Accelerating Innovation through Complementary Human Capital: Revisiting First-Mover Advantages

Abstract

Strategic management literature has long acknowledged the role of resources and capabilities in enabling early entry into new markets, recognizing that both incumbents and startups can become pioneers, albeit in different ways. Yet, little is known about why incumbents often prefer late entry or why startups choose to compete as non-followers. Conceptualizing complementary human capital as a superior resource, this study abductively develops the most plausible explanation for these “why” questions through the lens of first-mover advantages (FMA). Drawing on quantitative data on biopharmaceutical innovations since the 1980s, the study traces the process of becoming innovators in the biologics market back to human capital at founding, revealing divergent innovation pathways between incumbents and startups. To explain this variability, a comparative historical analysis of innovators that collectively formed the first group of non-follower pioneers in gene therapy, which emerged from the biologics market, shows that only incumbents were able to achieve first-mover advantages and/or benefits across the two markets. Although lacking such advantages, non-follower startup pioneers competed by forming founding teams with complementary human capital grounded in academic entrepreneurship and by creating value through serial entrepreneurship. In contrast, solely founded startup pioneers compensated for their lack of complementary human capital through employee entrepreneurship.

Keywords: complementary human capital, first-mover advantages, founding teams, market entry, resource-based view

INTRODUCTION

Strategic management research on incumbent–startup competition in nascent industries has long recognized that both the Goliaths and Davids can become market pioneers (Bayus & Agarwal, 2007; Moeen et al., 2020; Agarwal et al., 2025), whether through dynamic collaboration (Kim et al., 2025) or bundled knowledge capital (e.g., Wormald et al., 2021). The literature has also acknowledged the role of founder attributes such as background and prior industry affiliation (e.g., Benner & Tripsas, 2012).

However, the rescue-based view (RBV) suggests that startups' successful competition against incumbents is considered an anomaly, given their constraints in resource endowments, complementary assets, and downstream and integrative capabilities (e.g., Helfat & Lieberman, 2002; Mitchell, 1991).[1] These explanations hold a premise that the commonly observed entry timing pattern—startups' early entry and incumbents' late entry—results from variability in resources and capabilities.

Yet a puzzle arises when the market entry pattern is examined through the lens of first-mover advantages (FMA, Lieberman & Montgomery, 1988), which indicate that incumbents should prefer early entry because first movers are intrinsically stronger and possess superior resources. The puzzle deepens when follower advantages and first-mover disadvantages are considered (Lieberman & Montgomery, 1998).

In reality, both incumbents and startups can be either followers or non-followers. Consequently, the question of how entry order is affected by inter-organizational asymmetries in resources remains unanswered. Thus, as Cirik and Makadok (2023) pointed out, it is necessary to consider ex ante factors that drive unobserved performance to account for "what a firm gains by pioneering, but also for what it loses by not following" (p. 411), which can only be observed through a comparison of the same company under different entry-order scenarios.

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[1]Following Lieberman and Montgomery (1998), this study defines resources and capabilities, respectively, as a company's "stock of tangible and intangible assets, including employees' individual skills" and its "collective capacity for undertaking a specific type of activity" (p. 1112).

To address this anomaly, this study follows best practices in applying the abductive method in strategic management research (Kim et al., 2025; Pillai et al., 2024) to develop the most plausible explanation for why incumbent and startup pioneers differ in their observed market entry order. Specifically, this study traces the pioneers' human capital composition to the founding stage, revealing how initial complementary human capital differentially shapes the innovation pathways of incumbents and startups.

Complementary human capital is broadly defined as "a set of capabilities and a complementary set of unique individuals" (Coff & Kryscynski, 2011, p. 1430). Dating the pathways to founder complementary human capital is based on a premise that the "complementary set" of human capital is a superior resource and that firm specific human capital is most complementary at founding. It is reasonable to think of co-founders as a simple team. When the team size is small, it would be costly to replace any members because they each possess unique knowledge and information that other members lack and/or have no access to, leading to their different roles in value creation and appropriation (Coff, 1999, p. 123-124).

Although previous studies have attempted to link complementary human capital and innovation by investigating how innovators' complementary human capital affects employee productivity and mobility (Campbell et al., 2012; Palomeras & Melero, 2010), they primarily focus on R&D employees. Additionally, they did not distinguish between human capital investments (education and experience) and the outcomes of those investments (knowledge and skills) (Unger et al., 2011). As a result, the questions of where initial complementary human capital originates and how it affects innovation performance over time remain unanswered.

Drawing on the incubation phase of the emerging gene therapy market within the broader context of biopharmaceutical innovations in biologics (1980–2025), this study's inference begins with longitudinal quantitative data on 66 publicly listed innovators in the biologics market and then incorporates historical data on the innovators that have collectively became the first group of market pioneers in gene therapy to compare the same companies'

FMA across different entry-order scenarios. The assumption is that the first group of market pioneers in an emerging market consists of non-followers from the established industry from which the market is born.

The analysis shows that only incumbents were able to achieve first-mover advantages and/or benefits across the two markets. Although lacking such advantages, non-follower startup pioneers competed by forming founding teams whose human capital complemented a bounded set of knowledge in business and science & technology with industry experience, thereby creating value through serial entrepreneurship. As a counterfactual, solely-founded startup pioneers compensated for their lack of founding team human capital through employee entrepreneurship.

Building on prior research that has primarily focused on complementary human capital among employees (Campbell et al., 2012; Palomeras & Melero, 2010), this study contributes to the RBV of strategic human capital research (Coff, 1999; Kim & Makadok, 2021) by showing that conceptualizing complementary human capital at founding as a superior resource, within a comparative and historical perspective, offers a useful approach for extending theories of how competitive advantage is sustained when human capital complementarities emerge and become inimitable, firm-specific resources (Barney, 1991; Teece et al., 1997). Addressing the call to revisit its framework (Lieberman & Montgomery, 1998; Cirik & Makadok, 2023), this study also contributes to FMA studies by providing empirical evidence on how complementary human capital influences the entry order of market pioneers in different ways.

FOUNDING TEAM HUMAN CAPITAL AND ITS UNEXPLAINED PATTERNS

A growing body of literature has focused on human capital and innovation in the context of entrepreneurship. This topic is important because analyzing entrepreneurial profit is less useful for assessing the competitive advantage of startups, given their rapid growth rates and the inherent trade-off between growth and profitability (Lieberman, 2021). Additionally, conventional performance measures may not accurately reflect true profits once the bargaining power of internal stakeholders, particularly CEOs, is taken into consideration (Coff, 1999). For example, previous studies have recognized the multidimensional nature of founders' human capital (Lehnihan et al., 2019), its indirect effects (Kato et al., 2016) and gender-based contingencies in high-technology industries (Woolley, 2019). Despite these insights, little is known about how founders' human capital influences firm innovation over time and how its impact differs at the individual and team levels. Consequently, the question of why incumbents and startups differ in their innovation performance remains unanswered.

Complementary Knowledge

The founding team literature has offered a more nuanced explanation of how human capital affects incumbents and startups differently by identifying sources of knowledge that complement one another among innovators (Palomeras & Melero, 2010; Wuchty et al., 2007). Premised on the idea that "innovations frequently result from the combination of different types of knowledge that mutually enhance their value" (Palomeras & Melero, 2010, p. 884), complementary knowledge occurs when "an inventor's knowledge is complementary to that of other researchers if the former needs to be combined with the latter to develop its full potential value" (Palomeras & Melero, 2010, p. 884). For example, several studies have shown that co-founders differ in their human capital types and that diversity within founding teams has varying effects on entrepreneurial performance across different team formation phases (El-Zayaty et al., 2025; Knight et al., 2020; Lazar et al., 2020). In addition to innovation outcomes, prior research has also examined the effects of complementary knowledge, sometimes referred to as expertise, on employee mobility (e.g., Campbell et al., 2012) and productivity (e.g., Guenther, 2023).

The assumption underlying complementary knowledge, as discussed by Palomeras and Melero (2010), is that innovations are team-level outcomes because individuals within a team who come from different backgrounds possess distinct, complementary pieces of knowledge. In this way, complementary knowledge operates both ex ante and ex post:

> Thus, the know-how of coinventors working in a project may be mutually complementary ex ante. Secondly, team-work in the development of an invention leads, in itself, to the generation of complementary knowledge. If research is organized by assigning interdependent tasks to team members, learning-by-doing will lead to ex post complementary knowledge even if all coworkers start the project with independent backgrounds. In this case, the complementarities generated are specific to the team members involved in the project. (Palomeras and Melero, 2010, p. 884)

Experience as a Complementor

In parallel, there is an extensive literature suggesting experience as a source of human capital complementarity. For example, previous studies have identified founders' pre-entry experience in the contexts of employee entrepreneurship, academic entrepreneurship, and user entrepreneurship (Agarwal & Shah, 2014), and have shown that such experience affects the outcomes of their ventures (e.g., Helfat & Lieberman, 2002; Honoré, 2022), as well as founders' initial choices in strategy (e.g., Eisenhardt & Schoonhoven, 1990), innovation types (e.g., Kapoor & Furr, 2015), and evolutionary paths (e.g., Beckman & Burton, 2008). Similarly, a successful first founding experience facilitates the success of subsequent startups

(Wasserman, 2012). Finally, founders' prior experience in different industries also affects their growth and alliance formation (Eisenhardt & Schoonhoven, 1990).

Although insightful, prior explanations of founding experience research have yet to address the puzzles surrounding how innovation performance is affected by entry order, particularly why startups tend to enter early, whereas incumbents prefer to enter later. Consequently, the mechanisms through which founders' human capital affects entry order remain understudied. Additionally, few studies have examined how founders' prior experiences in entrepreneurship and market entry complement academic knowledge of founding teams. Prior research indicates that academic founders often lack access to complementary assets, such as operational expertise and industry networks (e.g., Agarwal & Shah, 2014).

Unobserved Patterns Arising from Assumptions within Prior Explanations of Founding Team Human Capital

The extant literature suggests that complementary human capital is both a cause and an effect, with distinct causal implications for startups and incumbents. For startups, founding team complementary human capital serves as a source of competitive advantage that leads to positive outcomes. In contrast, for incumbents, the complementarity can only be observed among employees as the outcome of a prior process of complementing initial human capital. In this sense, both the complementary knowledge framework and the literature on founders' prior experience imply that complementary human capital at founding accounts for startups' early entry and innovation pathways but not for those of incumbents.

However, it remains uncertain whether founders' complementary human capital has long-term effects and, if so, how it shapes incumbents' innovation pathways over time. Additionally, knowledge and experience are fundamentally different, even though both constitute human capital in a broad sense. While experience represents a form of human capital investment, knowledge is typically an outcome of such investment, often through education (Unger et al., 2011).

Differently put, incumbent and startup market pioneers are anomalous to explanations that assume the quantity of founders can be directly translated into the quality of complementary human capital aggregated at the firm level.

Due to its multidisciplinary nature, human capital has been measured in different ways not only within strategic management but also across fields of management and business scholarship. A common approach differentiates types of human capital based on Becker's (1962) concepts of firm-specific human capital (FSHC) and general human capital (GHC) (Campbell et al., 2012; Kryscynski & Coff, 2024). Although this distinction offers research opportunities to study the dynamics of FSHC–GHC interrelatedness and the emergence of human capital complementarities, further confusion arises when FSHC is measured as employee tenure especially through the theoretical lens of perceived FSHC (Raffiee & Coff 2016; Coff et al., 2020).

Another approach categorizes human capital into business-oriented, technology-oriented, and rhetoric-oriented types based on educational backgrounds (e.g., El-Zayaty et al., 2025). However, once again, this categorization risks conflating human capital investments (e.g., education and experience) with the outcomes of those investments, such as knowledge and skills (Unger et al., 2011).

Consequently, the empirical evidence regarding which type of human capital qualifies as a superior resource remains inconsistent and even contradictory, leading to less accurate explanations of why founders' human capital enables early entry.

QUANTITATIVE ANALYSIS

Sample and Data

The sampling process of this study's quantitative analysis began with over 250 applicants identified from the FDA's Purple Book database, which contains 2,106 entries and was accessed on August 8, 2025. Applicants were filtered to those with submission type "Original" and restricted to products approved after 1980. Since the 1980s, pharmaceutical innovations have increasingly required the combination and recombination of knowledge in biology and chemistry to complement traditional medical expertise. After removing biosimilar entries (license type 351(k), the resulting sample of 229 companies represents innovators that received FDA approval for novel products in biologics. After excluding companies founded before 1980, as well as private and foreign companies and those with missing values for founders or founding year, the final sample consists of 66 U.S. publicly listed companies, encompassing 153 founders and 38 acquisition activities.

This study draws on four datasets (founding teams, acquisition targets, strategic alliances, and financial information) that were gathered from different sources. Founding team data, including entrepreneurial information such as educational background and venture capital funding, were manually collected from Crunchbase and LinkedIn.

Acquisition target data were also manually collected from Crunchbase for all acquisitions made by startups and incumbents in the founding team dataset, spanning from each company's founding year through the FDA approval date of its first biologic product. For each acquisition target, individual founder information was gathered using the same variable definitions and coding schemes as those applied to the founding team data. Financial information was directly downloaded from WRDs using companies' ticker symbols.

Strategic alliance data were collected from Factiva by restricting the search to the period between each focal company's founding year and its first FDA approval year. The results were then filtered using the subject category "Joint Ventures/Consortia". Although Factiva also includes related categories such as "Licensing Agreements" and "Partnerships/Collaborations", the "Joint Ventures/Consortia" category provided a less redundant yet more comprehensive capture of alliance formations, encompassing joint ventures, licensing agreements, and broader collaborative partnerships.

Variables not originally contained in the founding team dataset were computed and added prior to analysis. Additionally, although the study restricted sampled companies to those founded after 1980, one company established in 1978 was retained in the sample. In addition, for academic founders , the study did not differentiate whether the professorship was held before or after founding, or throughout a founder's career. However, in one case where a founder held only a nine-month assistant professorship, the professor flag was not applied.

Moderated Mediation Analysis

This study applies the principles of moderated mediation analysis (Edwards & Konold, 2020; Preacher et al., 2007) for a test of the effects of initial complementary human capital on innovation pathways. By definition, "moderated mediation occurs when the strength of an indirect effect depends on the level of some variable, or in other words, when mediation relations are contingent on the level of a moderator"(Preacher et al., 2007, p. 193).

The study models the conditional indirect effect of founder complementary human capital on innovating speed at the time when biopharmaceutical companies received their first FDA approval in biologic products. A conditional indirect effect is defined "as the magnitude of an indirect effect at a particular value of a moderator" (Preacher et al., 2007, p. 186). Figure 1 illustrates the hypothesized relationships, proposing that the indirect effect of founder complementary human capital is mediated through internal R&D investment and externally moderated by acquired founders' human capital.[2] Focusing on founders' human capital enables this study to better "control" for the temporal order between superior resources and early entry, thereby explaining the why within the broader question of how early entry is enhanced by initial resources and capabilities. Due to the study's relatively small sample size, the bootstrapping method was employed as a resampling strategy to assess indirect effects, which is a common practice in implementing moderated mediation analysis (Edwards & Konold, 2020; Preacher et al., 2007).

[2] This study does not test all direct and indirect paths due to theoretical justifications.

———INSERT THE FIGURE ONE OF HYPOTHESIZED RELATIONSHIPS HERE———

Key Variables

The dependent variable for the moderated mediation analysis is innovation speed. This variable captures the timing of a biopharmaceutical company's successful regulatory innovation outcome from its drug research and development efforts. It is measured as the difference between the year of the first FDA approval in biologic products and the company's founding year. The average time to receive the first FDA approval in the sample is 17.827 years.

The explanatory variable, founder complementary capital, is a firm-level construct that captures founders' human capital investment, measured by the interaction between founder human capital composition and industry-specific human capital. Founder human capital reflects complementary knowledge aggregated from individual founders' educational backgrounds. Following El-Zayaty et al. (2025), each founder's educational background (degrees and certificates) was coded into three categories: business-oriented (e.g., MBA, certificate in leadership), science & technology–oriented (e.g., MD, PhD in Biochemistry, MS in Engineering, MD), and rhetoric-oriented (e.g., JD, BA in History). A ratio was then computed to measure founder human capital composition, defined as the number of distinct human capital types present among the founders divided by three (the total number of categories).

For example, a founding team possessing human capital in business and science & technology is coded as 2/3. An individually founded company whose founder possesses all three types of human capital (e.g., JD, MD, and MBA) is coded as 3/3. In the sample, only six companies (6.06%) possessed all three types of human capital at founding, regardless of founder number, while approximately 65% of companies possessed only one type. This ratio was then multiplied by the number of years of experience in the biopharmaceutical industry accumulated before the founding team was formed, serving as a proxy for prior industry-specific human capital. For co-founded companies, the measure reflects the maximum years of industry experience among the founders. For sole-founded companies with an academic founder, industry-specific human capital was coded as one year. In the sample, the average number of years of industry experience was 10.145, ranging from 1 to 45. The natural logarithm of this measure was used in the analysis.

The study's mediating variable is (internal) research investment, which captures the outcomes of firm-level human capital investment, measured as knowledge output. Following and extending Kapoor and Klueter (2015), for each company, patent counts were retrieved from the U.S. Patent and Trademark Office (USPTO) using the applicant name and publication date, covering the period from the founding year through the first FDA approval year. Because the USPTO dataset provides limited coverage prior to 2013, pre-2013 research investment was proxied by counts of scientific publications in the Web of Science database using the company name as the affiliation, an approach consistent with Kapoor and Klueter (2015). Patent and publication counts were then summed to construct a firm-level measure of research investment, which was log-transformed to reduce skewness.

The moderator, Acquired Founders, captures external human capital investment through M&As, measured as the career outcomes of individual founders post-acquisition. Specifically, a binary variable was first created to classify each founder into one of three categories using information gathered from Crunchbase and LinkedIn: (1) acquired hire, (2) (co)founder of another startup, or (3) other post-acquisition employment. To aggregate acquired founders' human capital at the firm level, the total number of acquired founders retained as employees by the acquiring company was computed for analysis.

This study controls for alternative explanations at the individual, firm, and acquisition-deal levels. Table provides details of all control variables as well as the key variables described above. Note that because this study is focused on differences in founder characteristics rather than temporal shocks, year dummies were not included in the models.

———INSERT THE TABLE ONE OF VARIABLE DESCRIPTION HERE———

Results

The direct association between founder complementary human capital and innovation speed was not founded to be moderated by acquired founder human capital. The association between founder complementary human capital and research investment was not conditional on acquired founders, either. However, the association between research investment and innovation speed was supported.

Since there is sample size imbalance between startups (n=19) and incumbents (n=47), it is necessary to re-estimate the model splitting the two groups. To compare startups and incumbents, a binary variable was created based on firm age at the time of first FDA approval. Firm age was calculated as the difference between the founding year and the year of first FDA approval in biologic products. Biopharmaceutical companies less than ten years old at the time of the approval were coded as startups, while those ten years or older were coded as incumbents.

Table 2 presents the results, revealing two distinct innovation pathways between incumbents and startups.[3] Unexpectedly, founder complementary human capital had a significant and positive direct effect on innovation for incumbents, but not for startups. At 90% CI, founder complementary human capital directly speeded up innovation in incumbents, as shown by X → Y ($c' = 1.004$, $SE = 0.393$, $p = 0.011$). Additionally, acquired founders had a negative effect (W → Y/b2 = –3.104, $SE = 1.394$, $p = 0.026$), suggesting that incumbents with more acquired founders have slower innovation outcomes. On the contrary, startups' estimates showed the positive effect of founder complementary human capital on innovation speed is small (c' path, X → Y = 1.519), the human capital might increase internal research investment (a path, X → M = 0.477), but invest more in R&D have slower innovation outcomes (b path, M

[3] Startups only have point estimates due to its small sample size.

→ Y = –12.748). Finally, the effect of research investment on innovation decreased as the level of acquired founders increased (bw path, MW → Y = –35.243).

———INSERT TABLE TWO COMPARISON OF STARTUPS AND INCUMBENTS HERE———

EXPLAINING DIVERGENT INNOVATION PATHWAYS: A COMPARATIVE AND HISTORICAL PERSPECTIVE

While the above moderated mediation analysis provides insights into how the conditional indirect effect of founder complementary human capital differentially affects the innovation pathways of incumbents and startups, it does not explain why. Analyzing these pathways from a comparative historical perspective helps uncover the most plausible causal relationships underlying the observed patterns. This comparative historical approach is broadly guided by historical methods in entrepreneurship and strategy (Agarwal et al., 2020; Pillai et al., 2024; Kim et al., 2025) and builds specifically on prior research that employs historical analysis as an alternative approach to studying market pioneers (e.g., Golder & Tellis, 1993) and product generations within industries (e.g., Tripsas, 1997).

Given that gene therapies are officially regulated as biologics, this study identified the most significant cases for developing the unique historical narratives of incumbents and startups by linking founders' human capital accumulation histories to entry order. Market pioneers in gene therapy were categorized by firm type (incumbent versus startup) and founding type (sole-founded versus co-founded). This design facilitates a comparison of FMA and FMB:

> FMA is a comparison based on the actual ex post performance difference between the pioneer in a market and the followers in that same market at the same time. However, that is not the managerially relevant comparison for a firm to consider. For a firm choosing its entry timing for a nascent market, the relevant difference is a counterfactual ex ante comparison between its own

performance if it pioneered the market and its own performance if it were a follower. (Cirik & Makadok, 2023, p. 410)

The market pioneers' entry order was determined based on the announcement date of their first FDA approval in Cellular and Gene Therapy Products. Most pioneers are co-founded incumbents, followed by sole-founded incumbents, co-founded startups, and sole-founded startups. The table below lists the pioneers in each category, along with their founding year and entry time.

———INSERT THE TABLE THREE OF MARKET PIONEERS IN GENE THERAPY HERE ———

The Pioneer 5 as Non-Followers

This study focuses on the first group of market pioneers in gene therapy from 2017 to 2019—KITE, ONCE, ORGO, VCEL, and DNDN—ranked by their entry order, based on the premise that they are non-followers in the established biologics product market due to the parent–child relationship between the two markets. This analytical focus justifies the application of first-mover benefits (FMB), which are conceptually characterized by a "forward-looking, prospective" temporal orientation, in contrast to FMA, which are "backward-looking, retrospective" (Cirik & Makadok, 2023, p. 411). Thus, comparing the entry order of the same set of pioneers across two scenarios where they act as empiricists or analysts in the parent biologics market but as strategists, consultants, or theorists in the child gene therapy market enables a comparison between FMA and FMB (Cirik & Makadok, 2023, p. 411).

In its narrow sense, FMB refers to "the first mover's hypothetical performance if it had been a follower" (Cirik & Makadok, 2023, p. 410). Building on this definition, the most ideal research design for comparison would involve the same set of pioneers—randomly selected startups or incumbents—observed across both the parent (biologics) and child (gene therapy) industries, or within one industry across comparable temporal stages. However, because the purpose of the comparative historical analysis is to explain why some incumbents and startups choose to be non-followers, focusing on the first cohort of market pioneers represents a more appropriate research design. This reasoning is based on the assumption that non-followers in the parent industry are more likely to become the first group of market pioneers in its child industry.

Startups as Non-Followers Lacking FMA and FMB

Do non-followers become market pioneers through the achievement of FMA and/or FMB? The comparison of all possible scenarios of market entry order between incumbents and startups in both biologics and gene therapy, based on the reasoning in the comparison of FMA and FMB discussed by Cirik and Makadok (2023, p. 410), suggests that becoming market pioneers as non-followers is a process more complex than expected (see the first Table in the Appendix for the comparison table extending Figure 1 in Cirik and Makadok (2023)).

Although comparing the two startup pioneers with their three incumbent counterparts yields six possible comparisons, only one FMA–FMB pattern is observed (see Appendix for all possible comparisons among the Pioneer 5). The comparisons show that only the incumbent pioneers were able to achieve FMB, since both startup pioneers entered the biologics and gene therapy markets at the same time. The absence of early or late entry among the startup pioneers indicates that they lacked prior experience in innovating biologic products before entering the gene therapy market, unlike their incumbent counterparts. In other words, all incumbents had already accumulated experience in biologics innovation before entering the gene therapy market, and this experience served as the source of their FMB.

Take the comparison between the startup KITE and the incumbent ORGO as an example. Founded in 2009, KITE received its first FDA approval for a gene therapy product on October 18, 2017. This date marked the first gene therapy innovation ever approved in history (the startup's second gene therapy approval followed in 2020). However, as illustrated in the table below, since FMB is defined as the performance derived from a firm that enters early in biologics but late in gene therapy, it is theoretically impossible for KITE to achieve FMB, even though it was the first to enter the gene therapy market. In comparison, although ORGO did not receive its FDA approval until February 20, 2018, the incumbent still achieved FMB due to its relatively early entry into the biologics market in 2012.

———INSERT THE TABLE (1) OF KITE-ORGO COMPARISON IN APPENDIX HERE———

Additionally, among the Pioneer 5, neither the startups nor the incumbents were able to achieve FMA, because achieving such advantages requires that (a) startups enter early and incumbents enter late in the biologics market, or (b) incumbents enter early and startups enter late in the gene therapy market. However, none of the six comparisons fit either condition. For example, KITE did not achieve FMA because it entered the biologics market in 2017—the same year it entered the gene therapy market—which was later than ORGO's entry into biologics in 2012. Likewise, ORGO did not achieve FMA in the gene therapy market as an incumbent because its entry into the market in 2018 occurred one year after KITE's entry.

However, incumbents were able to achieve both FMA and FMB when competing with startup pioneers that were followers. Take the comparison between ORGO and KRYS as an example. KRYS is considered a follower, as its entry into the biologics and gene therapy markets occurred in 2023—relatively late compared to the first group of market pioneers. Therefore, as shown in the table below, the startup was unable to achieve FMA in biologics or FMB in gene therapy. In contrast, ORGO achieved both FMA and FMB because it entered the biologics and gene therapy markets earlier than the startup.

———INSERT THE TABLE (7) OF KRYS-ORGO COMPARISON IN APPENDIX HERE———

How Non-Follower Startups Compete

The comparisons above have helped explain incumbents' choice of late entry into a new market, as later entry may increase the likelihood of achieving FMB in the emerging gene therapy market when competing with non-follower startups, while simultaneously creating FMA in the biologics market. However, what remains puzzling is why startups that lack both FMA and FMB choose to compete with incumbents as non-followers, and what enables them to succeed through value creation.

Are non-follower pioneers' market entry enhanced by their initial human capital? The answer is positive for co-founded pioneers, but not for sole-founded ones. As the Figure 2 illustrates, although showing divergent innovation pathways from their incumbent counterparts, all co-founded startup pioneers (KITE, ONCE, and JUNO) accelerated their innovation through engagement with their first M&As within ten years of founding, but were being acquired by incumbents either right before or soon after receiving a FDA approval in gene therapy.

———INSERT THE FIGURE2 STARTUP PIONEERS' INNOVATION PATHWAYS HERE———

Tracing the human capital development of the Pioneer 5 reveals both similarities and differences. First, being an academic founder appears to be a necessary condition for becoming a non-follower pioneer in an emerging market. For the co-founded startup pioneers KITE and ONCE, the ratios of academic to non-academic founders were 1:2 and 3:5, respectively. Among the incumbent pioneers, all of whom were sole-founded, each founder possessed academic knowledge either before or at the time of market entry. Additionally, the fact that, surprisingly, all three incumbent pioneers were sole-founded, whereas both startup pioneers were co-founded, points to the necessity to compare initial founder human capital at the individual versus team level, and how that human capital composition evolves over time.

Academic Knowledge as a Necessary Condition

Further, comparing the startup pioneers' founding teams with the incumbent pioneers' individual founders indicates that the former possessed a greater diversity of human capital types than the latter. All individual founders of incumbents consistently possessed only science and technology human capital, as reflected in their MD or PhD degrees in fields such as chemical engineering. This homogeneous human capital composition among sole-founded incumbents aligns with the broader pattern observed in the data. Across the 154 individual founders in the sample, only two (1%) possessed all three types of human capital, while 20 (13%) accumulated at least two types. Collectively, these founders held 65 PhDs, 33 MDs, 26 MBAs, and 7 JDs.

In comparison, the co-founded startups' founding team human capital was far more complementary and, therefore, superior, driving their innovation performance despite the absence of both FMA and FMB. Aggregating the individual human capital of KITE and ONCE to the firm level shows that both possessed human capital in science & technology as well as in business. The two founders of KITE had educational backgrounds in MD and economics, respectively. Likewise, ONCE's five founders collectively possessed these two types of human capital: one MD, two PhDs (in Biological Chemistry and Cellular and Molecular Immunology, respectively), two MBAs, one MPA in Public Health, and bachelor's degrees in both STEM and the social sciences.

The fact that academic entrepreneurship characterizes all startup market pioneers in gene therapy aligns with prior findings that academic experience constitutes a superior resource, providing domain-specific knowledge and capabilities in abstract thinking that enable the formulation of effective strategies (e.g., Chattopadhyay et al., 2025).

Creating Value by Becoming Serial Entrepreneurs

Further, although most non-follower startup pioneers become acquisition targets within ten years, their founders create and capture value not as acquired hires but through serial entrepreneurship. Among the seven non-follower startup founders, only one was acquired for a brief period before rejoining a prior co-founder's organization. This case reflects a broader pattern of short tenure among acquired founders: across all sampled companies, every acquired founder departed within two years.

More important, this study found that the founding experiences of non-follower startups entering the emerging gene therapy market marked the beginning of serial entrepreneurship, defined as founders "who have sequentially established and sold multiple entrepreneurial ventures in the past" (Lazar et al., 2020, p. 49), thereby advancing the understanding of when and how entrepreneurial teams form. Among the seven founders from the two non-follower startup pioneers, five subsequently founded eight additional startups. The two founders of KITE later co-founded three startups and served on each other's boards when they were not co-founders. Similarly, all founders of ONCE became serial entrepreneurs, except for the two (female) academic founders.

Additionally, the finding suggests a potential reversal in the temporal order between the processes of searching for / matching with co-founders and the formation of entrepreneurial teams in serial entrepreneurship. While previous studies have shown that founders team up either simultaneously (Mindruta, 2013) or sequentially (Lazar et al., 2020), this study indicates that although team formation and co-founder matching typically follow a linear process where co-founders find each other first and then start a venture, the process can extend across ventures. Sequential team formation in one startup can enable simultaneous teaming in subsequent entrepreneurial ventures.

Taken together, non-follower startup pioneers' ability to create value derives from their proprietary preemption potential (Cirik & Makadok, 2023). Moreover, this potential may be sustained and realized through serial entrepreneurship within the same market, as founders replicate and extend their networks of co-founders long after being acquired.

The Case of Solely Founded Startup Pioneers

How do solely founded startup pioneers lacking academic knowledge compete with their co-founded counterparts and incumbents? Among all startup pioneers, only one company, KRYS, was not co-founded. Its innovation pathway represents the reverse of its counterparts. Whereas co-founded startup pioneers leveraged superior complementary human capital and M&A experience to enhance market entry and create value through serial entrepreneurship, the founder of KRYS compensated for his lack of academic knowledge through employee entrepreneurship, drawing on nearly 25 years of industry experience at major pharmaceutical companies such as Pfizer and two prior founding experiences before entering the gene therapy market.

Although additional cases are needed to determine whether KRYS's innovation pathway can be generalized to other solely founded startup pioneers in other industries, this case supports prior findings that founders who spin off from incumbents may outperform other entrants by inheriting industry-specific knowledge and mindsets (e.g., Benner & Tripsas, 2012).

DISCUSSION

An implication of this study's findings is that complementary human capital at founding affects the innovation outcomes of incumbents and startups differently, and that its effects are indirect and contingent on mechanisms such as M&As. The analysis showed that only a few founders were acquired and that their tenure was short. However, it did not clarify how the mechanism of strategic alliances matters, as the control variable for alliances unexpectedly showed significance across all models and sampled companies.

To address this limitation, future research could explore when complementary human capital matters by comparing merger and acquisition (M&A) mechanisms with alliance mechanisms and examining how competition and collaboration within and across organizations influence innovation outcomes. Prior studies have shown that alliance network positions affect innovation in the biotechnology industry, particularly by enabling firms to bridge disconnected partners (e.g., Hernandez et al., 2025). Moreover, collaboration dynamics have been found to shape individual employee mobility (Campbell et al., 2012) and firm-level rent appropriation (e.g., Ethiraj & Garg, 2012).

Alliance Mechanisms

For market entry, strategic alliance seems to play a more important role than M&As, at least in quantity. In the observed data, there are 426 alliances in total, and, on average, a biopharmaceutical company formed 8.667 alliances. In total, there are 461 alliances. Among 364 distinct partners, 23 partners allied with more than one company. Thus, future research can identity who the most desirable partners are.

More broadly, this topic addresses the conceptual and empirical distinction between *complementary human capital* and *human capital complementarity*. Mindruta et al. (2016) applied a two-sided matching approach to partner selection in alliance formation and identified research alliances as a source of complementarity that enhances firm performance in the biopharmaceutical industry. A key contribution of their study lies in distinguishing between complementarity and compatibility as partner attributes: whereas the former is market-based (Dushnitsky & Shaver, 2009), the latter arises from status and network positions (Hallen, 2008).

More specifically, Mindruta et al. (2016) assess both complementarity and substitution in partner characteristics by highlighting the competitive element in sorting markets. Complementarity refers to positive sorting, where “having more of any one attribute increases the returns of having more of the other attribute” (p. 6). In contrast, substitution represents negative sorting: “two attributes are substitutes if having less (more) of one raises the marginal value of having more (less) of the other” (p. 15). In this way, realized matching reflects true preference—that is, securing the best partner available.

A growing body of literature has built on this concept to analyze how joint value is created through the synergies emerging from collaborations between star employees and their colleagues (Mindruta et al., 2025), how resource complementarity between entrepreneurs and seed investors drives selection and the role of founders' prior industry experience in shaping the matching between startups and their new hires (Honore & Ganco, 2023).

Lastly, this study does not consider human capital transition over time and how it interacts with transitions in leadership to affect the people-profit link. Thus, future study can apply sequence analysis of transition timing by looking into career trajectories among focal and non-focal employees. This is particularly important in entrepreneurship, because founders are stars, the most valuable asset in this context. Thus, whether synergy emerges depends on their interpersonal relationships with other employees. their human capital is rare because it is highly specialized (Coff & Kryscynski, 2011). Further, their exiting directly influence the founding team's mobility as they tend to previously work together (Coff et al., 2020). The negative relationship between FSHC and employee mobility is not applied to founders. Agarwal et al. (2016) showed the role of founders as a team catalyst and their power of taking their founding team with them when exiting because of their ability of facilitating co-mobility of the founding team with complementary skills. Previous studies have shown that founders and their founding teams play a more important role in human capital-based competitive advantage and that the employee mobility of top teams have a more serious, negative effect than that of general employees (Campbell et al., 2012).

CONCLUSION

This study examines the impact of initial complementary human capital on pharmaceutical innovation using a multi-method design. While the quantitative analysis did not corroborate the hypothesis in the empirical setting of 66 biopharmaceutical companies that received their first FDA approvals from the 1980s to the present, additional analyses estimating the model separately for startups and incumbents revealed that founder complementary human capital accelerated innovation speed for incumbents but not for startups. Furthermore, incumbents relied on their founders' complementary human capital to directly enhance innovation speed, rather than through R&D mediation or acquired-founder moderation. By contrast, for startups, the moderated mediation pathway was strong but negative, indicating that they struggled to translate R&D investment into faster innovation—particularly when bringing in acquired founders.

To abductively develop the most plausible explanation for why incumbents and startup pioneers compete as non-followers with different entry orders, a comparative-historical analysis showed that pioneers possess complementary human capital as a superior resource within their founding teams, combining academic knowledge with prior experience in entrepreneurship and market entry from industry. However, although non-follower startups became market pioneers in the emerging gene therapy market, only incumbents achieved FMA and FMB in both established and new markets. Co-founded startups that integrated academic knowledge with serial founding experience were able to compete despite lacking these advantages, whereas founders of solely founded startups exhibited a reversed innovation pathway. Finally, the boundary between founders of incumbents and startups becomes blurred when their career histories and the flow of their human capital are transferred across different types of entrepreneurship (academic, serial, and employee), suggesting that founding team formation is a more complex and dynamic process than previously assumed.

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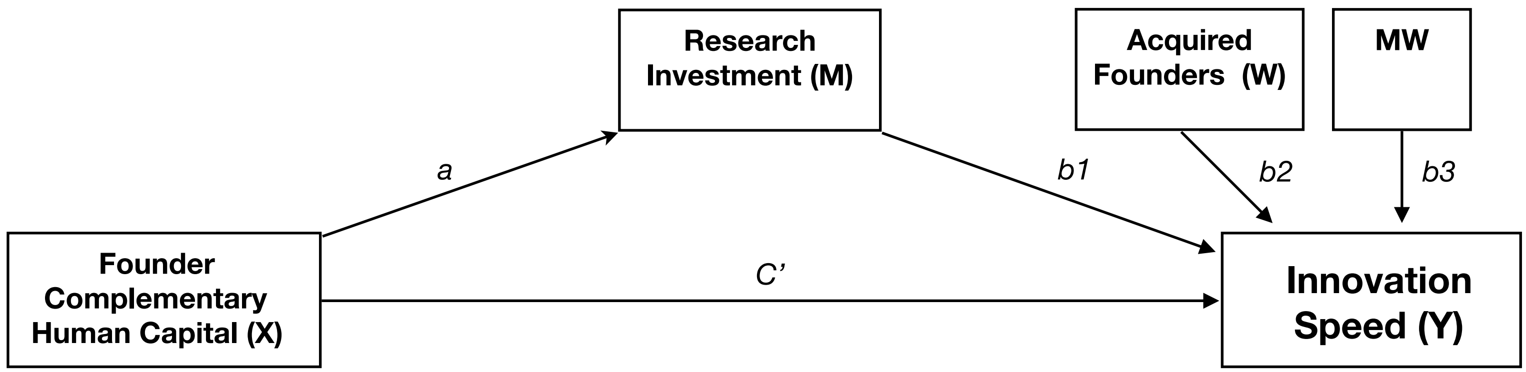
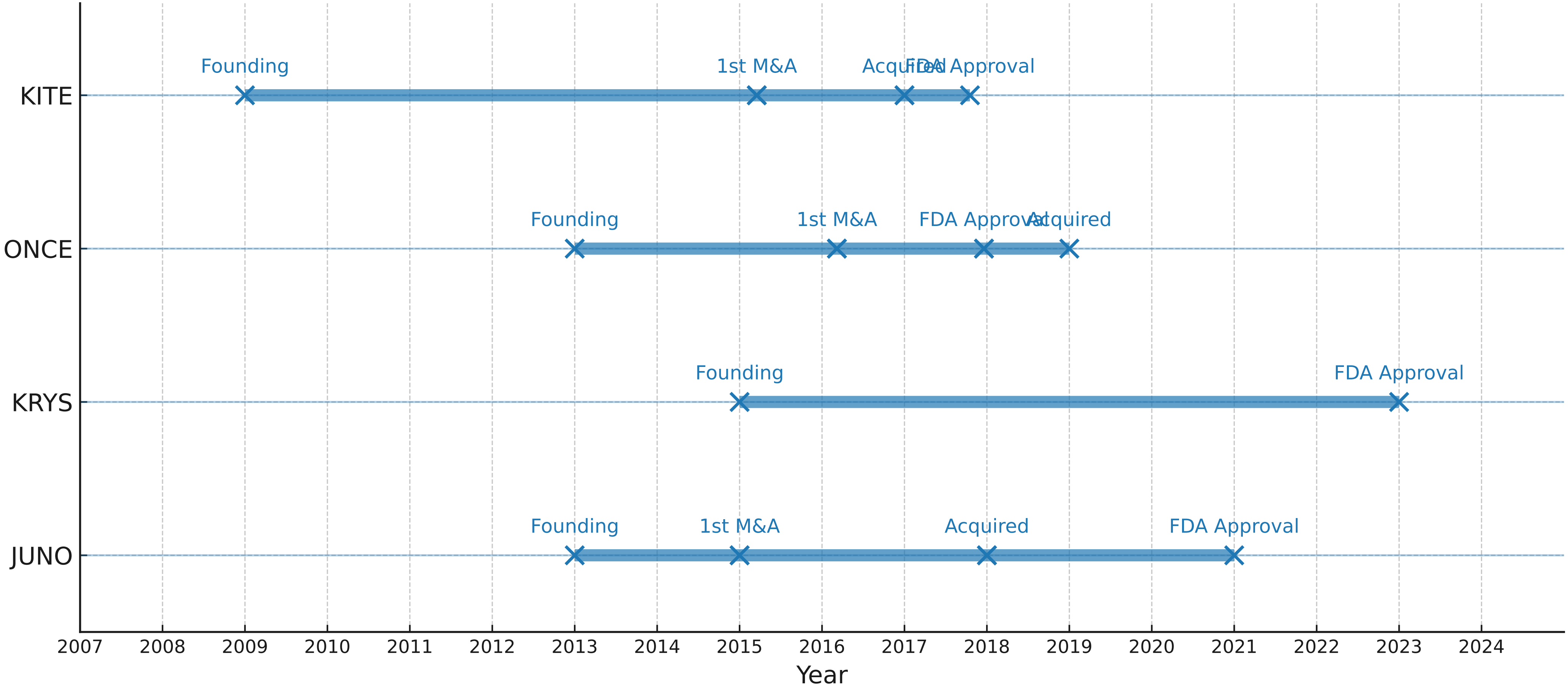
Author’s Note

I acknowledge the use of ChatGPT (OpenAI, GPT-5, 2025) as a digital research assistant in preparing this manuscript. ChatGPT was used to (a) check grammar and spelling throughout the document, (b) generate R code for data analysis, (c) create Figure 2, and (d) generate and format the list of cited references in APA style. All substantive ideas, theoretical framing, research design, analyses, and interpretations are solely my own.

Figure 1. Moderated mediation model linking founder complementary human capital (X) to innovation outcomes (Y), with research investment (M) as mediator and acquired founders (W) as moderator. This study estimated this model separately for startups and incumbents to assess whether the proposed process operates differently across firm types.





KITE
ONCE
KRYS
JUNO
Founding
1st M&A
Acquired
FDA Approval
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1st M&A
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FDA Approval
Founding
1st M&A
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FDA Approval
2007
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Table1. Variable Description

Variable Type	Variable Name	Definition	Measure
Dependent Variable	Innovation Speed	The time a company takes to achieve a successful regulatory innovation outcome from its drug research and development efforts.	The difference between the company's founding year and the year of its first FDA approval in biologic products.
Explanatory Variable	Founder Complementary Capital	A firm-level construct that captures founders' complementary knowledge and industry-specific human capital.	The interaction between founder human capital composition—measured by educational background—and prior industry experience.
Mediator	Research Investment	A firm-level construct that reflects knowledge output as the outcome of internal human capital investment.	The sum of a company's patent counts and scientific publications prior to its first FDA approval in biologic products.
Moderator	Acquired Founders	A firm-level construct that captures a company's external investment in founder-level human capital through M&As.	The total number of acquired founders retained as employees by the acquiring company.
Firm-Level Controls	Drug Development	A company's drug development pipeline across all categories.	Measured as the total number of FDA approvals received from the company's founding year through the year of its first FDA approval in biologic products, with a three-year window applied around that approval. The total number of FDA approvals per company was summed, and a log transformation of this measure was applied in the analysis to reduce skewness.
	Financial Factors	Factors that may influence a biopharmaceutical company's likelihood of initiating preclinical trials, including return on assets (ROA), total assets, R&D intensity, and financial slack.	ROA is calculated as net income divided by total assets; R&D intensity is measured as R&D expenditures relative to total assets; and financial slack is measured as the current ratio of current assets to current liabilities.
	Founder Number	The total number of founders of a company.	For sole-founded companies, the value is coded as 1; for co-founded companies, the value equals the size of the founding team.
	General Human Capital	Indicates whether a founder possesses general managerial training.	A binary variable coded as 1 if a founder holds an MBA degree and 0 otherwise.
	Strategic Alliances	Captures companies' external research investment in strategic alliances prior to their first FDA approval.	For each company, the total number of alliances was computed and log-transformed to reduce skewness and account for zero values.
Individual-Level Controls	Academic Founder	Indicates whether a company's founder held an academic position prior to or after founding the company.	Coded as a binary variable: founders who held a professorial appointment at any point before or after founding are coded as 1; non-academic founders are coded as 0.
	Founder Gender	The gender identity of the company's founder(s).	Coded as a binary variable, with female founders coded as 1 and male founders coded as 0.
	Serial Founder	Indicates whether a founder has prior entrepreneurial experience.	For each founder, a binary variable was created to classify pre-founding employment status into one of four categories: employee, founder, professor, or non-employment.
Deal-Level Controls	Post-Acquisition Integration	Indicates whether the acquired company remained operational as an independent entity following the acquisition.	A binary variable coded as 1 if the acquired company remained a stand-alone entity in its pre-acquisition location three years after the acquisition, and 0 otherwise.
	Target Founder Founding Experience	Indicates whether any acquired founder had prior founding experience.	A binary variable coded as 1 if at least one acquired founder had founded another company prior to acquisition, and 0 otherwise.
	Target Founder Gender	The gender identity of the acquisition target's founders.	Measured as the number of female founders within each acquired company.
	Target Founder Pre-Acquisition Mobility	Founders' employment status prior to their company being acquired.	Calculated as the total number of founders with prior employment experience outside the focal company.
	Venture Capital Funding	The amount of external equity financing a company received from venture capital investors.	Measured as the total amount of venture capital raised (in millions of U.S. dollars). The measure was log-transformed to reduce skewness in the analysis.

Variable Type	Source
Dependent Variable	FDA
Explanatory Variable	Crunchbase, Linkedin
Mediator	FDA, USPTO, Web of Science
Moderator	Crunchbase, Linkedin
Firm-Level Controls	FDA
	WORDs
	Crunchbase, Linkedin
	Crunchbase, Linkedin
	Crunchbase, Factiva
Individual-Level Controls	Crunchbase, Linkedin
	Crunchbase, Linkedin
	Crunchbase, Linkedin
Deal-Level Controls	Crunchbase
	Crunchbase, Linkedin
	Crunchbase, Linkedin
	Crunchbase, Linkedin
	Crunchbase

Table 2. Comparison of Startups and Incumbents

Predictor	Startups	Incumbents	90% CI (Inc.)	p (Inc.)
X → M (a)	0.477	-0.062 (0.091)	[-0.211, 0.087]	0.493
W → Y (b2)	1.929	-3.104 (1.394)	[-5.396, -0.811]	0.026
M → Y (b1)	-12.748	0.350 (0.654)	[-0.725, 1.425]	0.592
M×W → Y (b3)	-35.243	-0.704 (0.593)	[-1.680, 0.272]	0.235
Direct X → Y (c′)	1.519	1.004 (0.393)	[0.357, 1.651]	0.011
Cond. indirect (W = -1 SD)	10.889	-0.066 (0.115)	[-0.255, 0.123]	0.567
Cond. indirect (W = mean)	-6.075	-0.022 (0.055)	[-0.113, 0.069]	0.695
Cond. indirect (W = +1 SD)	-23.038	0.022 (0.065)	[-0.084, 0.129]	0.730
Index of moderated mediation	-16.794	0.044 (0.075)	[-0.079, 0.166]	0.557

Table 3. Market Pioneers in Gene Therapy

	Sole-Founded	Co-Founded
Startups	KRYS (2015-2023)	KITE (2009-2017)
		ONCE (2013-2017)
		JUNO (2013-2021)
Incumbents	ORGO (1985-2018)	BMRN (1997-2023)
	VCEL (1989-2019)	CELG (1986-2021)
	DNDN (1992-2019)	VRTX (1989-2023)
	BLUE (2010-2022)	SRPT (1980-2024)
	GMDA (1998-2023)	PTCT (1998-2024)
	IOVA (2007-2024)	ADAP (2008-2024)
		ABEO (1989-2025)

Table X. Historical Analysis of Startup and Incumbent Pioneers

Firm ID	Company Name											Founder Human Capital		
		Founding Year	1st_Approval_Biologic	1st_Approval_Innovation_Biologics/BLA Number	Clinical Trials_GeneTherapy	1st_Approval_GeneTherapy	Collaborators	1st Innovation_Gene Therapy	Year of Being Acquir	Acquirer	Clinical Studies/NCT number	Founder Number	Founder ID	Founder Name
DNDN	Dendreon Pharmaceuticals LL	1992	April 29, 2010	sipuleucel-T/125197	2003-07	05/28/2019	N	PROVENGE (sipuleucel-T)	2017	Sanpower Group	PROVENGE (NCT00065442)	1	DNDN_f1	Edgar G. Engleman
													DNDN_f1	
KITE	Kite Pharma, Inc.	2009	October 18, 2017	axicabtagene ciloleucel/125643	2018-01-25	10/18/2017	N	YESCARTA (axicabtagene cilo	2017	Gilead Sciences	ZUMA-7 (NCT03391466)	2	KITE_f1	Arie Belldegrun
						07/24/2020	N	TECARTUS (brexucabtagene autoleucel)					KITE_f2	Joshua Kazam
ONCE	Spark Therapeutics, Inc.	2013	December 19, 2017	Voretigene Neparvovec/125610	2012-10	12/19/2017	Y(Children's Ho	LUXTURNA (voretigene nepar	2019	Roche	LUXTURNA/Study 2 (NCT 00999609)	5	ONCE_f1	Beverly L. Davidson
													ONCE_f1	
													ONCE_f2	Fraser Wright
													ONCE_f2	
													ONCE_f3	Jeffrey Marrazzo
													ONCE_f3	
													ONCE_f3	
													ONCE_f3	
													ONCE_f4	Junwei Sun
													ONCE_f4	
													ONCE_f5	Katherine A. High
													ONCE_f5	
ORGO	Organogenesis, Inc.	1985	Mar 9, 2012	Allogeneic Cultured Keratinocytes and Fibroblasts	2013-07	02/20/2018	N	GINTUIT	NA		GINTUIT (NCT01929954)	1	ORGO_f1	Eugene Bell
VCEL	Vericel Corporation	1989	August 22, 1997	Autologous Cultured Chondrocytes/103661	2008-07	05/31/2019	N	MACI (Autologous Cultured Ch	NA		SUMMIT (NCT00719576)	1	VCEL_f1	Bernhard Palsson

	Education			Industry Experienc	Knowledge	Founding Experience	M&A Experience						
Founder Gender	degree_typ	degree_field	degree_yea	industry_entry_yea	Academic Fo	Serial Founder	Pre_Approval_Acquisitior	Announcement Year	Target Name	Target_FoundingYear	Price_Million	target_founder_number	Target_Founders
M	MD	MD	NA	1992	Y		1	2003	Corvas International	NA	NA	NA	
	BA	NA	NA	1992	Y								
M	MD	MD	NA	1996	Y	4 / Bellco Capital, Vida Ventures (2017), Allogene Therapeutics (2017), Kite Pharm	0	2015					
M	BS	Economics	NA	2004	N	5 / Two River (2004), Allogene Therapeutics. Kronos Bio, Vida Ventures, Kite Pharma (2009)							
F	PhD	Biological Chemistry	1987	2014	Y	1 / Spark	1	2016	Genable Technologies	2001	152.5	2	Jane Farrar
	BS	Biology, Chemistry,	1981										
M	PhD	Cellular and Molecular immunol	1989	1991	Y	2 / Kriya (2019), Spark							
	BS	Chemistry, Psychology	1983										
M	MBA	MBA	NA	2011	N	2 / Generation Health, Spark							
	MPA	Public Health	NA										
	BS	Engineering	NA										
	BA	Economics	NA										
M	MBA	MBA	2002	2004	N	2 / VintaBio, Spark							
	BS	Business	2001										
F	MD	MD	NA	2002	Y	1 / Spark							
	BA	Chemistry	NA										
M	PhD	NA	NA	1986	Y		0						Paul Kenna
M	PhD	Chemical Engineering	1984	1989	Y		0						

				Alliance Experience			Resource Endowment	Knowledge Output		Being Acquired	Year_Being Acquired
Target_Founder_Field	Target_Founder_Academ	Target_Serial_Founder	Acquired Founder	Preapproval_Alliances	Joint Ventures	Partner Name	Venture capital_million	Pre-Approval Publications (Found	Pre-Approval Patent Applications (since 2013)		
		0	0	0	0		NA	0	0	Sanpower Group	2017
		0	0	13	2017	Fosun pharma	335.4	0	6	Gilead Sciences	2017
		0	0								
Human Genetics, Certifi	1	0	0	3	2007	National Tissue Enginee	763.8	0	2	Roche	2019
Genetics	1	0	0	4	2016	Selecta BioSciences, Ur	614.7	3	0		
		0	0	0	0		157.3	0	0		

Appendix: Comparisons of FMA and FMB by Entry Order

Table (0): Comparison Template (Extended from Figure 1 in Cirik and Makadok (2023, p. 410))

		Performance of Firm		
		Startups	**Incumbents**	
Under Entry Order Scenario	**Scenario a (A before B)**	Early Entry	Late Entry	Startups' FMA
	Scenario b (B before A)	Late Entry	Early Entry	Incumbents' FMA
		Startups' FMB	Incumbents' FMB	

Table (1): KITE-ORGO Comparison

		Performance of Firm		
		KITE	**ORGO**	
Under Entry Order Scenario	**Biologics**	2017	2012	(-) Startups' FMA
	Gene Therapy	2017	2018	(-) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (2): KITE-VCEL Comparison

		Performance of Firm		
		KITE	**VCEL**	
Under Entry Order Scenario	**Biologics**	2017	1997	(-) Startups' FMA
	Gene Therapy	2017	2019	(-) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (3): KITE-DNDN Comparison

		Performance of Firm		
		KITE	**DNDN**	
Under Entry Order Scenario	**Biologics**	2017	2010	(-) Startups' FMA
	Gene Therapy	2017	2019	(-) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (4): ONCE-ORGO Comparison

		Performance of Firm		
		ONCE	**ORGO**	
Under Entry Order Scenario	**Biologics**	2017	2012	(-) Startups' FMA
	Gene Therapy	2017	2018	(-) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (5): ONCE-VCEL Comparison

		Performance of Firm		
		ONCE	**VCEL**	
Under Entry Order Scenario	**Biologics**	2017	1997	(-) Startups' FMA
	Gene Therapy	2017	2019	(-) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (6): ONCE-DNDN Comparison

		Performance of Firm		
		ONCE	**DNDN**	
Under Entry Order Scenario	**Biologics**	2017	2010	(-) Startups' FMA
	Gene Therapy	2017	2019	(-) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (7): The Scenario When Incumbents Have Achieved both FMA and FMB

		Performance of Firm		
		KRYS	**ORGO**	
Under Entry Order Scenario	**Biologics**	2023	2010	(-) Startups' FMA
	Gene Therapy	2023	2018	(+) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (8): KRYS-ORGO Comparison

		Performance of Firm		
		KRYS	**ORGO**	
Under Entry Order Scenario	**Biologics**	2023	2012	(-) Startups' FMA
	Gene Therapy	2023	2018	(+) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (9): KRYS-VCEL Comparison

		Performance of Firm		
		KRYS	**VCEL**	
Under Entry Order Scenario	**Biologics**	2023	1997	(-) Startups' FMA
	Gene Therapy	2023	2019	(+) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	

Table (9): KRYS-DNDN Comparison

		Performance of Firm		
		KITE	**DNDN**	
Under Entry Order Scenario	**Biologics**	2023	2010	(-) Startups' FMA
	Gene Therapy	2023	2019	(+) Incumbents' FMA
		(-) Startups's FMB	(+) Incumbents' FMB	