a SpaceX indicator. The results reinforce evidence of firm-specific learning-by-doing, i.e., cumulative own payload significantly reduces launch costs, whereas rivals' cumulative experience has no significant effect. However, the results suggest that, beyond the cost reductions generated by learning-by-doing, launch providers could reduce costs by approximately an additional 10% on average if they fully achieved the minimum-cost frontier associated with their accumulated production experience. Patent activity, market share, and the New Space period are significantly associated with lower cost inefficiency. In contrast, after

controlling for these factors and accumulated experience, SpaceX is associated with greater conditional inefficiency.

Keywords: Learning-by-Doing; Cost Efficiency; Innovation; Stochastic Frontier Analysis; New Space Economy

1 Introduction

The global space economy is undergoing a profound transformation, evolving from a predominantly government-led sector into a dynamic commercial ecosystem driven by private investment, technological innovation, and public-private partnerships (PWC, 2025). As space-based technologies become increasingly embedded in everyday economic activity, the global space economy is forecasted to expand from approximately $630 billion in 2023 to $1.8 trillion by 2035, growing at an annual rate of about 9%, substantially faster than projected global GDP growth (McKinsey & Company, 2024). This expansion extends well beyond traditional launch services and satellite manufacturing, with space-enabled applications increasingly supporting transportation, supply chains, communications, navigation, Earth observation, and numerous other industries. Nevertheless, commercial launch services constitute a critical subsector of this broader space economy and the focus of this study. Global launch revenues increased from approximately $7.2 billion in 2023 to $9.3 billion in 2024, an increase of nearly 30%, while the number of commercially procured launches rose from 190 to 224 over the same period[1]. Within this broader transformation, the United States has emerged as the dominant commercial space power. The growing economic significance of the U.S. commercial space sector was further underscored by the public-market debut of SpaceX, founded by Elon Musk in 2002. SpaceX

[1] https://sia.org/commercial-satellite-industry-continues-historic-growth-dominating-global-space-business-27th-annual-state-of-the-satellite-industry-report/?utm_source=chatgpt.com

began trading publicly on June 12, 2026, following one of the largest initial public offerings in history, and reached a market capitalization of approximately $2.1 trillion by the end of its first trading day. Although this valuation reflects SpaceX's broader portfolio of launch, satellite, and communications businesses rather than launch services alone, it illustrates the scale of private capital and market value now associated with leading commercial space firms. At the policy level, recent federal policy has reinforced this transition by promoting streamlined regulation, expanded launch infrastructure, greater reliance on commercial providers, and increased competition in space transportation (Office of Space Commerce, 2025). In 2025, the United States conducted 193 orbital launches, accounting for more than half of global launch activity, while Falcon 9 alone performed approximately 51% of all launches worldwide (Space Stats, 2026). During the same year, global launch activity reached 324 launches, and the number of spacecraft placed into orbit increased by 58% to 4,556, driven largely by rapid growth in U.S. investment (Space Stats, 2026).

A key driver of this transformation has been the dramatic decline in the cost of accessing space. Over the past two decades, launch costs have fallen by approximately an order of magnitude, while the annual number of satellites launched grew at a cumulative rate exceeding 50% between 2019 and 2023 (McKinsey & Company, 2024). Declining launch costs is one of the principal forces accelerating the expansion of the space economy because lower launch costs facilitate satellite deployment, broadband connectivity, Earth observation, navigation services, and numerous downstream commercial applications. At the same time, reusable launch vehicles, increasing launch cadence, and larger-capacity launch systems are fundamentally changing the economics of space transportation (ESA, 2026).

The persistent decline in launch costs can be understood through the economic theory of learning-by-doing, which views productivity improvements as an endogenous consequence of production experience rather than as purely exogenous technological progress. In other words, knowledge is generated through the process of production itself, such that firms improve their productive capabilities by repeatedly performing the same activities (Arrow, 1962). Rather than treating technological change as an external force, experience accumulated through investment and production leads to continuous improvements in efficiency, making learning an endogenous driver of economic growth. This concept was closely linked to Wright's Law, which demonstrates that unit production costs decline systematically with cumulative output, giving rise to the well-known experience curve (Roser, 2023).

Learning-by-doing reduces production costs because firms accumulate knowledge and experience through repeated production, enabling them to perform production processes more efficiently over time. As cumulative output increases, workers acquire skills, production routines become standardized, managers optimize production processes, and firms identify opportunities for process innovation, resulting in lower unit costs and improved productivity. These dynamic cost reductions provide firms with a competitive advantage by encouraging higher production levels to accelerate learning and strengthen future market positions, thereby influencing market structure and competitive behavior (Fudenberg & Tirole, 1983; Lieberman, 1987). Moreover, learning is not entirely firm-specific nor permanently retained. A portion of accumulated knowledge spills over to other firms and industries through worker mobility, supplier networks, and technological diffusion, generating broader productivity gains beyond the originating firm (Irwin & Klenow, 1994). At the same time, organizational knowledge depreciates when production slows, experienced workers leave, or firms introduce new product generations,

implying that learning is a dynamic process in which both the accumulation and retention of experience determine long-run productivity and cost performance (Benkard, 2000). As a result, declining production costs are driven not only by cumulative production experience but also by innovation, knowledge spillovers, and the effective preservation of organizational capabilities.

Research on the commercial space industry consistently identifies learning-by-doing as one of the primary mechanisms underlying the dramatic decline in launch costs (Rao, 2026; Su et al., 2026; Terzi & Nicoli, 2026). Empirical evidence shows that cumulative launch experience generates substantial productivity gains, with repeated launches enabling firms to improve production processes, enhance launch reliability, optimize manufacturing operations, and exploit economies associated with reusable launch technologies. As launch cadence increases, these learning effects accumulate, reinforcing reductions in unit costs and accelerating the commercialization of space activities. Recent studies further suggest that technological innovation and reusable launch systems have strengthened the traditional experience curve by enabling firms to acquire operational knowledge more rapidly than in earlier generations of launch vehicles (Cornet et al., 2026; Corrado et al., 2025; Gaetani & Whalley, 2026). Consequently, learning-by-doing is now widely regarded as a fundamental driver of the New Space Economy (NSE), contributing not only to lower launch costs but also to greater industry competitiveness, higher launch frequency, and the expansion of downstream space-based markets.

While the literature on learning-by-doing and the commercial space industry has been growing in recent years, two important research gaps remain. First, existing studies use experience curves to demonstrate how cumulative production reduces launch costs, but they do not examine whether launch providers could achieve additional cost reductions for a given level

of accumulated production experience. Consequently, it is unknown about the extent to which observed launch costs deviate from the minimum attainable costs implied by the learning curve, or whether providers differ systematically in their ability to translate accumulated experience into cost-efficient production. Second, although previous research has separately examined technological innovation, the emergence of the NSE, and changes in market structure, these factors have not been integrated into a unified framework for explaining cost inefficiency in the commercial launch industry.

This study addresses these gaps by extending Wright's Law within a stochastic frontier framework, introducing a one-sided error component that measures cost inefficiency relative to the experience-adjusted cost frontier. The model further examines whether heterogeneity in cost inefficiency is associated with technological innovation, measured by patent activity, market share, the transition to the New Space era, and SpaceX. The empirical results provide strong evidence of firm-specific learning-by-doing. However, the results indicate that launch providers could reduce costs by approximately an additional 10% on average if they operated on the estimated minimum-cost frontier associated with their accumulated production experience, demonstrating that the economic potential for cost reduction extends beyond the conventional learning-by-doing effect captured by Wright's Law. In addition, the results show that patent activity, greater market share, and the New Space period are significantly associated with lower cost inefficiency. In contrast, after controlling for accumulated experience, innovation, market share, and the New Space environment, the SpaceX indicator is associated with greater conditional inefficiency, suggesting that its cost performance operates substantially through measurable channels such as accumulated experience and market position rather than an additional unexplained firm-specific efficiency advantage.

The remainder of this paper is organized as follows. Section 2 provides an overview of the NSE while Section 3 reviews the relevant literature on learning-by-doing and innovation in the space sector. Section 4 presents the empirical methodology, including the extension of Wright's Law with a stochastic cost frontier framework to estimate firm-level cost efficiency. Section 5 describes the data, variables, and descriptive statistics. Section 6 presents the empirical results and discusses their implications for learning-by-doing, innovation, market structure, and the New Space economy. Finally, Section 7 concludes with the main findings, policy implications, and directions for future research.

2 The Emergence of the New Space Economy

The New Space Economy (NSE) represents a fundamental transformation in the organization, financing, technological development, and economic objectives of space activity. Historically, space programs were primarily government-led and motivated by national security, scientific exploration, and geopolitical prestige. Governments defined mission objectives, financed major programs, and relied on established aerospace contractors to develop technologies under government-directed procurement arrangements. This structure was partly consistent with the economic characteristics of space activities, which were traditionally understood as having important public-good features that justified distinctive institutional arrangements and substantial government involvement (Sandler & Schulze, 1981). Over time, however, commercialization, technological innovation, regulatory reform, and changing relationships between public and private actors progressively altered this model.

The evolution of the space economy can be characterized by three overlapping phases: a government-driven space economy, the subsequent development of commercial space markets, and, from approximately the beginning of the twenty-first century, the emergence of New Space,

in which entrepreneurial firms increasingly use private equity and other forms of private financing to develop space applications and services (Peeters, 2021). The transition to the NSE should therefore not be understood as the disappearance of government involvement or as a discrete shift from a purely public to a purely private industry. Instead, it represents an evolutionary change in the respective roles of governments and firms, the mechanisms through which space activities are financed and procured, and the economic incentives governing technological development.

Commercialization began well before the emergence of what is now described as New Space. Commercial telecommunications developed as early as the 1960s, followed by the gradual commercialization of launch services and remote sensing. Private companies increasingly assumed investment risk and responded to market incentives rather than operating exclusively as government contractors (Peeters, 2021). An important institutional milestone in the United States was the Commercial Space Launch Act of 1984, which established a legal framework for private launch activity. Subsequent regulatory changes further clarified the conditions for commercial participation and helped establish markets in which private space firms could operate (Gaetani & Whalley, 2026). The foundations of New Space were therefore established gradually through commercialization, regulatory reform, technological development, private investment, and the creation of markets for space-based goods and services.

A more significant transformation occurred during the 2000s as the relationship between government agencies and private firms began to change. Under the traditional model, agencies such as NASA largely determined system architecture and relied on contractors operating within government-designed programs. The emerging commercial model increasingly positioned government as a customer, partner, and market creator, while private companies assumed greater

responsibility for technological design, investment, and operational decisions. NASA's Commercial Orbital Transportation Services (COTS) program in 2006, Commercial Resupply Services (CRS) contracts beginning in 2008, and the Commercial Crew Program initiated in 2010 were important milestones in this transition. These programs created procurement commitments supporting privately developed launch and transportation capabilities and represented a broader movement toward commercially oriented procurement (Gaetani & Whalley, 2026).

These institutional changes are consistent with a broader shift in New Space governance toward collaborative arrangements and public–private partnerships. Such arrangements combine public and private expertise and distribute technological and financial risks differently from the government-owned infrastructure and traditional contracting structures characteristic of Legacy Space (Zancan et al., 2024). Public–private partnerships can facilitate risk sharing, mobilize private R&D, and stimulate innovation, although their effectiveness depends substantially on governance structures and contractual design (Rausser et al., 2023). Government therefore remains central to the NSE, but its role increasingly extends beyond directly financing and managing technological development to include establishing regulatory frameworks, creating markets, structuring incentives, and purchasing commercially provided services. However, private-sector innovation in launch vehicles and satellites has transformed the economics of space operations and expanded the potential for market-oriented space activity (Weinzierl, 2018).

What distinguishes New Space economically is therefore not simply the presence of private firms, since private aerospace contractors and commercial satellite companies existed for decades. Instead, the transformation involves a change in the economic logic governing space

activity. This change can be characterized as a movement from a regime of technological achievement, in which technological performance, prestige, and national objectives dominated decision-making, toward an innovation regime in which customer preferences, commercial opportunities, and costs become increasingly important determinants of success (Cornet et al., 2026). This distinction is particularly relevant to the launch industry, where commercial viability increasingly depends on reducing the cost of access to orbit while maintaining reliability and increasing launch frequency.

A defining technological development in this process was the emergence of practical launch-vehicle reusability. Earlier attempts at reusable transportation, particularly the Space Shuttle, demonstrated the technical feasibility of recovering major vehicle components but did not deliver the low-cost and high-frequency operations originally anticipated because refurbishment requirements remained extensive and turnaround times were long (Gaetani & Whalley, 2026). The successful recovery of a Falcon 9 first-stage booster in 2015 therefore represents an important milestone in the evolution of commercial launch economics. Reusability changes the traditional expendable-launch model by creating the possibility of spreading hardware costs over multiple missions, while higher launch cadence can facilitate learning, operational experience, and more intensive utilization of launch infrastructure.

These technological and institutional developments have implications extending beyond launch services. The economic benefits of space activities can spill over into digital infrastructure, communications, environmental monitoring, and other sectors, expanding the economic significance of the NSE beyond firms directly involved in producing spacecraft and launch vehicles (Corrado et al., 2023). At the same time, increasingly complex and concentrated supply chains, together with geopolitical fragmentation, introduce vulnerabilities that may affect

the resilience and performance of the sector (Corrado et al., 2023). Consequently, the economic effects of New Space depend not only on technological innovation but also on the organization of markets, supply chains, institutions, and complementary infrastructure.

Similarly, commercialization and increased private participation do not necessarily produce lower costs automatically. Although greater private-sector involvement and technological innovation have altered the organization of launch markets, evidence from NASA launch procurement indicates persistent increases in inflation-adjusted launch-service costs despite the entry and expansion of commercial providers (Kim, 2025). This finding highlights an important distinction between technological innovation, productivity improvement, and realized cost efficiency. Innovations such as reusability, miniaturization, modularity, and improved manufacturing processes may expand technological capabilities or increase physical productivity, but the extent to which these gains translate into lower observed costs depends on market structure, procurement arrangements, capacity utilization, input costs, competition, and firms' ability to convert technological improvements into productive efficiency.

3 Previous Research

The rise of the NSE has renewed interest in understanding how accumulated production experience contributes to improvements in the economic performance of the space launch industry. As commercial launch activity has expanded, launch frequency has increased, and private providers have assumed a larger role in the market, learning-by-doing has become particularly relevant for explaining the evolution of launch costs and reliability. Consequently, a growing literature has begun to examine the relationship

between cumulative launch experience, technological innovation, and the economic performance of launch providers.

Su et al. (2026) develop a structural dynamic model of the U.S. space launch industry to estimate the effects of learning-by-doing, competition, and government procurement on industry performance. Using a newly assembled dataset covering unmanned medium-to-heavy orbital launches since 2002 together with a novel database of U.S. government launch procurement prices, the authors estimate a dynamic game using the Simulated Method of Moments (SMM). Their model incorporates firms' accumulated launch experience as a state variable affecting both production costs and launch reliability while allowing the government to make forward-looking procurement decisions. Through counterfactual simulations, the study evaluates several policy questions, including the effects of the United Launch Alliance (ULA) joint venture, forward-looking procurement strategies, and innovations such as SpaceX's Falcon 9 and ULA's Vulcan rocket. The results indicate that learning-by-doing substantially lowers launch costs while simultaneously improving launch reliability, generating significant welfare gains for both producers and government buyers. Despite these important contributions, the study primarily focuses on procurement policy, market structure, and welfare analysis rather than measuring the productive efficiency of launch providers.

Terzi and Nicoli (2026) estimate the long-run experience curve of global launch technology using the largest standardized dataset currently available. Their database contains more than 4,400 launches conducted between 1960 and 2025 across sixteen major spacefaring countries. Employing Wright's Law, they estimate how launch costs evolve as cumulative launch experience increases. Their empirical results suggest that each doubling of cumulative payload launched reduces the average cost of placing one kilogram into orbit by approximately 21.2%,

implying one of the steepest experience curves observed among major technologies. The authors further decompose historical cost reductions using a Bennett decomposition, separating within-rocket-family learning effects from changes resulting from shifts in market structure. They conclude that recent cost reductions increasingly reflect genuine technological learning rather than simply reallocating launches toward more efficient launch systems.

However, the experience curve estimated by Terzi and Nicoli (2026) captures learning at the aggregate industry level rather than learning accumulated by individual launch providers. Because cumulative global experience combines launches undertaken by different firms, organizations, and countries, the estimated relationship may reflect a combination of firm-specific learning, technological progress, and knowledge spillovers across industry participants. Industry-wide and firm-specific learning would converge if knowledge generated through launch experience diffused rapidly across organizations. Such an assumption may be particularly restrictive in the launch industry, however, where proprietary technologies, trade secrets, specialized engineering know-how, intellectual property protection, and historically government-controlled technologies can limit the transfer of operational knowledge across organizations. Consequently, cumulative industry experience need not correspond to the experience actually available to an individual launch provider. In contrast, the present study focuses on firm-specific learning by examining how a launch provider's own accumulated operational experience affects its subsequent performance. This distinction allows the analysis to isolate learning-by-doing within firms rather than attributing the accumulated experience of the entire launch industry to each individual provider.

A second and rapidly expanding literature examines innovation in the space economy. Rather than focusing on launch costs, these studies investigate how technological innovation has

evolved during the transition from government-led "Old Space" to commercially driven "New Space." For example, Gaetani and Whalley (2026) construct a comprehensive database of space-related patents to measure changes in innovation activity over several decades. Using patent classification techniques and descriptive empirical analysis, they examine when the transition from Old Space to New Space occurred and identify which firms contributed most to technological development. Contrary to the conventional narrative, they find that the largest surge in space innovation occurred during the 1990s, well before the emergence of SpaceX and other entrepreneurial firms. Furthermore, incumbent aerospace companies continue to account for the majority of patenting activity, while new entrants contribute an increasing but still relatively small share. The authors interpret these findings within the framework of directed technical change, arguing that government-created markets, procurement policies, spectrum allocation, and licensing institutions largely determine the direction of private innovation.

Although Gaetani and Whalley (2026) identify the firms responsible for patenting activity, their primary analysis characterizes the evolution and composition of innovation across the space industry. This industry-level perspective is distinct from firm-specific innovation, which reflects technological capabilities and innovations developed and accumulated within an individual launch provider. The distinction is particularly relevant in the space launch industry because proprietary technologies, intellectual property protection, trade secrets, and specialized engineering capabilities may limit the extent to which innovations are immediately transferable across firms. Accordingly, industry-wide growth in innovative activity does not necessarily imply that all launch providers have access to the same technological capabilities. The present study therefore complements this literature by focusing on firm-specific technological innovation

and examining how differences in launch providers' own technological capabilities are associated with their operational performance.

Similarly, Cornet et al. (2026) investigate the transformation of the space sector through the concept of "innovatisation," defined as the transition from a regime emphasizing technological achievement toward one driven by economically valuable innovation. Their study combines historical institutional analysis with descriptive evidence on market evolution, industrial organization, and technological development over the past sixty years. Rather than relying on formal econometric estimation, the authors synthesize qualitative evidence, descriptive statistics, and patent indicators to demonstrate how commercial incentives, customer demand, and cost considerations have become central determinants of innovation. They argue that previous government-led space programs prioritized technological achievement regardless of economic efficiency, whereas New Space firms increasingly compete by reducing costs and generating commercial value.

More recently, researchers have begun examining how the changing industrial organization of the launch market affects pricing behavior and competition. Rao (2026) develops a theoretical model of vertically integrated launch markets to explain why substantial reductions in launch costs have not translated into proportional reductions in launch prices. Using industry launch statistics and stylized evidence on Falcon 9 operations between 2012 and 2026, the paper constructs a model combining Bertrand competition in launch services with Cournot competition in satellite constellation markets. The analysis shows that vertically integrated firms, such as SpaceX through Starlink, may retain the benefits of learning-by-doing as capacity rents instead of passing efficiency gains on to external customers. The model predicts that vertical integration

increases market power, raises equilibrium launch prices, and influences incentives for market entry.

Considering aforementioned studies, an important gap remains in understanding how learning-by-doing and the broader transformation of the space industry have affected the cost efficiency of launch providers. Existing studies demonstrate that accumulated launch experience can reduce production costs through learning-by-doing, but they primarily focus on estimating experience curves or the evolution of expected costs at the industry level rather than examining whether firms operate efficiently relative to the cost frontier implied by that experience. At the same time, studies of technological innovation and the New Space Economy have largely examined patent activity, commercialization, and changes in market structure without directly assessing their implications for cost efficiency. This study brings these strands of the literature together by extending Wright's Law within a stochastic frontier framework, allowing firm-specific learning-by-doing to determine the cost frontier while separately estimating firm-level cost inefficiency. It then examines whether technological innovation and the structural transition to the New Space Economy are associated with changes in cost efficiency, with particular attention to the growing role of SpaceX. As reflected in its unprecedented public-market valuation following its 2026 IPO, SpaceX has become a particularly prominent firm in the commercial space industry and a defining participant in the transition toward New Space. Its rapid accumulation of launch experience, development of reusable launch technologies, and vertically integrated business model make its emergence especially relevant for understanding changes in the cost structure and efficiency of commercial launch services. In doing so, the study shifts the focus from whether experience reduces launch costs to the related but distinct question

of how efficiently individual launch providers translate their accumulated experience and technological progress into lower costs.

4 Methodology

4.1 Wright's Law and the Experience Curve

The empirical framework begins with Wright's Law which describes the relationship between accumulated production experience and unit production costs (Roser, 2023). The central proposition is that production costs decline at a systematic rate as cumulative production increases. Economically, cumulative output serves as a proxy for accumulated experience, namely, repeated production allows firms to refine production routines, standardize processes, develop worker and organizational capabilities, and implement technological and process improvements. This learning-by-doing mechanism is conceptually distinct from economies of scale. Learning-by-doing reflects cost reductions and potential performance improvements arising from accumulated production experience, whereas economies of scale arise when higher production volumes reduce average costs, for example by spreading fixed and common costs over a larger number of units. Although both mechanisms can contribute to declining unit costs and may be empirically correlated, Wright's Law primarily captures the experience-curve relationship between cumulative production and cost. Accordingly, the estimated experience effect in this study is interpreted as firm-specific learning-by-doing, while recognizing that some cost reductions associated with cumulative production may also reflect correlated changes in production scale. The conventional Wright's Law can be expressed as

$$C_t = AQ_t^{\beta} \tag{1}$$

where C_t denotes unit production cost at time t, Q_t represents cumulative production or accumulated experience, A is the cost associated with the initial level of production, and $\beta$is the experience-curve coefficient. Taking logarithms yields the standard log-linear specification:

$$\ln C_t = \alpha + \beta \ln Q_t + \varepsilon_t \quad (2)$$

where $\alpha = \ln A$, and ε_t captures random deviations from the experience curve. Under learning-by-doing, the expected sign of β is negative, indicating that greater cumulative production is associated with lower unit costs. Thus, β can be interpreted as the elasticity of unit cost with respect to cumulative experience: a 1% increase in cumulative production is associated with an approximately β change in unit cost.

For launch technology, cumulative experience can be represented by cumulative payload delivered to orbit rather than simply the number of launches. This measure accounts for differences in the productive capacity of launch vehicles and therefore captures both the frequency and scale of launch activity (Terzi and Nicoli, 2026). The magnitude of learning is conventionally summarized by the progress ratio (PR) or, equivalently, the learning rate. From Equation (1), doubling cumulative production changes unit cost according to $PR = 2^{\beta}$, and the corresponding learning rate is $LR = 1 - 2^{\beta}$.

A negative β therefore implies $PR < 1$ and a positive learning rate. This transformation makes the estimated experience coefficient economically intuitive and facilitates comparisons of learning rates across technologies.

In addition, in industries characterized by technological diffusion, supplier linkages, worker mobility, imitation, and observable operational practices, firms may also benefit from experience accumulated elsewhere in the industry. The learning-by-doing literature therefore

distinguishes between internal learning, generated by a firm's own production activities, and external learning spillovers, whereby knowledge created through rivals' production reduces the cost of other firms (Irwin and Klenow, 1994).

To capture both channels, the standard Wright specification is extended as

$$C_{it} = AQ_{it}^{\beta_1} R_{it}^{\beta_2} \tag{3}$$

where R_{it} represents cumulative production experience accumulated by rival launch providers. Taking logarithms gives

$$\ln C_{it} = \alpha + \beta_1 \ln Q_{it} + \beta_2 \ln R_{it} + \varepsilon_{it} \tag{4}$$

Here, β_1 measures the elasticity of cost with respect to the provider's own accumulated experience, while β_2 captures the effect of rivals' accumulated experience. Under conventional learning-by-doing, $\beta_1 < 0$, indicating that greater own experience lowers unit cost. If knowledge generated by rival firms spills over across the industry, β_2 is also expected to be negative. A statistically insignificant β_2 would instead imply that learning is predominantly firm-specific, while a positive coefficient could indicate that rivals' expansion raises the focal firm's costs through competitive pressures, input constraints, or other market interactions rather than technological spillovers.

For the launch industry, rivals' experience can be defined as the cumulative payload of all other providers:

$$R_{it} = \sum_{j \neq i} \text{Cumulative Payload}_{jt} \tag{5}$$

This definition is consistent with the concept of external learning in Irwin and Klenow (1994), where the authors separate the effect of a firm's own cumulative production from cumulative

production elsewhere in the industry. Their evidence shows that own experience has a substantially stronger cost-reducing effect than external experience, illustrating that knowledge spillovers may exist without completely eliminating firm-specific learning advantages.

The inclusion of rivals' experience is also important from an industrial-organization perspective. Dasgupta and Stiglitz (1988) show that when learning does not spillover completely, accumulated experience creates dynamic scale economies: firms with larger historical production volumes may move down the learning curve more rapidly and reinforce their cost advantage over rivals. In such settings, initial cost or market-share advantages may accumulate over time, potentially contributing to greater industry concentration. Thus, distinguishing own learning from rivals' learning is particularly relevant in the commercial space launch market, where production experience is highly concentrated among a small number of providers and where technological knowledge may be only partially transferable across firms.

4.2 Stochastic Frontier Extension of Wright's Law

The extended Wright's Law specification developed above captures the systematic relationship between accumulated production experience and production cost. Own cumulative output represents internal learning-by-doing, while cumulative output of rival providers captures potential external learning and knowledge spillovers. However, the conventional Wright specification implicitly assumes that deviations from the estimated experience curve are symmetric random disturbances. This assumption is restrictive when firms with comparable levels of accumulated experience differ systematically in their ability to translate that experience into lower production costs. The learning-by-doing literature recognizes such heterogeneity, showing that differences in management, training, research, infrastructure, and organizational capabilities can cause firms with similar production experience to achieve different productivity

outcomes (Shee & Stefanou, 2016). Consequently, an observed cost above the conventional Wright curve may reflect not only random variation but also a provider's inability to operate at the minimum cost attainable given its accumulated experience.

A natural framework for distinguishing these two sources of deviation is Stochastic Frontier Analysis (SFA). SFA was independently introduced by Aigner et al. (1977) and Meeusen and Van Den Broeck (1977) as a parametric approach for estimating production frontiers while separating inefficiency from random statistical noise. Unlike conventional regression models, in which unexplained deviations are represented by a single symmetric disturbance, SFA specifies a composite error structure consisting of a two-sided random component and a one-sided inefficiency component (Karanki & Lim, 2021). The symmetric component captures measurement error, random shocks, and other stochastic factors outside the control of the decision-making unit, whereas the one-sided component represents systematic deviation from best-practice performance. The principal advantage of this approach is therefore that deviations from the estimated frontier are not automatically interpreted either as inefficiency or as random noise; instead, the stochastic frontier decomposes the residual into these two conceptually distinct components (Karanki & Zhang, 2026).

Subsequent developments in SFA extended the framework to panel data and allowed observable characteristics to explain differences in inefficiency across decision-making units and over time. Importantly, these developments also permit the frontier and determinants of inefficiency to be estimated simultaneously rather than using a two-stage procedure in which predicted efficiency scores are subsequently regressed on explanatory variables (Greene, 2004). The latter approach can be internally inconsistent because the first-stage frontier estimation generally imposes distributional assumptions on inefficiency that conflict with the second-stage

assumption that inefficiency varies systematically with observable characteristics. The single-stage maximum-likelihood approach addresses this issue by jointly estimating the frontier and inefficiency process (Kumbhakar et al., 2015).

Following this methodological foundation, the present study combines Wright's Law with SFA by interpreting the experience curve as an experience-adjusted stochastic cost frontier. While Wright's Law identifies how the attainable level of production cost changes as production experience accumulates, the stochastic-frontier extension makes it possible to determine whether observed costs systematically exceed the minimum cost attainable at a given level of experience. Accordingly, the conventional Wright error term is decomposed into a symmetric random component and a non-negative one-sided cost-inefficiency component. To account for persistent heterogeneity across launch providers, the stochastic extension of Wright's Law is estimated using a True Fixed Effects (TFE) stochastic frontier model. The TFE framework allows provider-specific, time-invariant heterogeneity to be separated from time-varying cost inefficiency (Greene, 2005). This distinction is particularly relevant to the launch industry, where providers may differ systematically in technological characteristics, organizational structures, production systems, and other persistent factors that are not directly observed in the data. The resulting model is specified as follows:

$$\ln C_{it} = \alpha_i + \beta_1 \ln Q_{it} + \beta_2 \ln R_{it} + v_{it} + u_{it} \tag{6}$$

where C_{it} denotes the unit production cost of launch provider i in period t, Q_{it} represents the provider's own cumulative production experience, and R_{it} represents cumulative production experience external to the provider. The provider-specific intercept, α_i, captures time-invariant unobserved heterogeneity across launch providers. The coefficient β_1 measures the effect of internal learning-by-doing on the cost frontier, whereas β_2 captures external learning or

knowledge spillovers arising from the accumulated production experience of rival providers. Under the learning-by-doing hypothesis, $\beta_1 < 0$, while $\beta_2 < 0$ would provide evidence that knowledge generated through rivals' production experience also contributes to reductions in the focal provider's attainable production cost. A negative β_1 may also contribute to a dynamic, self-reinforcing process in the launch market. As a provider accumulates launch experience, learning-by-doing can reduce its attainable unit cost; lower costs may, in turn, support greater launch activity, generating additional experience and further opportunities for cost reduction. Thus, cumulative experience and cost reductions may evolve jointly through a reinforcing feedback mechanism. Equation (6), however, identifies the cost-side learning relationship within this broader process and does not separately estimate the subsequent response of launch demand or production volume to declining costs. The methodological extension from the conventional Wright model occurs through the composite disturbance:

$$\varepsilon_{it} = v_{it} + u_{it} \tag{7}$$

where v_{it} is the conventional two-sided stochastic error term capturing measurement error, random production shocks, and other factors outside the provider's control, while $u_{it} \geq 0$ represents cost inefficiency. The random-noise component is assumed to follow a normal distribution, $v_{it} \sim N(0, \sigma_v^2)$ whereas the one-sided inefficiency component is assumed to follow an exponential distribution, $u_{it} \sim \text{Exp}(\lambda_{it})$. Under the exponential specification, the inefficiency term is restricted to be non-negative, reflecting the assumption that inefficient operation can increase observed production cost above the minimum attainable cost frontier but cannot reduce cost below the frontier. The symmetric normal component v_{it}, in contrast, permits observed costs to deviate in either direction as a result of random shocks. This asymmetric

decomposition therefore enables the model to distinguish stochastic variation in launch costs from systematic excess costs attributable to inefficiency.

This decomposition provides an economically meaningful distinction between learning and efficiency. The Wright component determines how the attainable cost frontier shifts as production experience accumulates, whereas u_{it} measures the distance between a provider's observed cost and that experience-conditioned frontier. Thus, two launch providers can possess similar accumulated production experience and face similar attainable costs but nevertheless exhibit different actual costs because one provider is more effective at transforming its technological and organizational capabilities into cost-efficient production.

4.3 Modelling Heterogeneity in Cost Inefficiency

An important extension of stochastic frontier analysis is to allow the distribution of inefficiency to vary systematically with observable characteristics. Early stochastic frontier models generally imposed a common inefficiency distribution across decision-making units, whereas subsequent developments introduced observable determinants of inefficiency into the frontier framework. Caudill et al. (1995) introduced heterogeneity through the variance of the inefficiency distribution, while later contributions allow both its location and scale to depend on observable characteristics. The general principle underlying this approach is that firms may face the same underlying production technology but differ systematically in their distance from the frontier because of differences in technological capabilities, organizational characteristics, competitive environments, and other observable factors. Such determinants can therefore be incorporated directly into the inefficiency distribution and estimated jointly with the parameters of the stochastic frontier using maximum likelihood.

Consistent with this approach, the present study allows the one-sided cost-inefficiency component to be heteroskedastic. Specifically, the scale of the inefficiency distribution is parameterized as a function of observable characteristics of launch providers and their competitive environment. Given the exponential distribution assumed for u_{it}, the inefficiency scale parameter is specified as

$$\sigma_{uit} = \exp(\delta_0 + \delta_1 \ln P_{it} + \delta_2 \ln MS_{it} + \delta_3 NEWSPACE_t + \delta_4 SPACEX_i) \quad (8)$$

Here, P_{it} represents the number of patents associated with launch provider i in period t and is included as a proxy for technological innovation. Patent activity is expected to affect cost efficiency because technological innovation may enable providers to improve launch-vehicle design, production processes, manufacturing techniques, and operational procedures. If greater innovative activity enables firms to operate closer to the minimum attainable cost frontier, the corresponding coefficient is expected to be negative, $\delta_1 < 0$. A negative coefficient implies that greater patent activity reduces the scale of the inefficiency distribution and is therefore associated with lower expected cost inefficiency.

The second determinant, MS_{it}, measures the provider's market share based on its share of total launches in period t. Market share is included to capture the relationship between market position and cost efficiency. A larger market share may improve efficiency by enabling providers to utilize production capacity more intensively, standardize operations, coordinate supply chains, spread organizational capabilities across a larger number of launches, and exploit advantages associated with greater operational scale. In this case, $\delta_2 < 0$ would indicate that providers with larger launch-market shares exhibit lower cost inefficiency. However, the expected relationship is theoretically ambiguous. Greater market dominance may also weaken competitive pressure to minimize costs, in which case increasing market share could be associated with greater

inefficiency. This ambiguity is particularly relevant in the contemporary launch market. SpaceX has achieved a dominant position in orbital launch, yet continued improvements in launch technologies and operations suggest that substantial opportunities for further learning and cost reduction may remain. At the same time, competition is evolving as established and emerging providers, including Blue Origin, Rocket Lab, and other U.S. firms, as well as new Chinese launch providers, seek to expand their presence in the market. Thus, a high market share may simultaneously provide operational advantages that enhance efficiency and reduce the competitive pressures that ordinarily encourage cost minimization. The estimated coefficient therefore provides empirical evidence on whether the efficiency advantages associated with market leadership outweigh potential inefficiencies arising from reduced competitive pressure.

To capture the structural transformation associated with the New Space Economy, $NEWSPACE_t$ is introduced as a period dummy taking the value of one for observations from 2015 onward and 0 otherwise. The variable is intended to capture changes in the operating environment of the launch industry associated with the transition toward a more commercially oriented space economy, including greater private-sector participation, increased launch cadence, technological innovation, reusable launch technologies, and changing public-private relationships. A negative δ_3 would indicate that, conditional on accumulated learning and the other determinants included in the model, the scale of cost inefficiency is lower during the New Space period. Importantly, this variable should be interpreted as a period effect associated with the New Space transition, rather than as identifying the causal effect of any single technological or institutional development occurring after 2015.

Finally, the model includes $SPACEX_i$, a provider-specific indicator equal to 1 for SpaceX observations and 0 for all other launch providers. This variable is designed to examine whether

the distribution of cost inefficiency associated with SpaceX differs systematically from that of other launch providers after controlling for own learning-by-doing, external learning spillovers, innovation, market share, and the broader New Space period. SpaceX represents a particularly relevant case because its production and operating model differs substantially from that historically employed by incumbent launch providers, particularly through high launch cadence, vertical integration, standardized production, and reusable launch systems. The coefficient δ_4 therefore captures whether SpaceX observations are associated with a systematically different scale of cost inefficiency relative to other providers, conditional on the remaining variables in the model.

This specification therefore separates two related dimensions of cost performance. The frontier equation determines how accumulated own and rival experience shifts attainable production costs through learning-by-doing and knowledge spillovers, whereas the inefficiency equation evaluates whether innovation, market position, the transition to the New Space economy, and SpaceX are systematically associated with the magnitude of excess costs relative to that frontier. The parameters of the frontier and inefficiency distribution are estimated jointly by maximum likelihood, thereby incorporating observed heterogeneity directly into the stochastic frontier framework rather than relying on a second-stage regression of estimated efficiency scores.

5 Data

5.1 Frontier Variables

The empirical analysis employs launch-level data covering the cost and production experience of space launch providers. The principal variables used to estimate the stochastic Wright's Law cost frontier are launch cost per kilogram and cumulative payload, obtained from

the dataset constructed by Terzi and Nicoli (2026). Their dataset is particularly suitable for the present analysis because it provides a comprehensive and standardized record of space launches from 1960 to 2025, covering more than 4,400 launches and over 330 rocket configurations across the major spacefaring economies. The authors compile the underlying information from multiple academic, governmental, and publicly available sources and provide source information at the rocket-configuration level.

The dependent variable, C_{it}, is measured as the cost of delivering one kilogram of payload to orbit, expressed in constant 2024 U.S. dollars per kilogram. Terzi and Nicoli (2026) define launch costs using the unit flyaway cost, which includes direct and indirect manufacturing costs, associated overhead, recurring engineering, sustaining tooling, and quality-control costs, while excluding the non-recurring research and development expenditures associated with the initial design of the launch vehicle. Since launch vehicles are designed for different orbital destinations, the original data standardize payload capacity to a Low Earth Orbit (LEO) equivalent using engineering conversion coefficients, thereby improving comparability across launch systems. All monetary values are also converted to constant 2024 U.S. dollars.

Production experience is measured using cumulative payload launched to orbit, consistent with the Wright's Law framework employed by Terzi and Nicoli (2026). Rather than using the simple number of launches as the measure of experience, cumulative payload captures the quantity of launch capacity produced and deployed over time and therefore accommodates substantial differences in the scale and carrying capacity of launch vehicles. In the original Wright's Law application, cumulative payload is used as the measure of accumulated experience against which changes in launch cost per kilogram are evaluated. For the provider-level analysis in this study, cumulative payload is separated into own production experience and rival

production experience. Own cumulative payload, Q_{it}, measures the accumulated payload associated with launch provider i up to period t and represents internal learning-by-doing. Rival cumulative payload, R_{it}, captures accumulated production experience external to provider i and is introduced to identify potential inter-firm learning or knowledge spillovers. This distinction allows the empirical model to determine whether reductions in the attainable cost frontier arise primarily from a provider's own accumulated launch experience or whether experience generated elsewhere in the industry also contributes to cost reductions.

5.2 Determinants of Inefficiency

The first determinant of cost inefficiency is technological innovation, measured using firm-level patenting activity. Patent data were obtained from the USPTO Open Data Portal for each company represented in the launch-provider dataset. The construction of this variable follows the patent-based approach of Gaetani and Whalley (2026), who use USPTO patent records to measure innovative activity in the space sector. Their underlying patent information includes filing and grant dates, and technology classifications. For each launch provider, we identify patents assigned to the company and construct an annual firm-level patent count, covering the period 1989–2025. The variable therefore measures the number of patents associated with provider i in year t. Using the patent assignee is important because it attributes the innovation to the organization holding the patent rather than to the individual inventor. Patent counts are used as a proxy for the intensity of technological innovation within the firm. This interpretation is particularly relevant in the space industry, where innovation is strongly associated with advances in hardware, propulsion, materials, manufacturing, and other patentable technologies. Gaetani and Whalley (2026) note that patents provide a consistent measure of innovative activity over time.

The second determinant of cost inefficiency is market share, which captures the relative position of each launch provider in the commercial launch market. This variable is constructed by using launch activity reported in the FAA Commercial Space Transportation data. Thus, the variable is based on launch frequency rather than revenues or payload mass, providing a direct measure of each firm's share of observed launch activity. The annual launch records are aggregated at the provider-year level and then used to calculate each provider's share of total launches in the corresponding year.

5.3 Summary Statistics

Table 1 reports the descriptive statistics for the main variables used in the empirical analysis, distinguishing between the Old Space and New Space eras. The comparison provides an initial indication of how launch costs, accumulated production experience, market structure, and patenting activity changed following the transition to the New Space era.

Table 1- Summary Statistics by Period

		Cost per KG	Cumulative Payload	Market Share	Number of Patents
Old Space Era	Mean	24010	502590	0.23	11
	SD	17613	694981	0.15	22
New Space Era	Mean	20039	1156535	0.19	3
	SD	14962	2267270	0.24	5

The descriptive statistics reveal several notable differences between the two periods. First, average launch cost declined from approximately $24,010 per kilogram in the Old Space era to $20,039 per kilogram in the New Space era, representing a reduction of approximately 16.5%. This decline is consistent with the broader transformation of launch economics associated with increasing commercialization, technological advances, and the growing use of reusable launch systems. At the same time, the standard deviation of cost per kilogram declined from

$17,613 to $14,962, indicating somewhat lower dispersion in launch costs during the New Space period.

The most substantial change is observed in cumulative payload, the measure of accumulated production experience used in the Wright's Law specification. Mean cumulative payload increased from approximately 502,590 to 1,156,535, more than doubling between the Old and New Space periods. This substantial increase is particularly important for the empirical analysis because cumulative payload represents the stock of production experience through which learning-by-doing is expected to shift the cost frontier. Market structure also changed between the two periods. Average provider market share declined moderately from 0.23 to 0.19, while its standard deviation increased from 0.15 to 0.24. The combination of a lower average and greater dispersion suggests increasing heterogeneity in launch activity across providers during the New Space era. This pattern is consistent with a market in which additional providers participate while launch activity is distributed unevenly across firms. Because market share is included as a determinant of the inefficiency distribution, the subsequent stochastic frontier analysis examines whether these differences in market position are systematically associated with providers' ability to operate close to the cost frontier.

Finally, the descriptive statistics show a substantial decline in the average annual number of patents, from 11 in the Old Space era to 3 in the New Space era, accompanied by a decline in the standard deviation from 22 to 5. This result should be interpreted cautiously. The lower patent count does not necessarily imply a decline in technological innovation during the New Space period. Patent counts measure only patented inventions and may be affected by changes in firms' intellectual-property strategies, differences in patenting propensity across providers, the composition of firms operating in each period, and the timing between innovation and patent

grants. Consequently, the relationship between patent activity and cost efficiency is evaluated formally through the inefficiency equation rather than inferred directly from these unconditional descriptive statistics.

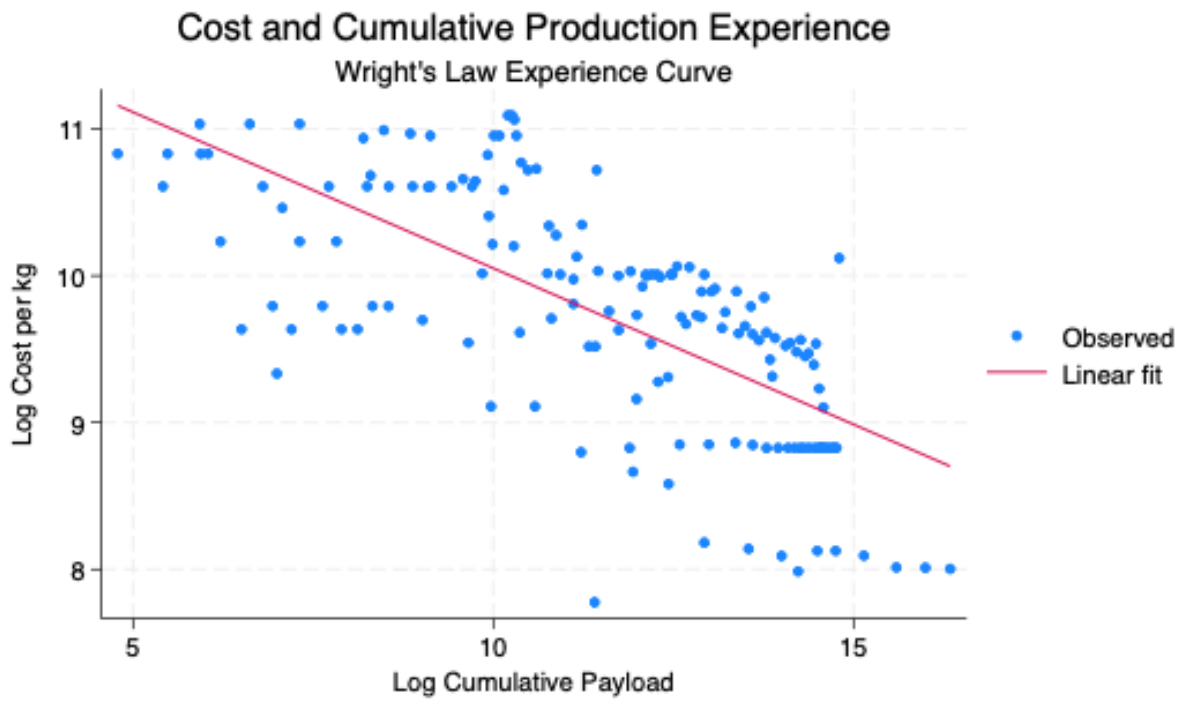


Figure 1-Learning-by-Doing: Cost per Kilogram and Cumulative Payload

Furthermore, Figure 1 illustrates the relationship between launch cost per kilogram and cumulative production experience in logarithmic form. The fitted line indicates a clear negative association between cumulative payload and launch cost per kilogram, consistent with the central prediction of Wright's Law that production costs decline as accumulated experience increases. Providers with relatively low cumulative payload generally exhibit higher costs per kilogram, whereas observations associated with greater cumulative production experience tend to be concentrated at lower cost levels. The log–log representation is particularly relevant because the slope corresponds to the cost elasticity with respect to cumulative production experience and therefore provides a descriptive representation of the learning curve employed in the empirical

model. The considerable dispersion of observations around the fitted line, however, indicates that accumulated experience alone does not fully explain differences in launch costs. In particular, substantial cost variation remains among observations with similar levels of cumulative payload, suggesting heterogeneity in providers' ability to translate accumulated experience into lower production costs. This dispersion provides additional motivation for the stochastic frontier framework employed in this study, which separates random cost variation from systematic cost inefficiency conditional on accumulated production experience.

Table 2 depicts the descriptive characteristics of SpaceX with those of other launch providers during the New Space era. The differences are substantial. SpaceX exhibits an average launch cost of approximately $3,419 per kilogram, compared with $24,120 per kilogram for other providers, indicating a markedly lower observed cost structure. At the same time, SpaceX has accumulated substantially greater production experience, with mean cumulative payload of approximately 3.62 million, more than seven times the corresponding mean of approximately 505,468 for other providers. SpaceX also accounts for a considerably larger share of launch activity, with an average market share of 0.58, compared with 0.19 among other providers. These descriptive patterns are consistent with the learning-by-doing mechanism underlying the empirical model: SpaceX combines substantially greater accumulated production experience and launch frequency with considerably lower unit launch costs. However, the comparison does not by itself establish that SpaceX's lower costs are caused by learning-by-doing or greater market share, since these characteristics are jointly determined and may also reflect technological and organizational differences across providers. SpaceX records an average of four patents, compared with nine patents among other providers during the New Space era. This suggests that the substantial cost advantage observed for SpaceX cannot be inferred from patent counts alone.

Patent counts capture only one dimension of technological innovation and may not fully reflect process innovation, proprietary knowledge, organizational improvements, vertical integration, or technologies protected through alternative intellectual-property strategies. The descriptive comparison therefore reinforces the importance of the stochastic frontier analysis, which jointly controls for accumulated experience and external learning in the cost frontier while examining patent activity, market share, the New Space transition, and SpaceX-related heterogeneity in the inefficiency distribution.

Table 2- Summary Statistics by SpaceX in New Space Era

		Cost per KG	Cumulative Payload	Market Share	Number of Patents
Others in New Space Era	Mean	24120	505468	0.19	9
	SD	16559	729928	0.15	19
SPACEX in New Space Era	Mean	3419	3615223	0.58	4
	SD	669	3948302	0.17	6

Figure 2 compares the relationship between launch cost and cumulative production experience for SpaceX and other providers during the New Space era. Both groups exhibit a negative relationship between cumulative payload and cost per kilogram, providing descriptive evidence consistent with the learning-by-doing mechanism predicted by Wright's Law. However, a pronounced difference in the level of costs is observed between SpaceX and other launch providers. SpaceX observations are concentrated substantially below those of other providers, including within the range of cumulative production experience where the two groups overlap. This suggests that accumulated experience alone may not fully explain the observed cost advantage associated with SpaceX. The fitted lines also indicate declining costs as cumulative

payload increases within both groups, although the SpaceX relationship appears comparatively flatter over the observed range.

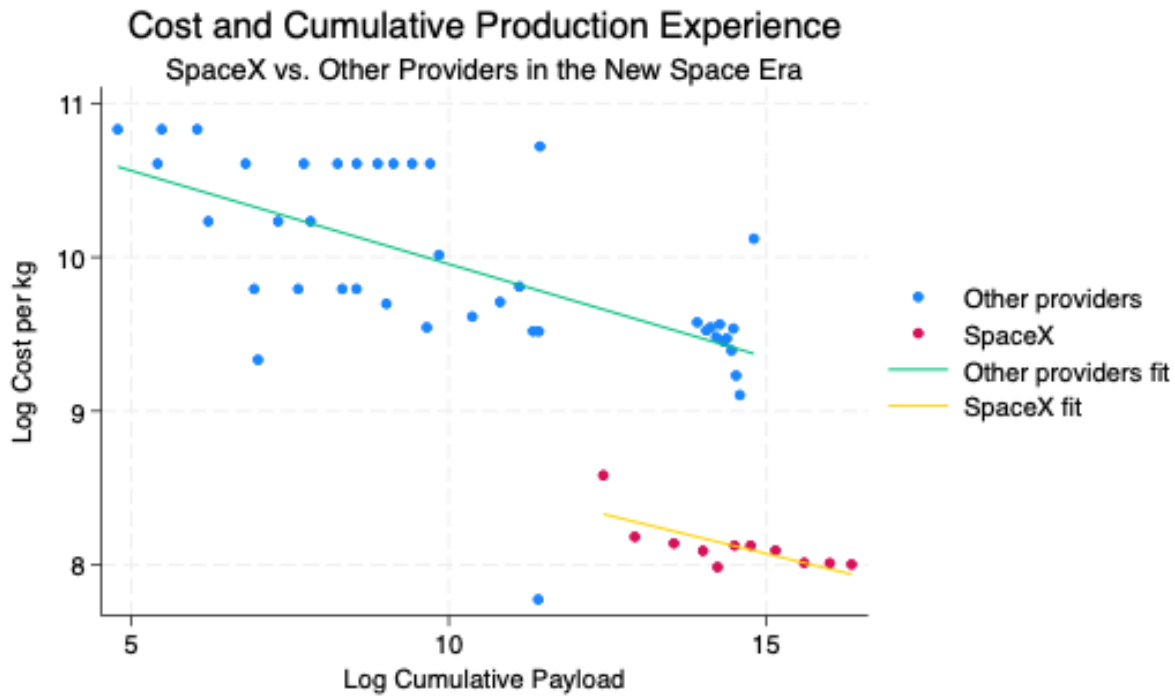


Figure 2- Experience Curves for Space X and Other Launch Providers in New Space Era

6 Results

Based on Equation (6), the stochastic cost frontier is estimated using the maximum likelihood (ML) method, allowing cost inefficiency to be separated from random statistical noise. Table 3 reports the estimated frontier parameters. Consistent with the prediction of Wright's Law, the coefficient on cumulative own payload is negative and statistically significant, indicating that greater accumulated production experience is associated with lower launch costs. This result provides empirical evidence of learning-by-doing, whereby launch providers move down the experience curve as cumulative production increases. In contrast, the coefficient on rivals' cumulative payload is also negative but statistically insignificant. Although the negative sign is consistent with potential knowledge spillovers from the production experience of

competing providers, the lack of statistical significance indicates that such external learning effects cannot be established empirically. Overall, the results suggest that learning-by-doing in the launch industry is predominantly firm-specific, with cost reductions driven primarily by a provider's own accumulated production experience rather than by experience accumulated by rival firms.

Table 3-Learning Curve Estimates

	Estimate	SE
Cumulative payload (Q_{it})	-0.091***	0.017
Rivals' Payload (R_{it})	-0.009	0.019

***, ** and * denote 1%, 5% and 10% significance levels, respectively.
Number of Obs.: 153
Wald chi2 (2): 38.56***

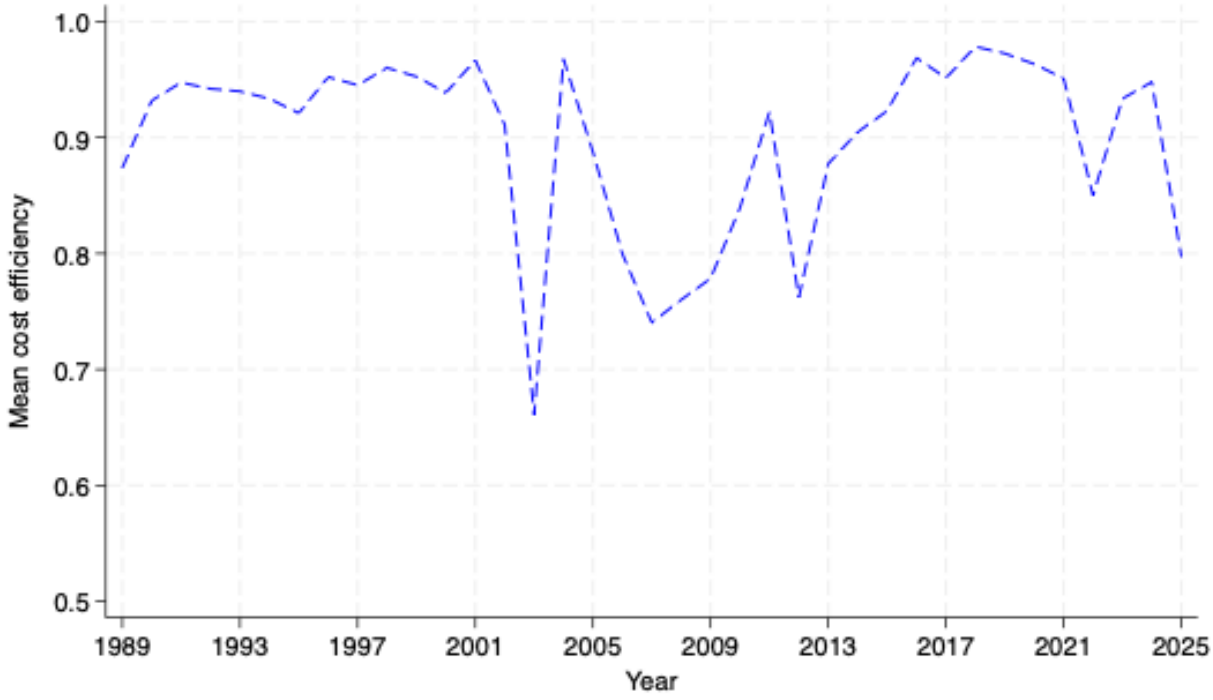


Figure 3- Cost Efficiency Over the Years

Figure 3 presents the evolution of mean cost efficiency across launch providers from 1989 to 2025. Overall, the industry exhibits relatively high levels of cost efficiency, with mean efficiency remaining above 0.90 during much of the sample period. During the 1990s, efficiency is comparatively stable, generally fluctuating between approximately 0.90 and 0.96. A pronounced deterioration occurs in the early 2000s, with mean efficiency falling sharply to approximately 0.67 in 2003. Although efficiency subsequently recovers, considerable volatility persists throughout the remainder of the 2000s and early 2010s, including another noticeable decline around 2012. From approximately 2014 onward, however, mean cost efficiency improves substantially and remains close to the estimated cost frontier for much of the late 2010s and early 2020s, reaching approximately 0.97–0.98 in its highest-performing years. This period of sustained improvement broadly coincides with the emergence of the New Space economy, characterized by greater commercialization, increasing launch frequency, and technological developments in launch systems.

In addition, Equation (8) allows heterogeneity in cost inefficiency to be systematically related to observable technological and market characteristics. Specifically, the scale of the one-sided inefficiency distribution is parameterized as a function of patent activity, market share, the New Space period, and a SpaceX indicator. This specification allows the analysis to identify factors associated with providers operating closer to or farther from the experience-adjusted cost frontier. The estimates of the inefficiency-effects equation are reported in Table 4.

Table 4- The Determinants of Cost Inefficiency

	Estimate	SE
P	-1.335**	0.599
MS	-1.324***	0.348
NEWSPACE	-1.973**	0.935
SPACEX	2.417**	0.957
Intercept	-6.442***	1.035

***, ** and * denote 1%, 5% and 10% significance levels, respectively.

The coefficient of patent is negative and statistically significant. Because the dependent parameter in this equation governs the scale of the one-sided inefficiency distribution, the negative coefficient indicates that greater patenting activity is associated with a smaller inefficiency scale and, consequently, lower expected cost inefficiency. This result suggests that technological innovation contributes not only to technological advancement in the launch industry but also to providers' ability to operate closer to their experience-adjusted minimum-cost frontier. In economic terms, firms with greater innovative activity appear better able to translate technological capabilities into cost-efficient launch operations.

Market share also has a negative and statistically significant coefficient. Thus, providers accounting for a larger share of annual launch activity tend to exhibit lower cost inefficiency, conditional on accumulated production experience and the other variables included in the model. This result is particularly important because the frontier equation already controls for cumulative payload as a measure of learning-by-doing. The market-share coefficient therefore captures an association beyond the direct cost reduction generated by accumulated production experience. One possible interpretation is that providers with stronger market positions benefit from greater utilization of launch infrastructure, more standardized operations, supply-chain coordination, and other organizational advantages associated with high launch activity.

One of the central findings of the study concerns the New Space economy. The NEWSPACE coefficient is negative and statistically significant, indicating that the scale of cost inefficiency is systematically lower in the period from 2015 onward, after controlling for learning-by-doing, innovation, market share, and provider-specific heterogeneity. The negative period coefficient indicates that the New Space era is associated with a more favorable cost-

efficiency environment after accounting for the other factors included in the model. This result is consistent with the view that the commercialization and technological transformation of the launch industry has been accompanied by improvements in providers' ability to operate closer to the attainable cost frontier.

The SPACEX indicator has a positive and statistically significant coefficient. Because the coefficient enters the parameterization of the one-sided inefficiency distribution, the positive sign indicates that, conditional on accumulated production experience, patent activity, market share, and the New Space period, SpaceX is associated with a larger scale of cost inefficiency relative to other launch providers. This result requires careful interpretation. It does not imply that SpaceX has higher observed launch costs or that SpaceX is generally less cost-efficient than its competitors. Rather, it captures the residual SpaceX-specific association with inefficiency after the model has already accounted for several mechanisms through which SpaceX may achieve its cost advantage. In particular, SpaceX's exceptionally high cumulative production experience is captured by the learning-by-doing variable in the cost frontier, while its strong competitive position is captured by market share in the inefficiency equation. The positive SPACEX coefficient therefore suggests that, once these observable advantages are held constant, there is no additional SpaceX-specific effect associated with lower inefficiency; instead, the remaining conditional SpaceX effect is associated with greater dispersion in the inefficiency component.

7 Conclusion

This study examines whether commercial launch providers have become more cost efficient, that is, whether they achieve lower costs relative to the minimum attainable cost for a given level of cumulative launch experience. To address this question, the study extends the conventional Wright's Law framework by incorporating rival production experience and

embedding the learning curve within a stochastic cost frontier. This approach distinguishes reductions in the attainable cost frontier generated by learning-by-doing from time-varying deviations from that frontier. The estimated mean cost-efficiency score of approximately 0.90 indicates that, on average, launch providers operate about 90% efficiently relative to their experience-adjusted cost frontier. Accordingly, the estimates suggest that providers could achieve approximately an additional 10% reduction in costs, on average, by eliminating inefficiency and operating on the minimum-cost frontier associated with their accumulated production experience. This represents potential cost savings beyond those already generated through movement down the learning curve.

The results provide strong evidence of firm-specific learning-by-doing. Own cumulative payload has a negative and statistically significant effect on launch cost, consistent with Wright's Law, whereas rivals' cumulative payload is statistically insignificant, providing little evidence of inter-firm learning spillovers. The inefficiency model further demonstrates that technological innovation, measured by patent activity, market share, and the transition to the New Space era are significantly associated with lower cost inefficiency. In particular, the negative and significant New Space coefficient indicates that the post-2015 transformation of the industry is associated with providers operating closer to their experience-adjusted cost frontiers. Patent activity is similarly associated with lower inefficiency, suggesting that technological innovation facilitates the conversion of production capabilities into cost-efficient operations. Greater market share is also associated with lower estimated inefficiency, indicating that providers accounting for a larger share of launch activity tend to operate closer to the cost frontier. In contrast, after controlling for accumulated experience, innovation, market share, and the New Space environment, the SpaceX indicator is positively and significantly associated with the scale of

cost inefficiency. This result suggests that SpaceX's observed cost advantage should not necessarily be interpreted as an unexplained firm-specific efficiency advantage. Rather, an important part of its cost performance appears to operate through mechanisms explicitly captured by the model, particularly its accumulated production experience and market position.

These findings have several implications for space policy and the organization of commercial launch markets. First, the favorable association between the New Space period and cost efficiency provides support for policies that facilitate commercial participation, technological experimentation, public-private collaboration, and a competitive environment for launch services. Second, the significant relationship between patent activity and lower cost inefficiency highlights the importance of maintaining incentives for technological innovation. Policies supporting private R&D, technology development, knowledge creation, and commercialization may therefore contribute not only to technological progress but also to improvements in the cost performance of launch providers. Third, the negative relationship between market share and inefficiency suggests that greater operational scale and competitive success can generate important efficiency benefits. This result should not, however, be interpreted as evidence that greater market concentration itself improves efficiency or that reduced competition is desirable. Market share may reflect successful competition, higher launch cadence, capacity utilization, and operational scale. Accordingly, policy should seek to preserve contestability and entry while enabling efficient providers to expand their launch activity. This distinction is particularly important given the growing position of SpaceX in the U.S. launch market. The results suggest that policies aimed simply at limiting the scale of successful providers could potentially sacrifice operational efficiency benefits, while excessive concentration could create longer-term concerns regarding competition, resilience, and

dependence on a limited number of suppliers. The policy objective should therefore be to maintain competitive pressure and market contestability while preserving the learning and scale advantages generated by high launch cadence.

Several limitations should be considered when interpreting the findings. First, the empirical analysis is constrained by the availability and comparability of launch-cost information. Cost observations are unavailable for some important commercial providers, including Blue Origin, which limits the coverage of the emerging launch market and may affect the representativeness of the estimated frontier. Greater disclosure and standardization of commercial launch-cost information would permit future studies to construct a more comprehensive provider-level panel. Second, as with all parametric stochastic frontier models, the estimated efficiency scores depend on assumptions regarding the functional form of the cost frontier and the distributions imposed on the composite error components. In this study, random noise is assumed to follow a normal distribution while the one-sided inefficiency component follows an exponential distribution. Alternative distributional assumptions, such as half-normal or truncated-normal specifications, may produce different estimates of inefficiency. Patent counts also provide only a partial measure of innovation because they do not capture process innovations, trade secrets, organizational innovations, or differences in the economic value and technological significance of individual patents.

Despite these limitations, the study contributes to the literature by linking three strands of research that have largely been examined separately: learning-by-doing, technological innovation, and cost efficiency in the New Space economy. Rather than treating declining launch costs as synonymous with learning, the stochastic extension of Wright's Law demonstrates that accumulated experience determines movements in the attainable cost frontier while providers

can simultaneously differ in how closely they operate to that frontier. The findings therefore suggest that the transformation of launch economics cannot be attributed to a single firm or technological development. Instead, cost performance reflects the interaction of accumulated firm-specific experience, innovation, market position, and the broader institutional and commercial transformation associated with the New Space economy. As commercial launch activity continues to expand, understanding these distinct channels will be increasingly important for designing policies that promote innovation and competition while sustaining long-term improvements in the affordability and efficiency of access to space.

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