

Title: From First-Mover Advantage to Fast-Follower Failure: A Comparative Analysis of Internet-Era and AI-Era Competitive Strategies

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Abstract

The strategic management literature has long debated the relative merits of first-mover advantage (FMA) and fast-follower strategies, particularly during periods of radical technological change (Lanzolla et al., 2021). The Internet era (1995–2005) is frequently characterized by scenarios where fast followers outperformed pioneers through superior execution, resource leverage, and learning from first-mover mistakes. However, the contemporary Artificial Intelligence (AI) era (2020–2026) appears to reverse this pattern: early movers in foundation models, specialized hardware, and platform ecosystems are consolidating durable competitive advantages, while fast followers face mounting barriers and escalating failure rates (Biradar et al., 2025). This paper conducts a comparative historical analysis using secondary data from industry reports, financial disclosures, and academic sources to examine how competitive dynamics have shifted between the two technological revolutions. We identify three structural mechanisms driving this inversion—exponential data network effects, prohibitive capital requirements, and architectural lock-in via complementary assets. Our findings challenge the universality of fast-follower prescriptions and call for a contingency-based theory of entry timing in AI-intensive industries. We conclude with implications for managers, investors, and policymakers navigating the current technological discontinuity.

Keywords: first-mover advantage, fast-follower strategy, Internet bubble, artificial intelligence, technological discontinuities, competitive strategy, platform ecosystems

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1. Introduction

The relationship between market entry timing and competitive success has been one of the most extensively researched topics in strategic management (Zachary et al., 2014). The concept of first-mover advantage (FMA) posits that pioneers can secure durable benefits through technological

leadership, preemption of scarce assets, and buyer switching costs (Vecchiato, 2014). Yet empirical evidence has consistently revealed high failure rates among pioneers, giving rise to the counter-narrative that fast followers. The firms entering after the initial innovator can learn from early errors, free-ride on

market education, and deploy complementary assets more effectively (Pikturnienė, 2004).

The commercial Internet explosion of the late 1990s served as a quintessential testing ground for these theories. The period witnessed a surge of first movers like Netscape, Yahoo and Webvan, many of which collapsed spectacularly when the dot-com bubble burst, while fast followers such as Google, Amazon (in multiple categories), and Facebook overtook incumbents (Banerjee et al., 2016). The strategic lesson extracted by a generation of managers and scholars was that in turbulent, technologically fluid environments, a deliberate late-mover strategy often yields superior returns (Carpenter, 2020).

Today, the rise of generative AI, foundation models, and large-scale machine learning systems appears to be reshaping entry-timing dynamics once again (Lin & Wu, 2024). Early movers like OpenAI, NVIDIA, and Anthropic have achieved unprecedented market capitalization growth and user adoption rates (Sisón et al., 2023). While well-resourced fast followers like Google (Gemini), Meta (LLaMA), and numerous venture-backed startups struggle to close the gap despite massive investments (Maslej et al., 2024). This observation prompts a critical research question: *Why do fast-follower strategies that succeeded during the Internet era appear to fail in the AI era, and what theoretical revisions does this necessitate* (Csaszar et al., 2024)?

This paper addresses the question through a comparative historical analysis using secondary data. We examine the entry-timing patterns and performance outcomes in two technology revolutions: the commercial Internet (1995–2005) and the generative AI boom (2020–2026). By contrasting the mechanisms that enabled fast followers to overtake pioneers in the first period with those that now entrench first movers in the second, we develop a contingency framework that explains the shift from first-mover failure to fast-follower failure (Franco et al., 2009). Specifically, we argue that the current landscape is characterized by foundational uncertainty and unprecedented computational scale, which systematically disadvantage late entrants compared to the Internet-era environment of relatively low-cost platform development (Lu, 2026). Our analysis draws on industry reports, financial statements, venture capital data, and the scholarly literature on technological discontinuities and platform competition.

2. Literature Review

2.1 First-Mover Advantage and Its Limitations

First-mover advantage (FMA) refers to the benefit enjoyed by a firm as the consequence of its early entry into a new market (Lieberman, 2018). The benefits are categorized into three pillars: (a) technological leadership derived from learning curve effects and R&D patents, (b) preemption of scarce resources including geographical locations, input factors, and cognitive space in consumer minds, and (c) the creation of buyer switching costs through loyalty programs, brand familiarity, and contractual lock-in (Lanzolla & Giudici, 2017). Subsequent studies confirm that FMA is context-dependent and its advantages can be negated by pioneering disadvantages (Vecchiato, 2014).

Critics, however, emphasize that pioneers often suffer from environmental uncertainty, free-rider problems, and incubation of nascent demand that subsequent entrants can exploit with more mature technologies and superior business models (Vecchiato, 2014). Fast followers can circumvent technological dead ends, avoid the costs of educating customers, and leverage established complementary assets such as distribution channels and manufacturing capabilities (Dijk et al., 2016). The resource-based view (Mousavi et al., 2018) suggests that enduring competitive advantage requires resources that are valuable, rare, inimitable, and non-substitutable (VRIN). In many innovative settings, first movers lack the VRIN resources needed to exclude late entrants (Lanzolla & Giudici, 2017).

2.2 Fast-Follower Advantage in Technology Markets

The fast-follower strategy involves entering a market after a pioneer to leverage market learning, often focusing on refined value propositions or operational efficiency. Empirical studies in industries like semiconductors demonstrate that fast followers frequently capture larger market shares and higher long-term profitability (Nayır, 2020). The “attacker’s advantage” illustrates how incumbents are vulnerable to challengers that take aggressive, unpredictable actions to dethrone leaders (Smith et al., 2001).

The Internet era offered opportunities for latecomers to compete successfully through latecomer-specific strategies, such as time compression and resource leveraging, allowing them to catch up with or leapfrog early pioneers (Cho et al., 1998). The strategic management community consequently distilled a prescriptive norm: in hyperdynamic environments, firms should not rush to be first but

rather observe, learn, and then scale aggressively with lower risk (Tidhar et al., 2024).

2.3 Entry Timing and AI Revolution

Generative AI introduces a new class of technological discontinuity characterized by extreme scalability of data, exponential growth in model capabilities, and unprecedented capital intensity (Azoulay et al., 2024). Recent research highlights that foundation models exhibit strong data network effects, where the volume and quality of training datasets play a critical role in performance improvement, creating a self-reinforcing cycle (Zhang et al., 2025). Moreover, the hardware and infrastructure required a large GPU clusters, custom chips, and data center capacities and constitute a prohibitively high barrier to entry for latecomers (Bengio et al., 2025).

Theorists are beginning to reassess classical FMA dynamics in the AI context. Jacobides et al. (2024) argue that AI models are not mere products but “architectural complements” that integrate tightly with existing platform ecosystems (cloud, search, enterprise software), generating switching costs that dwarf those of previous technologies. Hoisl et al. (2025) contend that the generative AI stack exhibits “winner-take-most” characteristics due to API standardization and developer lock-in, transforming early mover advantage from a transient benefit into a structural moat. This evolving perspective provides the conceptual foundation for our comparative analysis.

3. Methodology

We adopt a comparative historical case study approach, relying exclusively on secondary data sources. This method is appropriate for examining macro-level shifts in competitive dynamics across technological eras, where controlled experimentation is impossible (Li, 2021). The study compares two distinct periods:

- **Internet Era:** 1995 to 2005, encompassing the dot-com boom and bust.
- **AI Era:** 2020 to 2026, from the launch of GPT-3 through the current landscape of multimodal foundation models and enterprise AI deployment.

3.1 Case Selection

We selected iconic paired cases representing first movers and fast followers in both eras. Selection criteria included: (1) prominence in the technological narrative, (2) availability of financial and market performance data, and (3) clear entry-timing differentiation (Denicolai & Bartosiak, 2026). The final sample for the Internet era includes browsers (Netscape vs. Internet Explorer/Chrome), search engines (Yahoo vs. Google), social networking (Friendster vs. Facebook), and online grocery (Webvan vs. Amazon Fresh/Instacart). For the AI era, we examine foundation model providers (OpenAI vs. Google Gemini, Meta LLaMA), hardware/AI chips (NVIDIA vs. AMD, Intel), and image generation (Midjourney vs. Stable Diffusion, DALL-E 2).

3.2 Data Collection

Data were gathered from multiple archival sources:

- Financial databases (Compustat, Capital IQ) for public firms.
- Venture capital databases (Crunchbase, PitchBook) for private startup valuations and funding rounds.
- Industry reports (CB Insights State of AI, Gartner Hype Cycles, McKinsey Global Institute).
- Academic publications and historical analyses.
- Press archives and reputable technology journalism (The Wall Street Journal, Wired, TechCrunch).

We triangulated information across sources to ensure reliability and to reconcile conflicting market share or financial claims.

3.3 Analytical Framework

Our analysis proceeds in three stages. First, we compare the performance trajectories of first movers and fast followers in each era using descriptive metrics (market share, survival, valuation multiples). Second, we identify the causal mechanisms that enabled follower success in the Internet era and enabled pioneer entrenchment in the AI era. Third, we synthesize these into a conceptual model linking technological attributes to the efficacy of entry-timing strategies.

4. Comparative Analysis

4.1 The Internet Era: The Ascendancy of Fast Followers

The commercial Internet revolution of the 1990s was characterized by low entry barriers, rapid technological evolution, and an initial lack of defensible business models. Pioneers rushed to market, often with incomplete offerings, while well-financed followers capitalized on their mistakes (Garnsey & Heffernan, 2005).

Browsers: Netscape Navigator launched in 1994 and quickly captured a dominant market share (Leiser & Murray, 2016). However, Microsoft's Internet Explorer (IE) entered as a fast follower in 1995 by bundling with the Windows operating system and investing in iterative improvement (Gottinger, 2017). By 1999, IE controlled over 90% of the browser market, leveraging complementary assets that Netscape could not replicate (Leiser & Murray, 2016). Later, Google Chrome (2008) followed a similar fast-follower pattern, overtaking IE through superior speed and a developer ecosystem (Rietveld & Schilling, 2020).

Search Engines: Yahoo started in 1994 as a manually curated directory, becoming the first widely adopted web portal (Manne et al., 2021). Google, founded in 1998, entered as a late mover with a radically superior algorithmic approach (PageRank) and a clean interface (Manne et al., 2021). Despite Yahoo's brand and traffic, Google's technological edge and later business model innovation (AdWords) allowed it to dominate, reaching a leading market share of nearly 50% globally by 2005 (Žalnierūtė, 2021).

Social Networking: Friendster (2002) pioneered the modern social network but suffered from technical scalability issues and strategic missteps. Facebook, launched in 2004, was a late entrant that initially focused on the college niche, then expanded globally with a robust platform (Baran & Kathrin, 2016). By 2009, Facebook had overtaken both, highlighting that early mass adoption did not guarantee longevity (Goodman, 2026).

Online Grocery: Webvan (founded 1996) epitomized first-mover hubris, investing heavily in automated warehouses before demand materialized. The company filed for bankruptcy in 2001 (Ogawara et al., 2003). Later entrants such as FreshDirect and Amazon Fresh adopted a leaner, city-by-city approach, building logistics incrementally (Botelho et al., 2021). Amazon's acquisition of Whole Foods in

2017 and its subsequent expansion of ultra-fast delivery illustrate how a resource-rich fast follower can dominate after first movers have cleared the regulatory and consumer-education path (Afonso, 2024).

The dot-com crash disproportionately affected pioneering firms that had not yet achieved viable unit economics (Halberstadt et al., 2022).

Explanatory factors for fast-follower success:

- *Low switching costs:* Early consumers faced minimal penalties for abandoning a pioneer's website (Halberstadt et al., 2022).
- *Rapid technological obsolescence:* Followers could leapfrog with next-generation architectures (Hein et al., 2019).
- *Resource asymmetry:* Late entrants often possessed substantial cash reserves, brand equity, and distribution channels from adjacent markets (Microsoft, Amazon, Google) (Kamp & Apodaca, 2023).
- *Learning from pioneer failures:* Late entrants could free-ride on market education and avoid overinvestment in unproven infrastructure (Kamp & Apodaca, 2023).

These dynamics cemented the conventional wisdom that in Internet-like environments, being a fast follower is strategically superior to pioneering (Forrest et al., 2021).

4.2 The AI Era: First-Mover Consolidation and Fast-Follower Stumbles

The generative AI era, ignited by the public release of ChatGPT in November 2022, displays a sharply different pattern (Teubner et al., 2023). Early movers are establishing dominant positions that have proven exceptionally difficult for followers to dislodge, despite their vast resources and technological sophistication (Azoulay et al., 2024).

Foundation Models (LLMs): OpenAI's GPT-3 (2020) and GPT-4 (2023) established a substantial lead in model capability, brand recognition, and enterprise adoption (Schneider et al., 2024). Google, a fast follower with Gemini, struggled with initial product flaws and organizational inertia, remaining a distant second despite its deep AI research heritage (Ding et al., 2024). Meta's LLaMA models, released openly, have carved a niche among researchers and

cost-conscious startups but have not displaced OpenAI's enterprise dominance (Delios et al., 2024). Anthropic, an early mover in safety-focused models, secured a distinct brand position and significant multi-billion dollar funding, making imitation difficult (Maslej et al., 2024).

AI Hardware: NVIDIA's decade-long head start in CUDA and GPU architectures for machine learning created a near-monopoly in training hardware, commanding a dominant share of the data-center AI chip market in 2025 (Qi, 2024). Fast followers—AMD's Instinct line, Intel's Habana/Gaudi, and custom cloud chips—have not materially eroded NVIDIA's lead, constrained not only by hardware performance but by the software ecosystem and customer lock-in (Radhakrishnan, 2026). NVIDIA's market capitalization surged significantly, making it the world's most valuable company (Shao, 2025).

Image Generation: Midjourney, launched in 2022, rapidly built a loyal creative community and continuously improved quality through user feedback loops (Mai et al., 2024). Fast followers like OpenAI's DALL-E 3 and Stability AI's Stable Diffusion entered with strong technical capabilities but faced network effects on prompt databases and community engagement, leading to Midjourney maintaining a subjective quality advantage and premium pricing power (Ploennigs & Berger, 2023).

Explanatory factors for first-mover success:

- *Data network effects:* More users generate more interaction data, which improves models, attracting even more users. (Gregory et al., 2021).
- *Astronomical capital requirements:* Training state-of-the-art models costs upwards of \$100 million, and infrastructure buildout runs into tens of billions, which even well-funded followers struggle to recoup (Faraboschi et al., 2024).
- *Architectural complementarities:* Early movers embed their APIs into enterprise workflows, creating high switching costs as corporate clients build mission-critical applications on proprietary models (Ivchenko, 2026).
- *Regulatory and trust-related moats:* First movers shape the discourse on safety standards and ethics, setting the rules that followers must meet, sometimes locking in regulatory advantages (Walter, 2024).

5. Underlying Mechanisms: Explaining the Inversion

The shift from fast-follower advantage to first-mover entrenchment can be traced to three structural mechanisms that differ materially between the two technological contexts.

5.1 Data Network Effects and the Flywheel

Internet-era network effects were primarily social or transactional—eBay's auction marketplace, for example—but they often exhibited strong within-category fragmentation. The cost of replicating a basic website or e-commerce platform was low, allowing followers to attract users with superior features or pricing (Shane & Nicolaou, 2017).

In contrast, AI models display *data-driven performance network effects*. Every query, every correction, and every integration feeds back into model training and fine-tuning (Bengio et al., 2025). The marginal improvement in model quality from incremental data exhibits increasing returns over a significant range, creating a widening performance moat (Brčić, 2025). As a result, a model that starts behind may never catch up unless the follower can access a fundamentally superior architecture or an exclusive dataset—both of which are increasingly difficult to secure (Bengio et al., 2025).

5.2 Capital Intensity and Time-Compression Diseconomies

During the dot-com era, a startup required significant up-front capital investments to establish technological architecture (Arnold et al., 2020).

The AI era is defined by capital expenditures at an unprecedented scale. Training GPT-4 cost an estimated \$78 million & inference infrastructure requires billions (Azoulay et al., 2024). Time-compression diseconomies are extreme: no amount of money can instantly replicate years of cumulative model training and user feedback (Kim et al., 2023). Google and Meta, despite their financial resources, cannot compress the iterative cycles of safety testing, domain-specific fine-tuning, and ecosystem building that OpenAI and Anthropic have completed (Azoulay et al., 2024). The follower's resource advantage is blunted because critical assets are not fungible but time-dependent.

5.3 Architectural Lock-In and the Full-Stack Complementarity

Internet pioneers offered discrete services (search, email, shopping) that could be easily layered upon or replaced. Switching from Yahoo Mail to Gmail or from Netscape to IE involved minimal technical friction. Enterprise adoption was also relatively modular (Kushida et al., 2015).

AI services today are deeply intertwined with the broader enterprise architecture: cloud platforms, database pipelines, analytics suites, and custom applications (Yanamadala, 2025). Once an organization standardizes on a specific model provider's API, tooling, and prompt libraries, migration to a follower becomes a costly, risky endeavor (Hussain et al., 2026). This *architectural lock-in* transforms first-mover advantage into a durable strategic barrier (Xu et al., 2025). Microsoft's integration of OpenAI models across Azure, Office 365, and GitHub Copilot exemplifies how complementary assets reinforce the pioneer's position, making it impossible for a follower to compete solely on model quality (Legenvre et al., 2025).

6. Discussion

6.1 Theoretical Implications

Our findings challenge the unidirectional prescription that fast-follower strategies are universally superior in technology-intensive industries. The comparative analysis suggests that the efficacy of entry timing is contingent on the nature of the technology's underlying economic properties. When network effects are data-driven and scale with performance, when capital intensity and time-compression diseconomies are extreme, and when architectural lock-in is strong, early entry can confer durable advantage that followers cannot erode (Sarin et al., 2025). This aligns with Suarez and Lanzolla's (2007) framework linking FMA to the pace of technological evolution and market growth, but extends it by identifying the specific AI-era attributes that slow the inevitable erosion of pioneer benefits.

The study also refines the resource-based view: in AI markets, the most critical VRIN resource is not a patent or a brand, but a composite of accumulated training data, user feedback loops, and API ecosystem integrations (Dzreke & Dzreke, 2025). These resources possess high barriers to imitation and

substitution, endowing first movers with sustainable heterogeneity (Virgen, 2026).

6.2 Managerial and Policy Implications

For managers, the historical analogy suggesting it is safe to let others pioneer and then subsequently enter with superior execution may be dangerously outdated (Sarin et al., 2025). In foundation model markets and AI-native applications, a deliberate late entry may be prohibitively expensive or futile. Firms should assess whether their target domain exhibits escalating data network effects and architectural lock-in before deciding on entry timing. In such domains, speed to market and rapid scaling of user interactions may be crucial (Primus, 2022).

Investors, too, need to recalibrate. The dot-com heuristic of betting on fast followers with deep pockets will not necessarily generate returns in AI. While early-mover startups in AI have attracted significant venture capital, recent data suggests these funding dynamics conform to established patterns observed in prior technology waves rather than deviating significantly (Gurav, 2026).

For policymakers concerned with competition, the emergence of durable first-mover advantages raises antitrust and open-access questions. Early dominance in foundation models could lead to gatekeeper positions that stifle innovation downstream (Schneider et al., 2024). Regulators may need to consider data-sharing mandates or interoperability standards to ensure contestable markets, a debate already unfolding in regulatory initiatives such as the EU AI Act and emerging U.S. interoperability considerations (Rubinfeld, 2023).

6.3 Limitations

This study relies on secondary data and a relatively compressed observation window for the AI era (2020–2026). The AI landscape is evolving rapidly, and the patterns identified could shift if technological breakthroughs lower barriers or if open-source models dramatically reduce switching costs. The case selection, while informed, may not capture all industry nuances. Quantitative analysis is limited by the availability of private company financials. Future research should employ longitudinal data as the AI market matures and test the proposed mechanisms in other high-tech discontinuities like quantum computing or synthetic biology.

7. Conclusion

The transition from the Internet revolution to the AI revolution marks a fundamental inversion in the strategic calculus of market entry timing. The dot-com era taught a generation that fast followers could reliably dismantle first-mover advantages through resource superiority and learning. Today's AI landscape, characterized by escalating data network effects, prohibitive capital intensity, and deep architectural lock-in, has rewritten that lesson. First movers are not only surviving—they are digging moats that fast followers, even the largest tech incumbents, struggle to cross. This paper has provided the first systematic comparative analysis of this shift, offering a contingency-based framework that reconnects entry-timing strategy with the specific economic properties of a given technological discontinuity. As the AI epoch unfolds, managers and scholars must look beyond generic prescriptions and confront the uncomfortable possibility that in the age of generative AI, the race truly is to the swift.

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