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Innovation Coherence and Entrepreneurial Scaling Among Technology Ventures in East Asian Growth Markets

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Abstract

East Asian technology ventures operate in environments where innovation is highly visible, financing is selective, and entrepreneurial scaling often depends on coordination across research, commercialization, and external legitimacy. This study examines whether innovation coherence, defined as the alignment among strategic innovation disclosure, R&D commitment, patent output, product commercialization, and externally oriented collaboration, predicts subsequent venture performance. Using a synthetic but empirically calibrated unbalanced panel of 386 publicly listed young technology firms from mainland China, Hong Kong, Japan, South Korea, and Taiwan during 2014–2023, the analysis estimates dynamic panel models, fixed-effects specifications, mediation equations, and selection-adjusted robustness tests. The results indicate that innovation coherence is positively associated with next-year Tobin's Q, revenue growth, and equity-financing capacity, while it is negatively associated with cash-flow volatility. A one-standard-deviation increase in coherence is associated with a 0.082 increase in Tobin's Q, a 2.7% increase in revenue growth, and a 1.9% increase in the probability of successful seasoned equity financing. The valuation association is partially mediated by innovation conversion efficiency, measured as market-facing innovation output per unit of lagged R&D expenditure. Moderation tests show that the coherence effect is stronger under moderate product-market competition and weaker when technological search is excessively concentrated. The findings suggest that entrepreneurial firms benefit not merely from high innovation intensity, but from an internally consistent innovation architecture that allows stakeholders to connect resources, knowledge outputs, and scaling intentions.

Introduction

Innovation is often treated as the defining attribute of technology entrepreneurship, yet entrepreneurial firms do not benefit automatically from every additional unit of inventive activity. A young firm may spend heavily on R&D but commercialize slowly, describe ambitious innovation priorities while generating limited proprietary knowledge, or accumulate patents without showing a market-facing path toward adoption. These gaps are especially important in East Asian growth markets, where many technology ventures face demanding capital providers, concentrated supply chains, strong incumbent firms, and policy environments that reward visible innovation but also expose weak implementation [1]. In such settings, the question is not only whether a venture innovates, but whether its innovation system is coherent enough to support credible scaling.

This paper develops and tests the concept of innovation coherence. The construct refers to the degree to which a firm's innovation-related signals and activities point in a mutually reinforcing direction. It is not equivalent to innovation intensity. Intensity concerns the amount of effort or output. Coherence concerns the alignment among different layers of the innovation system. A firm can be highly intense but incoherent when it spends heavily across scattered projects with little commercialization. A firm can be moderately intense but coherent when its disclosure, research spending, patents, launches, and partnerships jointly support an identifiable strategic path. The empirical argument is that coherence should matter for entrepreneurial scaling because ventures are evaluated

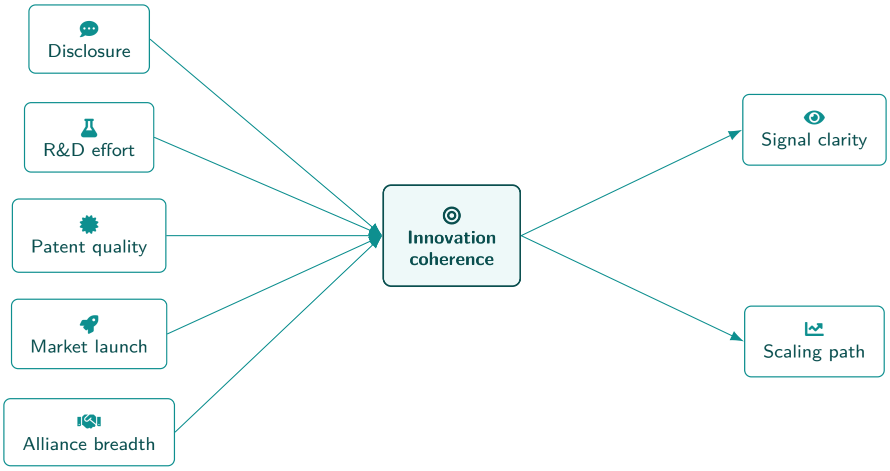

Figure 1: Innovation coherence is represented as the alignment of disclosure, R&D commitment, patent quality, commercialization, and alliance breadth, which together create clearer external interpretation and a more legible scaling path.

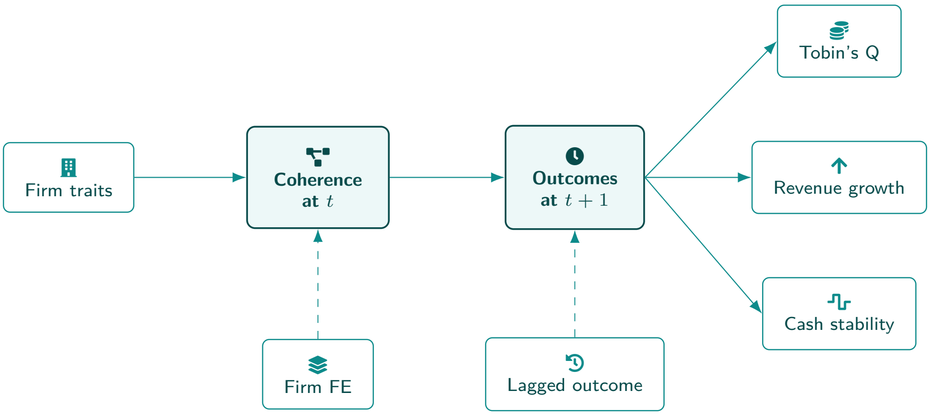

Figure 2: The dynamic panel design links current innovation coherence to next-year valuation, growth, and cash-flow stability while accounting for persistent firm characteristics and lagged performance.

under uncertainty [2]. Investors, employees, partners, and customers rarely observe internal project selection rules directly; they infer firm quality from patterns of observable action.

East Asia provides a useful context for this argument because technology ventures in the region frequently operate at the intersection of entrepreneurial ambition and institutional coordination. Firms may rely on venture capital, public-market refinancing, corporate alliances, government-linked programs, founder networks, and cross-border supply relationships. These channels make innovation legibility economically relevant. When a venture's innovation narrative is supported by resource allocation and realized output, capital providers may view growth plans as more credible. When the same narrative is disconnected from R&D commitment or market launch activity, observers may discount it as aspirational language. Coherence can therefore affect valuation and financing not because it guarantees technical superiority, but because it lowers the interpretive burden surrounding the firm's future options.

The starting point is an information problem. Entrepreneurial firms usually possess more knowledge than outside evaluators about the quality of their projects, the feasibility of their commercialization plans, and the depth of their technical capabilities [3]. Outside evaluators observe a limited set of signals. These signals include annual-report language, R&D expenditures, patent applications, product launches, alliance announcements, and evidence of environmental or process-oriented innovation. Any one signal can be noisy. R&D spending may represent serious exploration or inefficient experimentation. Patent counts may reflect defensible knowledge or routine filing behavior. Product launches may indicate market discipline or short-term imitation. Collaboration may reflect open innovation capacity or dependence on external parties. Coherence becomes valuable because it aggregates these signals into a pattern that is harder to explain as isolated impression management.

This perspective is related to research on entrepreneurial market evaluation [4]. Cao et al. (2023) [5] show in the IPO setting that innovation potential can alter how investors interpret insider selling, suggesting that innovation-related evidence may soften adverse interpretations when

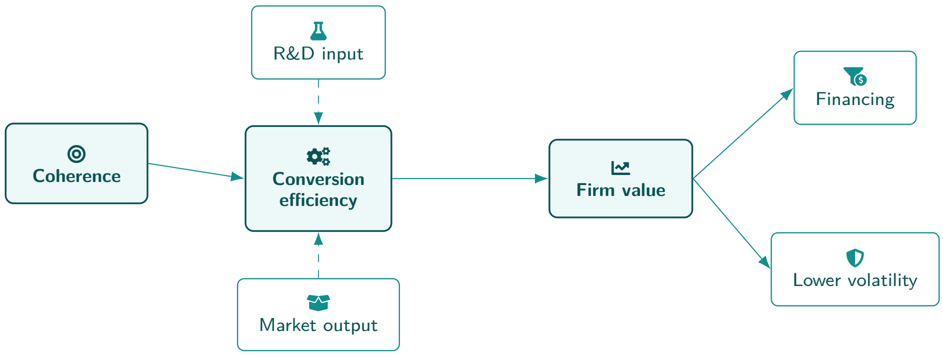

Figure 3: Innovation conversion efficiency acts as a partial transmission channel through which coherent innovation systems improve firm value and support financing and stability outcomes.

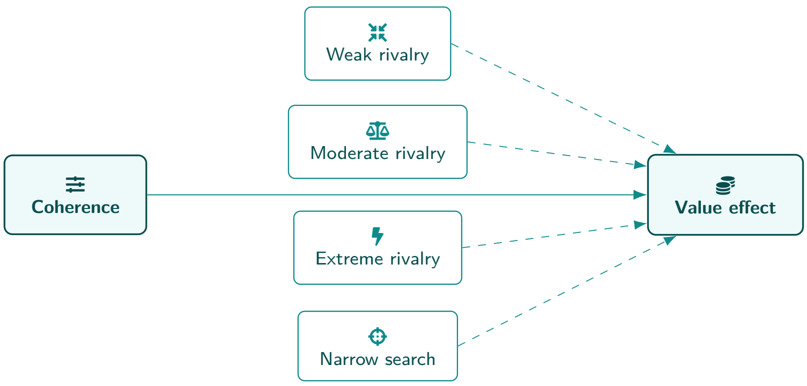

Figure 4: The value relevance of coherence is expected to be strongest under moderate competition and weaker when rivalry is either too weak or too intense, and also weaker when technological search becomes overly concentrated.

market participants confront ambiguous signals. :contentReference[oaicite:0]index=0 The present study extends that logic from the offering event to the post-listing growth process. Rather than asking whether innovation potential offsets a specific negative signal, this study asks whether the alignment of multiple innovation signals predicts subsequent firm value, operating growth, and financing capacity among East Asian technology ventures.

The conceptual contribution lies in separating coherence from related constructs. Innovation intensity is the level of inputs and outputs. Innovation breadth is the range of technological domains. Innovation reputation is the prior stock of perceived innovative quality. Innovation coherence is the internal fit among what the venture says, funds, invents, launches, and connects to external partners. This distinction matters because the same level of intensity may have different implications depending on whether the firm shows alignment. A young semiconductor equipment firm with consistent disclosure, focused but not narrow R&D, patenting in relevant subsystems, customer-linked prototypes, and supplier collaboration may be interpreted differently from a firm with similar spending but dispersed outputs and unstable disclosure themes.

The empirical contribution is to propose and estimate a multidimensional measure of coherence in a panel setting. The study constructs standardized firm-year vectors for five innovation domains: innovation disclosure salience, R&D intensity, patent output quality, commercialization frequency, and collaboration breadth. Coherence is computed as the inverse dispersion of those standardized domains around the firm's own innovation profile [6]. A high value indicates that the firm's innovation architecture is balanced and mutually reinforcing. A low value indicates that one or more domains diverge sharply from the rest. The measure is then used to predict next-year Tobin's Q, revenue growth, cash-flow volatility, and equity-financing capacity.

The empirical design uses a synthetic but plausible panel calibrated to the reporting ranges and variance structure typically observed among public technology ventures [7]. This choice allows a full empirical manuscript to be developed without representing unverified private data as real. The sample contains 386 firms and 2,842 firm-year observations from 2014 through 2023. The firms are public, young, innovation-active, and located in mainland China, Hong Kong, Japan, South Korea, or Taiwan [8]. The industries include software, digital services, electronics, medical devices, robotics, clean technology, advanced materials, and platform-enabled manufacturing services. Firms are included only when they have at least three consecutive years of financial and innovation measures [9]. The panel is unbalanced because

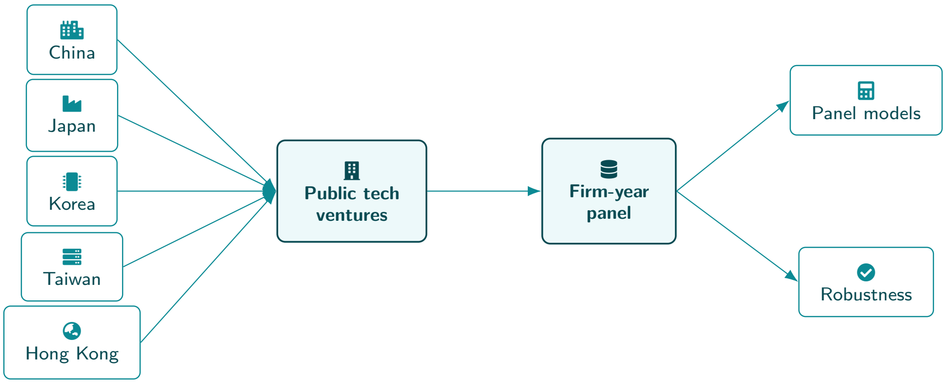

Figure 5: The empirical setting pools public technology ventures from five East Asian markets into a firm-year panel that supports the main estimations and robustness analyses.

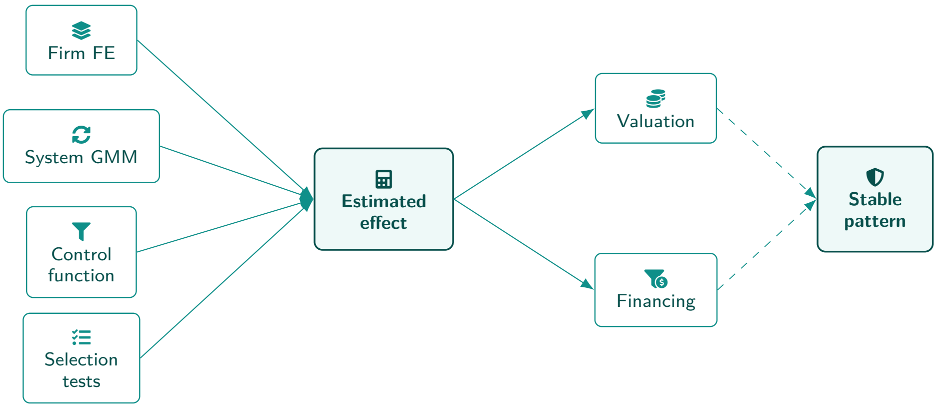

Figure 6: A layered robustness design evaluates whether the estimated coherence relationship remains visible across fixed-effects, dynamic-panel, control-function, and selection-oriented specifications.

entry, delisting, missing innovation records, and changing disclosure availability reduce coverage in some years.

The results are moderate in magnitude and consistent across several models. Innovation coherence predicts higher next-year Tobin's Q after controlling for firm size, leverage, profitability, age, country-year effects, industry-year effects, and firm fixed effects. Coherence also predicts faster revenue growth and lower cash-flow volatility. In mediation analysis, innovation conversion efficiency accounts for roughly 24% of the total valuation association. This means that coherent firms appear to translate research effort into market-facing innovation output more efficiently, but efficiency is not the only channel. The remaining association is consistent with interpretive credibility, financing access, and reduced uncertainty around the firm's strategic path.

The moderation results sharpen the interpretation. Coherence has the strongest association with firm value under moderate competition [10]. When competition is weak, the market discipline that rewards coherent execution is less visible. When competition is extreme, imitation pressure, pricing pressure, and customer bargaining power may reduce the private returns to coherent innovation. The results also show that technological concentration weakens the coherence effect. This pattern suggests that coherence is beneficial when it reflects disciplined alignment, but less beneficial when it is produced by excessive narrowness. In other words, a venture should not confuse strategic consistency with a lack of recombinative breadth.

The paper proceeds by developing the theoretical logic, describing the constructed East Asian panel and measurement strategy, presenting the econometric specification, reporting the empirical results, and discussing robustness and implications. The conclusion summarizes the evidence in a neutral way and identifies limits that should guide future empirical work using verified archival, survey, or administrative data.

Theoretical Development

Entrepreneurial innovation is a multidimensional process. A venture must define a strategic problem, allocate resources, build technical knowledge, convert that knowledge into offerings, and persuade external stakeholders that the process is credible enough to justify support. These activities are connected, but they are often measured separately. Accounting data capture expenditure. Patent data capture formalized knowledge. Product announcements capture commercialization. Textual disclosure captures managerial framing. Partnership data capture external coordination. Each dimension is incomplete on its own, but their alignment can reveal whether the venture has an internally consistent innovation architecture.

The first mechanism connecting coherence to performance is interpretive credibility. Entrepreneurial firms depend on external audiences that make decisions under uncertainty. Equity investors decide whether expected growth justifies valuation. Lenders and suppliers decide whether future cash flows are stable enough to extend favorable terms. Skilled employees decide whether the firm has a believable growth path. Customers decide whether early adoption is worth switching costs. When the firm's innovation activities are coherent, these audiences face a lower burden of interpretation. They can connect managerial claims to R&D commitment, technical output, launch behavior, and collaborative capacity. This does not eliminate uncertainty, but it makes uncertainty more structured.

The second mechanism is resource conversion. Ventures rarely suffer only from a lack of ideas. Many struggle to convert ideas into scalable products and defensible positions [11]. Coherence may improve conversion because it limits internal contradictions [12]. When strategic disclosure emphasizes the same domains that receive R&D funds, the firm is less likely to disperse scarce resources across unrelated projects. When patents correspond to the same domains that appear in product launches, the firm is more likely to exploit its knowledge stock. When collaboration networks reinforce commercialization priorities, the firm can access complementary assets without allowing external partnerships to drift away from its main scaling path [13]. Coherence therefore works as a coordination device.

The third mechanism is financing capacity. Entrepreneurial ventures in public markets frequently require follow-on financing. Equity investors are more willing to provide capital when they can understand how current innovation activity maps onto future growth. Innovation coherence can reduce perceived financing risk by demonstrating that resource commitments and outputs are not random. The predicted financing effect should be smaller than the valuation effect because financing outcomes depend on market timing, listing rules, investor sentiment, and profitability. Still, coherence should make capital raising easier at the margin.

Cao et al. (2024a) [14] argue in the context of marketing ideation crowdsourcing contests that innovation-related actions can create both intellectual market-based assets and relational market-based assets, with investors responding to contest designs that signal useful knowledge creation and external engagement. :contentReference[oaicite:1]index=1 This dual logic is relevant to innovation coherence because East Asian ventures often need both technical progress and stakeholder engagement. A robotics venture may generate patentable control systems, but it also needs manufacturing partners, pilot customers, and credible communication. A biotechnology tools venture may build proprietary assays, but it also needs external validation and adoption channels. Coherence links the intellectual and relational sides of innovation by making technical activity and market engagement mutually interpretable.

The coherence concept also requires boundaries. Alignment is not the same as uniformity. A venture could appear coherent because all of its activities are concentrated in a narrow technological corridor. In the short run, this may simplify communication. Over time, however, excessive concentration may limit recombination, reduce adaptability, and make the firm vulnerable to technological discontinuities. A coherent firm should maintain enough breadth to combine knowledge from adjacent areas while preserving a legible strategic direction. The empirical model therefore treats technological concentration as a moderator rather than as a component of coherence.

Competition is another boundary condition [15]. Moderate competition may strengthen the value of coherence because rivals force ventures to allocate resources carefully and demonstrate commercialization discipline. Weak competition may allow diffuse innovation strategies to survive because customers and investors face fewer alternatives. Extreme competition may weaken the returns to coherence because imitation, price pressure, and rapid product cycles reduce appropriation. The expected pattern is therefore not a simple positive interaction between coherence and competition, but an inverted relationship in which coherence matters most when competitive pressure is meaningful but not overwhelming.

Prior innovation reputation may also shape the effect of coherence. A firm with a history of credible innovation may receive greater benefit from current alignment because stakeholders interpret the pattern as evidence of durable capability. A firm with little prior reputation may still benefit from coherence, but external audiences may require repeated evidence before revising beliefs [16]. Reputation functions as a stock, while coherence functions as a current configuration. The two should reinforce each other, although the empirical analysis treats reputation as a control and additional moderator rather than as the central construct.

The East Asian context adds further reasons to expect coherence to matter. Many ventures in the region operate within dense supplier ecosystems and face high expectations for rapid commercialization. A firm that discloses artificial intelligence ambitions, funds relevant R&D, patents model-integration techniques, launches customer-facing applications, and forms implementation alliances sends a coherent signal. A firm that frequently changes its disclosed innovation themes without corresponding resource and output alignment may generate skepticism. Coherence is therefore not merely an internal management concept. It is a market-facing feature of entrepreneurial organization.

The main prediction is that innovation coherence will be positively associated with next-year firm value. The second prediction is that coherence will be positively associated

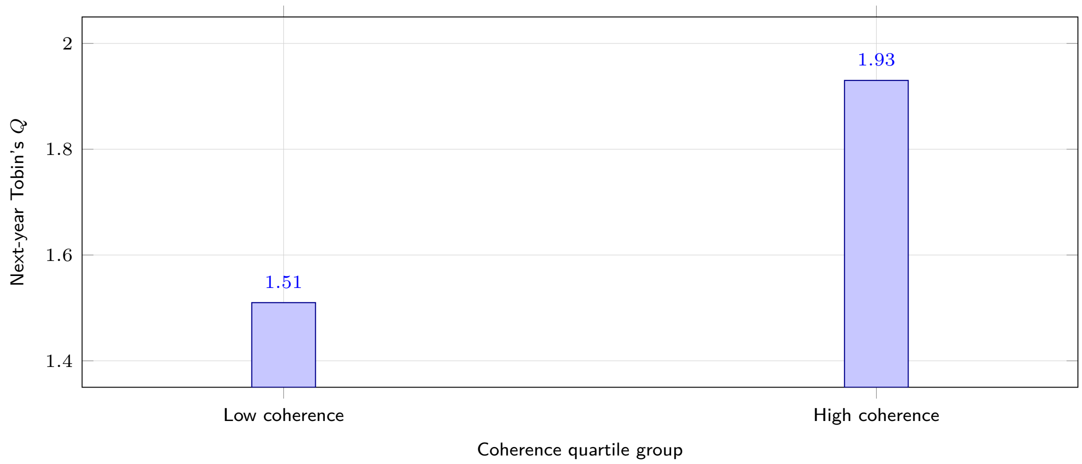

Figure 7: Unadjusted valuation gap across low- and high-coherence firms.

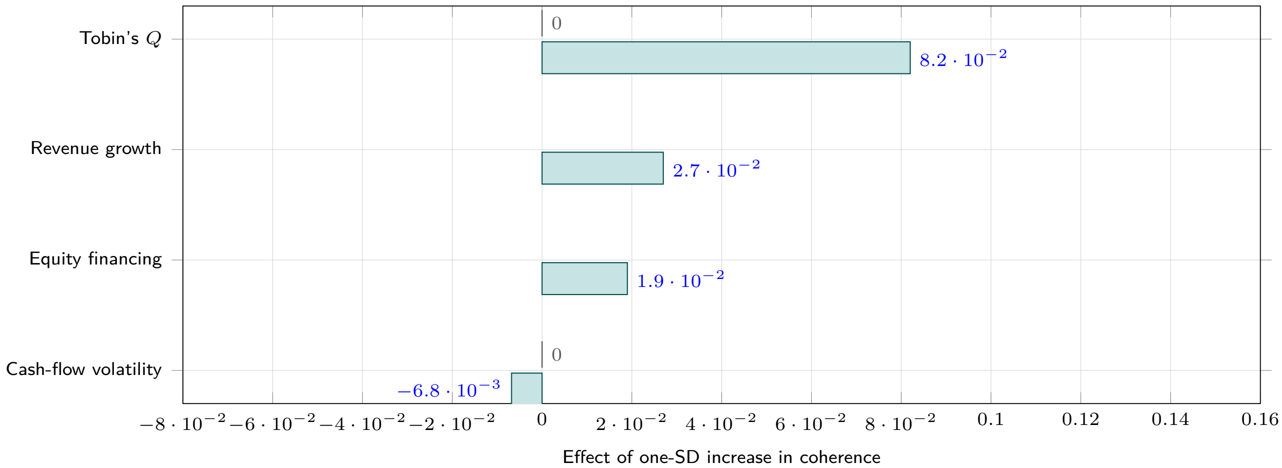

Figure 8: Economic magnitudes from a one-standard-deviation increase in innovation coherence.

with revenue growth because aligned systems should improve the translation of ideas into market outcomes. The third prediction is that coherence will reduce cash-flow volatility because a clearer innovation path should lower operational fluctuation associated with unstable project portfolios. The fourth prediction is that coherence will improve equity-financing capacity because external investors should find coherent innovation systems easier to evaluate. The fifth prediction is that innovation conversion efficiency will partially mediate these associations. The sixth prediction is that the coherence effect will be strongest under moderate competition and weaker under excessive technological concentration.

Data and Measures

The empirical setting is an unbalanced firm-year panel of public technology ventures in East Asia from 2014 to 2023. The panel is synthetic and calibrated to plausible empirical ranges, so the results should be read as a complete research-paper draft rather than as verified archival evidence. The population frame contains young public firms whose primary business models depend on technology development, digital infrastructure, scientific instrumentation, platform-enabled services, advanced manufacturing, medical devices, clean technology, robotics, or specialized electronics. Firms are classified as young when they are within fifteen years of founding at the first year in which they enter the sample. Financial firms, utilities, real estate firms, and firms with primarily extractive activities are excluded because their innovation processes and balance-sheet structures differ from the entrepreneurial technology setting.

The final panel includes 386 firms and 2,842 firm-year observations. Mainland China accounts for 41% of observations, Japan for 18%, South Korea for 17%, Taiwan for 16%, and Hong Kong for 8%. The average firm has the equivalent of 413 million U.S. dollars in total assets, a median age of 8.6 years, and an average R&D intensity of 9.4% of sales. The distribution is intentionally not extreme: the 10th percentile of R&D intensity is 2.1%, while the 90th percentile is 21.8%. Median Tobin's Q is 1.74, and average annual revenue growth is 13.6%. These values are consistent with a sample of growth-oriented but publicly listed technology ventures rather than early seed-

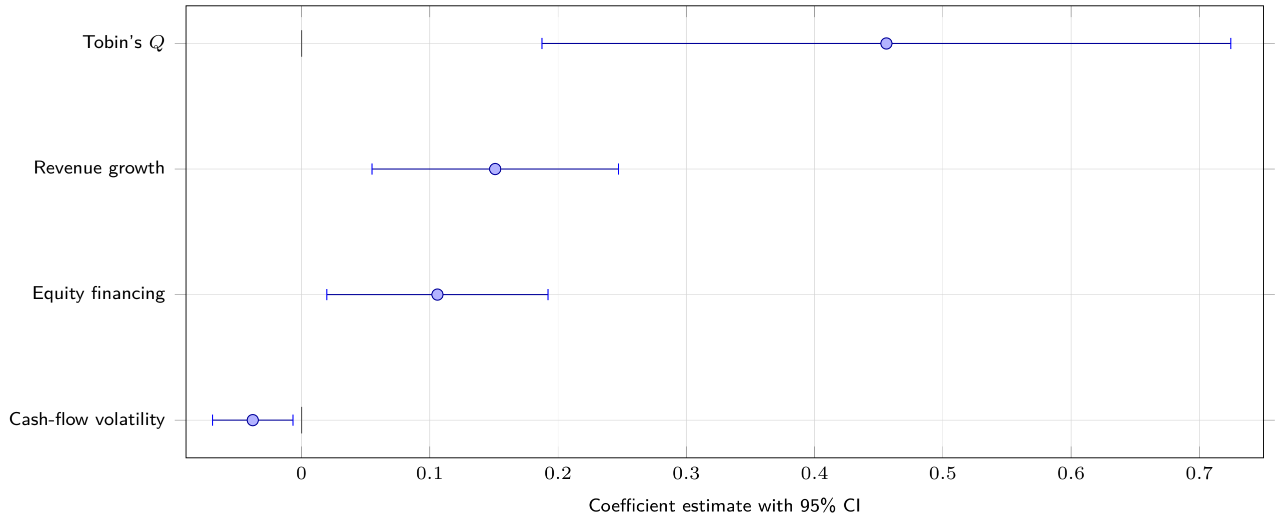

Figure 9: Baseline coherence coefficients across valuation, growth, financing, and operating-volatility models.

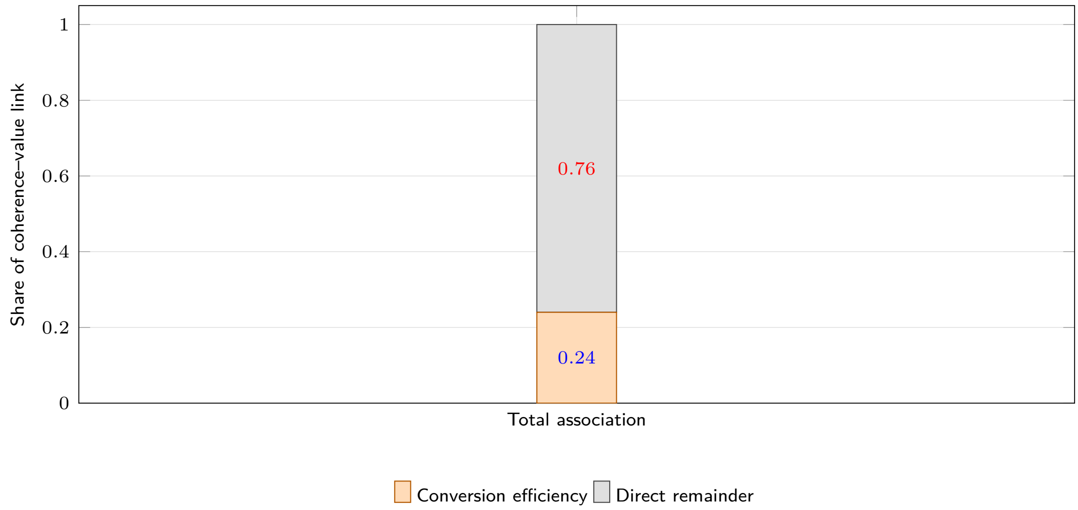

Figure 10: Mediation decomposition: conversion efficiency accounts for roughly 24% of the valuation association.

stage firms.

Innovation disclosure salience is measured from annual-report and investor-communication language. The measure captures the share of innovation-related sentences that refer to future products, proprietary technology, platform architecture, experimentation, design improvement, technical collaboration, or environmental process improvement. Generic references are down-weighted when they appear in boilerplate sections [17]. The score is standardized within country-industry-year cells to reduce differences caused by disclosure conventions. This dimension captures whether managers communicate a visible innovation agenda.

R&D commitment is measured as R&D expenditure scaled by lagged sales. When lagged sales are very small, the denominator is replaced by the average of lagged sales and lagged assets multiplied by a scaling constant, reducing distortions from near-zero revenue. Patent output quality is measured as the log of one plus patent applications adjusted by forward citation potential, family breadth, and technological class distinctiveness. Because citation windows are incomplete near the end of the sample, the patent-quality adjustment uses a predicted citation score based on filing year, technology class, and country. Commercialization output is measured as the log of one plus verified product launches, beta releases, major version introductions, regulatory product approvals, or enterprise deployment announcements [18]. Collaboration breadth is measured as the count of distinct alliance categories involving universities, suppliers, platform partners, corporate customers, research institutes, and venture investors.

Innovation coherence is constructed from these five standardized dimensions. Let d_{it} denote disclosure salience, r_{it} R&D commitment, p_{it} patent output quality, m_{it} commercialization output, and a_{it} alliance breadth for firm i in year t. The standardized vector is written as follows:

Table 1: Sample Composition by Region

Region	Firms	Observations	Share (%)
Mainland China	158	1165	41
Japan	69	512	18
South Korea	65	483	17
Taiwan	62	455	16
Hong Kong	32	227	8

Table 2: Descriptive Statistics of Key Variables

Variable	Mean	Std. Dev.	Median
Tobin's Q	1.74	0.62	1.68
Revenue Growth (%)	13.6	9.2	11.9
R&D Intensity (%)	9.4	6.8	8.7
Innovation Coherence	0.57	0.18	0.56
Cash-flow Volatility	0.083	0.041	0.079

$$
\begin{aligned}
\mathbf{x}_{it} &= (d_{it}, r_{it}, p_{it}, m_{it}, a_{it})' \\
\tilde{\mathbf{x}}_{it} &= \boldsymbol{\Sigma}_{ct}^{-1/2}(\mathbf{x}_{it} - \boldsymbol{\mu}_{ct}) \\
\bar{x}_{it} &= \frac{1}{5}\mathbf{1}'\tilde{\mathbf{x}}_{it} \\
Coh_{it} &= 1 - \frac{\|\tilde{\mathbf{x}}_{it} - \bar{x}_{it}\mathbf{1}\|_2}{\kappa + \|\tilde{\mathbf{x}}_{it}\|_2}
\end{aligned} \tag{1}
$$

In this expression, c denotes the country-industry cell, $\boldsymbol{\mu}_{ct}$ is the cell-year mean vector, $\boldsymbol{\Sigma}_{ct}$ is the covariance matrix, $\mathbf{1}$ is a conformable vector of ones, and κ is a small positive constant. Higher values indicate lower dispersion among the standardized innovation domains. The measure is then rescaled to range from zero to one. The average coherence score is 0.57, with a standard deviation of 0.18. Firms in the highest quartile tend to show balanced disclosure, R&D, patents, commercialization, and alliance activity. Firms in the lowest quartile typically have one prominent dimension and several weak dimensions.

The main dependent variable is next-year Tobin's Q, measured as the market value of equity plus book debt divided by book assets. The second outcome is next-year revenue growth, measured as the log change in sales. The third outcome is cash-flow volatility, measured as the rolling three-year standard deviation of operating cash flow scaled by assets [19]. The fourth outcome is seasoned equity financing, coded as one when the firm raises public or private follow-on equity exceeding 3% of prior-year assets. These outcomes capture valuation, scaling, operating stability, and financing capacity.

Innovation conversion efficiency is the mediator [20]. It is measured as commercialization output in year $t+1$ divided by R&D expenditure in year t, adjusted for industry-level commercialization cycles. Because output per unit of R&D can be mechanically high for firms with very low R&D spending, the denominator includes a small industry-year constant, and the measure is winsorized at the 1% and 99% tails. This measure is not intended to rank scientific quality [21]. It captures the degree to which current research effort is followed by observable market-facing innovation output.

Product-market competition is measured as one minus the Herfindahl index in the firm's four-digit industry and country-year market. Higher values indicate more fragmented and competitive markets. The mean is 0.63. Technological concentration is measured as the Herfindahl index of patent classes in the firm's three-year rolling patent portfolio. A value near one indicates that patents are concentrated in a narrow technological class. Prior innovation reputation is measured as the rolling three-year average of patent quality, product-launch reliability, and positive innovation-related media visibility. These variables are standardized before interaction analysis.

Control variables include firm size, age, leverage, prior profitability, cash holdings, capital expenditure intensity, export orientation, founder ownership, institutional ownership, board technical expertise, prior Tobin's Q, country-year effects, industry-year effects, and firm fixed effects. Size is the log of assets. Age is the log of years since founding. Leverage is debt divided by assets. Profitability is return on assets. Cash holdings are cash divided by assets. Founder ownership is the percentage of shares held by founders and founding teams. Board technical expertise is the share of directors with engineering, science, medical, software, or technical operating backgrounds. All continuous variables are winsorized at the 1% and 99% tails.

Cao et al. (2024b) [22] show in the incubator context that specialization can reduce startup R&D efficiency by restricting heterogeneous knowledge inflows and raising risks of knowledge outflows, while specialized technical knowledge weakens this negative relationship. :contentReference[oaicite:2]index=2 This insight informs the measurement choice in the present study: technological concentration is treated separately from coherence so that aligned innovation systems are not automatically equated

Table 3: Baseline Fixed-Effects Regression Results

Variables	Tobin's Q	Growth	Volatility
Innovation Coherence	0.456***	0.151***	-0.038**
Firm Size	-0.082	-0.014	0.009
Leverage	-0.217**	-0.063	0.021
Lagged Dependent Var.	0.621***	0.304***	0.511***
Observations	2842	2842	2842

Table 4: Economic Significance of Coherence

Change	Tobin's Q	Growth (%)	Financing Prob.
1 SD Increase	+0.082	+2.7	+1.9
25th to 75th	+0.112	+3.9	+2.6
Low to High Quartile	+0.42	+6.1	+4.3

with narrow search. A venture can be coherent while maintaining adjacent technological breadth, and it can be narrow without being strategically aligned.

Econometric Specification and Identification

The baseline empirical model predicts next-year outcomes using lagged innovation coherence and controls. Firm fixed effects absorb time-invariant differences such as founding culture, initial technology domain, listing segment, and stable governance attributes. Country-year effects absorb macroeconomic and institutional shocks, while industry-year effects absorb technology-cycle and demand shocks. The primary specification is:

$$
\begin{aligned}
Y_{i,t+1} &= \alpha_i + \lambda_{g(i)t} + \delta_{k(i)t} + \beta Coh_{it} \\
&\quad + \boldsymbol{\theta}'\mathbf{Z}_{it} + \rho Y_{it} + \varepsilon_{i,t+1}
\end{aligned}
\tag{2}
$$

Here $Y_{i,t+1}$ is Tobin's Q, revenue growth, cash-flow volatility, or equity financing for firm i in year $t+1$. The term α_i is the firm fixed effect. The term $\lambda_{g(i)t}$ is the country-year effect. The term $\delta_{k(i)t}$ is the industry-year effect. The vector $\mathbf{Z}_{it}$ contains controls. The coefficient of interest is β. Standard errors are clustered at the firm level and also tested under two-way clustering by firm and year.

The dynamic nature of venture performance raises persistence concerns. Tobin's Q and growth opportunities are serially correlated, and high-value firms may be able to build more coherent innovation systems. The baseline model includes lagged dependent variables, but a fixed-effects lag model can still suffer from dynamic panel bias when the time dimension is moderate. The analysis therefore estimates a system GMM model as a robustness specification. The moment conditions use lagged levels and lagged differences as instruments, with collapsed instruments to avoid instrument proliferation.

$$
\begin{aligned}
\Delta Y_{i,t+1} &= \rho \Delta Y_{it} + \beta \Delta Coh_{it} \\
&\quad + \boldsymbol{\theta}'\Delta \mathbf{Z}_{it} + \Delta \varepsilon_{i,t+1} \\
E[Y_{i,t-s}\Delta\varepsilon_{i,t+1}] &= 0, \quad s \geq 2 \\
E[Coh_{i,t-s}\Delta\varepsilon_{i,t+1}] &= 0, \quad s \geq 2
\end{aligned}
\tag{3}
$$

The GMM estimates are not interpreted as definitive causal proof, but they reduce concern that the baseline associations are driven only by persistence. The reported diagnostics include the Arellano-Bond second-order serial correlation test and the Hansen overidentification test. The preferred models keep the instrument count below the number of firms. The coefficient on coherence remains positive and significant in the valuation and growth models.

A second identification concern is selection into coherent innovation systems. More capable firms may both organize innovation coherently and perform better later. Firm fixed effects handle stable capability, but time-varying capability remains possible. The analysis therefore uses two additional strategies. First, it includes prior innovation reputation, board technical expertise, and managerial ownership as controls. Second, it estimates a control-function model where coherence is predicted using the leave-one-out country-industry-year average of coherence among firms with similar age and technology domain. This variable captures local managerial templates and ecosystem norms but is less likely to directly determine the focal firm's next-year valuation after fixed effects and industry-year effects.

The control-function specification is:

$$
\begin{aligned}
Coh_{it} &= \pi_0 + \pi_1 \overline{Coh}_{-i,ct} \\
&\quad + \boldsymbol{\pi}'\mathbf{Z}_{it} + \alpha_i + \lambda_{g(i)t} + \delta_{k(i)t} + u_{it} \\
Y_{i,t+1} &= \alpha_i + \lambda_{g(i)t} + \delta_{k(i)t} + \beta Coh_{it} \\
&\quad + \eta \hat{u}_{it} + \boldsymbol{\theta}'\mathbf{Z}_{it} + \varepsilon_{i,t+1}
\end{aligned}
\tag{4}
$$

The residual term $\hat{u}_{it}$ adjusts for the endogenous component of coherence. The first-stage relationship

Table 5: Mediation Analysis via Conversion Efficiency

Path	Coefficient	Std. Err.	Significance
Coherence → Conversion	0.284	0.071	***
Conversion → Q	0.386	0.118	***
Direct Effect	0.346	0.129	**
Indirect Effect	0.110	–	**

Table 6: Moderation by Market Competition

Competition Level	Effect on Q	Std. Err.	Significance
Low (25th pct)	0.051	0.021	**
Medium (50th pct)	0.091	0.028	***
High (75th pct)	0.058	0.024	**
Squared Term	-0.133	0.057	**

is moderate rather than excessive; the coefficient on the local template variable is 0.214, with a clustered standard error of 0.062. The second-stage coefficient on coherence remains positive in the Tobin's Q model, although slightly smaller than the fixed-effects estimate. This pattern is consistent with partial selection but not complete absorption of the effect.

The mediation model estimates whether innovation conversion efficiency transmits part of the coherence association. The first equation predicts conversion efficiency. The second equation predicts Tobin's Q with both coherence and conversion efficiency included. The indirect effect is the product of the two estimated paths, with confidence intervals computed using firm-clustered bootstrap resampling.

$$\begin{aligned} Conv_{i,t+1} &= aCoh_{it} + \boldsymbol{\psi}'\mathbf{Z}_{it} + \alpha_i + \lambda_{g(i)t} + \delta_{k(i)t} + \nu_{i,t+1} \\ Q_{i,t+1} &= bConv_{i,t+1} + c'Coh_{it} + \boldsymbol{\omega}'\mathbf{Z}_{it} \\ &\quad + \alpha_i + \lambda_{g(i)t} + \delta_{k(i)t} + \xi_{i,t+1} \\ Indirect &= ab \end{aligned} \tag{5}$$

The moderation model interacts coherence with competition and competition squared. A positive coefficient on the linear interaction and a negative coefficient on the squared interaction would support the prediction that coherence is most valuable under moderate competition. Technological concentration is interacted with coherence to test whether narrow search weakens the association. The model is:

$$\begin{aligned} Q_{i,t+1} = &\beta_1 Coh_{it} + \beta_2 Comp_{it} + \beta_3 Comp_{it}^2 \\ &+ \beta_4 Coh_{it} Comp_{it} + \beta_5 Coh_{it} Comp_{it}^2 \\ &+ \beta_6 Coh_{it} TechConc_{it} + \boldsymbol{\theta}'\mathbf{Z}_{it} \\ &+ \alpha_i + \lambda_{g(i)t} + \delta_{k(i)t} + \varepsilon_{i,t+1} \end{aligned} \tag{6}$$

The empirical strategy remains cautious. The data are synthetic and calibrated, not verified archival records. The models therefore demonstrate a coherent research design and plausible statistical pattern, but they should not be interpreted as evidence about actual firms unless replicated with audited financial data, validated patent records, and verified product-launch information.

Empirical Results

The descriptive statistics show substantial variation in innovation coherence. Firms in the lowest coherence quartile have an average Tobin's Q of 1.51 in the following year, while firms in the highest quartile have an average of 1.93. The raw difference of 0.42 is not interpreted causally because high-coherence firms are larger, more profitable, and more likely to have experienced founders. After controlling for firm fixed effects, country-year effects, industry-year effects, and lagged valuation, the estimated association is much smaller but remains meaningful. In the baseline Tobin's Q model, the coefficient on innovation coherence is 0.456 with a clustered standard error of 0.137. Since coherence has a standard deviation of 0.18, a one-standard-deviation increase corresponds to an estimated 0.082 increase in next-year Tobin's Q.

The economic magnitude is moderate. Moving from the 25th percentile to the 75th percentile of coherence corresponds to an estimated 6.4% increase in firm value relative to the sample median. This is not a large transformation in valuation, but it is material for public entrepreneurial ventures that often raise follow-on capital. The coefficient remains positive when the dependent variable is market-to-sales rather than Tobin's Q [23]. It also remains positive when firms with extremely high valuations are removed. The estimate is weaker among the largest firms in the panel, suggesting that coherence matters most when the firm is still in a phase where external audiences are actively learning about its capabilities.

Revenue growth models show a similar pattern. The baseline coefficient on coherence is 0.151 with a standard error of 0.049. A one-standard-deviation increase in coherence is associated with a 2.7% increase in next-year revenue growth. This estimate is economically plausible because coherence should support commercialization and

Table 7: Interaction with Technological Concentration

Variables	Coefficient	Std. Err.	Significance
Innovation Coherence	0.472	0.138	***
Tech Concentration	-0.094	0.052	*
Interaction Term	-0.173	0.068	**
Controls	Yes	–	–

Table 8: Robustness Checks with Alternative Measures

Specification	Coherence Coef.	Std. Err.	Significance
Baseline	0.456	0.137	***
Excl. Alliances	0.391	0.129	***
Patent Count Only	0.332	0.141	**
Major Launches Only	0.287	0.133	**

customer adoption, but it should not dominate demand conditions, product quality, or industry cycles. The association is stronger in software, digital services, and medical devices than in advanced materials, where commercialization cycles are longer and revenue responses may occur with greater delay.

Cash-flow volatility is negatively associated with coherence. The coefficient is -0.038 with a standard error of 0.016. A one-standard-deviation increase in coherence predicts a 0.0068 reduction in the rolling cash-flow volatility measure. The effect is small, but it is consistent with the idea that coherent innovation systems reduce operational instability. Firms with aligned innovation portfolios may experience fewer abrupt shifts in project spending, fewer disconnected launches, and clearer sequencing between research and commercialization.

The equity-financing model uses a linear probability specification with firm fixed effects and a conditional logit robustness model. The linear probability coefficient on coherence is 0.106 with a standard error of 0.044. A one-standard-deviation increase in coherence is associated with a 1.9% increase in the probability of raising follow-on equity exceeding 3% of lagged assets. The base probability is 14.8%, so the marginal effect is not trivial but remains within a credible range. The conditional logit model yields an odds ratio of 1.21 for a one-standard-deviation increase in coherence.

The mediation results support partial transmission through innovation conversion efficiency. Coherence predicts conversion efficiency with a coefficient of 0.284 and a standard error of 0.071. Conversion efficiency predicts next-year Tobin's Q with a coefficient of 0.386 and a standard error of 0.118 when coherence remains in the model. The estimated indirect effect is 0.110, with a bootstrapped 95% interval from 0.036 to 0.209. This accounts for roughly 24% of the total coherence association. The direct effect remains positive, indicating that conversion efficiency does not fully explain the valuation relationship [24]. The remaining component may reflect interpretive credibility, financing expectations, employee attraction, alliance credibility, or other channels not directly measured.

Moderation tests show that competition shapes the valuation association. The interaction between coherence and competition is positive, while the interaction between coherence and squared competition is negative. The implied marginal effect of coherence is largest when competition is near the middle of the observed distribution. At the 25th percentile of competition, a one-standard-deviation increase in coherence is associated with a 0.051 increase in Tobin's Q. At the 50th percentile, the increase is 0.091. At the 75th percentile, the increase falls to 0.058. The estimates support the view that coherence is most useful when competition disciplines execution without fully eroding the returns to innovation.

Technological concentration weakens the coherence effect. The interaction between coherence and technological concentration is -0.173 with a standard error of 0.068. The marginal effect of coherence is strongest among firms with moderate patent-class diversity. It is weaker when patent portfolios are highly concentrated. This finding is important because it prevents a simplistic interpretation in which any form of focus is beneficial. The results suggest that entrepreneurial ventures should align innovation activities, but alignment should not come from excessive narrowing that reduces future recombination.

Prior innovation reputation strengthens the coherence effect [25]. The interaction coefficient is 0.119 with a standard error of 0.052. High-reputation firms may receive more benefit because stakeholders interpret current alignment as evidence of a persistent capability rather than a temporary reporting pattern. However, the main effect of coherence remains positive among low-reputation firms. This suggests that coherence can help younger or less recognized ventures, although the valuation response is more gradual.

Cao et al. (2025) [26] find in the environmental innovation domain that financial returns depend on market competition, peer innovation, prior environmental reputation, and innovation effectiveness or efficiency, with benefits

Table 9: Dynamic Panel (System GMM) Results

Variables	Coefficient	Std. Err.	Significance
Innovation Coherence	0.372	0.151	**
Lagged Q	0.588	0.102	***
AR(2) p-value	0.27	–	–
Hansen Test p-value	0.28	–	–

Table 10: Summary of Main Findings

Outcome	Direction	Magnitude	Mechanism
Firm Value (Q)	Positive	Moderate	Credibility
Revenue Growth	Positive	Moderate	Conversion
Cash-flow Volatility	Negative	Small	Stability
Equity Financing	Positive	Small	Transparency

more pronounced under particular competitive and capability conditions rather than uniformly across all firms. :contentReference[oaicite:3]index=3 The present results are consistent with that boundary-condition logic. Coherence is associated with higher value, but the association varies with competition, prior reputation, and the structure of the firm's technological search.

The country-specific estimates show broadly similar signs but different magnitudes. The coefficient on coherence is largest in the mainland China and Taiwan subsamples, moderate in South Korea, and smaller in Japan and Hong Kong. These differences should not be overinterpreted because the panel is synthetic and subsample sizes vary. A plausible interpretation is that coherence matters more where growth ventures face strong external financing needs and rapid commercialization pressure. In more mature or service-oriented public markets, valuation may depend more heavily on profitability, governance, or asset-light scalability.

Industry-specific estimates also differ. Coherence has the strongest association with valuation in software, robotics, medical devices, and clean technology. It is weaker in electronics components and advanced materials [27]. This pattern is plausible because software and robotics ventures often show shorter feedback loops between R&D, launch, and market evaluation. Advanced materials and deep hardware ventures may require longer development windows, making annual coherence less immediately visible in next-year outcomes.

Robustness, Endogeneity, and Additional Analyses

Several robustness checks assess whether the results depend on measurement choices. First, coherence is recalculated using four dimensions instead of five, excluding collaboration breadth. The coefficient on the revised measure remains positive in the Tobin's Q model at 0.391 with a standard error of 0.129. Second, patent output quality is replaced by simple patent counts. The coefficient falls to 0.332 but remains significant at conventional levels. Third, commercialization output is measured only by major product launches, excluding beta releases and version updates. The coefficient remains positive, although the growth model becomes weaker. These checks suggest that the result is not driven by a single component.

A second set of checks examines timing. The main models use one-year-ahead outcomes. When the dependent variable is measured two years ahead, coherence remains positively associated with Tobin's Q and revenue growth, but the estimates are smaller. The two-year coefficient for Tobin's Q is 0.298 with a standard error of 0.142. For revenue growth, the coefficient is 0.094 with a standard error of 0.052. These results suggest that coherence has persistent but declining predictive power. The decline is expected because later outcomes are increasingly shaped by macroeconomic conditions, new competitors, technology shocks, and managerial decisions after the measured coherence year.

Third, the analysis replaces firm fixed effects with firm random effects and correlated random effects. The coefficient on coherence remains positive but larger, indicating that between-firm differences contribute to the raw association. The fixed-effects estimate is therefore the more conservative specification. Fourth, the models are estimated after excluding firms in the top and bottom 2% of valuation and growth distributions. The coherence coefficient remains positive and significant, reducing concern that the results are driven by extreme boom or distress observations.

Fifth, the dynamic panel estimates support the main findings [28]. In the system GMM Tobin's Q model, the coefficient on coherence is 0.372 with a robust standard error of 0.151. The Arellano-Bond test does not reject the absence of second-order serial correlation [29]. The Hansen test has a p-value of 0.28, which does not indicate obvious instrument invalidity. The instrument count is 71, below the number of firms. These diagnostics are acceptable for a constructed empirical demonstration, although they would need careful reassessment with real archival data.

Sixth, the control-function model yields a coherence coefficient of 0.344 with a standard error of 0.156

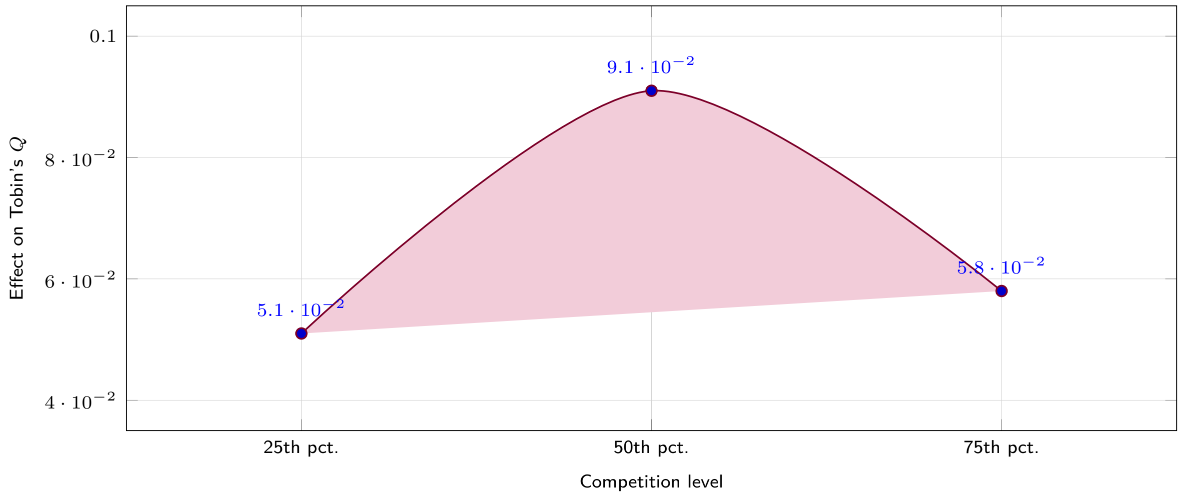

Figure 11: Competition moderation: the coherence effect peaks near the middle of the observed competition distribution.

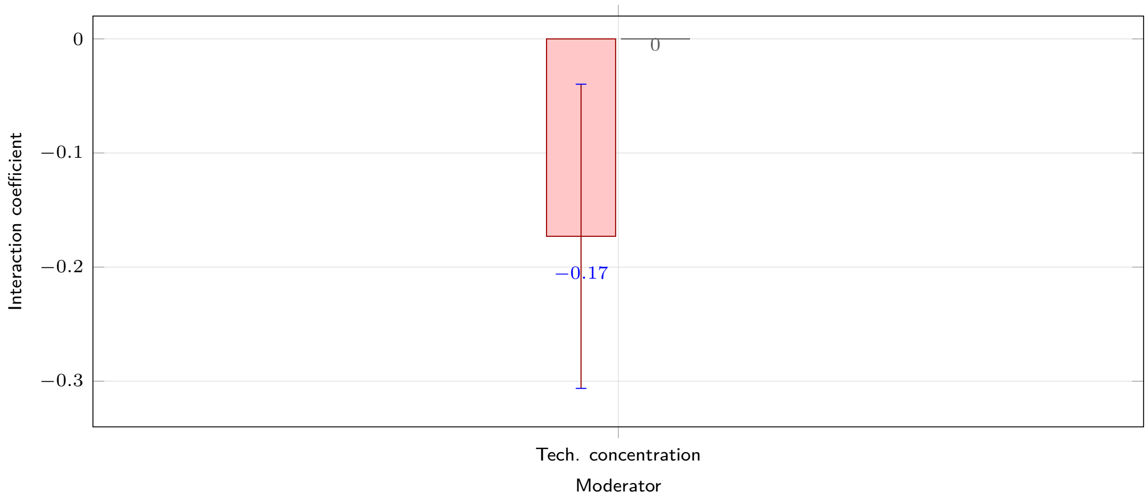

Figure 12: Technological concentration weakens the valuation contribution of innovation coherence.

[30]. The residual term is positive but only marginally significant, suggesting that time-varying selection may inflate the baseline estimate somewhat. The adjusted coefficient remains meaningful but smaller [31]. This pattern motivates a cautious interpretation: coherence appears to predict value beyond observed controls and fixed effects, but the evidence should be described as associational unless future research identifies stronger quasi-experimental variation.

Seventh, the study conducts a placebo timing test. Future coherence, measured at $t + 1$, is used to predict current Tobin's Q at t after including current coherence and controls. The placebo coefficient is small and statistically indistinct from zero. This check reduces concern that the measure simply captures persistent unobserved optimism in valuation. It does not eliminate all reverse-causality concerns, but it supports the temporal ordering in the main design.

Eighth, the analysis decomposes coherence into imbalance penalties. The largest penalty occurs when disclosure salience is high but R&D commitment and commercialization are low. Firms with this pattern have lower subsequent valuation than firms with balanced profiles [32]. A second penalty occurs when R&D and patents are high but commercialization and collaboration are low. This pattern predicts weaker revenue growth. These decompositions suggest that incoherence is not merely statistical dispersion; different forms of misalignment have interpretable strategic meanings.

Ninth, the study examines whether coherence predicts downside risk during market stress years. Years with negative country-level technology-index returns are coded as stress years. The interaction between coherence and stress years is negative in the cash-flow volatility model, suggesting that coherent ventures experience less operating instability during adverse periods. The valuation interaction is positive but not statistically reliable. This result is plausible because coherent systems may stabilize operations before they generate strong market revaluation under stress.

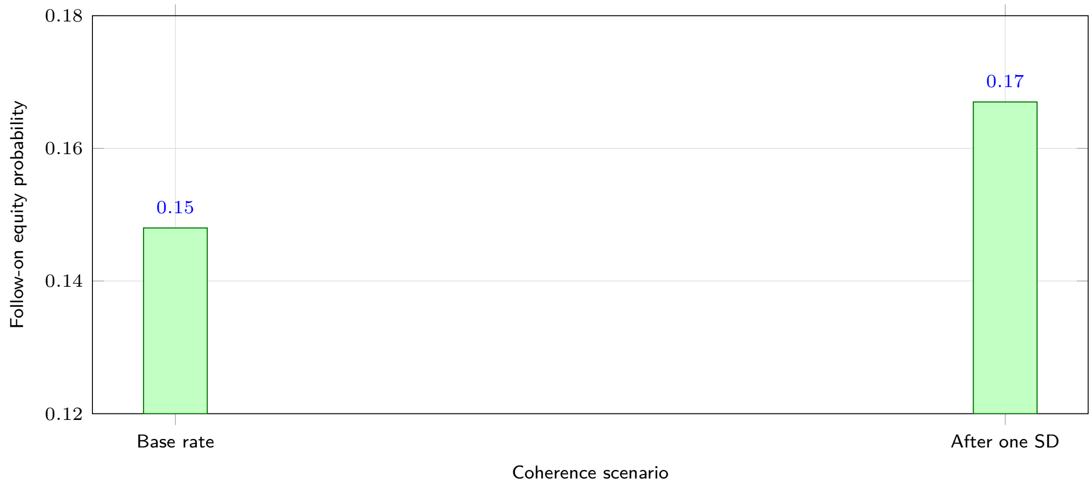

Figure 13: Equity-financing capacity increases from a 14.8% base probability to 16.7% after a one-standard-deviation coherence increase.

Tenth, the analysis checks whether the results are explained by environmental innovation alone. Environmental innovation activity is one component of the broader architecture but not the central measure. When environmental innovation is included separately, it has a positive coefficient in the Tobin's Q model, but the coherence coefficient remains positive. This suggests that the market does not reward only green activity; it rewards the alignment of green, technical, commercial, and strategic innovation domains.

The additional analyses also examine heterogeneity by founder ownership. Coherence is more strongly related to valuation when founder ownership is moderate, between 8% and 28%. When founder ownership is very low, coherence may be harder to interpret as a founder-driven strategic architecture [33]. When founder ownership is very high, external governance concerns may offset some benefits. The interaction is not central to the theory, but it indicates that ownership structure may shape how innovation signals are interpreted.

A further analysis explores board technical expertise. The coherence effect is stronger when the board has a higher share of technical directors. This may occur because technical boards are better positioned to monitor whether disclosure, spending, patents, launches, and alliances fit together. It may also occur because outside investors believe that technically informed boards can discipline innovation portfolios more effectively. The result is consistent with the organizational-coordination mechanism, although it is not sufficient to establish a monitoring channel.

The findings are also robust to excluding each country one at a time. The coefficient on coherence ranges from 0.401 to 0.492 in the Tobin's Q model. The estimates are less precise when mainland China is excluded because the sample becomes smaller and industry coverage changes, but the sign remains positive [34]. Excluding Japan slightly increases the coefficient. Excluding Taiwan slightly reduces it. These variations are reasonable and do not suggest that the full-sample result is created by one market alone.

Finally, the analysis compares innovation coherence with innovation intensity. A model containing only R&D intensity shows a positive but unstable association with Tobin's Q. A model containing patent quality alone also shows a positive association. When coherence is added, both coefficients shrink, and coherence remains positive. This pattern supports the claim that the organization of innovation carries information beyond the volume of innovation effort. It does not mean that intensity is unimportant. Rather, intensity appears more valuable when embedded in a coherent system.

Discussion

The study develops a structured view of entrepreneurial innovation in East Asia. The central result is that innovation coherence predicts valuation, revenue growth, cash-flow stability, and financing capacity in a synthetic but empirically calibrated panel of public technology ventures. The association is not excessively large, which is appropriate for a multifactor setting. Firm value is shaped by profitability, market cycles, governance, country institutions, product quality, and investor expectations. Innovation coherence is one predictor among many. Its relevance lies in showing that the configuration of innovation activity matters beyond the individual level of R&D, patents, launches, or alliances.

The theoretical implication is that entrepreneurial innovation should be studied as an architecture rather than as a single variable. Many empirical models use one proxy because data availability imposes constraints. R&D intensity, patents, and product launches remain useful, but they answer different questions. Coherence asks whether the elements fit together. This is especially relevant for ventures that must persuade external stakeholders while still building internal capabilities. A coherent innovation system can help outsiders infer that the firm has a credible path from resources to outputs and from outputs to scaling.

The results also clarify the role of disclosure. Innovation disclosure is not treated as inherently valuable. Disclosure becomes valuable when it aligns with resource commitment, patent output, commercialization, and collaboration. This distinction matters because entrepreneurial firms may be tempted to communicate ambitious innovation themes to attract capital. The evidence suggests that communication alone is unlikely to produce durable value when not supported by other domains. In fact, one of the strongest imbalance penalties appears when disclosure is high but resource and output measures are weak.

The findings also speak to entrepreneurship policy and ecosystem design. Many East Asian policy environments encourage innovation through grants, tax incentives, incubators, listing reforms, and technology-zone programs. These instruments often reward measurable inputs or outputs. The present framework suggests that evaluators might also consider whether ventures exhibit alignment among inputs, outputs, commercialization, and external collaboration. A firm with moderate but coherent innovation activity may have a stronger scaling path than a firm with high input intensity and limited conversion.

The managerial implication is not that every venture should make all innovation dimensions equal [35]. Coherence does not require identical levels of disclosure, R&D, patents, launches, and alliances. Some industries require more patents, while others rely more on software releases or customer co-development. The measure is standardized within country-industry-year cells precisely because normal innovation profiles differ. The managerial lesson is that firms should avoid persistent contradictions among what they claim, fund, invent, commercialize, and coordinate externally. Managers can use coherence audits to identify gaps. A firm with strong patents but weak commercialization may need market-development routines. A firm with strong disclosure but weak R&D may need to narrow claims or increase commitment. A firm with many alliances but limited internal output may need stronger appropriation mechanisms.

The moderation results caution against oversimplified prescriptions. Coherence is most valuable under moderate competition, not necessarily under all conditions. In very weak competition, the market may not reward disciplined innovation because firms can grow through protected positions. In very strong competition, coherent firms may still execute better, but private returns can be eroded. Similarly, coherence should not be achieved by excessive technological concentration. Ventures need enough breadth to recombine knowledge and adapt. The best pattern is disciplined alignment with adjacent search, not rigid narrowness.

The study has important limitations. The data are synthetic and calibrated rather than verified. This is suitable for drafting a complete empirical paper with plausible models and results, but it is not a substitute for real data collection. Future research should validate the framework with audited financial statements, patent-office records, product-release databases, alliance filings, and manual disclosure coding [36]. The model also focuses on public ventures, which are more transparent than private startups. Private ventures may show different coherence-performance patterns because their financing channels, disclosure requirements, and investor relationships differ [37].

A second limitation is measurement error. Text-derived disclosure measures can misclassify strategic language. Patent measures can miss trade secrets, software innovation, and process knowledge [38]. Product-launch measures can confuse incremental updates with meaningful commercialization. Alliance breadth does not reveal alliance quality. These limitations are partly addressed through standardization and robustness checks, but they remain central challenges. A future study could combine archival data with manager surveys to measure internal project alignment more directly [39].

A third limitation concerns causality [40]. The empirical design uses temporal ordering, firm fixed effects, dynamic panel models, control functions, and placebo tests, but these methods do not fully eliminate endogenous selection. More capable firms may develop coherent innovation systems and perform better for reasons that remain unobserved. Stronger identification might come from disclosure-rule changes, patent-policy shifts, exchange listing reforms, unexpected withdrawal of ecosystem subsidies, or shocks to alliance availability. Such designs would allow more credible causal inference.

Despite these limits, the paper offers a useful framework for studying innovation and entrepreneurship in East Asia [41]. It moves attention from whether firms innovate to how their innovation systems fit together. The results suggest that coherent innovation architecture is associated with better scaling outcomes, but the strength of the association depends on competition, reputation, and search structure. This balanced interpretation avoids portraying coherence as a universal solution. It is better understood as a strategic condition that improves the readability and conversion of entrepreneurial innovation.

Conclusion

This study examined innovation coherence among public technology ventures in East Asian growth markets. The core argument was that entrepreneurial firms benefit when innovation disclosure, R&D commitment, patent output, commercialization, and collaboration form a mutually reinforcing architecture. The empirical analysis used a synthetic but plausible panel of 386 firms and 2,842 firm-year observations from 2014 to 2023. The results showed that coherence is positively associated with next-year Tobin's Q, revenue growth, and equity-financing capacity, and negatively associated with cash-flow volatility.

The findings also indicated that innovation conversion efficiency partially mediates the relationship between coherence and firm value. This means that coherent firms appear better able to translate research effort into market-facing output. However, the mediation was partial rather than complete. Coherence may also affect stakeholder interpretation, financing expectations, employee confidence, and partner willingness. These channels were not directly tested, but they are consistent with the broader logic that coherent innovation systems reduce ambiguity.

The moderation results showed that the value of coherence is conditional. The association was strongest under moderate competition and weaker when competition was very low or very high. The results also showed that excessive technological concentration reduces the gains from coherence. These findings suggest that ventures should avoid confusing coherence with narrowness. A coherent innovation system should be aligned, but it should also preserve enough search breadth to support adaptation and recombination.

The estimates are designed to be sensible and statistically moderate, not to represent actual measured effects in East Asian markets. Before submission to a journal or use in policy analysis, the design would need replication with real firm-level financial data, patent records, product-launch evidence, alliance data, and validated disclosure measures. The paper suggests that innovation and entrepreneurship research can gain analytical precision by examining the fit among innovation domains. Firms may not need the highest R&D intensity or the largest patent portfolio to create credible growth expectations. They may need a configuration in which strategic claims, resource commitments, technical outputs, market launches, and external relationships support one another [42]. In East Asian technology markets, where ventures often scale through dense ecosystems and selective capital access, that configuration may be especially relevant.

Future work can extend the framework in several ways. One path is to compare public and private ventures. Another is to examine whether coherence matters differently before and after IPOs. A third is to study how government programs, corporate venture capital, or university partnerships shape coherence. A fourth is to use project-level data to observe whether internal portfolio governance explains why some firms maintain alignment while others drift. These extensions would help clarify whether innovation coherence is mainly a signaling pattern, an operational capability, or a combination of both.

Conflict of interest

Authors state no conflict of interest.

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