Who Starts Up When? Market Cycles and the Psychological Composition of Entrepreneurs

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Abstract
This paper shows that market cycles systematically reshape the psychological composition of entrepreneurial cohorts, with lasting consequences for strategy and performance. To study this, I estimate 16 psychological traits from pre-entry digital traces of more than 21,000 technology founders. Using multiple measures of market cycles, including a difference-in-differences design around the 2018 cryptocurrency crash, I find that market booms attract founders who are less risk-taking, less overconfident, and less aligned with the canonical entrepreneurial profile. These shifts arise through three mechanisms: increased entry by otherwise-unlikely founders, reallocation across industries, and changes in feeder roles. Startups founded during booms pursue more differentiated strategies, are shorter-lived, and more likely to achieve modest exits than outsized success. The results suggest that boom-time founders act as niche opportunists, targeting quick wins in specialized markets rather than pursuing broad-appeal, winner-take-all strategies. These findings contribute to the microfoundations of entrepreneurial strategy by showing how resource-rich environments shape not only the quantity but also the quality of new entrepreneurs.

1 Introduction

"*Easy money flooding the startup world infects it with the wrong kinds of people starting businesses.*"

- Zachary Slayback, Venture Capital Partner (1517 Fund)

A startup's competitive advantage often stems not just from its market position or product, but from the distinctive characteristics of its founders (Eisenhardt and Schoonhoven, 1990; Gompers et al., 2010; Eisenhardt, 2013). Founders differ in how they frame problems, respond to setbacks, and navigate uncertainty (Shepherd et al., 2015; Peterson and Wu, 2021) - behaviors that shape the strategic trajectory and ultimate success of their ventures (Camuffo et al., 2020; Valentine et al., 2024; Agarwal et al., 2025; Gans, 2025; Gans et al., 2025). Underlying these behaviors are enduring psychological traits - such as risk tolerance, overconfidence, and emotional stability - that influence how entrepreneurs act under uncertainty (Knight, 1921; Puri and Robinson, 2007; Åstebro et al., 2007; 2014). Reflecting this view, a growing body of research finds that founder traits influence startup performance, from raising financing to exit outcomes (Rauch and Frese, 2007; Zhao et al., 2010; Kerr et al., 2018; Freiberg and Matz, 2023).

If personality shapes startup performance, what determines which personalities become entrepreneurs? While prior work has explored how environmental factors and structural frictions shape entrepreneurial entry by demographics (Guzman and Kacperczyk, 2019; Marx, 2022; Stroube and Dushnitsky, 2025) and past experience (Sørensen, 2007; Sørensen and Fassiotto, 2011), it has largely overlooked how these forces influence the psychological profile of a cohort of entrepreneurs. This paper provides the first evidence that macro-environmental conditions

systematically influence the psychological composition of those who select into entrepreneurship.

I examine a defining feature of the technology ecosystem: boom and bust cycles. Boom cycles - also known as hot markets - are characterized by optimism about startups, abundant venture capital, and organizational enthusiasm for partnering with early-stage ventures. In contrast, bust cycles bring capital scarcity, investor caution, and reduced receptivity to innovation (Nanda and Rhodes-Kropf, 2013; Pontikes and Barnett, 2017; Janeway et al., 2021). The 2000 Dot Com Bubble illustrates this dynamic: the period leading up to the crash saw soaring valuations and a pervasive belief that the internet would transform the world overnight, while the aftermath brought a wave of startup failures and a climate of skepticism toward internet-driven business models (McCullough, 2018).

How might market cycles influence who chooses to become an entrepreneur? In hot markets, legitimacy signals from media coverage and liquidity events can foster a sense of inevitability about success (Stuart and Sorenson, 2003; Pontikes and Barnett, 2017). Such conditions can attract more risk-averse, less overconfident individuals who might not otherwise found startups. At the same time, abundant capital and investor appetite for high-risk, high-reward ideas (Nanda and Rhodes-Kropf, 2013; Howell et al., 2020; Janeway et al., 2021) can attract highly risk-taking, visionary entrepreneurs seeking to commercialize radical innovations. Thus, it is unclear whether booms primarily draw cautious opportunists exploiting favorable conditions or bold visionaries pushing new frontiers - complicating assumptions about who enters and why.

Uncertainty over who enters during boom periods has important implications for investors and corporate managers seeking to support innovation. One reason boom markets may

shift founder composition is that they reduce the perceived risks of starting a company - through abundant capital, strong signaling, and lower barriers to early traction. These same mechanisms are often present in organizational efforts to promote entrepreneurship (Miller and Bound, 2011; Bradley et al., 2021): corporate accelerators and investment vehicles similarly lower downside risk and raise the visibility of startup efforts. As a result, such programs may not only increase startup activity, but also shape who chooses to enter - with implications for the psychological makeup of the founder pool and the strategic trajectory of the ventures they build.

A central challenge in studying entrepreneurial psychology is that personality is typically measured through surveys - instruments that are difficult to administer at scale and often suffer from nonresponse bias, particularly among busy or high-profile individuals like startup founders. As a result, much of what we know about entrepreneurial psychology is based on small, potentially unrepresentative samples. In studies linking traits to startup outcomes, surveys are often conducted post-founding, raising concerns about reverse causality, as the experience of founding and running a startup may shape how individuals perceive or report their traits. These limitations - along with reliance on subjective outcomes - constrain the reliability and generalizability of prior findings (Kerr et al., 2018). To address these challenges, I develop a new approach that infers psychological traits from digital traces left by prospective founders. Building on recent advances in computational personality profiling (e.g., Kosinski et al., 2013; Freiberg and Matz, 2023; Ziems et al., 2024), I use supervised and large language models to estimate 16 validated traits from the Twitter activity of 21,887 entrepreneurs who posted before founding. This method enables pre-entry, nonreactive, and scalable measurement of traits such as risk-taking, overconfidence, self-efficacy, and the Big Five - allowing me to assess how industry-

and market-level shocks shape entrepreneurial selection and how this selection process affects subsequent performance. I obtain three core findings.

First, market cycles systematically shape who becomes an entrepreneur. Exploiting the 2018 cryptocurrency crash as an exogenous transition from boom to bust in a difference-in-differences design, I find that individuals founding startups during the boom period scored lower on traits commonly associated with entrepreneurial entry: they were less optimistic and overconfident, less tolerant of risk and volatility (higher neuroticism, lower risk-taking), showed weaker beliefs in personal agency (lower self-efficacy and internal locus of control), and were less open and innovative. These patterns are robust to alternative measures of boom conditions based on media attention, liquidity events and venture capital flows. Together, the results suggest that hot markets attract founders who are less characteristically entrepreneurial - that is, they score lower on the traits that typically distinguish entrepreneurs from non-entrepreneurs.

Second, changes in the psychological composition of founders emerge through distinct selection processes. During boom periods, individuals who might not otherwise become entrepreneurs - such as those who are more risk-averse or less overconfident - are more likely to enter. At the same time, boom cycles shift where different types of founders go: personality types less typical of entrepreneurship are more likely to found in hot sectors, reallocating traits across the startup landscape. Finally, boom periods also reshape the entrepreneurial pipeline: individuals entering common feeder roles - such as early stage employees at technology firms - tend to exhibit less canonical entrepreneurial traits, altering the future pool of potential founders.

Third, startups founded during hot markets follow different performance trajectories - shaped, in part, by shifts in the psychological profile of their founders. Boom-period startups

pursue more differentiated strategies, often in domains where founders have greater prior experience, tend to have shorter lifespans, and are more likely to achieve modest exits (e.g., acquisitions) than outsized outcomes (e.g., IPOs). These patterns align with a model in which hot market founders act as "niche opportunists": they leverage favorable conditions to target specialized segments where their expertise offers an edge, aim for quicker wins, and shut down earlier when traction is weak. In contrast, bust-period founders resemble "explorers" - more intrinsically motivated, patient without early success, and inclined to pursue unproven ideas with broader market appeal. Their ventures typically have longer development horizons, greater uncertainty over exit, and are more likely to produce rare, high-impact successes ("unicorns") sought by investors (Gompers and Lerner, 2001).

This paper contributes to entrepreneurial strategy by showing how market cycles shape the behavioral foundations of startup strategy. A growing literature highlights that a startup's strategic direction is often inseparable from its founder (Eisenhardt and Schoonhoven, 1990; Eisenhardt, 2013), from how they interpret uncertainty to how they make decisions under pressure (Camuffo et al., 2020; Agarwal et al., 2025; Gans, 2025). I extend this perspective by demonstrating that market conditions, including capital availability and legitimacy signals, systematically influence who enters entrepreneurship, shifting the psychological traits of founders across cycles. These psychological differences help explain variation in strategic choices at founding - such as the degree of differentiation - and contribute to differences in long-term outcomes including survival, acquisition, and IPO. In doing so, the paper offers a behavioral account of how macroeconomic environments shape entrepreneurial strategy through founder selection.

It also contributes to research on entrepreneurial psychology by showing that market conditions systematically influence who becomes an entrepreneur. Apparent inconsistencies in prior trait-based findings, often attributed to methodological artifacts (Kerr et al., 2018), may instead reflect differences in market context at the time of data collection. By linking founder selection to venture performance, the paper bridges also two long-standing questions: (1) which traits distinguish would-be entrepreneurs, and (2) which traits predict startup success (Rauch and Frese, 2007; Rauch et al., 2009; Zhao et al., 2010; Kerr et al., 2019; Freiberg and Matz, 2023). These findings clarify the psychology–performance connection and open new avenues for understanding how organizational and policy interventions shape the founder talent pool.

2 Theoretical Development

2.1 Who Enters When? Psychological Selection Across Market Cycles

The decision to become an entrepreneur is frequently modeled as an expected utility problem: individuals weigh the potential rewards of founding a venture against its costs and risks (Kihlstrom and Laffont, 1979). Psychological traits such as risk tolerance and overconfidence shape how individuals perceive these tradeoffs. More overconfident or risk-tolerant individuals may overestimate potential upside or discount downside risk, making them more likely to pursue entrepreneurship even in uncertain conditions.

However, market conditions dynamically alter the salience and perceived feasibility of entrepreneurial opportunities. Boom periods - marked by abundant funding, high valuations, and widespread enthusiasm - may reduce the perceived risks of failure and elevate the perceived likelihood of success. These shifts may lower the threshold for entry and draw in individuals who are less naturally risk-tolerant or overconfident, but who are enticed by visible success stories

and supportive market infrastructure. During bust periods, by contrast, heightened uncertainty and capital constraints may effectively screen out all but the most intrinsically motivated or psychologically resilient individuals. This hypothesis - that booms expand the founder pool to include individuals less aligned with the canonical entrepreneurial profile - is what I refer to as the "diluted-founder" hypothesis, illustrated in Figure 1.

[**Figure 1:** How Market Cycles Shift the Psychological Threshold for Entrepreneurial Entry]

Alternatively, boom cycles may amplify entry by the most risk-tolerant and visionary individuals, rather than diluting it. Hot markets are associated with increased investor appetite for radical, high-variance ideas and greater receptivity to novel business models (Nanda and Rhodes-Kropf, 2013). If individuals high in overconfidence and risk tolerance are more intrinsically motivated to pursue these kinds of ideas, boom environments may enable their entry by making these ventures seem more viable or fundable. In this view, market exuberance expands - not lowers - the psychological bar for entry by attracting founders with bold visions and high tolerance for uncertainty.

These divergent selection dynamics have downstream consequences. Entrepreneurs entering during boom periods may be more motivated by perceived opportunity than deep conviction, more likely to pursue niche strategies or narrowly defined market positions, and quicker to exit if traction falters. In contrast, bust-period founders may be more ideologically committed and willing to take on riskier, longer-term bets, which may delay early success but increase the odds of transformative outcomes - consistent with the idea that leaner times attract more resilient, high-upside founders.

2.2 Entry Mechanisms: How Market Cycles Reshape the Founder Pool

Founder selection can be reshaped through multiple mechanisms. First, market booms may lower the psychological barriers to entrepreneurship - such as perceived downside risk or uncertainty - prompting individuals who might not otherwise found to enter. These entrants may be more risk-averse or less overconfident than the canonical entrepreneur, consistent with a diluted-founder hypothesis in which favorable conditions attract founders less inherently predisposed to entrepreneurship.

Second, market cycles may alter where different types of entrepreneurs choose to enter. Founders with highly risk-tolerant or visionary profiles may always intend to start companies, but selectively target sectors with abundant capital and enthusiasm. In this way, booms reallocate founder types across industries rather than changing the overall level of entrepreneurship. Relatedly, hot sectors may attract a new pipeline of talent - such as early-stage employees or venture investors - whose traits differ from the existing pool and who may go on to found in the future.

These pathways have distinct implications. If boom-driven entry primarily expands who founds, then organizational policies that lower barriers to entrepreneurship may increase startup volume but shift the trait composition of the founder pool. If booms primarily reallocate effort across sectors, then such policies may influence the types of ventures launched - altering the strategic portfolio of startups without changing the total number.

3 Empirical Context

3.1 Growth-Oriented Technology Entrepreneurship

The empirical setting is U.S. technology founders who launched growth-oriented startups between 2008 and 2022. Although a small share of all new businesses, technology ventures account for a disproportionate share of job creation, innovation, and aggregate growth (Guzman and Stern, 2015; 2020). The sector also satisfies three conditions central to my theory. First, it experiences pronounced boom–bust cycles that shift the perceived risk–reward calculus for potential founders (Nanda and Rhodes-Kropf, 2013; Pontikes and Barnett, 2017). Second, founder psychology has been shown to predict performance in this context (Freiberg and Matz, 2023; McCarthy et al., 2023). Third, it is a frequent target of policy programs and managerial initiatives aimed at "stimulating startups" (Bradley et al., 2021).

I focus on three boom-sensitive resource signals. Media salience reflects industry optimism and shapes founders' perceptions of legitimacy and access to critical partners (Pontikes and Barnett, 2017; Chahrour et al., 2021; Bybee et al., 2024). Liquidity events - acquisitions and IPOs - reflect market receptivity to startup exits and shape founders' perceptions of the likelihood of success (Sorenson and Audia, 2000; Stuart and Sorenson, 2003; Pastor and Veronesi, 2005). Venture financing volume reflects investor willingness to fund risky projects and shapes founders' expectations of raising capital (Gompers et al., 2008; Nanda and Rhodes-Kropf, 2013; Howell et al., 2020; Janeway et al., 2021).

3.2 A Natural Experiment: The 2017–18 Cryptocurrency Crash

Cryptocurrency and its underlying blockchain technology supply a sharp transition from boom to bust. From 2014 to December 2017, soaring coin prices, upbeat press, and record

venture funding signaled a hot market. In January 2018 prices collapsed by over 80 percent and stayed depressed through 2020, triggering a funding drought and widespread skepticism (Kharif, 2017; Rooney, 2018). The boom's reversal is apparent across multiple indicators: venture funding growth rates for cryptocurrency-adjacent startups collapse after 2017 (Appendix Figure A4), public interest in blockchain declines sharply (Appendix Figure A5), financial news sentiment turns strongly negative (Appendix Figure A6), and bitcoin market capitalization contracts by more than 80 percent (Appendix Figure A3).

I exploit this crash as a quasi-experimental shock: entrepreneurs who started ventures after January 2018 faced a markedly different risk–reward environment than those launching during the boom. This setting lets me test whether boom conditions dilute the founder pool (by attracting less risk-tolerant or overconfident individuals) or amplify it (by enabling entry by the most risk-tolerant visionaries), and how those selection effects influence subsequent venture outcomes.

4 Data and Empirical Strategy

Section 4 describes the data and sample (4.1), details variable construction (4.2), and outlines the empirical strategy used to estimate the main effect, mechanisms, and startup outcomes (4.3). Additional robustness checks are reported in the Appendix.

4.1 Data Sources and Sample Construction

To examine founder psychology and its relationship to market cycles, I construct a novel dataset covering U.S.-based technology founders who launched startups between 2008 and 2022. I integrate information from five primary sources: (1) Crunchbase, which provides data on

startups and their founding teams; (2) public Twitter data, used to infer founders' psychological attributes at the time of founding; (3) a training dataset from the MyPersonality project linking social media language to validated personality questionnaires; (4) large language models, which enable the measurement of additional traits emphasized in the entrepreneurship literature (e.g., risk-taking, overconfidence); and (5) LinkedIn, which provides biographical details used for demographic and career controls. The final dataset contains 21,887 unique founders and their associated startups.

4.2 Variable Construction

4.2.1 Founder-Psychology Measures

This section details the construction of founder psychology measures. I begin by outlining the traits studied, then describe how these traits are inferred from founders' social media language using recent advances in natural language processing. I conclude by explaining how individual-level predictions are aggregated to the industry-year level.

Trait selection. My primary dependent variable is the psychological profile of founders at the time they launch their startups. While I emphasize four exemplar traits - risk-taking, overconfidence, self-efficacy, and innovativeness - each representing one of four core psychological domains, I study 16 traits frequently discussed in the entrepreneurship literature (Kerr et al., 2018; 2019). These include risk-taking, risk aversion, optimism, overconfidence, self-efficacy, internal locus of control, need for achievement, innovativeness, growth mindset, need for autonomy, tolerance for stress and uncertainty, and the Big Five personality traits. These traits can be grouped into broad psychological domains - the same domains represented by my four exemplar traits: (1) tolerance for uncertainty (e.g., risk-taking, risk aversion, stress

tolerance), (2) beliefs about outcomes (e.g., overconfidence, optimism), (3) perceived agency or control (e.g., self-efficacy, locus of control, growth mindset, autonomy), and (4) cognitive openness (e.g., innovativeness, openness to experience). This grouping is illustrated in Table 1.

[**Table 1:** Psychological Traits by Four Core Domains]

Prediction from digital footprints. A common limitation in prior research on entrepreneurial psychology is the reliance on surveys administered after founding, which introduces concerns about reverse causality and response bias. To address this, I predict psychological traits from digital traces using entrepreneurs' Twitter data from before founding, an approach validated in recent work (Kosinski et al., 2013; Youyou, et al., 2015; Freiberg and Matz, 2023).

I identify all U.S.-based technology entrepreneurs in Crunchbase who founded startups between 2008 and 2022 and who had an active, valid Twitter account. I extract their tweets from the two-year period prior to startup founding, excluding entrepreneurs with fewer than 50 tweets in that window. This yields a sample of 21,887 entrepreneurs and approximately 22 million tweets (306 million words).

I then use two complementary approaches to estimate psychological traits. To measure 11 traits beyond the Big Five, I apply large language models ("LLMs"), following recent findings that LLMs can reliably infer psychological constructs from text in zero-shot scenarios (Ziems et al., 2024; Peters and Matz, 2024). I prompt GPT-4o with structured instructions (e.g., "*Pretend you are a social psychologist...*") to estimate trait scores on a 1–7 scale, later standardized for analysis. This approach is detailed in Appendix 1A. To predict the Big Five, I apply supervised

models trained on the MyPersonality project, which matched Facebook status updates with validated personality questionnaires from over 66,000 users (Kosinski et al., 2015). These models, trained using sentence embeddings and cross-validated with correlations between 0.3–0.4, output point estimates on a 1–5 scale (also standardized).

Both approaches are validated in Appendix 1B. Supervised model predictions are benchmarked against self-report surveys, and LLM-predicted traits are evaluated by (a) testing whether their correlations with supervised Big Five traits match theoretical expectations (e.g., neuroticism inversely related to risk-taking), and (b) verifying that they predict downstream entrepreneurial outcomes in expected ways (e.g., higher risk-taking associated with greater likelihood of extreme startup outcomes).

Aggregation to industry-years. Because my identification strategy exploits within-industry variation in founder traits over time, I aggregate individual-level estimates to the industry-year level. I follow Crunchbase's categorization of startups into 697 "categories" (e.g., Blockchain, CleanTech, Lending), treating each as a distinct industry. Each startup may belong to up to five such categories. For each industry-year combination with at least one founder in my sample, I calculate the average value of each trait across all entrepreneurs who founded startups in that industry and year.

This results in an unbalanced panel of 6,325 industry-year observations, each with average scores for all 16 psychological traits. For example, the average risk-taking score for Blockchain founders in 2015 is calculated by averaging the risk-taking estimates of all entrepreneurs who launched Blockchain startups that year. These aggregated measures serve as the basis for my industry-level analyses linking boom–bust cycles to shifts in the psychological composition of new founders.

4.2.2 Psychology Estimates for Non-Founders

In addition to trait estimates for entrepreneurs, I compile personality estimates for a broader set of individuals who are not founders but work in comparable sectors and roles. These non-founder person-years come from the same market domains and time periods as the founder sample, providing a relevant comparison group for examining how market conditions shape the traits of those who become entrepreneurs versus those who remain employees.

To build this dataset, I leverage the fact that many employees in technology, early-stage startups, and venture capital include "@" tags for their employers or former employers in their Twitter bios. For technology companies listed in Crunchbase, I retrieve all Twitter users tagging the company and cross-reference these accounts to a historical snapshot of LinkedIn profiles. Individuals are matched to employers using fuzzy name matching. For each matched employee, I collect tweets from the period before they joined the company and apply the same personality estimation methods used for founders (Section 4.2.1), which combine supervised models trained on social media text with large language model prompts. This process produces personality estimates for approximately 6,352 employees across 5,632 companies and 13,368 jobs, drawing on 10M tweets.

4.2.3 Market-Cycle Indicators

To capture boom–bust variation at the industry–year level, I use two approaches: a quasi-experimental event study of the 2018 cryptocurrency crash and continuous indicators of industry salience, exit activity, and capital availability measured across the full dataset.

Cryptocurrency crash (event indicator). I treat the December 2017 collapse of the cryptocurrency market as a sharp transition from boom to bust. During the boom phase

(2014–2017), coin prices soared, press coverage and venture funding reached record highs, and new crypto startups proliferated; after the crash, prices fell by more than 80 percent and media salience, funding volume, and venture formation declined steeply (Kharif 2017; Rooney 2018; Appendix 2A–E). The crash was driven by speculative overvaluation and abrupt regulatory interventions - including China's ICO ban and U.S. SEC enforcement actions - that rapidly deflated crypto prices (Cheah et al., 2015; Corbet et al., 2018; Huber and Sornette, 2022). These developments were unrelated to the underlying quality or psychological traits of prospective founders, creating a plausibly exogenous shock and natural experiment in entrepreneurial entry. To capture this shift, I construct two indicator variables: *Crypto* equals 1 for industries tagged by Crunchbase as Blockchain, Bitcoin, or Ethereum, and *PostCrash* equals 1 for years 2018 and onward. Section 4.3 explains how these indicators are used in a difference-in-differences framework.

Media salience. To capture industry visibility, I use the number of unique startups issuing press releases in each industry as a proxy for public attention. This avoids results being dominated by a few very large firms and instead reflects broad-based momentum. Press releases are widely followed by investors, partners, and employees, and serve as a key channel for firms to signal legitimacy (Pontikes and Barnett, 2017). I use the cumulative number of press-releasing firms in the two years prior to startup founding, which smooths short-term fluctuations and better captures sustained salience. A log transformation - $\log(PressReleases_{t-1,t-2} + 1)$ - adjusts for skewness.

Liquidity events. As a complementary indicator of market cycles, I measure IPOs and acquisitions in each industry. These events signal entrepreneurial success and increase sector legitimacy, shaping founders' beliefs about potential payoffs (Stuart and Sorenson, 2003;

Gompers et al., 2005; Howell et al., 2020). I use the cumulative number of events in the two years before founding, which provides a stable measure of the signals prospective founders observe, and apply a log transformation - $\log(LiquidityEvents_{t-1,t-2} + 1)$ - to adjust for skewness.

Venture capital availability. As a financial counterpart to media attention and liquidity events, I measure capital availability using the total venture financing raised in each industry. These financings signal investor willingness to back new ventures and shape founders' perceptions of viability (Nanda and Rhodes-Kropf, 2013). I use the cumulative sum raised in the two years prior to founding, which dampens temporary fluctuations and reflects the environment entrepreneurs observe. A log transformation - $\log(VentureDollars_{t-1,t-2} + 1)$ - reduces skewness and accounts for diminishing marginal effects.

4.2.4 Startup-Level Measures: Strategic Choices and Performance Outcomes

To examine how market cycles and founder psychology relate to downstream venture trajectories, I construct four startup-level measures. One captures an early strategic choice - differentiation at founding - while the others capture longer-term performance outcomes: survival, acquisition, and initial public offering (IPO). Because these measures do not require psychological trait predictions, I analyze them across the full set of U.S. technology startups founded between 2008 and 2022 (N = 398,169), enhancing statistical power and generalizability.

Strategic Choices. I proxy early strategic positioning using a startup-level differentiation score developed by Guzman and Li (2023). This text-based measure captures how distinct a startup's website language is relative to other startups at the time of founding, based on semantic analysis of product descriptions. Higher values indicate a more differentiated market position. I merge these scores to my sample using Crunchbase-listed website URLs. Prior work links

differentiation strategy to differences in the likelihood of raising early financing and the probability of exit.

Performance Outcomes. I analyze three downstream performance outcomes: organizational survival, acquisition, and initial public offering (IPO). Survival is estimated using LinkedIn employment data by matching Crunchbase startups to LinkedIn profiles and tracking whether they maintain at least one active non-founder employee in each year following founding, up to a 10-year cap. This provides a proxy for ongoing organizational activity during the high-risk startup phase. Acquisition and IPO status are identified from Crunchbase's event data, with binary indicators capturing whether a startup experienced either outcome. While financial details are often unavailable, acquisitions typically represent moderate exits and IPOs larger ones: the median acquisition of a venture-backed technology startup is valued at approximately $100M, while the median IPO exceeds $600M (Lennon, 2013).

4.3 Identification and Model Specification

I exploit two complementary units of analysis. Industry-year observations enable a difference-in-differences design that identifies within-industry shifts in the average psychological profile of new founders as markets transition from boom to bust. Entrepreneur-level observations provide generalizable evidence across industries and link market cycles, founder traits, and subsequent startup outcomes, with mediation tests for psychological pathways.

4.3.1 Main Effect: Psychological Selection into Entrepreneurship Across Market Cycles

I test whether boom–bust transitions alter the average psychological profile of new entrepreneurs using a difference-in-differences ("DiD") design centered on the 2018

cryptocurrency crash. The panel consists of industry-year observations defined in Section 4.2.1. The estimating equation is:

$$Trait_{it} = \beta Crypto_i \, x \, PostCrash_t + \alpha_t + \delta_i + \varepsilon_{it} \qquad \textbf{[1]}$$

where $Trait_{it}$ is the average standardized score of a given psychological trait among entrepreneurs who entered industry i in year t, $Crypto_i$ equals 1 for Blockchain, Bitcoin, or Ethereum industries, $PostCrash_t$ equals 1 for 2018 and later years, and α_t and δ_i represent year and industry fixed effects, respectively. In robustness checks, I additionally include time-varying controls for the percentage of female entrepreneurs and mean entrepreneur age; results are unchanged.

To improve covariate balance between treated and comparison industries, I implement coarsened exact matching (CEM) prior to estimation. For each psychological trait, I construct a matched sample of crypto-adjacent and non-crypto industries with similar pre-crash trait values, acknowledging that baseline levels differ across traits (e.g., average pre-period overconfidence may differ from neuroticism). The matched DiD specification is my preferred approach, as it reduces reliance on functional form assumptions and strengthens comparability across groups. Results are largely consistent with the unmatched design and are reported in Appendix Table A5; details on the matching procedure are provided in Appendix 3A.

Alternative market-cycle models. To assess generality, I estimate analogous OLS models that replace the DiD interaction with continuous indicators of industry "hotness." Specifically, I use three measures described in Section 4.2.3: press release activity, liquidity events (IPOs and acquisitions), and venture capital raised. For entrepreneur-level analyses, each startup inherits the

average value of its industries' scores, weighted by the number of categories assigned on Crunchbase

4.3.2 Channels of Psychological Selection

To illuminate how boom and bust cycles shape the psychological composition of new founders, I explore four complementary channels. While the main analysis estimates the net effect of market cycles on founder psychology, the analyses below help unpack how these changes arise - distinguishing between changes in the predictive power of traits for entry, behavioral shifts in personality itself, and patterns of sorting into industries and entrepreneurial pipelines.

Trait-Contingent Entry. This analysis examines whether the relationship between psychological traits and the likelihood of founding a startup - among individuals at risk of entry - changes across market cycles. For example, someone more risk averse might be willing to found a startup during boom periods, when resources and collective optimism are high, but not during busts. I focus on individuals with prior professional experience in the cryptocurrency sector, who are most likely to be affected by the 2018 crash. Using person-year panel data covering both founders and non-founders, I estimate Cox hazard models in which the dependent variable is founding a cryptocurrency startup in a given year. The key regressors are interactions between the post-crash indicator and trait scores (e.g., risk-taking, overconfidence, self-efficacy, innovativeness). This approach identifies whether the effect of a trait on the likelihood of founding is amplified or diminished in bust periods for those most exposed to the downturn.

Trait Plasticity. This channel asks whether individuals' psychological traits themselves shift in response to boom and bust conditions - reflecting changes in mindset, motivation, or

affective orientation shaped by the market environment. For example, a person working in a surging sector may become more overconfident over time. To examine this, I estimate fixed-effects OLS models on a person-year panel. The outcome is the inferred trait score in year *t*, and the key regressors is an indicator for post-crash. Individual fixed effects absorb time-invariant differences in baseline personality, isolating within-person change over time.

Sectoral Reallocation. This analysis tests whether market booms attract individuals to found in industries outside their area of prior experience - and whether these "sectoral switchers" differ in psychological traits. Using OLS models, I regress founder traits on interactions between sectoral switcher status and industry-year measures of market booms (e.g., log press coverage). The unit of analysis is the individual founder. This approach reveals whether hot markets disproportionately attract individuals without prior experience in the sector, and whether these individuals are psychologically distinct - for example, less risk-taking or less overconfident.

Pipeline Shifts. Finally, I test whether market cycles change the traits of individuals entering early-stage startup employment - a well-documented pathway into future entrepreneurship. Using OLS regressions, I relate industry-year measures of market booms to the traits of individuals entering these roles. The sample consists of employee-job observations, and models include city, industry, and year fixed effects. This analysis captures whether hot markets shift the psychological composition of the broader entrepreneurial pipeline - even if the trait–founding relationship remains constant.

Together, these complementary analyses shed light on how boom and bust cycles reshape the entrepreneurial landscape by influencing both who enters and how traits shape entry behavior.

4.3.3 Strategic Choice and Performance Models

I estimate two sets of models that together link market cycles to early strategic choices and startup performance, respectively.

Strategic Differentiation Models. First, I examine whether founding conditions - measured using market cycles and media salience - are systematically associated with differences in a startup's initial strategic positioning. This analysis assesses a potential pathway by which shifts in founder traits in response to market cycles might influence performance: variation in early strategy. Differentiation is measured using the semantic distinctiveness score of Guzman and Li (2023), as described in Section 4.2.4. By isolating the relationship between founding context and strategic differentiation, I provide the first step in linking market cycles to eventual performance outcomes.

Performance Models. Next, I estimate whether startups founded under different market conditions exhibit different performance outcomes. I analyze three outcomes defined in Section 4.2.4: survival (years with active non-founder employees on LinkedIn, capped at 10; OLS), acquisition (binary; logit), and IPO (binary; logit, estimated on venture-financed startups). The key regressors are industry-level measures of founding-year market conditions: lagged press coverage aggregated over $t-2$ to $t-1$ for the broader sample of startups. All models include fixed effects for founding city, industry, and year, and cluster standard errors by year founded, industry, and state. Robustness specifications add founder gender and age where available.

To assess whether market cycles affect outcomes through founder selection, I conduct supplementary mediation analyses using inferred founder trait estimates (constructed from pre-founding digital traces; Section 4.2.1) as mediators. Indirect effects are computed using the product-of-coefficients approach with bootstrap confidence intervals, following Hayes (2017),

after estimating the mediator and outcome models. Results are reported in Appendix Table A10 and interpreted cautiously given the usual limitations of mediation in observational settings (Imai et al., 2010; Hicks and Tingley, 2011).

5 Results

Section 5 presents the main empirical findings of the paper. I begin by estimating the net impact of market cycles on the psychological traits of new entrepreneurs (Section 5.1), followed by a series of robustness checks. I then unpack the channels through which these changes occur (Section 5.2) and examine how they shape the strategic choices and performance trajectories of startups that are founded (Section 5.3). Descriptive statistics for the sample are provided in Table 2.

[**Table 2:** Descriptive Statistics]

5.1 Main Effect: Market Cycles and the Psychological Composition of New Entrepreneurs

5.1.1 Event Study: The 2018 Cryptocurrency Crash as a Natural Experiment

The 2018 cryptocurrency crash provides a sharp transition from boom to bust, offering a natural experiment to test how market cycles shape entrepreneurial entry. Entrepreneurs who founded startups in the bust period differ systematically from those who entered during the boom: they are more tolerant of volatility (e.g., higher risk-taking, lower neuroticism, greater stress tolerance), more optimistic about outcomes (e.g., higher overconfidence and optimism), more internally driven (e.g., greater self-efficacy, internal locus of control, and growth mindset), and more intellectually curious (e.g., higher innovativeness and openness). Figures 2 and 3

illustrate these shifts: Figure 2 highlights the four exemplar traits (risk-taking, overconfidence, self-efficacy, and innovativeness), and Figure 3 demonstrates that across the broader domains of personality, traits move in similar directions - e.g., with openness increasing and risk aversion declining.

Table 3 reports difference-in-differences estimates for the four exemplar traits among new entrepreneurs in cryptocurrency-adjacent sectors before and after the 2018 crash. Across specifications, the results show a statistically and economically significant increase in all four traits post-crash. For instance, risk-taking increases by 0.45–0.67 SD depending on the model specification (Columns 1–2), while overconfidence rises by 0.35–0.68 SD (Columns 3–4), self-efficacy increases by 0.58–0.81 SD (Columns 5–6), and innovativeness rises by 0.55–0.64 SD (Columns 7–8).

Prior research suggests that changes of this magnitude in founder personality can have sizable consequences for venture outcomes: Freiberg and Matz (2023) show, for example, that a one–standard deviation increase in traits such as neuroticism or conscientiousness is associated with a 15–16% lower likelihood of successful exit via acquisition or IPO. This underscores that the shifts observed here are not only statistically significant but also of a magnitude likely to shape entrepreneurial trajectories - a possibility I test directly in Section 5.3.

[**Figure 2:** DiD Event Study - Exemplar Traits]

[**Table 3**: DiD Event Study - Exemplar Traits]

[**Figure 3:** DiD - All Traits]

5.1.2 Alternative Indicators of Market Cycles: Press Coverage, Liquidity Events and Venture Capital

To test whether the results generalize beyond cryptocurrency, I replicate the analysis with three indicators of boom conditions measured across all industries: press coverage, liquidity events, and venture capital financing. Table 4 presents estimates for the four exemplar traits - risk-taking, overconfidence, self-efficacy, and innovativeness - using press coverage and liquidity events as indicators. Industries with heightened media coverage are associated with the entry of less risk-taking, less overconfident, lower self-efficacy, and less innovative entrepreneurs. These patterns closely track the cryptocurrency event study findings. Liquidity events reinforce the media salience results, offering convergent evidence that boom conditions shift the psychological composition of entrants away from canonical entrepreneurial traits. Appendix results (Table A7) using venture capital availability are also broadly supportive: two traits are significant and aligned, while two others are directionally consistent though less precisely estimated.

[**Table 4**: Alternative Indicators of Market Cycles: Press Coverage and Liquidity Events]

These patterns also hold after controlling for founder gender and age at the industry-year level, ruling out demographic shifts as the primary driver (Appendix Table A6).

5.2 Channels of Psychological Selection

To unpack how market cycles alter founder psychology, I examine four channels of psychological selection: shifts in trait–entry relationships, sectoral sorting, pipeline shifts, and reallocation across industries.

5.2.1 Trait-Contingent Entry

Do booms and busts change *who* becomes an entrepreneur? This analysis tests whether the relationship between psychological traits and startup entry shifts across market cycles. Using a person-year panel of individuals with prior professional experience in the cryptocurrency sector - those most exposed to the 2018 crash - I estimate Cox hazard models in which the likelihood of founding a blockchain startup is regressed on interactions between *PostCrash* and trait scores.

Table 5 reports results for the four exemplar traits. After the crash, individuals higher in risk-taking and overconfidence were at significantly greater risk of entry (Columns 1–2). Self-efficacy and innovativeness also show positive, marginally significant effects (Columns 3–4). The magnitudes are striking: a 1 SD increase in risk-taking is associated with nearly a fourfold increase in the hazard of founding post-crash, while a similar increase in overconfidence corresponds to an even larger gain. Even the smaller coefficients - for self-efficacy and innovativeness - imply meaningful shifts, on the order of three- to fourfold increases. These patterns highlight how strongly market cycles sort potential founders, concentrating entry among those with unusually high tolerance for risk and confidence in their own abilities.

[**Table 5:** Trait-Contingent Startup Entry After the 2018 Cryptocurrency Crash]

5.2.2 Trait Plasticity

Another possible mechanism is trait plasticity - changes in an individual's psychological traits in response to market conditions. Prior work suggests that personality can shift in the face of major life events or sustained exposure to certain environments or narratives (Helson et al., 2002; Caspi et al., 2005). For example, prolonged immersion in a booming technology sector might gradually increase a person's overconfidence or reduce their risk aversion.

If such adaptation were occurring, it could provide an alternative explanation for the observed changes in the psychological composition of entrepreneurs: rather than selection effects, market cycles might shape individuals' traits before they found. This channel would generally predict that boom periods lead individuals to become more risk-taking and overconfident - in contrast to my main results, which show that less risk-taking and less overconfident individuals tend to enter during booms.

Nonetheless, to directly evaluate whether more subtle or delayed forms of adaptation might still operate, I estimate individual fixed-effects regressions on a person-year panel, where the outcome is the inferred trait score and the key regressor is an indicator for the post-crash period. Across all specifications, I find no evidence of systematic trait change in response to boom or bust conditions (Appendix Table A8), suggesting that trait plasticity is not a meaningful channel in this setting.

5.2.3 Sectoral Reallocation

Hot markets may not only affect whether individuals found startups, but also where they choose to do so. In particular, booms may draw prospective entrepreneurs into industries outside their prior work experience - a process of "sectoral reallocation." If entrants without prior sector

experience differ systematically in psychological traits from incumbents, this inflow could shift the overall psychological profile of new founders.

Table 6 examines this channel by interacting industry-level press coverage with founder traits in predicting whether a new founder is a sectoral switcher (i.e., launching in an industry without prior work experience). Results show that during periods of heightened media attention, sectoral switchers tend to be significantly less risk-taking, less self-efficacious, and less innovative, with no systematic change in overconfidence. This pattern suggests that booms attract entrants who are more cautious, less confident in their capabilities, and less oriented toward novelty than typical industry insiders. These results suggest that sectoral reallocation is a mechanism contributing to the observed changes in founder psychology during boom periods.

[**Table 6:** Sectoral Reallocation]

5.2.4 Pipeline Shifts

Market cycles may also shape the psychological composition of founders indirectly, by changing who enters common "feeder" roles into entrepreneurship - such as early-stage employees at technology startups. If booms attract different types of people into these roles, they may alter the future founder pool even if the trait–entry relationship remains constant.

Table 7 examines this pipeline mechanism by regressing founder-relevant traits of new early-stage employees on industry-level press coverage. Booms are associated with significantly lower risk-taking, overconfidence, and self-efficacy among entrants - a pattern consistent with my main results on who founds during booms - and with significantly higher innovativeness. This last finding runs counter to the founding-stage patterns, potentially reflecting that

boom-time feeder roles attract individuals more open to novelty but less willing to assume personal risk or overestimate their capabilities. Such shifts in the feeder pool may help explain longer-term changes in the psychological makeup of entrepreneurs, even years after the boom has passed.

[**Table 7**: Pipeline Shifts]

5.3 Startup Consequences: Strategic Choices and Performance Outcomes

Having established that market cycles shape the psychological composition of entrepreneurial cohorts, I now examine how these shifts manifest in the startups that founders create. I distinguish between two sets of downstream consequences. First, I analyze early-stage strategic choices, focusing on product and business model differentiation at founding. These reflect initial positioning decisions that are plausibly shaped by founder psychology. Second, I assess longer-run performance outcomes, including organizational survival, acquisition, and IPO. Together, these analyses shed light on how hot markets not only influence who enters entrepreneurship, but also what kinds of ventures they build - and how those ventures perform.

5.3.1 Strategic Choices: Differentiation at Founding

Startups founded during market booms are significantly more strategically differentiated at founding than those launched during bust periods (Table 8). Because differentiation is standardized, the coefficient estimates imply that a one-unit increase in log press releases - roughly equivalent to tripling the number of releases - is associated with a 0.02–0.09 SD increase in differentiation. Put differently, moving from the 25th to 75th percentile in press release

activity corresponds to about a 0.03 SD higher differentiation score. While modest at the firm level, these shifts are systematic across the sample and, in combination with evidence that boom-time founders are more likely to have domain expertise (Appendix Table A9), suggest that boom-time entrants tend to pursue narrower, more specialized positions rather than broad exploratory plays. Additionally, prior research shows that greater differentiation is associated with a lower likelihood of IPO (Guzman and Li, 2023), a pattern echoed in the performance results below.

[**Table 8:** Strategic Choices]

5.3.2 Performance Outcomes

How do market cycles at founding shape startups' long-term trajectories? Building on earlier results showing that booms shift the founder pool toward individuals who are less risk-taking, less self-efficacious, and less overconfident, Table 9 shows that these ventures also follow systematically different performance paths. Startups launched in boom periods tend to survive for fewer years on average, are more likely to be acquired, and are less likely to reach an IPO than those founded during bust periods. The estimated magnitudes are meaningful: a one-unit increase in log press releases - roughly equivalent to tripling the number of releases - is associated with a 0.1–0.16 year reduction in survival, an 8–26% increase in the probability of acquisition, and a 14–19% decrease in the probability of IPO. While the survival effect is modest in absolute terms, the acquisition and IPO effects represent sizeable shifts in venture trajectories. Together, these patterns underscore that boom-time entrants disproportionately achieve modest exits rather than outsized successes.

[**Table 9:** Performance Outcomes]

To better understand the mechanisms linking market conditions to these outcomes, I conduct mediation analyses using founder traits as mediators. While interpretation requires caution due to empirical limitations, the results suggest that changes in the psychological composition of founders - particularly in traits such as risk-taking and overconfidence - partially mediate the effects of boom periods on IPO and acquisition likelihood (Appendix Table A10). These findings point toward founder psychology as a key mechanism linking market cycles to venture trajectories.

Taken together, the evidence paints a consistent picture: boom-time founders, drawn in by favorable conditions, tend to pursue quick wins in specialized markets rather than building ventures with broad appeal and long-run growth potential. As a result, their startups are more likely to achieve modest exits through acquisition, less likely to sustain survival over the long run, and rarely achieve transformative outcomes like IPO. These patterns highlight how shifts in founder psychology shape both the strategic choices entrepreneurs make and the performance trajectories their ventures follow.

6 Conclusion

This paper demonstrates that market booms and busts do not just change the number of entrepreneurs - they change who they are and the kinds of ventures they build. Founders entering during hot markets are, on average, less risk-taking, less overconfident, and less psychologically aligned with the canonical entrepreneurial profile. These shifts emerge through distinct selection

processes: booms draw in individuals who might not otherwise found, reallocate founder types across industries, and alter the composition of roles that feed into entrepreneurship.

These psychological differences carry strategic and performance consequences. Boom-time founders build ventures that are more differentiated at founding yet have shorter survival durations, are more likely to exit through acquisition, and less likely to go public. Mediation analyses suggest that differences in traits - particularly risk-taking and overconfidence - partially explain these patterns. Taken together, the results depict boom-period founders as niche opportunists: drawn by favorable conditions, more focused on targeted opportunities than on long-term exploration, and consequently more likely to produce modest exits than transformative outcomes.

For managers, investors, and accelerators, the findings highlight that lowering barriers to entrepreneurship - via capital, visibility, or signaling - changes not only the quantity of startups, but also the types of individuals who enter. These shifts can cascade into differences in strategic orientation and risk profile at founding. Effective support for early-stage entrepreneurs therefore requires attention to both who is entering and how their psychological profile may shape the ventures they create.

For research on entrepreneurship and strategy, this paper provides a behavioral account of how macroeconomic conditions shape venture outcomes through founder selection. Building on work linking founder characteristics to strategic decision-making and performance (Eisenhardt and Schoonhoven, 1990; Eisenhardt, 2013; Camuffo et al., 2020; Agarwal et al., 2025; Gans, 2025), I show that market cycles systematically shift the psychological traits of new founders. This helps explain variation in early strategic choices like differentiation and in outcomes such as survival, acquisition, and IPO. The findings also help clarify inconsistencies in prior trait-based

research, which may reflect not only measurement limitations but also systematic shifts in who enters across market contexts. Finally, by connecting entry traits to venture performance across market conditions, the paper bridges two core questions in the literature - which traits predict entry, and which predict success (Rauch and Frese, 2007; Zhao et al., 2010; Kerr et al., 2019; Freiberg and Matz, 2023).

This study has several limitations. It focuses on technology-driven, growth-oriented startups, and may not generalize to necessity entrepreneurs or those in non-technology sectors. Trait estimates are derived from social media data, which while offering advantages in scale and pre-founding timing, may underrepresent founders who avoid public platforms. In particular, I may over-sample more extraverted or outward-facing individuals, though Twitter remains a key platform in the startup ecosystem. Finally, while I identify net shifts in founder composition, I cannot fully disentangle all underlying causal mechanisms - and future work may explore these pathways in greater depth.

This study opens several avenues for future research. While I focus on naturally occurring market cycles, many programs - from accelerators to corporate innovation grants - also aim to lower barriers to entry. Do such interventions shape the psychological makeup of founders in similar ways, and which design features influence who enters? Beyond entry, an open question is how market conditions affect the behavior of those who have already founded. Prior work shows that capital providers take greater risks in hot markets (Nanda and Rhodes-Kropf, 2013); might founders do the same? If so, the selection effects documented here could dampen or amplify risk-taking at the ecosystem level - depending on how traits and incentives align. Understanding how environmental conditions jointly influence who becomes an entrepreneur and how they behave remains an important direction for future work.

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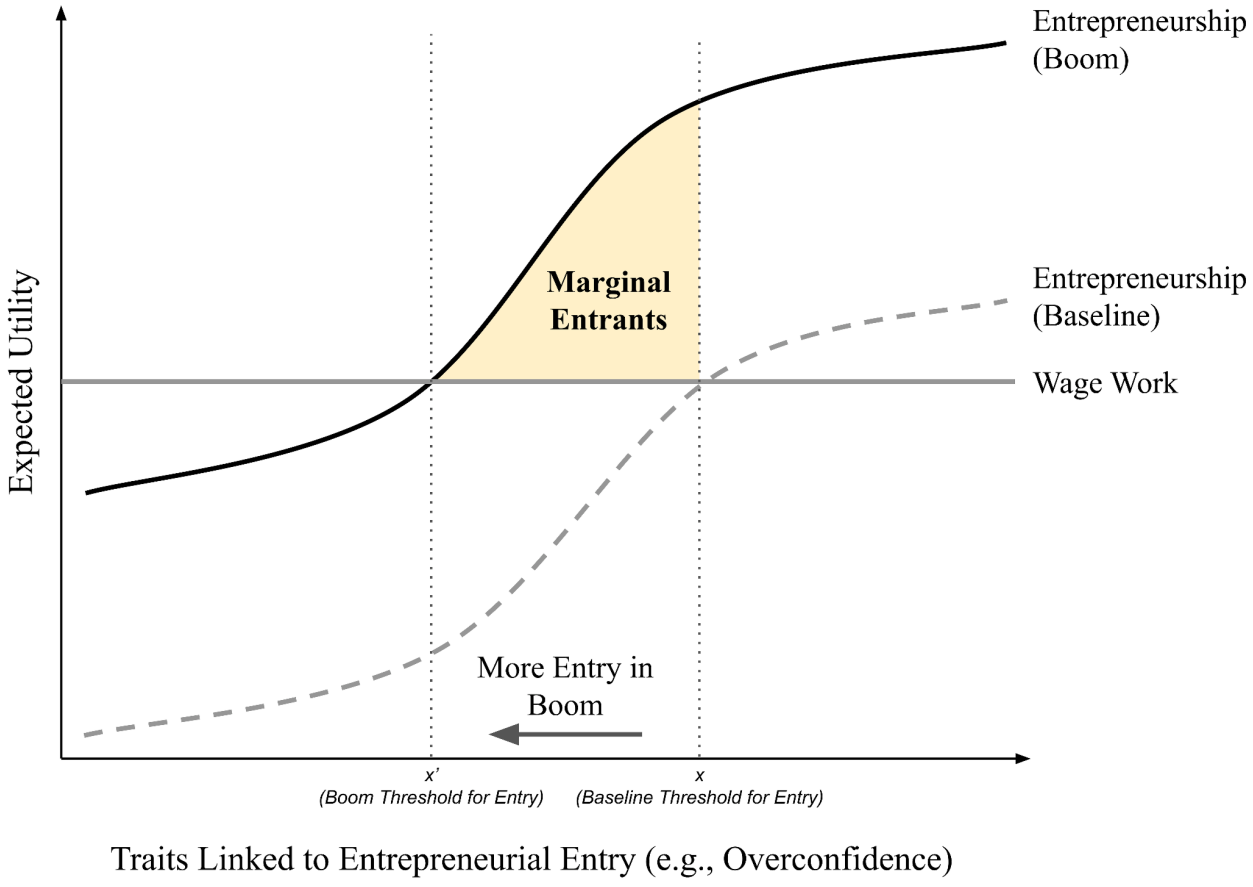
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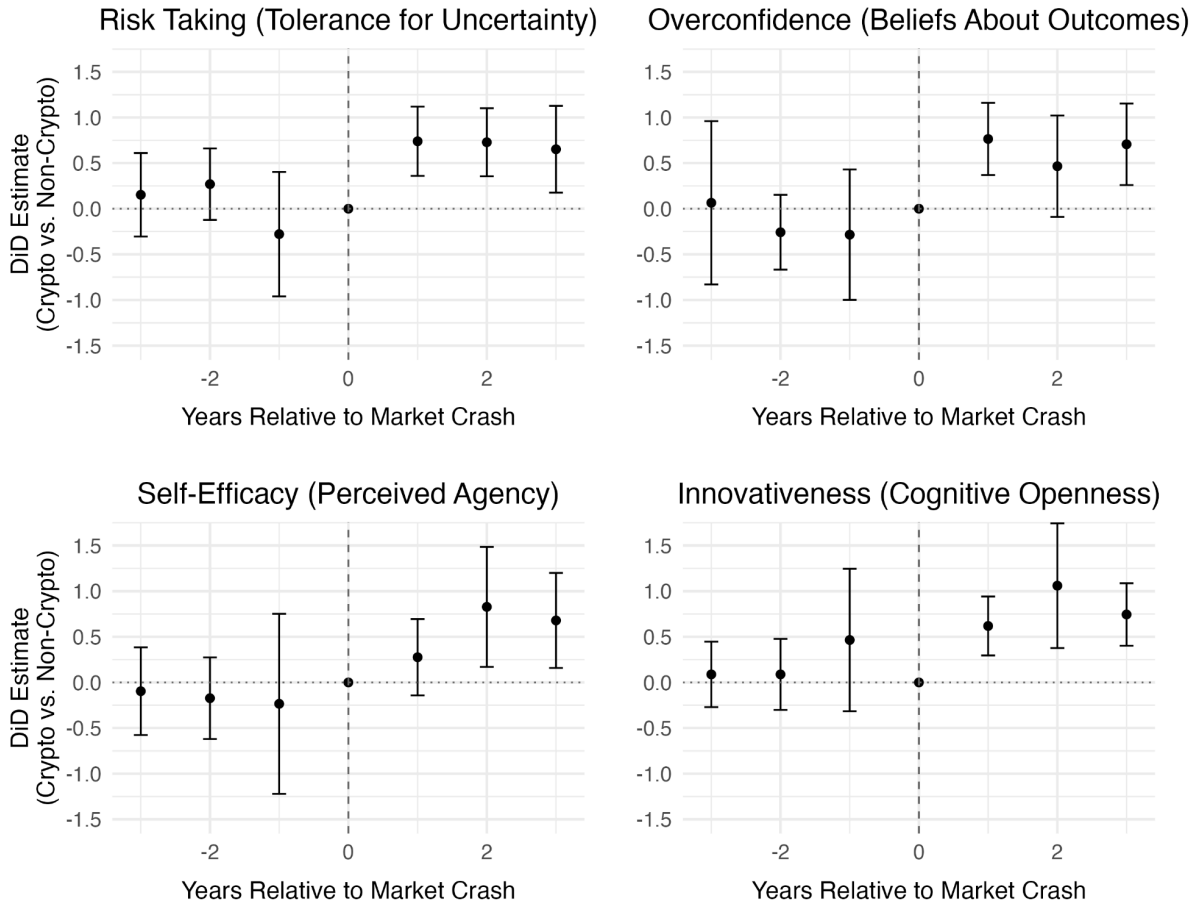
Figures

Figure 1: How Market Cycles Shift the Psychological Threshold for Entrepreneurial Entry



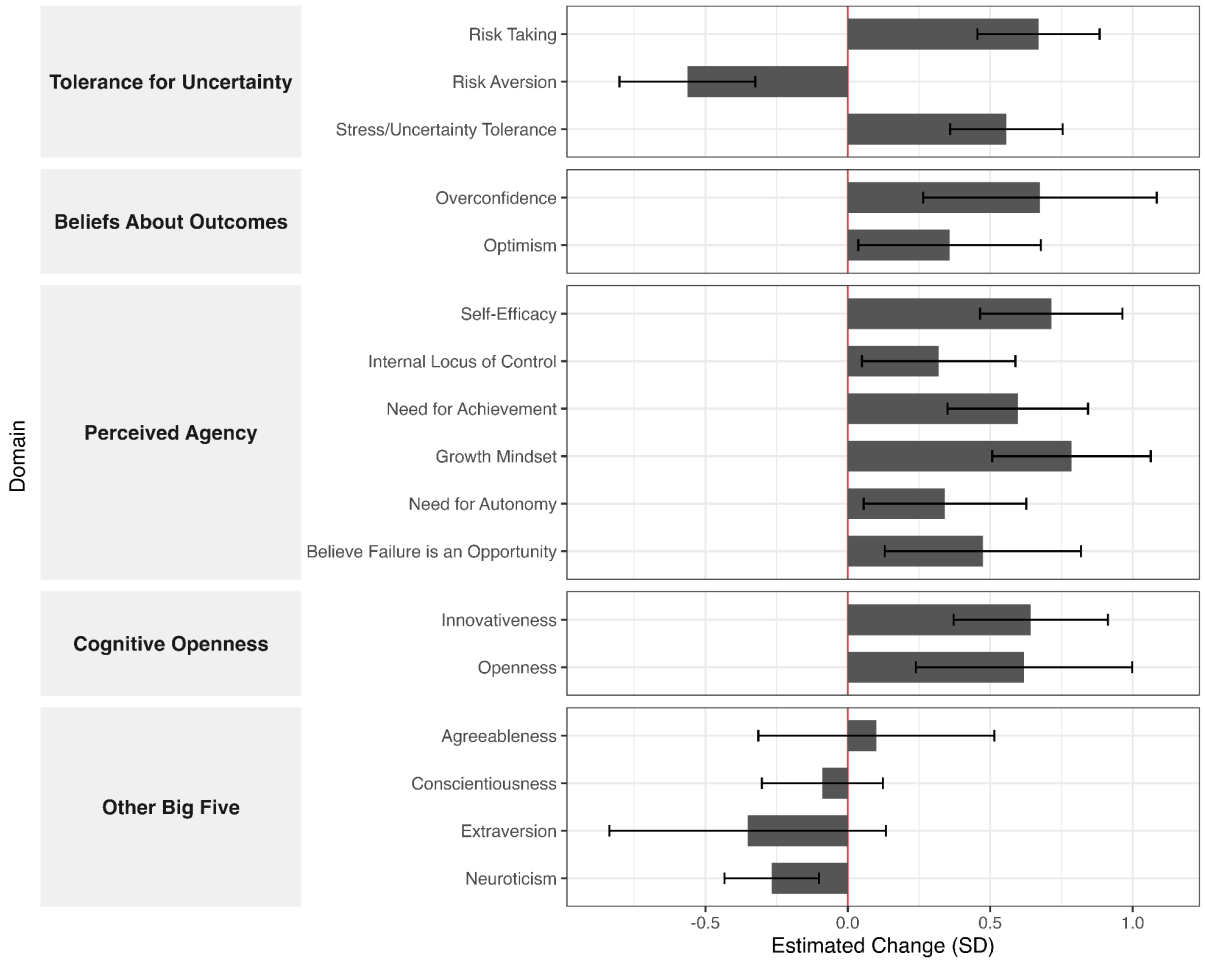
NOTES: Illustration of how economic booms lower the psychological threshold for entrepreneurial entry. The horizontal axis represents a psychological trait linked to entry (e.g., overconfidence or risk-taking). The solid black line shows expected utility from entrepreneurship during a boom, the dashed gray line shows the baseline, and the horizontal gray line shows expected utility from wage work. Entry occurs when the entrepreneurship curve lies above the wage work line. In booms, the threshold shifts from x (baseline) to x' (boom), bringing in marginal entrants (shaded region) who enter only during booms.

Figure 2: Psychological Composition of New Entrepreneurial Cohorts Before and After the 2018 Crypto Crash (Crypto vs. Non-Crypto Industries)



NOTES: Points show difference-in-differences (DiD) estimates from OLS regressions. The dependent variable is the average inferred psychological trait (e.g., overconfidence) among new entrepreneurial entrants in a given industry-year. Each coefficient reflects the standard deviation (SD) difference in trait levels between crypto-exposed and non-crypto industries. Trait names are followed by clarifying descriptions (in parentheses) that indicate the broader psychological domain each represents. The four traits shown are exemplars from four core domains; estimates for all traits are reported in Figure 3. Estimates are based on event-time indicators relative to the 2017 crypto market peak, interacted with a treatment indicator for crypto exposure. Models include industry and year fixed effects, are estimated on matched samples, and cluster standard errors at the industry level. The vertical line (Year 0) marks 2017 - the year of the market peak and onset of the 2018 crash, indicating the transition from boom to bust. Bars represent 95% confidence intervals.

Figure 3: Changes in Psychological Composition of Entrepreneurial Cohorts Before and After the 2018 Crypto Crash - All Traits by Domain (Crypto vs. Non-Crypto Industries)



NOTES: Shows difference-in-differences (DiD) estimates from OLS regressions. The dependent variable is the average inferred level of each psychological trait among new entrepreneurial entrants in a given industry-year. Each coefficient reflects the standard deviation (SD) difference in trait levels between crypto-exposed and non-crypto industries in the post-2018 period, following the crypto market peak in 2017. Traits are grouped into four core psychological domains (e.g., Tolerance for Uncertainty, Motivational Orientation), with trait names listed to the right of each domain label. Models include industry and year fixed effects, are estimated on matched samples, and cluster standard errors at the industry level. Bars represent 95% confidence intervals; the vertical reference line marks zero.

Tables

Table 1: Psychological Traits by Four Core Domains

	Trait	Definition	Primary Citations
		Tolerance for Uncertainty	
**Exemplar Trait*	Risk-Taking	Willingness to engage in behavior with uncertain outcomes, especially when potential gains are high.	Knight (1921); Kerr et al. (2019)
	Risk Aversion	Tendency to avoid uncertain or risky situations, even if they offer potential rewards.	Knight (1921); Kihlstrom and Laffont (1979); Hall and Woodward (2010)
	Stress / Uncertainty Tolerance	Ability to function effectively in stressful or high-pressure environments.	Rauch and Frese (2007)
		Beliefs About Outcomes	
**Exemplar Trait*	Overconfidence	Overestimation of one's abilities or likelihood of success.	More and Healy (2008); Åstebro et al. (2014)
	Optimism	General expectation that good things will happen in the future.	Puri and Robinson (2007); Åstebro et al. (2014)
		Perceived Agency	
**Exemplar Trait*	Self-Efficacy	Belief in one's ability to achieve goals and influence outcomes.	Zhao et al. (2005); Barbosa et al. (2007)
	Internal Locus of Control	Belief that outcomes are largely determined by one's own actions rather than external forces.	Shapero (1975); Gartner (1985); Levine and Rubinstein (2017)
	Need for Achievement	Desire to accomplish difficult tasks and excel through personal effort.	Frank et al. (2007); Stewart and Roth (2007)
	Growth Mindset	Belief that abilities and intelligence can be developed over time.	Burnette et al. (2020)
	Need for Autonomy	Desire to act independently and make one's own choices.	Rauch and Frese (2007)
		Cognitive Openness	
**Exemplar Trait*	Innovativeness	Willingness to explore and implement new ideas, products, or methods.	Utsch and Rauch (2000)
	Openness	Tendency to seek out novelty, engage with new ideas, and appreciate art and creativity.	Zhao et al. (2010); Freiberg and Matz (2023)
		Other Big Five	
	Agreeableness	Tendency to be cooperative, compassionate, and value social harmony.	Zhao et al. (2010); Freiberg and Matz (2023)
	Conscientiousness	Tendency to be organized, responsible, and goal-directed.	Zhao et al. (2010); Freiberg and Matz (2023)
	Extraversion	Tendency to be sociable, energetic, and assertive.	Zhao et al. (2010); Freiberg and Matz (2023)
	Neuroticism	Tendency to experience negative emotions such as anxiety or mood swings under stress.	Zhao et al. (2010); Freiberg and Matz (2023)

NOTES: Traits are organized into four primary domains, drawing on prior taxonomies in entrepreneurial psychology (e.g., Rauch and Frese, 2007): (1) Tolerance for Uncertainty, (2) Beliefs About Outcomes, (3) Perceived Agency, and (4) Cognitive Openness, with other traits classified as "Other Big Five." One exemplar trait from each domain is emphasized in the main analyses.

Table 2: Descriptive Statistics

	Observations	Mean	Median	SD	Min	Max
Entrepreneurial Psychology (Exemplar Traits)						
Risk-Taking (Tolerance for Uncertainty)	21887	4.46	4.5	0.88	2.0	6.5
Overconfidence (Beliefs About Outcomes)	21887	3.77	4.0	0.66	1.0	6.9
Self-Efficacy (Perceived Agency)	21887	5.22	5.5	0.78	2.0	7.0
Innovativeness (Cognitive Openness)	21887	5.12	5.5	1.01	2.0	7.0
Founder Characteristics						
# Tweets (Pre-Founding)	21887	1247.97	435.0	2126.5	50	24688
Approximate Age (at Founding)	21887	33.86	33.0	8.38	18.0	85.0
Went to a Top University	21887	0.11	0.0	0.31	0.0	1.0
Technical Founder	21887	0.24	0.0	0.43	0	1
Female	21887	0.14	0.0	0.35	0	1
Market Cycle Indicators						
Crypto Crash Exposure	21887	0.04	0.0	0.18	0	1
Sector - Press Releases	21887	2210.1	1417.88	2432.27	0.0	22710.0
Sector - Liquidity Events	21887	247.65	155.5	277.95	0.0	2485.0
Sector - Venture Capital Raised ($M)	21887	13000.15	6055.68	18821.57	0.0	208445.62
Year Founded	21887	2015.15	2015.0	3.39	2008	2022
Strategic Choices						
Strategic Differentiation	3765	0.68	0.7	0.07	0.46	0.83
Startup Performance						
Years Survived	9508	4.3	4.0	3.63	0.0	10.0
Acquisition	21887	0.13	0.0	0.34	0	1
IPO	21887	0.01	0.0	0.08	0	1

NOTES: Descriptive statistics reported at the entrepreneur level. Four psychological traits are shown here as exemplars from the full set of 16 traits. While this table focuses on founders, other analyses in the paper also include non-founders (e.g., early-stage employees, other technology workers, and investors) and use data structured at the individual, industry-year, and person-year levels. Approximate Age equals 22 plus the years elapsed since the founder finished their undergraduate education studies (bounded at 18 and 85). Went to a Top University is a binary indicator equaling 1 if the founder attended a university ranked by U.S. News among the top 25 universities between 2012 and 2019 and 0 otherwise. Technical Background equals 1 if the founder had a university degree in STEM or worked as an engineer prior to founding and 0 otherwise. Strategic differentiation represents the product-level differentiation from public firms, estimated via language similarity on a startup's website at time of founding, as reported in Guzman and Li (2023). Startup survival represents the number of years after founding that a startup has active employees listed on LinkedIn (bounded at 10).

Table 3: Impact of the 2018 Cryptocurrency Crash on Core Traits of New Entrepreneur Cohorts

	Dependent Variable: Average Psychological Attributes Among New Entrepreneurs (SD)							
	Risk-Taking		Overconfidence		Self-Efficacy		Innovativeness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crypto x PostCrash	0.677***	0.669***	0.742***	0.675***	0.734***	0.714***	0.727***	0.642***
	(0.108)	(0.109)	(0.204)	(0.209)	(0.130)	(0.127)	(0.148)	(0.138)
N	6325	6325	6325	6325	6325	6325	6325	6325
Industry FE		Y		Y		Y		Y
Year FE		Y		Y		Y		Y
Pseudo R Squared	0.05	0.36	0.07	0.34	0.02	0.25	0.05	0.33

NOTES: Reports difference-in-differences estimates from OLS regressions at the industry-year level. The dependent variable is the average inferred psychological trait (in standard deviations) among new entrepreneurial entrants. The four traits shown - risk-taking, overconfidence, self-efficacy, and innovativeness - are exemplars from the four core psychological domains described in Table 1. Models are estimated on matched samples, include industry and year fixed effects, and cluster standard errors at the industry level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Press Coverage and Liquidity Events as Alternative Indicators of Market Cycles: Core Traits of New Entrepreneur Cohorts (Full Sample - All Industries)

	Dependent Variable: Entrepreneur Psychology (SD)							
	Risk-Taking		Overconfidence		Self-Efficacy		Innovativeness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(# Press releases)	-0.063***		-0.043***		-0.031**		-0.023*	
	(0.016)		(0.014)		(0.012)		(0.012)	
log(# Liquidity Events)		-0.070***		-0.047***		-0.043***		-0.042***
		(0.010)		(0.012)		(0.009)		(0.011)
N	21887	21887	21887	21887	21887	21887	21887	21887
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Year Founded FE	Y	Y	Y	Y	Y	Y	Y	Y
Pseudo R Squared	0.13	0.13	0.12	0.12	0.12	0.12	0.14	0.14

* p < 0.1, ** p < 0.05, *** p < 0.01

NOTES: Reports OLS estimates relating industry-level indicators of market cycles - press coverage and liquidity events (IPOs/acquisition) - to the psychological traits of all new entrepreneur cohorts in the sample. Greater press coverage and liquidity events are typically associated with boom periods. Press coverage and liquidity events are measured as the sum of the number of companies in the industry issuing press releases and getting acquired or experiencing an IPO over the preceding two years, respectively. Traits shown are the four exemplar traits representing core psychological domains. Models include city, industry, and founding-year fixed effects. Standard errors are clustered at the founding-year, industry and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 5: Trait-Contingent Startup Entry After the 2018 Cryptocurrency Crash

	Dependent Variable: Launch a Blockchain or Cryptocurrency Startup			
	(1)	(2)	(3)	(4)
PostCrash x Risk-Taking	1.765***			
	(0.756)			
PostCrash x Overconfidence		3.051**		
		(1.071)		
PostCrash x Self-Efficacy			1.453*	
			(0.827)	
PostCrash x Innovativeness				1.365*
				(1.000)
Years Work Experience	0.030	0.044	0.039	0.039
	(0.032)	(0.034)	(0.034)	(0.034)
Technical Expertise	-1.237	-1.305	-1.098	-1.125
	(0.718)	(0.669)	(0.669)	(0.700)
Elite University	0.716	0.683	0.479	0.613
	(0.716)	(0.710)	(0.691)	(0.708)
N	193	193	193	193
Control for Big Five	Y	Y	Y	Y
Control for Year	Y	Y	Y	Y
Cluster at the Individual Level	Y	Y	Y	Y
AIC	143.4	139.8	148.8	147.1
BIC	182.6	178.9	187.9	186.2

NOTES: Reports Cox hazard model estimates of the interaction between the 2018 cryptocurrency market crash and an individual's traits (four exemplar traits: risk-taking, overconfidence, self-efficacy, innovativeness) on their likelihood of launching a blockchain- or cryptocurrency-related startup (associated with at least one industry of Blockchain, Cryptocurrency, Bitcoin, or Ethereum). The sample includes individuals with pre-crash work experience in cryptocurrency - those most likely to be impacted by the crash. Models control for Big Five traits, years work experience, technical expertise, elite university status, and year. Results are robust to defining the outcome as founding any startup.

Table 6: Sectoral Reallocation

	Dependent Variable: Sectoral Switcher			
	(1)	(2)	(3)	(4)
log(# Press Releases) x Risk-Taking	-0.031***			
	(0.008)			
log(# Press Releases) x Overconfidence		-0.009		
		(0.008)		
log(# Press Releases) x Self-Efficacy			-0.020***	
			(0.006)	
log(# Press Releases) x Innovativeness				-0.019**
				(0.008)
Went to a Top University	-0.612***	-0.608***	-0.609***	-0.609***
	(0.058)	(0.058)	(0.057)	(0.053)
Technical Expertise	-1.137***	-1.139***	-1.137***	-1.138***
	(0.144)	(0.147)	(0.143)	(0.142)
N	27648	27648	27648	27648
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year Founded FE	Y	Y	Y	Y
Pseudo R Squared	0.14	0.14	0.14	0.14

* p < 0.1, ** p < 0.05, *** p < 0.01

NOTES: Reports logit interaction estimates testing whether founder traits moderate the relationship between industry-level boom conditions and the likelihood of entering a sector without prior experience ("sectoral switcher"). Press coverage is computed as the log average of industry-level measures over the prior two years. Standard errors clustered at the year founded, industry and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 7: Pipeline Shifts

	Dependent Variable: Early-Stage Technology Employee Psychology (SD)			
	Risk-Taking	Overconfidence	Self-Efficacy	Innovativeness
	(1)	(2)	(3)	(4)
log(# Press releases)	-0.033***	-0.030***	-0.014***	0.011***
	(0.011)	(0.000)	(0.000)	(0.000)
N	17995	17995	17995	17995
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year Founded FE	Y	Y	Y	Y
Pseudo R Squared	0.11	0.11	0.12	0.14
* p < 0.1, ** p < 0.05, *** p < 0.01				

NOTES: Reports OLS regressing industry-level measures of boom (bust) periods against the personality traits of new employees at early-stage technology startups (“feeder roles” to technology entrepreneurship). Greater press coverage in an industry is typically associated with a boom period. Unit of observation is the individual. Each observation represents one employee-job dyad. Press releases are calculated on the preceding two years as a weighted average among all industries the employer is associated with. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 8: Strategic Choices

	Startup Differentiation	
	(1)	(2)
log(# Press Releases)	0.089***	0.023**
	(0.027)	(0.011)
N	16618	16618
City FE		Y
Industry FE		Y
Year Founded FE		Y
Pseudo R Squared	0.01	0.14

* p < 0.1, ** p < 0.05, *** p < 0.01

NOTES: Reports the relationship between industry-level press releases (with greater press releases reflecting boom periods) and the strategic differentiation of startups founded during those periods. Startup differentiation represents the product-level differentiation from public firms at time of founding, as reported in Guzman and Li (2023), and is z-standardized prior to analysis so coefficients represent changes in SD. Standard errors are clustered at the year founded, industry and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Table 9: Startup Performance by Market Cycle at Founding

	Startup Survival (Years)		Acquisition		IPO	
	(1)	(2)	(3)	(4)	(5)	(6)
log(# Press Releases)	-0.108**	-0.162***	0.259***	0.077**	-0.189*	-0.141**
	(0.046)	(0.034)	(0.032)	(0.032)	(0.112)	(0.071)
N	16618	16618	16135	16135	16135	16135
City FE		Y		Y		Y
Industry FE		Y		Y		Y
Year Founded FE		Y		Y		Y
Pseudo R Squared	0.53	0.57	0.09	0.13	0.04	0.18
* p < 0.1, ** p < 0.05, *** p < 0.01						

NOTES: Reports the relationship between industry-level press releases (with greater press releases reflecting boom periods) and the performance of startups founded during those periods. Startup survival represents the number of years after founding that a startup has active employees listed on LinkedIn. Models treating acquisition and IPO as dependent variables consider startups which have raised venture financing. Standard errors are clustered at the year founded, industry and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

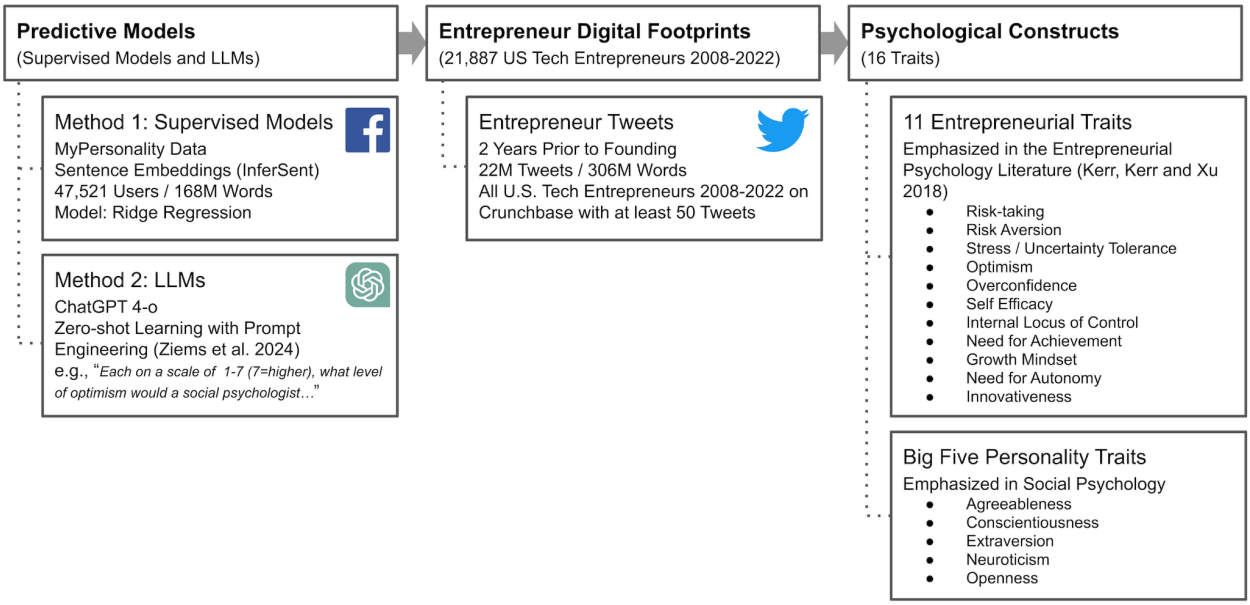
Appendix

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1 Predicting Entrepreneur Psychology from Digital Traces

1A) Prediction Methodology

Figure A1: Data Processing Flow Chart - Overview



NOTES: This figure outlines the procedure for estimating 16 psychological traits from entrepreneurs' digital traces. Entrepreneurs are identified in Crunchbase, restricted to those with valid Twitter profiles who founded U.S.-based startups between 2008 and 2022. Tweets are drawn from the two-year period prior to founding.

Predicting the Big Five Personality Traits Using Supervised Models

To predict the Big Five personality traits, I follow the approach outlined in Freiberg and Matz (2023). Specifically, I leverage a matched dataset from the MyPersonality project (Kosinski et al., 2013) that pairs traditional survey measures of the Big Five personality traits (via questionnaires) and users' Facebook data. MyPersonality was a Facebook application operating between 2007 and 2012 which enabled users to take validated psychological assessments and get immediate results as to their traits. This included a 100-item measure of the Big Five personality traits. Millions of users participated in MyPersonality, with a subset (approximately 70,000) voluntarily opting to grant all of their Facebook data to researchers for academic study. This included their status updates - and as such, communications text with which to train supervised models.

My training sample was the subset of users who shared their data, had at least 50 status updates, and resided in the United States (N = 47,521). I first transformed each status update into a 4,096-dimensional vector using Facebook's *InferSent* (Conneau et al., 2017), a sentence embedding model trained on social media text and web data. For each user, I computed their element-wise mean vector, resulting in an input matrix of 47,521 users x 4,096 features. I then

split the data into training and test sets (test size = 10%), and trained predictive models using ridge regressions and 10-fold crossvalidation. Reflecting prior literature, the Pearson correlation coefficient between actual and estimated traits, a measure of model performance, ranged between 0.3 and 0.4 (Freiberg and Matz, 2023).

Predicting Psychology Using Large Language Models

To predict the remaining 11 traits emphasized in the entrepreneurial literature, I adapt the approach used by Ziems et al. (2023). The authors show that LLMs using zero-shot prompting can accurately predict sociological, political and psychological constructs. For example, persuasiveness, emotion, humor and political ideology. Specifically, they prompt LLMs to take the perspective of an *[X]* researcher, and ask how they would label textual communications on the desired construct. In some ways, this resembles using LLMs to do tasks often undertaken by human coders in social science research. To predict social psychology, I supply the following content prompt using ChatGPT-4o:

> "*Each on a scale of 1-7 (7=higher), what level of the following traits: [risk-taking, risk aversion, optimism, ..., innovativeness] would a social psychologist say the person who made the following tweets exhibits? For each trait, please respond with a single integer or float with no more than two decimal points (not a range). If you are unable to make a determination for a specific trait, please respond with 'N/A' for that trait rather than making a random determination or leaving it blank. The tweets are as follows: [tweet 1, tweet 2, ..., tweet n]*"

and the subsequent role content prompt:

> "Provide output in valid JSON. The data schema should look like this: *{risk-taking: 1, risk aversion: 1, ..., innovativeness: 1}*."

Finally, I used the starting seed 42 with temperature 0.05. Because LLMs including ChatGPT on occasion provide unintelligible responses (e.g., those in a format other than that requested, containing null responses, or in any other way which produces an error), I reran this code 3 times for each entrepreneur, increasing the temperature and seed by 1 and 0.05 respectively for each failed attempt until valid predictions were returned. I excluded those for whom valid predictions could not be appropriately predicted.

1B) Validating Inferred Estimates

I validate that the inferred trait scores capture the psychological constructs they are intended to represent using three complementary approaches:

1. **Direct validation against gold-standard survey measures** - For the Big Five personality traits, I match social media–based predictions to traditional survey-based measures from a dataset containing both text and validated questionnaires. This allows me to assess predictive accuracy against benchmarks widely used in social psychology.
2. **Convergent validity via inter-trait correlations** - For traits inferred from large language models (LLMs) without training data, I test whether their correlations with the Big Five match established empirical patterns (e.g., neuroticism is typically inversely correlated with risk-taking).
3. **Predictive validity via theoretical expectations** - I examine whether inferred traits behave as theory predicts in my entrepreneurial context. For example, higher inferred risk-taking should be associated with a greater likelihood of extreme venture outcomes, including both failure and standout success (e.g., IPO).

Accuracy Against Validated Survey Questionnaires

To directly assess the validity of my inferred personality estimates, I compare them against "gold standard" survey-based measures - the traditional approach used by social psychologists to assess the Big Five. I use the MyPersonality dataset (Kosinski et al., 2015), a large-scale study in which over six million Facebook users completed validated psychological questionnaires and, in many cases, shared their status updates. I focus on a U.S. subsample of 47,521 users with at least 50 status updates (mean = 3,531 words), which is comparable in format and tone to the Twitter posts used in my main analyses.

For each Big Five trait (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), I train predictive models on a portion of the MyPersonality text data and evaluate them on a held-out test set by correlating predictions with the survey-based "gold standard" measures. Following the same linguistic feature extraction and modeling framework used in my main data, predicted scores achieve correlations of $r = 0.30$ (Agreeableness), 0.34 (Conscientiousness, Neuroticism), and 0.40 (Extraversion, Openness). These accuracies match or exceed benchmarks reported in the social psychology literature for language-based personality prediction, and indicate that the inferred Big Five traits in my main dataset have comparable construct validity.

Established Inter-Trait Correlations

While prior work shows that large language models can accurately recover psychological constructs in zero-shot learning settings (Ziems et al., 2024; Peters and Matz, 2024), it remains important to assess whether these measures perform as intended in the present context and sample. For the LLM-based traits in my study - which lack a direct ground-truth dataset -

convergent validity checks provide a key way to do so, by comparing inter-trait correlation patterns against established norms from the psychology literature. If the inferred measures capture the intended constructs, they should display the same general pattern of associations seen in prior work - for example, neuroticism should correlate negatively with risk-taking, and openness should correlate positively with innovativeness.

The inferred traits display theoretically coherent associations with the Big Five, consistent with prior psychology research. For example, neuroticism is negatively correlated with risk-taking ($r \approx -0.17$), overconfidence ($r \approx -0.19$), self-efficacy ($r \approx -0.24$), and innovativeness ($r \approx -0.26$), while openness is positively correlated with innovativeness ($r \approx 0.25$) and risk-taking ($r \approx 0.16$). Similarly, conscientiousness is positively associated with self-efficacy ($r \approx 0.16$). These patterns align with well-established empirical regularities (e.g., Oehler and Wedlich, 2018; Ali, 2019) and support the interpretation that the LLM-derived measures capture meaningful psychological constructs.

Theoretical Predictions

A key validation step for the inferred personality measures is to assess whether they behave in ways consistent with well-established theoretical expectations from entrepreneurship and psychology. This section examines four such predictions, each grounded in prior literature linking specific traits to entrepreneurial choices or outcomes. The goal is not to comprehensively test all trait–outcome relationships, but to confirm that the LLM-inferred measures exhibit sensible and interpretable patterns in an entrepreneurial context.

For each trait, I identify a canonical prediction from the literature, specify an observable outcome available in the Crunchbase data, and report the results from targeted regressions. Across traits, the predictions span risk tolerance, persistence, novelty-seeking, and over-placement - constructs theorized to play distinct roles in the entrepreneurial process.

Risk-Taking → Tail Venture Outcomes.

- *Prediction*: Entrepreneurs with higher risk tolerance will have a greater probability of extreme venture outcomes - both high failure rates and standout successes such as IPOs - relative to moderate exits like acquisitions (e.g., Caliendo et al., 2010; Stewart & Roth, 2001).
- *Test*: Model the association between pre-founding risk-taking and three mutually exclusive exit types: failure, acquisition, IPO.
- *Result*: As predicted, higher risk-taking is positively associated with both failure and IPO, and negatively associated with acquisition (Table A1).

Table A1: Risk-Taking and Startup Tail Outcomes

	Dependent Variables:		
	Failure	Acquisition	IPO
	(1)	(2)	(3)
Risk-Taking (SD)	0.063***	-0.070***	0.138***
	(0.022)	(0.019)	(0.029)
N	9350	10659	10659
State FE	Y	Y	Y
Industry FE	Y	Y	Y
Year Founded FE	Y	Y	Y
Pseudo R Squared	0.10	0.13	0.14

* p < 0.1, ** p < 0.05, *** p < 0.01

NOTES: Reports logit regression estimates. Failure is a binary indicator which equals 1 if a startup that raise financing, with at least 6 years post-founding history, neither achieves acquisition or IPO. Standard errors are clustered at the year founded and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Self-Efficacy → Persistence Through Adversity.

- *Prediction*: Entrepreneurs with higher self-efficacy will be more likely to persist in ventures despite challenges, consistent with Bandura (1997) and Zhao, Seibert & Hills (2005).
- *Test*: Among startups that eventually fail, estimate whether founders with higher self-efficacy remain active longer before dissolution.
- *Result*: Higher self-efficacy predicts longer survival in ultimately unsuccessful ventures (Table A2).

Table A2: Self-Efficacy and Persisting in Startups that Eventually Fail

	Dependent Variable: Years Startup Survives / Continues		
	(1)	(2)	(3)
Self-Efficacy (SD)	0.083**	0.116*	0.162***
	(0.036)	(0.064)	(0.045)
N	7126	7126	7126
State FE	Y	Y	Y
Industry FE	Y	Y	Y
Year Founded FE	Y	Y	Y
Pseudo R Squared	0.53	0.22	0.18

* p < 0.1, ** p < 0.05, *** p < 0.01

NOTES: Reports OLS regression estimates. Models 1-3 estimate survival when there are at least 1,3 or 5 active employees listed at the startup on LinkedIn, respectively.

Standard errors are clustered at the year founded and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Innovativeness → Entry into Younger Companies.

- *Prediction*: More innovative individuals will self-select into younger, less established companies, consistent with novelty-seeking and preference for dynamic environments (e.g., Kirton, 1976; Shane, 2000).
- *Test*: For non-founders, regress company age at joining on innovativeness.
- *Result*: Innovativeness is negatively associated with company age at joining, indicating preference for younger, more nascent firms (Table A3).

Table A3: Innovativeness and Joining Young Firms

	Dependent Variables:	
	Early Stage Joiner	Company Age in Years When Joining
	(1)	(2)
Innovativeness (SD)	0.320***	-0.126***
	(0.022)	(0.016)
N	17995	17995
State FE	Y	Y
Industry FE	Y	Y
Year Founded FE	Y	Y
Pseudo R Squared	0.09	0.28
* p < 0.1, ** p < 0.05, *** p < 0.01		

NOTES: Reports logit and poisson regression estimates at the employee-job level for non-founders. Early Stage Joiner is a binary indicator which equals 1 if the job is with a company younger than or equal to 3 years old. Model 1 reports results of a logit regression while Model 2 reports results of a Poisson. Standard errors are clustered at the year founded and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

Overconfidence → Solo Founding.

- *Prediction*: Entrepreneurs with higher overconfidence are more likely to found solo, consistent with over-placement - believing one's own ability substitutes for cofounders (e.g., Camerer & Lovallo, 1999).
- *Test*: Logit regression of solo-founder indicator on overconfidence, controlling for demographics, experience, and domain expertise.

- *Result*: Higher overconfidence predicts greater likelihood of solo founding, net of controls (Table A4).

Table A4: Overconfidence and Doing it On Your Own

	Dependent Variables:	
	Solo Founder	Number of Founders
	(1)	(2)
Overconfidence (SD)	0.043**	-0.008***
	(0.020)	(0.003)
N	21887	21887
State FE	Y	Y
Industry FE	Y	Y
Year Founded FE	Y	Y
Pseudo R Squared	0.06	0.01
* p < 0.1, ** p < 0.05, *** p < 0.01		

NOTES: Reports logit and poisson regression estimates at the founder-startup level. Solo Founder is a binary indicator which equals 1 if the startup has one founder and 0 otherwise. Model 1 reports results of a logit regression while Model 2 reports results of a Poisson. Standard errors are clustered at the year founded and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

2 2018 Cryptocurrency Crash Supporting Documents

2A) Contemporary Commentary

Figure A2: Examples of Representative Enthusiasm Before and After the Bust

Early 2017: Bullish Optimism

> *"2017 is the year when crypto/blockchain entered the frenzy phase… Over $3.7 bn was raised by various crypto teams/projects to build out the infrastructure of Internet 3.0… The frenzy in the crypto/blockchain sector will provide the capital to build out the infrastructure for the decentralized Internet."*

Late-2017: Incoming Skepticism

> *"I am certain the big crash will happen. I don't know when it will happen and I think it may be some time before it does… Unlike some crypto skeptics, Wilson is a believer in the new blockchain-based currencies. But… he believes some bitcoin bulls may be blind to the risk they're facing."*

Post-Crash (late 2018+): Pragmatic Cautiousness

> *"Unlike all the other use cases that demand scalability (gaming, media, e-commerce), DeFi is managing to catch on and offer real use cases for crypto beyond trading and speculation."*
>
> - Fred Wilson (Venture Partner, Union Square Ventures)

Before 2018:

> Don Tapscott (author of *The Blockchain Revolution*): *"Blockchains… have the potential to revolutionize the world economy."*
>
> NASDAQ article: *"Since its inception in 2009, blockchain has been primed for a breakout year… 2017 could be the year that finally changes that."*

After 2018:

> Warren Buffet described Bitcoin as *"probably rat poison squared"*
>
> Paul Krugman (nobel prize winning economist) called cryptocurrency *"a bubble wrapped in techno-mysticism inside a cocoon of libertarian ideology"*

2B) Bitcoin Market Value

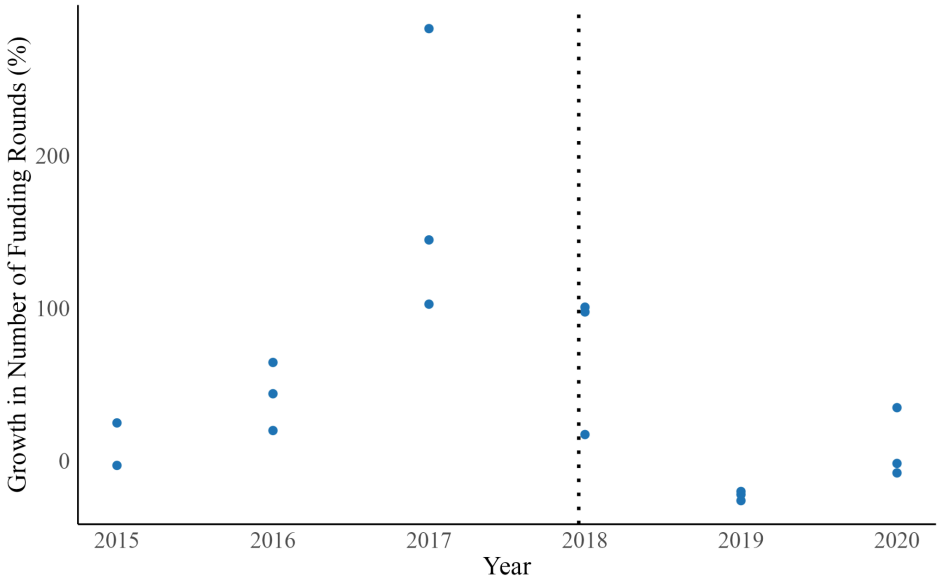
Figure A3: Bitcoin Market Collapse



Notes: Total outstanding bitcoin market capitalization. Data extracted from CoinGecko. The vertical black line is December 2018, representing the approximate start of the cryptocurrency crash.

2C) Funding Growth

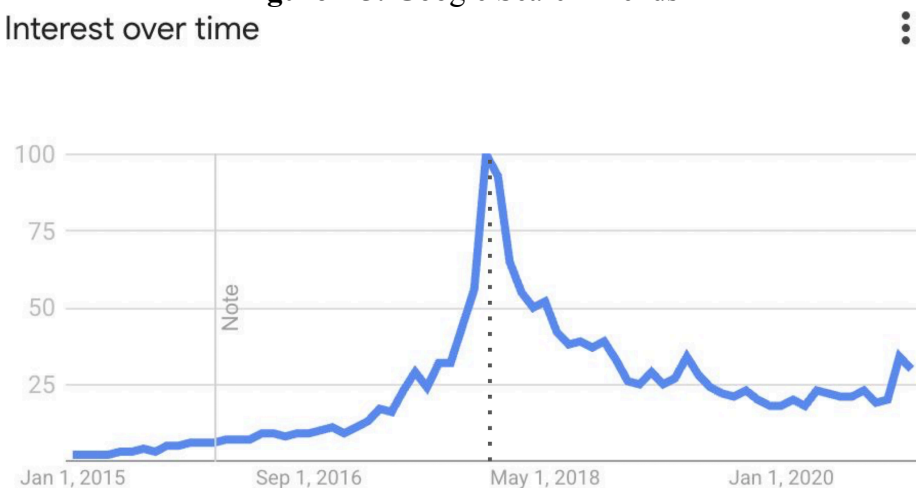
Figure A4: Funding Round Growth



Notes: Depicts year over year growth rates (%) in number of initial funding rounds for cryptocurrency adjacent startups using the Crunchbase dataset. Each point represents an industry adjacent to cryptocurrency as defined by the following categories on Crunchbase: Blockchain, Bitcoin, Ethereum. The vertical black line is December 2018, representing the approximate start of the cryptocurrency crash.

2D) Google Search Trends

Figure A5: Google Search Trends

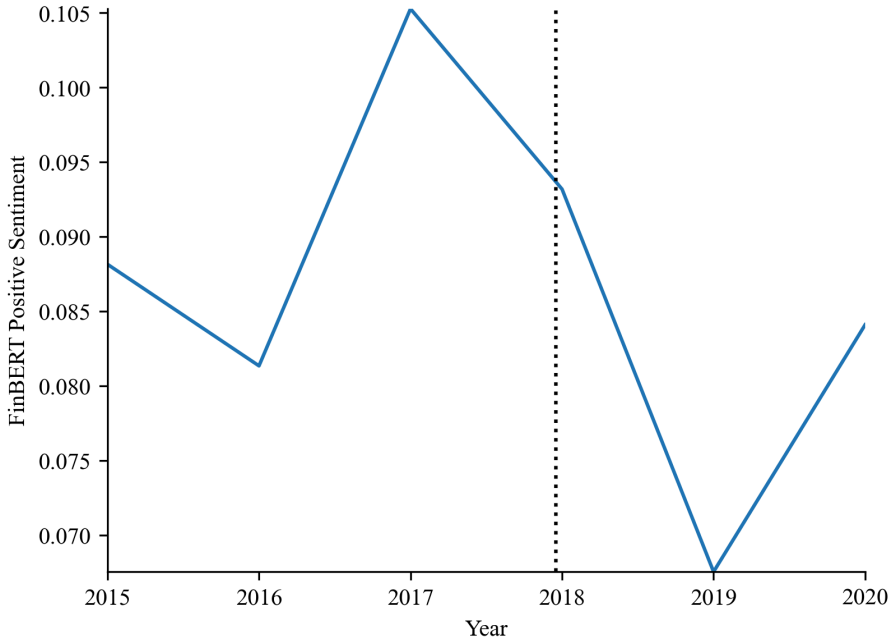


Search term: "*blockchain*"

Notes: Depicts Google Trends for search terms "*blockchain*." Reflects U.S. results between 2015 and 2020. The vertical black line is December 2018, representing the approximate start of the cryptocurrency crash.

2E) News Sentiment

Figure A6: News Article Sentiment



Notes: Portrays average FinBERT positive sentiment for the top 100 weekly news articles on Google Search in response to the search term "*cryptocurrency startup*". FinBERT is a pre-trained BERT based language model trained using financial text data, especially well suited towards understanding the nuances of financial sentiment. The vertical black line is December 2018, representing the approximate start of the cryptocurrency crash.

3 Main Effect - Empirical Strategy and Robustness Checks

3A) Matching Procedure

For each psychological trait, I apply coarsened exact matching (CEM) to improve covariate balance between crypto-adjacent and non-crypto industries in the pre-crash period (2014–2017) for the industry-year analysis. The matching is performed separately by trait, as baseline pre-period levels vary across constructs (e.g., average overconfidence differs from neuroticism). Within each pre-crash year, I standardize trait scores to have mean zero and unit variance, then match industries on these z-standardized values. I allow for partial matches across years by computing CEM weights over the full pre-period, generating a set of fractional weights that reflect similarity in baseline trait levels. These weights are incorporated into all matched difference-in-differences regressions at the industry-year level. This approach reduces reliance on functional form assumptions and enhances the plausibility of parallel pre-trends.

Table A5: Impact of the 2018 Cryptocurrency Crash on Core Traits of New Entrepreneur Cohorts - Unmatched Sample

	Dependent Variable: Average Psychological Attributes Among New Entrepreneurs (SD)							
	Risk-Taking		Overconfidence		Self-Efficacy		Innovativeness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crypto x PostCrash	0.445***	0.409***	0.349*	0.294	0.583***	0.538***	0.547***	0.479***
	(0.094)	(0.092)	(0.196)	(0.211)	(0.115)	(0.111)	(0.138)	(0.131)
N	6325	6325	6325	6325	6325	6325	6325	6325
Industry FE		Y		Y		Y		Y
Year FE		Y		Y		Y		Y
Pseudo R Squared	0.01	0.31	0.00	0.29	0.00	0.28	0.01	0.31

NOTES: Reports difference-in-differences estimates from OLS regressions at the industry-year level on the unmatched sample. The dependent variable is the average inferred psychological trait (in standard deviations) among new entrepreneurial entrants. The four traits shown - risk-taking, overconfidence, self-efficacy, and innovativeness - are exemplars from the four core psychological domains described in Table 1. Models include industry and year fixed effects, and cluster standard errors at the industry level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3B) Controls for Gender and Age

Table A6: Impact of the 2018 Cryptocurrency Crash on Core Traits of New Entrepreneur Cohorts - With Demographic Controls

	Dependent Variable: Average Psychological Attributes Among New Entrepreneurs (SD)							
	Risk-Taking		Overconfidence		Self-Efficacy		Innovativeness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crypto x PostCrash	0.630***	0.585***	0.727***	0.625***	0.609***	0.561***	0.658***	0.579***
	(0.170)	(0.155)	(0.163)	(0.182)	(0.158)	(0.145)	(0.188)	(0.169)
Percentage Founders Women	0.017	0.240	-0.339**	-0.100	0.154	0.315	-0.198	-0.110
	(0.170)	(0.192)	(0.163)	(0.199)	(0.243)	(0.223)	(0.134)	(0.175)
Average Founder Age	-0.003	-0.002	0.000	-0.002	-0.005	-0.003	-0.002	0.002
	(0.006)	(0.007)	(0.005)	(0.005)	(0.008)	(0.007)	(0.007)	(0.007)
N	6325	6325	6325	6325	6325	6325	6325	6325
Industry FE		Y		Y		Y		Y
Year FE		Y		Y		Y		Y
Pseudo R Squared	0.05	0.41	0.08	0.46	0.01	0.35	0.05	0.40

NOTES: Reports difference-in-differences estimates from OLS regressions at the industry-year level controlling for the percentage of women among and average age of new entrants in an industry-year. The dependent variable is the average inferred psychological trait (in standard deviations) among new entrepreneurial entrants. The four traits shown - risk-taking, overconfidence, self-efficacy, and innovativeness - are exemplars from the four core psychological domains described in Table 1. Models are estimated on matched samples, include industry and year fixed effects, and cluster standard errors at the industry level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

3C) Alternative Indicator of Market Cycles: Venture Capital Financing

Table A7: Venture Capital Financing as an Alternative Indicator of Market Cycles: Core Traits of New Entrepreneur Cohorts (Full Sample - All Industries)

	Dependent Variable: Entrepreneur Psychology (SD)			
	Risk-Taking	Overconfidence	Self-Efficacy	Innovativeness
	(1)	(2)	(3)	(4)
log(Venture Dollars Raised)	-0.035**	-0.021	-0.022***	-0.007
	(0.014)	(0.013)	(0.007)	(0.010)
N	21887	21887	21887	21887
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year Founded FE	Y	Y	Y	Y
Pseudo R Squared	0.13	0.12	0.12	0.14

* p < 0.1, ** p < 0.05, *** p < 0.01

NOTES: Reports OLS estimates relating industry-level indicators of market cycles - venture capital financing (total dollars raised) - to the psychological traits of all new entrepreneur cohorts in the sample. Greater venture capital financing is typically associated with boom periods. Venture dollars raised is measured as the total dollars raised across all startups in an industry over the preceding two years. Traits shown are the four exemplar traits representing core psychological domains. Models include city, industry, and founding-year fixed effects. Standard errors are clustered at the founding-year, industry and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

4 Channels of Psychological Selection

4A) Trait Plasticity

This table reports estimates for the trait plasticity channel of psychological selection - testing whether individuals with prior crypto-sector experience experienced systematic shifts in personality traits following the 2018 crash.

Table A8: Trait Plasticity

	Dependent Variable: Psychological Trait (SD)							
	Risk-Taking		Overconfidence		Self-Efficacy		Innovativeness	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Crypto Experience x PostCrash	-0.042	-0.007	-0.099	-0.116	0.054	0.054	-0.095	0.006
	(0.175)	(0.240)	(0.162)	(0.212)	(0.152)	(0.152)	(0.178)	(0.188)
N	41130	41130	41130	41130	41130	41130	41130	41130
Industry FE		Y		Y		Y		Y
Year FE		Y		Y		Y		Y
Pseudo R Squared	0.01	0.67	0.01	0.67	0.68	0.68	0.00	0.72

NOTES: Reports OLS estimates testing whether individuals with prior experience in the cryptocurrency sector (those most directly exposed to the boom-and-bust cycle) exhibit changes in psychological traits following the 2018 crypto crash. The interaction term *Crypto Experience* × *PostCrash* captures whether traits shifted disproportionately among those with pre-crash crypto exposure. Unit of observation is the individual, including both founders and non-founders. Traits are standardized within the sample (SD = 1). Standard errors are clustered at the year and individual level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5 Strategic Choice

5A) The Niche Opportunists Hypothesis

This analysis tests whether founders entering during booms tend to have deeper domain expertise. Establishing this matters because it helps explain why boom-time founders pursue more differentiated strategies. If they possess relevant expertise, it supports the "niche opportunists" view - that these founders are targeting small, high-fit market opportunities others might overlook - rather than alternatives like an "overreaching experimenters" model, where differentiation stems from overconfidence or novelty-seeking despite lacking industry fit, or a "boom-enabled explorers" model, where abundant resources encourage broad exploration regardless of capability. For example, under an "overreaching experimenters" narrative, a founder might launch a highly novel AI health startup during a boom without prior healthcare experience, betting differentiation alone will win market share - a pattern that, if we only examined differentiation data, could look similar to niche opportunism yet would be driven by a fundamentally different underlying mechanism.

Table A9: Founders who Enter During Booms Have Greater Domain Expertise

	Dependent Variable: Founder Has Domain Expertise			
	(1)	(2)	(3)	(4)
log(# Press Releases)	0.532***	0.382***		
	(0.038)	(0.050)		
log(# Liquidity Events)			0.484***	0.349***
			(0.029)	(0.046)
N	27648	27648	27648	27648
City FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year Founded FE	Y	Y	Y	Y
Pseudo R Squared	0.04	0.13	0.04	0.13

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: Reports logit estimates testing whether founders who enter during booms (proxied by press releases and liquidity events) are more likely to have domain expertise. Domain expertise is a binary indicator which equals 1 if the founder had prior work experience, as reported on LinkedIn, with a company that shared a Crunchbase category tag with the venture they launched. Press coverage and liquidity events are computed as the log average of industry-level measures over the prior two years. Standard errors clustered at the year founded, industry and state levels in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01

6 Startup Performance

6A) Mediation Analysis

Table A10: Founder Psychology Partially Mediates the Link Between Market Cycles and Startup Performance

		Conditional Indirect Effect Analyses			
Mediator	Startup Outcome	Effect	Effect / Total Effect	Bootstrap SE	Bootstrap CI
Entrepreneurial Traits					
Optimism	IPO	-0.0007	3.5%	0.0004	[-0.0015, -0.0001]
Overconfidence	IPO	-0.0006	3.0%	0.0003	[-0.0015, -0.0001]
Risk-taking	IPO	-0.0005	2.6%	0.0003	[-0.0014, -0.0001]
Stress Tolerance	IPO	-0.0004	1.9%	0.0003	[-0.0010, <0.0000]
Big Five Personality Traits					
Conscientiousness	Acquisition	0.0008	1.5%	0.0004	[0.0001, 0.0018]
Extraversion	Acquisition	0.0021	3.8%	0.0005	[0.0011, 0.0032]
Neuroticism	Acquisition	0.0007	1.3%	0.0004	[<0.0000, 0.0018]
Openness	Acquisition	-0.0004	-0.7%	0.0002	[-0.0010, -0.0001]
Conscientiousness	IPO	-0.0008	2.9%	0.0004	[-0.0020, -0.0002]
Neuroticism	IPO	-0.0005	1.6%	0.0003	[-0.0015, <0.0000]

NOTES: N = 21,877. Bootstrap sample = 1,000. SE = standard error; CI = confidence interval. Reports OLS estimates for all coefficients with significant results across two models for each trait, investigating the mediation pathway between the trait and acquisition and IPO, respectively.