Lean Thinking, Deep Impact?
Early Exploration Strategies and Commercialization of Deeptech Ventures

ABSTRACT: This paper examines how early exploration strategies, sequential or parallel, affect the financial and innovation outcomes of deeptech ventures. These firms must navigate multiple dimensions of uncertainty, including the underlying technology. Moreover, they rely on physical assets to commercialize, incurring significant opportunity costs for search. While entrepreneurial strategy research has emphasized on experimentation to resolve uncertainty, it has largely focused on asset-light contexts such as software. Even lean methods, which promote early commercial exploration for learning, are better suited to digital ventures where the primary risk is market-based. As a result, less is known about the implications of exploration strategy in high uncertainty, asset-intensive settings. To analyze this, I assembled a novel longitudinal dataset of 13,790 hardware-oriented firms using primary and archival sources, augmented by machine learning and NLP techniques. Employing multiple empirical approaches including an exogenous technology development (3D-Printing), the study finds that parallel exploration improves the likelihood of early commercial outcomes by mitigating information frictions with potential resource providers. In contrast, sequential exploration fosters organizational learning, yielding long-run financial and technological performance.

These findings highlight the trade-offs faced by boundedly rational entrepreneurs as they navigate uncertainty and information asymmetry while enhancing learning. This research contributes to work on entrepreneurial strategy and experimentation, especially in contexts with high uncertainty and opportunity costs. It also offers managerial insights on the boundary conditions for deploying lean methods for scaling science and technology ventures.

1. Introduction and motivation

Deeptech startups, also referred to as “hardtech” or “toughtech”, are a distinct category of entrepreneurial firms grounded in breakthrough science and engineering innovation (MIT: Basilio, Murray & Frolund, 2023). Spanning sectors such as life sciences, advanced materials, robotics and quantum computing, these ventures operate under high levels of scientific, technological, commercial, and often regulatory uncertainty. Unlike software startups, deeptech firms face long gestation periods and require considerable capital to commercialize and scale (Arora, Fosfuri, & Roende, 2024). Digital ventures contend primarily with commercial risk in environments where the underlying technology is well-established. For instance, Airbnb used mature cloud technologies to build a multi-sided platform and address market uncertainty, leading to commercial success. In contrast, deeptech firms grapple with multiple dimensions of uncertainty, including the underlying technology, which necessitates a more complex and deliberate approach to early exploration. A battery technology venture like QuantumScape faced significant technological uncertainty when developing a prototype using novel materials, while also battling commercial risks in the competitive energy storage market. Moreover, deeptech firms often rely on physical complementary assets to commercialize, posing considerable challenges in experimentation and testing. Formulating entrepreneurial strategy can be a complex endeavor, requiring exploration to resolve uncertainty and chart a path forward yet demanding early commitment to specific strategic choices (Gans, Stern & Wu, 2019). But these trade-offs are especially pronounced for deeptech firms, which operate in asset-intensive contexts while navigating multiple vectors of uncertainty.

Extant research on entrepreneurial strategy has studied how startups use experimentation to resolve uncertainty when pursuing new opportunities (Agrawal, Camuffo, Gans, Scott & Stern, 2024; Koning, Hasan & Chatterji, 2022). Lean methods have been widely adopted by startups as an entrepreneurial approach, emphasizing rapid experimentation and learning from customers (Contigiani & Levinthal, 2019; Felin, Gambardella, Novelli & Zenger, 2024; Blank & Eckhardt, 2024). Yet, we still lack a clear understanding of the early experimental design choices that entrepreneurs make and their downstream implications on strategy and performance (Camuffo et al., 2024). Moreover, much of the academic and practitioner literature in entrepreneurship has focused on startups in asset-light contexts such as software, where the main source of uncertainty is commercial. In contrast, early exploration choices are especially critical for asset-intensive deeptech firms as experimentation and testing entail significant commitment and opportunity costs. *The paper addresses these gaps by examining how the timing and sequencing of exploration affects the outcomes of deeptech firms.*

Deeptech firms typically undertake at least two distinct phases of exploration: technological and commercial. They search along an axis of technological uncertainty, and separately, along a commercial axis to identify product-market fit. While these vectors are not necessarily orthogonal, they are characterized by distinct routines, organizational dynamics and performance dimensions. Crucially, both types of searches represent uncharted territory for the nascent organization. Firms are said to engage in parallel exploration when technological and commercial search occur somewhat concurrently; when commercial follows technological exploration, the strategy is considered sequential (Levinthal & Posen, 2007; Loch, Terwiesch & Thomke, 2001). *This paper investigates how parallel versus sequential exploration strategies influence the financial and technological performance of deeptech ventures.*

When firms engage in parallel exploration, the resulting insights from experimentation can offer clearer signals of early commercial viability to external stakeholders such as potential investors, thereby reducing information frictions. Accordingly, I hypothesize that parallel exploration enables higher likelihood of early funding outcomes but also heightens the risk of failure. However, the intensity of concurrent experimentation may strain the cognitive capacities of entrepreneurs leading to inefficiencies in organizational learning. In contrast, sequential exploration allows for slower learning and more deliberate problem-solving, enabling firms to overcome technological bottlenecks before engaging in commercial exploration. I therefore hypothesize that a serial approach supports long-run technological and financial performance.

To empirically test my hypotheses, I assembled a novel longitudinal dataset comprising 13,790 firms (~118,000 firm-year observations) using a combination of primary information, archival sources, machine learning (ML) and natural language processing (NLP). The empirical setting involves hardware-oriented deeptech sectors such as aerospace, advanced manufacturing, and life sciences, where firms depend on tangible complementary assets for commercialization and face considerable challenges in exploration and scaling. I employed multiple empirical strategies to help mitigate the confound of unobserved entrepreneurial selection into exploration modes. These include a difference-in-difference specification exploiting the exogenous emergence of 3D printing (3DP) or additive manufacturing, following approaches akin to Ewens, Nanda & Rhodes-Kropf (2018) and Furman & Teodoridis (2020). I also incorporated behavioral measures that leverage the variation in firms' patenting and trademarking practices, as well as the timing of their first business-related job posting.

Empirical evidence suggests that parallel exploration is indeed associated with a greater likelihood of early financial outcomes but also a higher risk of failure when experiments yield negative signals. In contrast, firms pursuing early serial exploration are more likely to go public and generate patents.

Interestingly, parallel exploration is also linked to a higher probability of the firm being acquired (M&A). Together, these findings support the argument that parallel experimentation fosters early commercial success by improving information parity with potential resource providers, including acquirers. A serial strategy, on the other hand, enhances organizational learning leading to sustained technological output that underpins long-run financial success.

This study contributes to research in entrepreneurship and technology strategy. While emerging work on entrepreneurial experimentation and learning has largely focused on digital-centric contexts (Koning et al., 2022), this study examines hardware-oriented deeptech firms that negotiate multiple dimensions of uncertainty while experimenting in costly settings. Gans et al. (2019) describe the "paradox of entrepreneurship" as the tension between using experimentation to resolve uncertainty and the need to commit to strategic choices early on. Choosing specific exploration pathways in the deeptech context necessitates considerable commitment as it can entail a degree of irreversibility (Pillai, Goldfarb & Kirsch, 2020). Prematurely engaging in commercial exploration before resolving core technological uncertainty may lock a firm into a trajectory that is hard to reverse. While parallel approaches have been shown to unequivocally yield superior outcomes for digital ventures, the effects of exploration strategies on deeptech firms are clearly more nuanced. They involve substantive trade-offs that further accentuate the entrepreneurial conundrum (Gans et al., 2019). Finally, the findings highlight managerial and policy implications, specifically on the boundary conditions for applying lean methods in science and technology ventures. While parallel exploration influences firm failures and acquisitions, potentially facilitating resource reallocation and "creative destruction" in the aggregate, sequential exploration appears to foster more individually innovative firms in the long run.

2. Research Context

2.1 Deeptech firms: exploration, multiple uncertainties and information asymmetry

Founded in 2008, Airbnb emerged as one of Silicon Valley's most innovative startups disrupting the hospitality industry. It navigated the commercial challenge of customer adoption by building a multi-sided platform, creating extensive network externalities and going public in 2020. Airbnb was able to accomplish this by leveraging established internet and cloud technologies, thereby avoiding fundamental technological uncertainty. Meanwhile, QuantumScape, a Stanford University spinoff, received an ARPA-E grant in 2010 to develop an "all-electron" battery technology with higher power and energy-density[1]. Confronted with severe technological challenges, the firm pivoted to Lithium-ion technology. After several years, proof of concept was demonstrated in collaboration with Volkswagen. Despite going public in 2020, QuantumScape has yet to "commercialize" its technology, having generated limited revenues since inception.

These cases illustrate the contrasting environments in which deeptech firms strive to grow, in comparison to other entrepreneurial firms (figure 1). Digital startups primarily navigate market risks, typically treating their technological degree of freedom as fixed. In contrast, deeptech firms are rooted in scientific or engineering innovation and thus face a broader, more complex set of risks on the path to commercialization. These firms must navigate commercial uncertainty even as the foundational technology remains nascent (figure 2). While technological and commercial uncertainty are often interrelated, they pose distinct challenges to entrepreneurial firms constrained by limited resources and bounded managerial cognition. Additional dimensions of uncertainty, such as regulatory risk, may further complicate progress (Gao & McDonald, 2019). Moreover, the choice of exploration strategy and experimental design demands strategic commitment. In digital ventures, it is feasible to engage in parallel experimentation with relatively low commitment but still acquire organizational learning (Pillai et al., 2020). In deeptech, however, selecting a particular exploratory path may entail irreversibility and longer-term lock-in. As such, the combination of multiple uncertainties and the high opportunity costs create a context that necessitates a more deliberate and nuanced approach to exploration.

Entrepreneurial firms face both internal uncertainty regarding the opportunity they pursue and information frictions in their interactions with external stakeholders (Shane & Venkatraman, 2000; Kerr,

[1] https://arpa-e.energy.gov/news-and-media/blog-posts/arpa-e-investor-update-vol-1-quantumscape-ev-phev-battery

Nanda & Rhodes-Kropf, 2014; Furr & Eisenhardt, 2021) (figure 3). Entrepreneurs experience Knightian uncertainty arising from the indeterminate nature of whether a given technology, product, or business model will succeed (Knight, 1921; Alvarez & Barney, 2005). Information asymmetry, by contrast, reflects the limited visibility external stakeholders (such as potential investors) have into a firm's viability (Akerlof, 1970). While conceptually similar, these constructs capture different aspects of the uncertainty dynamic and can vary in intensity for the same opportunity. For instance, an entrepreneur operating a laundromat may experience little uncertainty, while investors might perceive information frictions due to limited insight into her execution capability. In the case of deeptech, both uncertainty and information asymmetry are likely to be amplified.

Experimentation enables entrepreneurs to reduce internal uncertainty and mitigate information frictions (Agrawal et al., 2024a; Kerr et al., 2014). However, the timing and sequencing of exploration can shape the uncertainty–asymmetry dynamic in distinct ways, thereby influencing firm outcomes. Equally, its effect on information asymmetry may vary across stakeholder groups. In the following section, I develop a categorization of the key explanatory variable, exploration strategy, into *sequential and parallel* forms, and elaborate on how these different approaches affect firm outcomes.

2.2 Timing and sequencing of exploration – parallel versus sequential

March (1991) defines exploration as experimentation with new alternatives, in contrast to exploitation, which involves the refinement and extension of existing competencies, technologies, and paradigms. The key distinction between explore and exploit comes from the locus of learning being further removed from the locus of realized returns, as is the uncertainty. Entrepreneurial strategy literature has typically employed the explore-then-exploit paradigm to examine venture lifecycles (Contigiani & Levinthal, 2019). New ventures initially explore to identify the right market and application, shifting towards exploit to implement the chosen business model and scale operations (Lee & Kim, 2024). This paradigm aligns well with the evolution of digital startups.

However, firms like QuantumScape confront multiple, interdependent (and potentially epistemic) uncertainties related to technology, markets, and ecosystems. In such contexts, uncertainty resolution may not occur in isolation, but rather through multiple, interconnected explorations—whether sequential, pooled, or reciprocal (Kapoor & Klueter, 2021). Moreover, the classification of an activity as exploration or exploitation depends on the observer and the performance dimension under consideration (Adner & Levinthal, 2008).

Building on this rationale, I introduce a conceptual nuance within the broader ambit of exploration. Deeptech firms typically engage in (at least) two distinct phases of exploration: technological and commercial. For example, QuantumScape first searched along an axis of technological uncertainty—evaluating alternative materials—and then along a commercial axis to identify product–market fit. While these vectors are certainly interrelated, they involve distinct routines and performance dimensions. Crucially, both represent uncharted territory for the nascent organization. I define firms as engaging in *parallel exploration* when technological and commercial search occur concurrently; when commercial follows technological, the strategy is considered *sequential*. The choice between sequential and parallel experimentation is not merely theoretical—it plays out in real time for deeptech ventures navigating uncertainty.

Levinthal and Posen (2007) explore this distinction in the context of organizational selection, suggesting that firms with separate R&D and marketing functions may decompose the problem and search either sequentially or in parallel. However, while such tasks may be functionally decomposable in established firms, resource-constrained startups often rely on the same founding team and limited cognitive bandwidth to conduct both forms of exploration. A related terminology describes sequential versus parallel strategy as a modular versus integrative approach, in which firms either address one strategic domain at a time or pursue multiple domains simultaneously (Ott & Eisenhardt, 2020).

The trade-offs associated with the sequencing of experimentation have been explored in product testing (Loch, Terwiesch, & Thomke, 2001) and machine learning contexts (Desautels et al., 2014). In these domains, 'parallel' typically refers to the simultaneous testing of multiple hypotheses, in contrast to evaluating a single hypothesis. While this differs slightly from how I define *parallel* and *sequential*, the broader insights remain highly relevant. Loch et al. (2001) find that parallel testing drives speedier implementation but the potential for learning between tests is underutilized. Furthermore, the interdependency between the unknowns determines the choice between fewer high-fidelity tests and many low-fidelity ones (Thomke & Bell, 2001). In asset-heavy settings, elevated opportunity costs associated with hypothesis testing further accentuate the trade-offs between sequential and parallel approaches (Agrawal, McHale, & Oettl, 2024). Whereas parallel testing accelerates decision-making, it comes at a higher economic cost; sequential testing, in turn, is associated with greater innovation and profitability.

Exploration choices have also been examined through the lens of reversibility and repeatability (Adner & Levinthal, 2024). One-time, irreversible experiments—such as a brand reorientation or strategic pivot—entail significantly higher stakes than repeatable experiments like laboratory trials or A/B testing (Pillai et al., 2020). In this framing, *sequential* exploration reflects a high-fidelity, high-commitment approach, while *parallel* exploration represents a lower-fidelity, lower-stakes alternative. Srikanth and Ungureanu (2024) further extend the dimensions of exploration by introducing the notion of propensity, emphasizing managerial agency in shaping search processes. Regardless of the specific framing, understanding how agentic experimentation choices shape firm trajectories remains a central concern in entrepreneurship research. In the following section, I outline the potential channels through which exploration strategies influence firm performance and develop specific hypotheses.

3. Hypotheses

3.1 Parallel exploration: information parity and cognitive limitations

Firms engaging in parallel exploration commit to pursuing technological and commercial search concurrently, often initiating market-facing activities before fully resolving technological uncertainty. Lean startup methods advocate for early customer discovery, using minimally viable products, as a core element of entrepreneurial strategy (Blank & Eckhardt, 2024). This approach enables boundedly rational entrepreneurs to selectively sample and satisfice, using market feedback to guide decision-making. Customer feedback gathered through A/B testing has been found to enhance product performance in digital ventures (Koning et al., 2022). Lean methods emphasize speed, and as Ries (2011) famously noted, “the only way to win is to learn faster than anyone else.”

Parallel exploration, by enabling early customer engagement, can reduce information asymmetry with potential resource providers (Figure 4). Entrepreneurial firms face internal uncertainty regarding the opportunities they pursue, which is closely linked to information frictions with external stakeholders (Shane & Venkatraman, 2000; Kerr et al., 2014). If unresolved, these frictions can impede early-stage fundraising, even for digital startups (Ewens et al., 2018; Cao, 2019). The challenge is more acute for deeptech firms, where both uncertainty and information asymmetry are amplified (Bolton et al., 2024). In such contexts, investors may place a premium on observable experimentation, especially when insights come in the form of early customer validation. These signals help investors assess a project’s commercial viability, rather than relying solely on its technological promise. Thus, firms that pursue this strategy may be better positioned to secure early financial outcomes (Howell, 2020).

However, greater information clarity may also lead to unfavorable outcomes. Not all experiments yield positive signals, and those that indicate limited commercial viability can result in firm failures (Koning et al., 2022). This may arise either from investor feedback or from the entrepreneur’s own interpretation of experimental results (Yu, 2020). In deeptech contexts, undertaking premature commercial exploration, before resolving core technology uncertainty, can prove costly. As a result, firms pursuing a parallel strategy may experience greater variability in early financial outcomes, ranging from funding success to outright failure.

Parallel exploration accelerates learning, enabling firms to develop products faster and potentially build early competitive advantages (Koning et al., 2022). However, two factors constrain the benefits of a parallel strategy: cognitive limitations within entrepreneurial teams and the myopia of learning. While idea generation is critical, idea evaluation is often more challenging, particularly when experiments involve significant opportunity costs, such as those associated with large R&D investments (Knudsen & Levinthal, 2007; Agrawal et al., 2024b). Rigorous experimentation requires substantial cognitive capacity to accurately interpret results (Koning et al., 2022), and although parallel exploration produces more data, the velocity of information may hinder learning across experiments, especially under noisy testing conditions (Loch et al., 2001).

As such, the influx of information across multiple dimensions can exceed the cognitive bandwidth of entrepreneurial teams, limiting their ability to synthesize and act on insights. Managerial cognition, or the lack thereof, has been shown to materially affect organizational outcomes such as market entry in emerging technologies (Adner & Helfat, 2003; Eggers & Kaplan, 2009; Ott & Eisenhardt, 2020). In parallel settings, entrepreneurs may encounter conflicting signals and struggle to reconcile competing objectives, reducing coordination and impairing performance (Eklund, Raj, & Eggers, 2024). These effects are amplified in smaller firms with inherently limited attentional capacity, especially given that deeptech founders are often more technically oriented than commercially (Hong et al., 2022).

Moreover, feedback from early commercial exploration can anchor firms in myopic search, discouraging exploration of more radical or uncertain technological pathways (Levinthal & March, 1993). A boundedly rational entrepreneur, overwhelmed by data, may satisfice by addressing commercial rather than technological uncertainty (Simon, 1959). Moreover, the type of learning is contingent on the underlying experimental design; testing incremental improvements is likely to yield only incremental insights (Koning et al., 2022). Thus, parallel exploration may drive deeptech ventures toward more "visible" or immediately commercializable outcomes, potentially at the expense of deeper, long-term technological breakthroughs. Therefore, I hypothesize that, ceteris paribus, deeptech firms engaging in parallel exploration i.e., pursuing early commercial exploration before resolving technological uncertainty are more susceptible to failure, but also more likely to achieve short-term financial and innovation outcomes.

<u>*Hypothesis 1a*</u>*: Firms that engage in parallel exploration are more susceptible to failure than those that pursue sequential exploration.*

<u>Hypothesis 1b</u>: *Firms that engage in parallel exploration are more likely to achieve superior short-term financial and innovation outcomes compared to those that pursue sequential exploration.*

3.2 Sequential exploration: focused problem-solving and deep learning

Beyond information frictions with investors, entrepreneurial firms face asymmetries in their relationships with potential customers i.e customers know more about their own preferences than firms. In digital ventures, lean methods help reduce this asymmetry through early customer discovery wherein firms shape their offerings based on market feedback (Blank & Eckhardt, 2024). However, deeptech firms operate on a different calculus. Information asymmetry often runs in the opposite direction: customers may lack the knowledge to assess novel offerings, requiring the firm to educate the market (Felin et al., 2024). In such cases, early customer engagement may yield noisy or misleading signals. Worse, it may lead to premature rejection of unconventional ideas due to 'belief asymmetry' (Felin et al., 2019; 2024). Relying solely on market-based feedback has been shown to be ineffective under high uncertainty. Even in established firms, Bayesian belief updating based on external signals can lead to managers disregarding the theoretical origins of their trajectory and overcorrecting (Kapoor & Wilde, 2023). Deeptech ventures that engage prematurely with incumbents also face risks of expropriation through imitation (Contigiani, 2023) or may encounter well-intentioned partners who lack the foresight or capability to offer constructive feedback (Christensen & Bower, 1996).

Therefore, a sequential approach to exploration, in which commercial search is deferred until technological uncertainty is resolved, allows firms to dedicate attention and cognitive resources to refining their core offering. Even in non-deeptech settings, cognitive demands often lead entrepreneurs to decompose strategy formulation into multiple domains, concentrating first on the focal domain—in this case, foundational technological uncertainty—before turning to the next (Ott & Eisenhardt, 2020). Once a robust technological foundation is in place, firms may be better equipped to address market-related information frictions. Deliberate, theory-driven experimentation, rather than reactive trial-and-error testing, is more suited to firms pursuing radical innovation (Felin et al., 2024; Agrawal et al., 2024a). A sequential strategy that prioritizes endogenous development of a well-substantiated technological solution can thus support stronger long-run commercial performance.

Furthermore, excessive experimentation can overwhelm organizational learning processes. While parallel exploration generates rich data, founders may lack the cognitive capabilities to evaluate it effectively (Agrawal et al., 2024a; Knudsen & Levinthal, 2007). In contexts where both discovery and evaluation are challenging, slower and more deliberate learning has been found to produce more sustained outcomes (Levinthal & Schliesmann, 2024). Gao and McDonald (2019) make a related argument in the context of regulatory uncertainty, showing that sequencing strategic choices i.e tackling regulation after formulating commercial approaches, can improve outcomes in nascent industries. Similarly, Pillai et al. (2020) find that in capital-intensive sectors such as automotive, exploration involves significant commitment and irreversibility. In such contexts, sequencing facilitates deeper problem-solving by enabling firms to focus on fewer dimensions at a time and engage in extended cycles of experimentation and learning (Loch et al., 2001; Gao & McDonald, 2019). Delaying commercial engagement allows firms to more thoroughly resolve technological uncertainty before turning to the market. This alignment is particularly beneficial for deeptech founding teams, who are typically more technically than commercially oriented (Hong et al., 2022). A serial strategy allows founders to align their strengths with the dominant uncertainty at a given stage, enhancing technological progress and long-term financial performance.

Moreover, entrepreneurial firms often exhibit lower absorptive capacity in their early stages, making it challenging to assimilate external information (Cohen & Levinthal, 1990). For deeptech firms engaged in multi-dimensional problem-solving, sequential learning i.e focusing on one dimension at a time, can facilitate the gradual accumulation of technological expertise. As absorptive capacity increases, firms become better equipped to extract actionable insights from subsequent rounds of exploration, resulting in more sustained technological outputs such as patents. Additionally, by delaying commercial engagement, firms may insulate themselves from potentially distracting market feedback, allowing them to focus on global search and pursue more radical or uncertain technological pathways (Levinthal & March, 1993). In this way, sequential exploration may enable deeptech ventures to achieve more sustained and novel technological performance. Consequently, I hypothesize that sequential exploration enables slower, more deliberate organizational learning that improves absorptive capacity and leads to superior invention outcomes. Establishing a strong technological foundation also positions the firm for sustained financial performance over the long run.

Hypothesis 2a: Firms that engage in sequential exploration are more likely to achieve superior long-term financial outcomes than those that pursue parallel exploration.

Hypothesis 2b: Firms that engage in sequential exploration are more likely to achieve sustained technological performance (e.g invention outcomes) than those that pursue parallel exploration.

4. Data & Methods

4.1 Data sources

This paper empirically tests the proposed hypotheses using a novel longitudinal dataset that integrates archival data sources with primary information. Primary insights were gathered through semi-structured interviews with deeptech entrepreneurs, investors, and other ecosystem participants. In addition, I incorporated proprietary data from a deeptech investment platform to aid in the classification of relevant deeptech sectors. To construct the observational dataset, I employed a combination of NLP, ML, and fuzzy matching techniques across multiple data sources. I began by identifying U.S.-based technology firms founded between 2007 and 2020 using Crunchbase and Pitchbook. Firms in digital-centric industries such as software, e-commerce, retail, and IT services were excluded, with the focus placed on hardware-oriented ventures that depend more heavily on tangible assets. Using fuzzy matching algorithms (e.g., Levenshtein distance) based on firm names, geographic information, and other identifiers, I linked firms across multiple datasets including the USPTO Patent Database (PatentView), USPTO Trademark Database, the USPTO Pre-Grant Patent Applications Database, and SBIR/STTR grant data (www.sbir.gov). I also used NLP and manual techniques to scrape website information using Wayback Machine akin to Guzman & Li (2023).

Within the USPTO Patent Database, I used unique patent identifiers to match assignees and extract key information such as filing dates, grant dates, and other relevant metadata. The filing date of a firm's first patent plays an important role in this study, which I elaborate on in later sections. I also collected data on CPC technology classifications, backward citations, and forward citations. A similar process was followed for the Pre-Grant Patent Applications Database to retrieve application and grant dates for early-stage filings. Including firms that filed pre-grant applications was essential, as relying solely on granted patents risks introducing selection bias by systematically excluding underperforming ventures. From the USPTO Trademark archive, I utilized datasets related to owners, case files, and classifications to extract trademark-level details, including filing and registration dates, type (e.g., "intent-to-use" vs. "use"), category (goods vs. services), and class. In addition, I identified firms that had received SBIR/STTR grants, along with the corresponding award years.

Focusing on hardware-oriented industries, I delineated the sectors included in the analysis: Advanced Manufacturing, Robotics, Advanced Materials, Agricultural Technologies, Space/Aerospace, Biotechnology, Medical Devices, Electronics/Semiconductors, Sustainable Energy, and Clean Technologies. This classification draws from topic areas used by the National Science Foundation (NSF) in their grant solicitation process. I further classified firms as deeptech if they met at least one of the following criteria: (1) received an SBIR/STTR Phase I grant; or (2) held at least one granted patent in selected CPC technology classes (e.g., chemistry/metallurgy, physics, mechanical engineering, electricity). I used university affiliation as a proxy for research intensity, identifying firms that had licensed patents from universities or had academic co-founders. Using this combination of archival, proprietary, and ML-driven methods, I triangulated a universe of ~13,790 deeptech firms. Financial and firm-level outcomes were extracted from Crunchbase and Pitchbook, including data on capital raised, liquidity events (IPOs and acquisitions), firm failures, and their respective dates. The resulting longitudinal dataset includes ~118,000 firm-year observations.

4.2 Key Variables

Dependent Variables: I constructed two categories of dependent variables at the firm-year level: *financial outcomes* and *innovation outcomes*. Financial outcomes include firm-year binary indicators for whether a firm shut down, went public, was acquired, or received venture capital (VC) or other forms of financing. Continuous financial outcomes include the magnitude of funds raised, post-money valuations, and acquisition or IPO pricing where available. Innovation outcomes include count measures of patents filed and granted, trademarks filed and registered, and forward citations—used as an indicator of innovation impact. All count variables are log-transformed to reduce skewness and enable comparability.

Control/ matching variables: I employed *firm fixed effects* and *industry x year fixed effects* to account for unobserved heterogeneity at the firm level and within industry-periods. To further mitigate selection bias on observables, I also implemented a coarsened exact matching (CEM) procedure, matching treated and control firms on a set of pre-treatment covariates for cross-sectional analysis. The ex-ante founding characteristics used for matching include *industry*, the *primary CPC technology class* of its foundational patent, a measure of *technology novelty*, receipt of *early-stage grants* (e.g., SBIR award), and *founding year*.

Independent variables: My main independent variable captures whether a firm engages in *sequential* or *parallel exploration*. I constructed this measure using three complementary empirical approaches.

4.3 Empirical strategy

4.3.1 Behavioral approach (patent and trademark filings)

I first employed a behavioral methodology to characterize whether a firm engaged in *sequential* or *parallel* exploration. This determination is based on the timing and sequencing of a firm's engagement in technological and commercial exploration (Figure 5).

Technological exploration: is proxied using patenting activity, following prior innovation research that treats patent filings as a behavioral indicator of technological search (Rosenkopf & Nerkar, 2001). This approach is particularly relevant for entrepreneurial firms as they often produce their most novel, impactful, and science-based inventions in the early years of their lifecycle (Ewens & Marx, 2023). Although the quantity of patenting tends to increase as firms scale, the quality typically declines. Importantly, this early innovation activity is attributable to venture funding, as similar patterns are observed among non-VCbacked firms. Building on these findings, I defined a firm's initial phase of technological exploration as the period from founding to the filing of its first patent (or first two patents). Since patent prosecution proceeds independently of firm-level strategic decisions once a filing is made, the act of filing itself serves as a meaningful marker of early technological exploration. Initial patents are often foundational in nature, helping to shape the firm's direction, and thus provide a reasonable proxy for early technological exploration activity (Ewens & Marx, 2023).

Commercial exploration: Next, I categorized commercial exploration based on a firm's trademarking activity. A trademark is a form of intellectual property used by firms to differentiate and protect their products/services in the form of brand names and logos (Hsu et al., 2022a). Unlike patenting activity that occurs in the initial phase of R&D, trademarks are generated when new products are closer to commercialization. They typically represent outputs towards the later part of the cycle, prior to ascertaining product-market fit. Firms file trademark applications with the USPTO in specific product/service classes. However, for a trademark to be registered, a firm must submit proof demonstrating that a trademark is currently used commercially in that class. The registration of a trademark therefore signals the commercial viability of a new product/service (Hsu et al., 2022a).

This distinction between patents and trademarks is instrumental to my categorization of exploration strategies. While the filing of a patent signifies the culmination of preliminary technological exploration, the filing of a trademark marks the onset of search for potential applications. The act of registration signals the product's commercial viability, effectively concluding the commercial exploration phase (for the specific product). A related measure employed in prior research, *commercialization lag*, measures the time between the invention and its first commercialization/ revenues (Budish et al., 2015).

Furthermore, firms filing a trademark are required to specify a legal basis; either "use" or "intent to use" in commercial applications (Graham, Hancock, Marco & Myers, 2013). Applicants filing under the "intent to use" basis cannot obtain registration until the mark is actively used in commerce and verified as such by submitting a specimen of use. Interestingly, most trademark applications filed in recent years have been of the “intent-to-use” category, indicating that firms seek to protect their intellectual property while still exploring the product’s viability before committing to commercial use. I leveraged this reasoning to define commercial exploration as the time between filing and registration of the first trademark (or first two). Next, I assigned technological exploration and commercial exploration indicator variables (1 or 0) for each firm-year based on the patent and trademark timings. Finally, I set a *parallel exploration* dummy, with a value of 1 for years in which the firm engaged in both types of exploration and 0 otherwise. While this approach has limitations in fully capturing exploration modes, the endeavor is to optimize the information extractable from observational data.

The econometric specification is provided below:

$$Y_{it}^{Firm-Year} = \beta_0 + \beta_1 X_{it}(Parallel\_Seq\_lag) + \alpha_i + \gamma_{n\,X\,t} + \varepsilon_{it} \tag{1}$$

For any firm-year outcome, $X_{it}(Parallel\_Seq\_lag)$ represents the lagged form of the *parallel exploration dummy*. α_i indicates *firm fixed effects* accounting for time-invariant heterogeneity of the firm, including unobservable factors such as founder quality and managerial capabilities. $\gamma_{n\,X\,t}$ represents *industry-year fixed effects* to control for idiosyncratic sectoral trends.

Additionally, I calculated DoP *degree of parallel exploration* variable in the cross-sectional collapsed dataset, that is a scaled measure of overlapping periods of commercial and technological exploration. This is calculated per the following equation:

$$\text{DoP} = \frac{(t_{TE_f} - t_0) - (t_{CE_i} - t_0)}{(t_{TEf} - t_0)} \tag{2}$$

t_{TE_f} represents the year when technological exploration was completed while t_{CE_i} is the year when commercial exploration, while t_0 is the year of firm founding. Thus, DoP represents the *degree of parallel exploration* that the firm undertakes early on.

4.3.2 Exogenous technology development (Additive manufacturing)

I also employed a difference-in-differences (DiD) strategy based on an exogenous technological development from the 2010s: the rise of 3D printing (3DP), also known as additive manufacturing. Unlike traditional fabrication methods such as lathing or milling which are subtractive in nature, 3DP builds products layer by layer from digital designs. This process has significantly accelerated production timelines and enabled greater customization across a range of industries[2]. While 3DP technologies emerged in the 1980s with the invention of stereolithography and selective laser sintering, key breakthroughs in the 1990s and 2000s—including filament deposition modeling, the open-source RepRap Project (2005), and the expiration of foundational 3DP patents—laid the groundwork for mainstream adoption (Figure 6). The 2010s marked a critical inflection point, with the introduction of affordable 3D printers by MakerBot and proliferation of 3DP applications through Kickstarter. These developments catalyzed widespread diffusion of 3DP across consumer and industrial markets, giving rise to a billion-dollar industry.

Additive manufacturing has had transformative effects in sectors such as healthcare, aerospace, automotive, construction, and consumer goods. It enables the production of complex, lightweight, and customized components at lower cost and with faster turnaround. 3DP had an impact even in the energy sector. As one decarbonization startup CEO explained, *"At [Company], 3D printing was helpful not only for prototypes but also for actual products."*

While the direct impact of 3DP is not the focus of this paper, I leveraged its adoption as an exogenous technological development that facilitated faster experimentation for hardware-oriented firms. Specifically, 3DP has impacted the downstream phase of R&D by enabling rapid prototyping, reducing the cost of iteration, and lowering barriers to exploratory learning (Peng, Zhu, Leu, & Bourell, 2020). I use 3DP in two different ways: 1. I use 3DP as an instrument for parallel exploration in an IV-2SLS regression. 2. I use the mainstream diffusion of 3DP in the early 2010s as a treatment proxy to identify the effects of parallel exploration on firm outcomes. The econometric specification for the two-way fixed effects model is presented below:

$$Y_{it}^{Firm-Year} = \beta_0 + \beta_1 X_i (3DP_{Treat}\, X\, Post) + \alpha_i + \gamma_{n\, X\, t} + \varepsilon_{it} \qquad (3)$$

[2] https://www.asme.org/topics-resources/content/infographic-the-history-of-3d-printing; https://www.makerbot.com/stories/history-of-3d-printing/

For any firm-year outcome, the coefficient of $X_{it}(Treated\ x\ Post)$ i.e β_1 represents the main measure of interest that estimates the effects of 3DP in the post-treatment period. Since the treatment is continuous in nature, it represents the change in ${Y_{it}}^{Firm-Year}$ caused by increasing degree of treatment (Angrist & Pischke, 2009).

To operationalize this approach, I developed a *3D Printing treatment score* that captures each firm's propensity to be impacted by additive manufacturing. This score was constructed using a range of ML approaches applied to textual data from Crunchbase, and Pitchbook descriptions at founding, as well as early patent filings. The methodology is inspired by prior work leveraging exogenous technological shocks to study firm outcomes. For instance, Ewens et al. (2018) exploit the introduction of Amazon Web Services in 2006 as a shock that lowered entry barriers for digital startups, while Furman and Teodoridis (2020) study the unanticipated arrival of Microsoft's Kinect system, which enabled automated motion-sensing capabilities for research applications.

In a similar spirit, I use the heterogeneous adoption of 3DP technologies as a firm-level treatment proxy. The resulting *3DP treatment score* captures both industry-level and firm-level variation in relevance to additive manufacturing. Although the score is estimated at the firm level and could be seen as potentially endogenous, all input data were collected from firm founding and thus predate product development or commercialization. As such, the score reflects a firm's ex-ante propensity to adopt 3DP technologies, rather than actual adoption or downstream outcomes.

4.3.3 Behavioral approach (timing of business-related hire)

I developed an additional behavioral measure that leverages the timing of a firm's first business-related job posting to identify the onset of commercial exploration. Lee & Kim (2024) equate the timing of a startup's first job posting for a manager or sales role with the onset of scaling. Their argument is that recruitment for specialized human resources, rather than actual employment, signals the firm's strategic intent to scale, which is typically difficult to observe. In the context of deeptech ventures, however, firms often engage in commercial exploration before entering a full scaling phase. I postulate that this intent can be approximated by the timing of the firm's first business-related job posting, particularly business development roles, rather than sales. While this signal is imperfect, some teams may already include individuals with relevant business skills, it offers a reasonable proxy for the onset of commercial exploration. Accordingly, I designate the commercial exploration year as the firm-year corresponding to the first observed posting for a business-related role. Given data sparsity, I deployed this method mainly in robustness checks as supplementary evidence to help corroborate the main findings.

In addition to the methods outlined above, I employed a staggered difference-in-differences design using the Callaway and Sant'Anna (2021) estimator[3] to exploit heterogeneity in treatment timing. Following the approach of Kim (2022), I constructed a control group of firms that all engage in parallel exploration but do so at different points in their lifecycle. This strategy leverages variation in treatment timing across both lifecycle stages and calendar years to strengthen identification. I present the event study and average treatment effect estimates in the results section. To capture a temporal dimension of firm outcomes, I also employed a semi-parametric Cox proportional hazards model to analyze how the timing of liquidity and commercialization events—such as IPOs, acquisitions, and product launches—is influenced by whether firms adopt *parallel or sequential exploration* strategies.

6. Results

6.1 Descriptive Statistics

Figure 8 presents the distribution of firms in the dataset by sector and primary CPC technology class. The sectors span energy, manufacturing, consumer products, drug discovery, biotechnology, medical devices, and agritech. The CPC classifications associated with each firm's primary patent provide insight into the core technological domain of the venture. These classifications predominantly include chemistry/metallurgy, physics, electricity, mechanical engineering, and human necessities.

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[3] I employ the CS-DiD, developed by Rios-Avila, et al. (2023), which implements the process outlined by Callaway & Sant'Anna (2021). CS-DiD exploits the timing heterogeneity of treatment, utilizing not-yet treated firms. These methods help address issues that can arise from using never-treated firms as the control group.

Table 1 reports summary statistics for key variables. On average, firms raise approximately three rounds of financing. Seventeen percent of firms raise an early-stage grant, and 44% receive some form of external funding. Despite this early resource mobilization—driven in part by the design of the dataset—only 14% of firms experience a positive liquidity event, with 4% completing an IPO and 10% undergoing acquisition. Eight percent of firms are explicitly reported as having failed; however, this likely reflects underreporting. When applying a broader classification i.e “zombie" firms, the incidence rate increases to 36%. This estimate aligns with prior work (Lee & Kim, 2024), though it may still understate the true rate of failures.

Deeptech firms are inherently oriented toward technology and innovation, as confirmed by key metrics. On average, firms file two granted patents and three trademarks within their first four years. These patents tend to be impactful, receiving an average of sixteen forward citations. Moreover, indicators such as generality and originality scores suggest that these innovations are characterized by a high degree of novelty. Trademark behavior further reflects exploratory activity: approximately 50% of trademarks filed by firms in the dataset are later abandoned, consistent with firms experimenting with different commercial pathways during early-stage development.

6.2 Main results – exploration modes and firm outcomes

The first empirical specification employs a continuous two-way fixed effects model using firm-level *3DP treatment scores*. Table 2 presents the average treatment effects on both financial and innovation outcomes. The sample is restricted to firms founded before 2012, aligning with a difference-in-differences framework in which the 2012 onset of 3DP adoption serves as the treatment period. The estimates for the *Treatment* × *Post* interaction term are statistically significant at the 1% level and show a negative effect on invention outcomes (as measured by *patents*), but a positive effect on short-run financial outcomes such as *early funding* and *firm failure*. Interestingly, the results for long-run financial outcomes are mixed: while the likelihood of *IPO* decreases, the likelihood of *acquisition* increases following treatment.

Table 3 presents results from the staggered difference-in-differences analysis using the CS-DiD estimator, implemented in a not-yet-treated specification with *3DP treatment scores*. The findings are consistent with those from the two-way fixed effects model: 3DP treatment is negatively associated with *patents* and *IPOs*, while positively associated with *early funding*, *firm failure*, and *acquisition*. While the coefficient estimates are somewhat less robust than those in the classic two-way fixed effects specification, this is expected given that the CS-DiD approach compares only within the treated group and relies on variation in treatment timing across lifecycle stages and calendar years for identification.

Table 4 presents panel regression results using *degree of parallel exploration* estimated from variation in the timing of patent and trademark filings. The findings are robust and consistent with earlier results: greater *parallel exploration* is positively associated with *early funding* and *firm failure*. Notably, the magnitude of *funding raised*, measured as a continuous variable, is also positive and statistically significant, further reinforcing the relationship between experimentation and financial outcomes. In contrast, the coefficient estimates for *IPO* and *acquisition* outcomes are not statistically significant but that may be caused by the short time lags used in the specification.

Table 5 mirrors the approach of Table 4 by using *degree of parallel exploration* but implements a cross-sectional specification in conjunction with CEM. The results largely replicate earlier findings, reinforcing the robustness of the relationship between exploration strategy and firm outcomes. Panel B reports coefficient estimates for the magnitude of *financing*, *acquisition price*, and *IPO valuations*. Interestingly, *parallel exploration* exhibits a weak but positive relationship with *acquisition price*, despite significantly reduced statistical power (n = 134).

Overall, the results across multiple DVs are consistent across within-firm and cross-sectional analyses. *Parallel exploration* is associated with an increase incidence of *firm failures*. In terms of economic significance that is a 2 - 4% positive impact (mean DV = 8%). There is also strong support for a positive relationship with *early-stage funding* with a 5 – 25% shift (mean DV = 44%). The relationship with *being acquired* is positive (1 - 4% with a mean DV of 10%). In a similar vein, the association with *IPO* is consistently negative with a 0.3 – 3% impact (mean DV = 4%). In terms of patents, the longitudinal and cross-sectional specifications offer different economic interpretations as they represent within-firm annual counts and across-firm aggregate counts. Despite this difference, the results are broadly aligned in showing that technological performance, as measured by *patent output*, is negatively associated with *parallel exploration*.

I conducted supplementary analyses and robustness checks to further validate the main findings. To examine the temporal dynamics of the DVs, I employed a semi-parametric Cox proportional hazards model, using *3DP treatment scores* (Figure 12). Consistent with the main parametric results, parallel exploration is associated with higher hazard rates for *failure*, *commercialization* (based on first trademark registration), and *acquisition*, and a lower rate for *IPO*. These findings reinforce the robustness and directional consistency of the main results. Table A1 (Appendix) presents results from robustness checks using job postings as a proxy for the onset of commercial exploration. These results corroborate the positive association between *parallel exploration* and both *early-stage funding* and *firm failure*. Table A6 presents results from non-linear regression models, Probit for binary outcomes and Poisson for count outcomes, serving as robustness checks consistent with the linear least squares methods used in the main analyses.

6.3 Mechanisms and alternate explanations

A core proposition underlying the hypotheses and analyses is that while parallel exploration facilitates faster discovery, it also imposes greater cognitive demands on nascent entrepreneurial teams. As such, one would expect research-oriented founders to face more difficulty absorbing and acting on insights generated through parallel exploration, compared to teams with prior business experience. Table A2 supports this proposition: a higher degree of research orientation attenuates the positive relationship between *parallel exploration* and *early-stage funding*. In fact, sub-sample analyses of firms led by faculty CEOs show a complete reversal of the positive effect—*parallel exploration* is associated with lower *early funding outcomes* in this group. Similarly, Table A3 shows that business experience among founders moderates the relationship between *parallel exploration* and *IPO* outcomes. Specifically, the negative effects of parallel search are reversed for firms with experienced business founders, with former CEOs having a particularly strong positive influence.

In a similar vein, technological uncertainty would be expected to moderate the effects of search with higher technological novelty exacerbating the effects of parallel exploration. Table A4 confirms this finding that technological novelty has a negative effect on the relationship between parallel exploration and firm outcomes. Furthermore, supplementary analyses (not shown but available upon request) comparing deeptech and non-deeptech firms support the postulate that greater technological uncertainty exacerbates the adverse effects of parallel exploration on firm outcomes.

An alternate mechanism that may be influencing the observed effects is access to early-stage resources. Firms that secure early financing may be better positioned to conduct parallel experimentation and allocate sufficient managerial capacity to process the resulting insights. Table A5 presents analyses restricted to firms conditional on them obtaining early funding. The results remain consistent, suggesting that the effects of parallel exploration are not solely driven by pre-existing resource advantages and thus unlikely to be driven by reverse causality.

Finally, industry heterogeneity may account for the observed performance differences, rather than firm-level variation. To assess this, Table 7 presents within-industry analyses for industrial and life sciences firms. The results remain consistent with prior findings, although the effects of *parallel exploration* appear more pronounced in the life sciences sector.

7. Discussion

The study formulates hypotheses based on entrepreneurial selection of parallel or sequential exploration strategies. Variation in firm outcomes is predicated on navigating the trade-offs between reducing information frictions through early commercial exploration and resolving uncertainty through sequential search and deeper learning. Hypotheses 1a and 1b posit that diminishing information asymmetry with potential resource providers enhances the likelihood of early financial outcomes—both positive (e.g., *funding*) and negative (e.g., *failure*). Parametric and non-parametric results support these predictions, showing that *parallel exploration* is associated with increased probabilities of *early-stage funding* and *firm failure*. Interestingly, *parallel exploration* influences not only the likelihood of *failure* but also its timing, confirming the ‘fail fast’ dynamic ascribed to lean methods.

Hypothesis 1c posits a positive relationship between *parallel exploration* and short-run innovation outcomes, driven by myopia of learning and limited managerial cognition. Evidence from non-parametric Cox proportional hazards models indicates that parallel strategy is associated with earlier commercialization. However, the regression results are mixed with respect to the certainty and magnitude of commercialization, as measured by trademark activity. These inconsistencies suggest that further analysis is needed to better interpret the findings.

Hypothesis 2a is grounded in the uncertainty-information asymmetry framework but centers on the entrepreneur–customer relationship. Under *sequential exploration*, firms that invest more time in technological discovery for novel products are expected to be better positioned for commercial adoption and long-run financial outcomes. The *IPO* findings support this expectation. However, somewhat surprisingly, the probability of *acquisition* is higher for firms engaging in *parallel exploration*. One possible explanation for this apparent contradiction is that, like early-stage investors, potential acquirers may also prioritize observable signals of commercial viability as indicators of technology readiness and integration potential. Established firms often seek entrepreneurial partners with an eye towards technological appropriation. However, incumbents aiming to collaborate with startups commercializing disruptive technologies often prefer to delay engagement until more explicit signals of viability emerge (Marx, Gans, & Hsu, 2014). Ex-ante information asymmetry has been found to influence the likelihood of joint ventures and acquisitions (Reuer & Koza, 2000; Cuypers et al., 2017). In this context, a parallel strategy may increase the likelihood of alliance formation or acquisition activity. Ironically, while *sequential explorers* may possess stronger underlying technological assets, the initial opacity of their commercial potence may diminish their attractiveness to acquirers. Nonetheless, the long-run orientation of sequential exploration does manifest in their *IPO* outcomes.

Hypothesis 2b is grounded in organizational learning, emphasizing the benefits of enhanced absorptive capacity and improved information processing. A *sequential approach* fosters slow learning and more deliberate problem-solving by allowing firms to focus on resolving one dimension of uncertainty at a time. This focused approach can build a stronger foundation for sustained innovation and long-term technological performance. The patent results support the hypothesis that a serial strategy enables deeper knowledge assimilation.

Several moderating factors shed light on the mechanisms underlying the effects of *parallel exploration*. Its benefits are dampened when entrepreneurial teams face cognitive constraints, such as those led by research-oriented or faculty founders, and amplified when founders bring prior business experience. Technological novelty exacerbates these challenges, while analyses controlling for early-stage funding confirm that the observed effects are not merely driven by differences in resource access or reverse causality.

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Table 1: Descriptive Statistics

Panel A: Summary Statistics

Variable	Obs	Mean	Std. Dev.
Founding Year	13791	2013.69	4.02
SBIR Grant Award	13791	.32	.47
Industry	13791	5.14	2.35
Patent CPC Class	8441	3.39	2.63
Aero/SpaceTech Industry	13791	.05	.23
Number Funding Rounds	6174	3.3	2.85
Investment Stage	10619	2.83	1.19
Total $ Raised	6390	57.83	201.36
First Financing $	6130	4.43	21.02
Firm Failure	13791	.08	.26
Firm Failure (incl. zombie)	13791	.36	.48
Acq. Likelihood	13791	.1	.3
IPO Likelihood	13791	.04	.19
Exit likelihood	13791	.14	.35
VC/ Seed Funding	13791	.44	.5
Filed TM Count	13791	3.24	7.71
Regd. TM Count	13791	1.58	3.78
Granted Patent Count	13791	2.19	7.9
Originality	7941	.5	.25
Fwd. Citation Count	13791	16.8	148.79
Generality	4392	.42	.27
Age at 1st Patent Filing	8467	2.13	2.35
Age at 1st TM Filing	7805	2.14	2.6
Technology Novelty	8441	46	130.53
Degree of Parallel Exploration	13791	.76	.43
3DPrinting Propensity Score	13791	.35	.36

Panel B: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Industry	1.00													
(2) Technology Novelty	-0.04	1.00												
(3) Investment Stage	0.03	-0.03	1.00											
(4) Total $ Raised	-0.07	-0.02	0.30	1.00										
(5) Firm Failure	-0.00	0.03	-0.03	-0.07	1.00									
(6) Acq. Likelihood	0.00	0.00	0.15	-0.02	-0.10	1.00								
(7) Funding Likelihood	-0.05	-0.04		0.03	0.12	-0.01	1.00							
(8) IPO Likelihood	-0.09	-0.03	0.30	0.38	-0.06	-0.06	0.05	1.00						
(9) Filed TMs	0.00	0.01	0.25	0.25	-0.04	0.08	0.06	0.08	1.00					
(10) Granted Patent	0.01	-0.00	0.17	0.13	-0.01	0.07	0.00	0.04	0.18	1.00				
(11) Fwd Citations	0.01	0.01	0.09	0.05	0.00	0.09	0.01	0.03	0.17	0.47	1.00			
(12) Age at PatentFiling	-0.06	-0.03	0.05	0.03	-0.06	-0.00	0.15	0.02	0.02	-0.22	-0.10	1.00		
(13) Age at TM Filing	-0.00	-0.02	0.06	0.01	-0.04	-0.03	0.17	0.03	-0.13	-0.09	-0.05	0.39	1.00	
(14) Parallel Expl.	-0.06	-0.01	-0.01	0.01	-0.01	0.02	-0.04	-0.02	0.16	-0.08	-0.04	0.48	-0.62	1.00
(15) 3DPrint Score.	-0.10	0.17	-0.10	-0.05	0.01	-0.01	-0.18	-0.12	0.01	0.05	0.02	-0.04	-0.10	0.07

Table 2: Panel regressions – Instrumented Difference-in-Difference (3D Printing)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Early Funding	Log $ Raised	Failure	Acquired	IPO	Log - Patent
			3DP – TWFE			
Treatment x Post	0.253***	0.364	0.041***	0.044***	-0.026***	-0.158***
	(0.049)	(0.436)	(0.008)	(0.012)	(0.005)	(0.053)
Constant	0.034***	2.187***	0.005**	0.005	0.011***	0.278***
	(0.012)	(0.078)	(0.002)	(0.003)	(0.001)	(0.012)
Observations	49,887	7,392	49,887	49,887	49,887	49,887
Firms	5,450	1,845	5,450	5,450	5,450	5,450
R-squared	0.379	0.888	0.133	0.166	0.169	0.482
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*This table reports the estimates of Average Treatment Effects for panel data. Independent variables are Post and Treatment. Post represents 1 for years 2012 and after, 0 otherwise. Treatment is a continuous variable that represents the likelihood of a firm being impacted by 3D Printing i.e the propensity score based on their textual descriptions at founding. Dependent variables are individual year financial outcomes of the firm (i.e indicator variables for early funding, failure, being acquired and IPO as well as $ amount raised) and individual year patents generated by the firm. Estimation uses difference-in-differences (DiD). The sample includes 5,450 firms that are identified as deeptech and were founded between 2007 - 2011. Robust standard errors clustered at firm-level are presented in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

Table 3: Panel regressions – Staggered Difference-in-Difference

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Early Funding	Log $ Raised	Failure	Acquired	IPO	Log - Patent
			3DP – CSDiD			
ATT	0.041*	0.109	0.010***	0.006**	-0.003*	-0.065***
	(1.97)	(0.87)	(5.16)	(2.79)	(-2.43)	(1.97)
Observations	60,389	7,054	60,389	60,389	60,389	60,389
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes	Yes

*This table reports the estimates of Average Treatment Effects for panel data. Independent variables are Post and Treatment. Post represents 1 for years 2012 and after, 0 otherwise. Treatment is a continuous variable that represents the likelihood of a firm being impacted by 3D Printing i.e the propensity score based on their textual descriptions at founding. Dependent variables are individual year financial outcomes of the firm (i.e indicator variables for early funding, failure, being acquired and IPO as well as $ amount raised) and individual year patents generated by the firm. Estimation based on the Callaway & Sant'Anna CS-DiD method developed by Rios-Avila, et al. (2023) using not yet as control group. The sample includes the 13,790 firms identified as deeptech. Robust standard errors clustered at firm-level are presented in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

Table 4: Panel/ FE regressions (Parallel/ Sequential using Patents and Trademark Filings)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Early Funding	Log $ Funding	Failure	Acquired	IPO
	Parallel/ Sequential – Panel OLS				
Degree of Parallel Exploration	0.036***	0.221***	0.015***	-0.001	0.001
	(0.004)	(0.026)	(0.002)	(0.001)	(0.001)
Constant	0.093***	2.229***	0.045***	0.014***	0.006***
	(0.001)	(0.006)	(0.000)	(0.000)	(0.000)
Observations	71,158	10,742	71,158	71,158	71,158
R-squared	0.364	0.904	0.298	0.227	0.254
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry x Year FE	Yes	Yes	Yes	Yes	Yes
CEM	Yes	Yes	Yes	Yes	Yes

*This table reports the estimates of least square regressions for panel data. Independent variable is Degree of parallel exploration which is a scaled measure of the overlap between preliminary technological exploration and commercial exploration; calculated using the distinction between preliminary patent and trademark filings. Estimation method uses linear least squares. Dependent variables are individual year financial outcomes of the firm (i.e indicator variables for early funding, failure, being acquired and IPO as well as $ amount raised). The sample includes the 13,790 firms identified as deeptech. Robust standard errors clustered at firm-level are presented in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.*

Figure 1: Classification of firms by types and degree of risk/ uncertainty

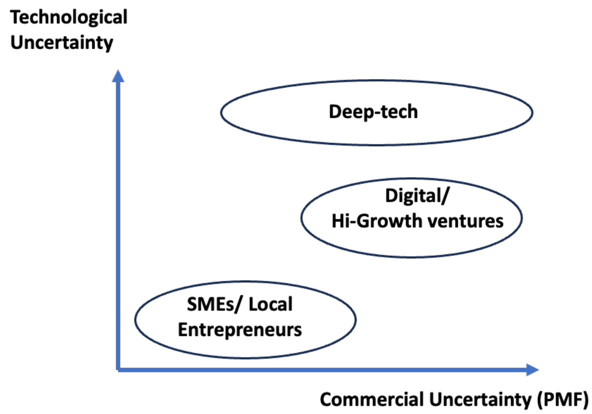


Figure 2: Information asymmetry (External) vs. Uncertainty (Internal)

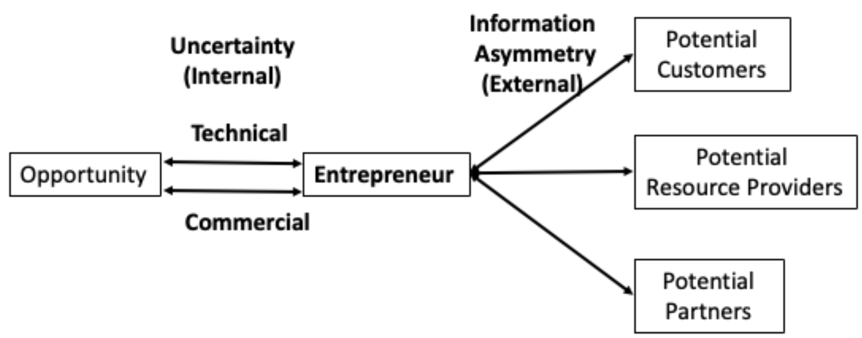


Figure 3: Commercial (Trademarks) and Technological (Patents)

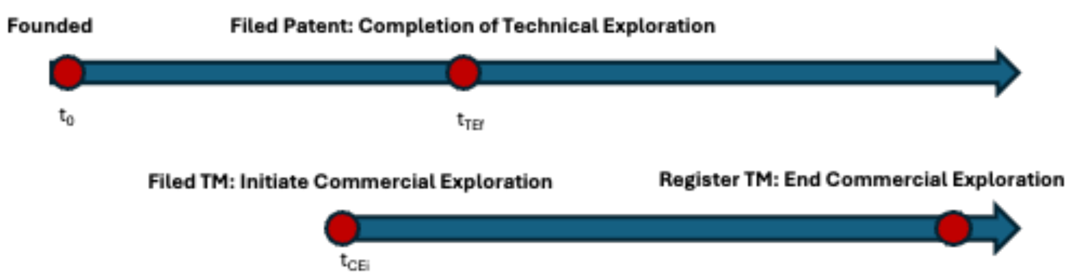


Figure 4: Evolution of 3D Printing technology

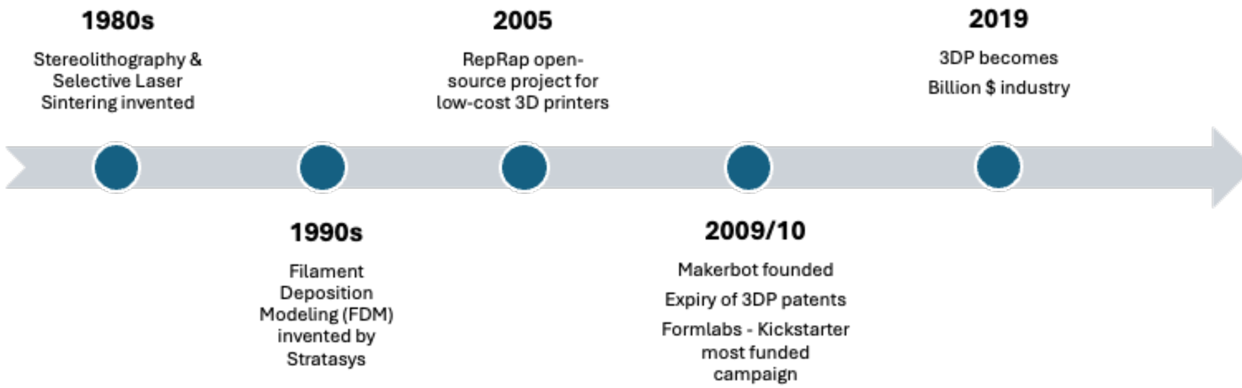


Figure 7: Google Search trends by Businesses/ Industrials for 3D Printing

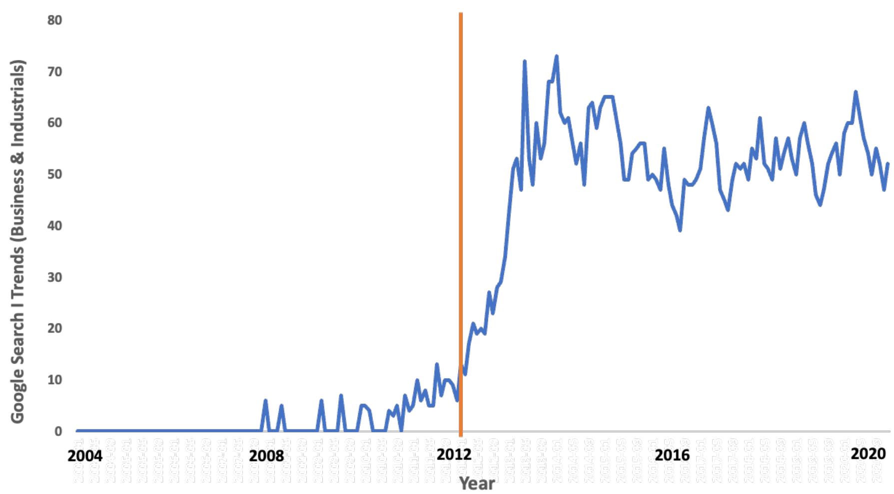
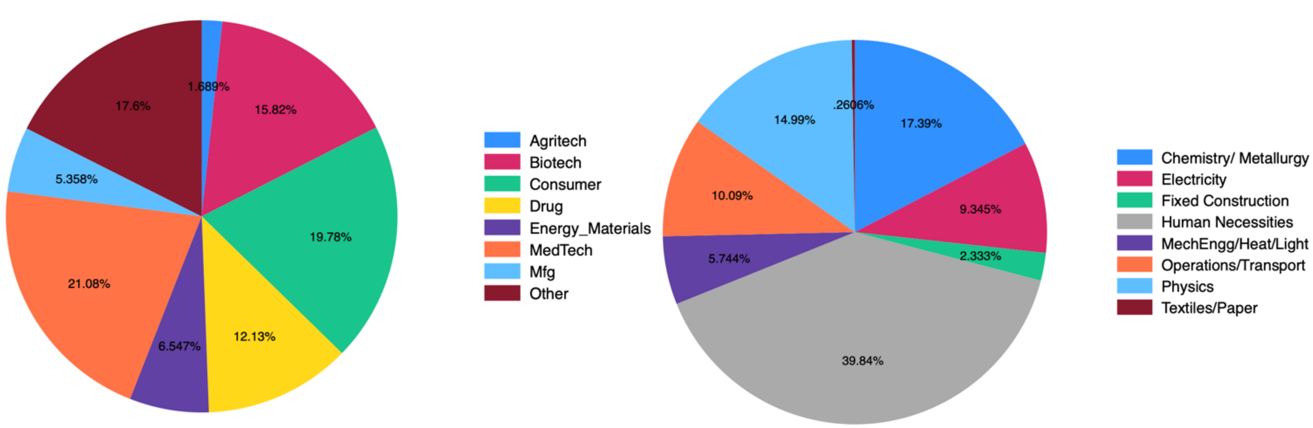


Figure 8: Firm distribution by Industry and CPC Class classification



`Figure 9: Benchmarking 3D Printing Treatment

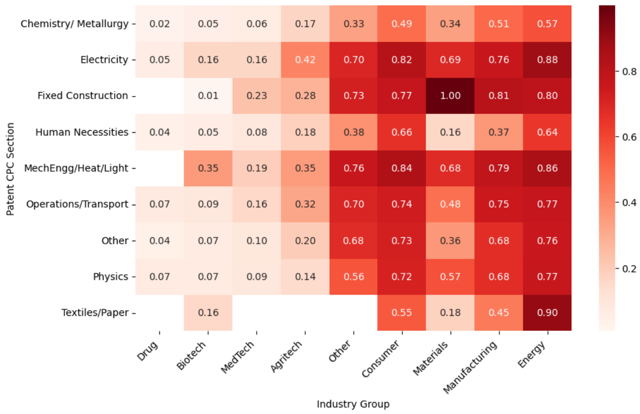
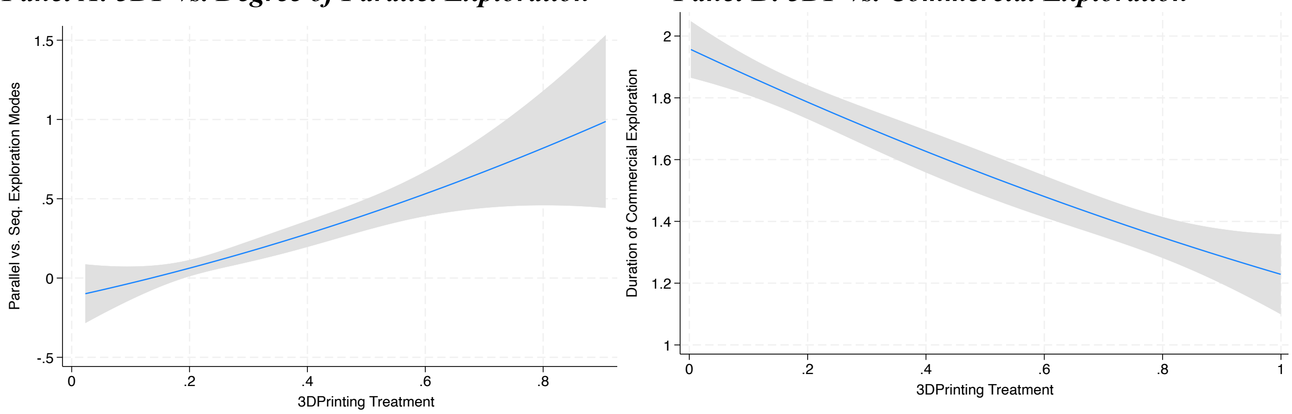


Figure 10: Calibration of 3D Printing Treatment versus Exploration

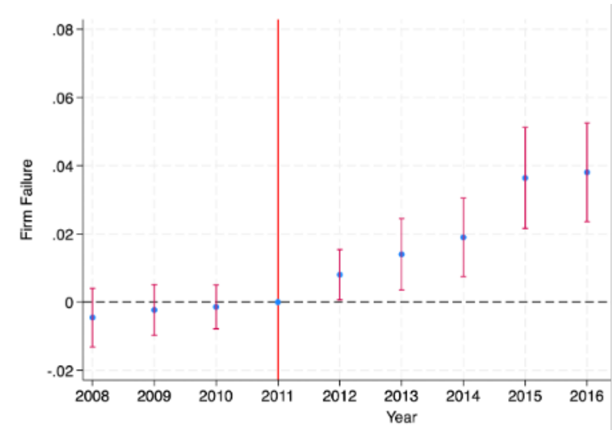
Panel A: 3DP vs. Degree of Parallel Exploration ***Panel B: 3DP vs. Commercial Exploration***



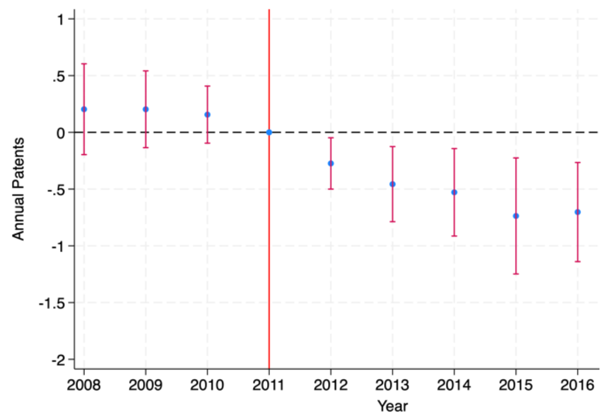
These figures represent non-parametric estimates i.e fitted regressions showing the relationship between 3DP treatment scores and degree of parallel exploration (panel A), duration of commercial exploration (panel B) and duration of technological commercialization (panel C).

Figure 11: Parallel pre-trends for 3D Printing Treatment versus Outcome variables

Panel A: Event study Failure likelihood

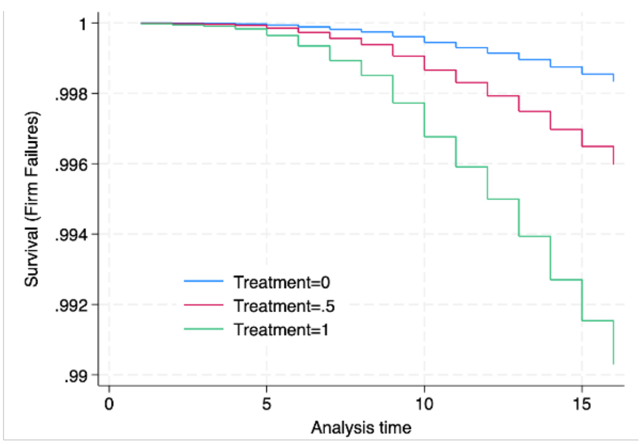


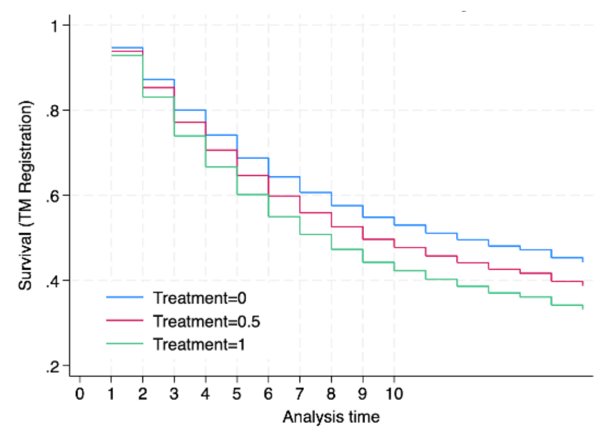
Panel B: Event study Patent count



These figures represent event study estimates for Failure, patent count variables illustrating parallel pre-trends for the treatment variable (3DP propensity scores). The sample includes the 13,790 firms identified as deeptech. Industry and Firm fixed effects have been applied. Robust standard errors clustered at firm-level.

Figure 12: Cox proportional hazards analysis survival results





Panel A: Failures

Panel B: Commercialization

These figures report the semiparametric Cox proportional hazards model results based on the 3D Printing Treatment scores. The plots estimate the survival probability of firm with respect to confirmed failures (panel A), failures incl. zombie firms i.e that have not raised capital (or reported) for 4 years (panel B), first commercialization (panel C), likelihood of being acquired (panel D) and IPO (panel E).