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Article

From Research Inputs to Market Outcomes: An Evidence-Based Framework for Research Commercialization in an Emerging Innovation System

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Abstract: This paper develops an evidence-based framework for evaluating research commercialization in an emerging innovation system, using Uzbekistan as the empirical and institutional setting. It first uses 2024 cross-sectional data for 14 regions to diagnose the association between innovation expenditure, research capacity and innovative product output. Innovation expenditure is positively associated with innovative output, but the estimates are statistically imprecise: the coefficient is 0.587 ($p = 0.129$) in the simple log-log model and 0.481 ($p = 0.388$) in the extended model. Because $N = 14$ and major identification problems remain, these results are interpreted as diagnostic rather than causal. The paper then proposes a prospective evaluation design for a commercialization-management pilot involving at least 24 research organizations and 600 research developments, with eight pre-intervention quarters and four to eight post-intervention quarters. The design combines matching, parallel-trend assessment, Difference-in-Differences and event-study analysis, while PPML, logit/probit, Kaplan-Meier and Cox models are matched to count, binary and time-to-event outcomes. The contribution is a mechanism-to-impact logic that links management interventions to intermediate change, stage conversion, verified transactions, repeat sales, private investment and economic impact.

Keywords: Research Commercialization, Innovation Policy, Technology Transfer, Impact Evaluation, Difference-in-Differences, Emerging Innovation System, University–Industry Collaboration, Market Outcomes

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1. Introduction

Governments invest in research and innovation expecting scientific knowledge to generate technological, economic and social value. Yet the relationship between research inputs and market outcomes is neither automatic nor linear. Research expenditure may rise without a proportional increase in licensing, commercial transactions or private investment; patents may remain unused; and technically successful prototypes may fail to generate repeat demand. These distinctions matter because a commercialization system can appear successful when measured through activities while producing limited observable market outcomes.

The challenge is particularly acute in emerging innovation systems, where institutional reform, expansion of public research support, changing statistical definitions, uneven technology-transfer capability and fragmented administrative databases may

occur simultaneously. Under these conditions, aggregate input indicators can improve faster than systems for measuring commercialization outcomes. The policy-relevant question is therefore not simply whether research resources and innovation outputs are correlated, but whether a specific commercialization-management mechanism generates additional market outcomes that would not otherwise have occurred.

Innovation-systems research emphasizes the institutional and interactive character of innovation [1]–[4], while commercialization studies show that the conversion of academic knowledge into economic value depends on appropriability, complementary assets, organizational capability, incentives and university–industry relationships [5]–[11]. Triple Helix and Open Innovation perspectives further stress cross-organizational interaction and knowledge flows [12], [13]. However, readily observable measures such as patents, disclosures, project counts and expenditure often capture only parts of the process and do not establish additional market impact.

This paper separates diagnosis from causal evaluation. It has four objectives: to establish what can and cannot be inferred from 2024 regional evidence for Uzbekistan; to specify a mechanism-to-impact evaluation chain; to propose a prospective pilot design capable of more credible impact identification; and to match empirical methods to the statistical nature of commercialization outcomes. The framework is summarized as:

management mechanism → intermediate change → stage conversion → commercial outcome → economic impact

The paper therefore contributes conceptually by framing commercialization as a conversion process, methodologically by separating descriptive association from causal inference, and managerially by linking empirical evidence to decisions on scaling, redesign and further observation.

Schumpeter treated innovation as a mechanism of economic transformation [1], while Arrow explained why uncertainty, appropriability problems and information asymmetry can justify public support for knowledge creation [2]. National innovation systems approaches subsequently emphasized that performance depends on relationships among firms, universities, research organizations, finance and public authorities [3], [4]. These perspectives imply that scientific capacity is necessary but insufficient: institutional conversion mechanisms determine whether knowledge becomes economically actionable.

Teece showed that innovators may fail to capture returns from valuable technology when complementary manufacturing, marketing or distribution assets are missing [5]. Jensen and Thursby found that many university inventions are licensed before they become fully developed commercial products and therefore require further development [6]. Thursby and Kemp documented variation in university licensing efficiency [7], while Siegel, Waldman and Link linked technology-transfer performance to organizational practices [8]. Lach and Schankerman highlighted incentive effects on university inventors [9], and Perkmann et al. distinguished commercialization from broader university–industry engagement [10]. Baglieri, Baldi and Tucci further showed that technology-transfer office models are context dependent [11].

Measurement and evaluation gap

The measurement problem arises because intermediate outcomes are observable before final commercial impact is known: a patent precedes licensing, a prototype precedes a transaction, and a first sale precedes evidence of repeat demand. Treating an intermediate indicator as the final outcome can therefore produce premature claims of success. OECD guidance on public-research commercialization and the Oslo Manual emphasize channel diversity and conceptual consistency [14], [15]. European work on knowledge-transfer metrics stresses harmonized indicators [16], while ISO 56008:2024 links innovation measurement to managerial decision making [17].

The remaining gap is the weak connection between commercialization-management mechanisms and impact-evaluation design, especially in systems with fragmented administrative data. A post-reform increase in transactions can reflect treatment effects, pre-existing trends, macroeconomic changes or altered reporting rules. Only the first is a causal program effect. The framework developed here therefore connects management mechanisms to testable intermediate outcomes and then to longitudinal counterfactual evaluation.

Conceptual Framework

The evaluation architecture distinguishes five levels of observation: M = management mechanism; I = intermediate institutional or behavioral change; C = stage conversion; O = commercial outcome; and IMP = economic or social impact. A mechanism should first alter an outcome it can plausibly influence. For example, standardized disclosure may reduce decision time, market validation may increase engagement with independent business partners, and proof-of-concept support may increase progression to pilot validation. Higher-level market outcomes are expected only after these intermediate changes.

Table 1. Mechanism-to-impact evaluation logic

Evaluation level	Illustrative question	Possible indicator
Mechanism	Was the intervention implemented?	Participation; service delivery
Intermediate change	Did institutional behavior change?	Decision time; validated demand
Stage conversion	Did more developments progress?	Conversion probability
Commercial outcome	Did market transactions occur?	Deals; first sales; repeat sales
Impact	Did measurable economic value increase?	Private investment; exports; jobs; value added

The central implication is that higher activity volume alone does not constitute commercialization success. A management mechanism should ultimately be judged by whether it increases the probability, speed or economic value of verified market outcomes relative to a credible counterfactual.

2. Materials and Methods

Diagnostic regional data and specifications

The first empirical component uses cross-sectional data for Uzbekistan's 14 regions for 2024. The outcome is innovative product volume; the principal explanatory variable is innovation expenditure. The extended specification also includes R&D personnel and R&D expenditure. Because the sample contains only 14 observations, the regressions are used solely to diagnose direction and rough magnitude, not to estimate causal policy effects.

$$\ln(Y_i) = \alpha + \beta_1 \ln(\text{INNOVEXP}_i) + \varepsilon_i$$

$$\ln(Y_i) = \alpha + \beta_1 \ln(\text{INNOVEXP}_i) + \beta_2 \ln(\text{RDSTAFF}_i) + \beta_3 \ln(\text{RDEXP}_i) + \varepsilon_i$$

A causal interpretation is precluded by reverse causality, omitted variables, the absence of longitudinal fixed effects, low statistical power and the fact that regional aggregates do not identify which research development received which commercialization

intervention. The diagnostic model can reveal patterns worth investigating, but it cannot establish the additional effect of a management mechanism.

Prospective impact-evaluation design

A more credible evaluation requires longitudinal data at the level where the mechanism is implemented. The proposed pilot therefore uses research organizations and individual developments as units of observation. It should include at least 24 organizations, with 12 treatment and 12 comparison organizations, at least 600 research developments, eight pre-intervention quarters and four to eight post-intervention quarters. Treatment must be defined as a specific management package—such as structured disclosure, screening, market validation, decision deadlines, dedicated commercialization support, milestone-linked support and standardized transaction reporting—rather than as generic "participation in reform."

Comparison organizations should be assessed on pre-intervention characteristics including portfolio size, research expenditure, sectoral profile, research staff and historical transaction activity. Matching can improve comparability but does not eliminate all selection bias. The central longitudinal estimator is Difference-in-Differences (DiD), with parallel pre-trends examined before post-treatment coefficients are interpreted as impact. For multiple periods or heterogeneous treatment timing, group-time average treatment effect methods such as Callaway and Sant'Anna are preferable [18].

$$Y_{it} = \alpha_i + \lambda_t + \beta(\text{Treatment}_i \times \text{Post}_t) + \varepsilon_{it}$$

An event-study extension estimates period-specific coefficients around the intervention date. Pre-treatment coefficients help diagnose anticipatory effects and non-parallel trends, while post-treatment coefficients show whether effects are immediate, delayed, increasing or temporary. This is especially relevant because commercialization outcomes may require several quarters to materialize.

3. Results

Across the 14 regions, the Pearson correlation between innovation expenditure and innovative product volume is 0.540, indicating a moderate positive association. The regression estimates are also positive but statistically imprecise.

Table 2. Diagnostic regional regression results

Variable	Model 1	Model 2
ln(Innovation expenditure)	0.587 (p = 0.129)	0.481 (p = 0.388)
ln(R&D personnel)	—	0.274 (p = 0.834)
ln(R&D expenditure)	—	0.103 (p = 0.928)
Observations	14	14
R^2	0.292	0.311
Adjusted R^2	0.233	0.105

In Model 1, the coefficient of 0.587 suggests that a 1% increase in innovation expenditure is associated with approximately 0.587% higher innovative output in the log-log specification, but the estimate is not statistically distinguishable from zero at conventional significance levels. In Model 2, the innovation-expenditure coefficient declines to 0.481 and its p-value rises to 0.388; the R&D personnel and R&D expenditure coefficients are also highly imprecise. The adjusted R^2 falls from 0.233 to 0.105. These results therefore do not support a claim that higher innovation expenditure causes higher innovative output. Their main value is diagnostic: the available cross-section is insufficient for evaluating commercialization-policy effectiveness, and the data structure should be improved rather than the narrative strengthened around weak coefficients.

Matching Methods to Commercialization Outcomes

Model choice should follow the statistical structure of the outcome rather than a preference for a particular estimator. Commercialization produces counts, binary events and time-to-event outcomes, each of which requires different treatment.

Transaction Counts and Binary Outcomes

Commercial transactions are non-negative counts and many organizations may record zero transactions in a quarter. Poisson pseudo-maximum likelihood (PPML) is therefore preferable to simply logging the dependent variable because it retains zero observations and can be used under quasi-maximum-likelihood interpretation. Relevant count outcomes include licenses, commercial contracts, independent buyers and investment transactions. Binary milestones—such as whether a verified deal or first sale occurs—can be modeled using logit or probit specifications, although nonlinear models should complement rather than automatically replace transparent panel-based policy-effect estimates.

Time to first and repeat sale

Whether commercialization occurs is only part of the management question; time also matters. Two developments may both reach first sale, yet one may require 9 months and another 42 months. Kaplan–Meier curves can initially describe differences in time-to-event distributions, treating projects without a sale by the end of observation as right-censored rather than permanent failures. Once sufficient events accumulate, the Cox proportional-hazards model can examine whether treated developments reach first transactions, first sales or repeat sales more rapidly while controlling for observed characteristics [19].

$$h(t|X) = h_0(t) \exp(X\beta)$$

Repeat sales are analytically distinct from first sales. A first payment confirms that at least one buyer was willing to pay; a repeat purchase provides stronger evidence that the value proposition is not purely one-off. Time to repeat sale should therefore be recorded and analyzed separately when follow-up becomes sufficient.

Outcome Architecture and Data Quality

Table 3. Outcome hierarchy for impact evaluation

Level	Outcome family	Examples
1	Process	Decision time; disclosure completeness
2	Conversion	Progression to validation, pilot or transaction
3	Market	Deal; first sale; repeat sale
4	Economic impact	Private investment; exports; employment; fiscal effect

This hierarchy helps identify where an intervention succeeds or fails. If decision time falls but transactions do not increase, administrative efficiency may have improved without addressing the binding market constraint. If first sales increase but repeat sales do not, the mechanism may improve initial market access without creating sustained demand. Accordingly, no single KPI should carry more interpretation than its position in the results chain supports.

Data quality is an identification condition rather than a secondary administrative issue. A credible panel requires stable development and organization identifiers, support histories, transaction identifiers, time stamps, payment verification and correction histories. If the same technology is recorded as multiple independent developments, stage-conversion estimates become biased; if transaction definitions change between pre- and post-treatment periods, apparent treatment effects may reflect measurement

discontinuities. Econometric sophistication cannot repair an unidentified observation, so data validation must precede causal estimation.

4. Discussion

The regional evidence illustrates why input expansion should not be confused with commercialization effectiveness. Innovation expenditure and innovative output move positively together across regions, but the cross-section cannot distinguish whether expenditure raises output or whether stronger industrial ecosystems both spend more and produce more. The scientifically defensible response is to obtain data capable of separating these explanations rather than selecting the preferred narrative.

For emerging innovation systems, this creates a practical tension. Institutional reforms often need to proceed before long-run impact evidence is available, but scaling every new mechanism before evaluation is equally risky. An adaptive implementation sequence offers a middle path: establish a credible baseline, pilot the mechanism, evaluate process and market outcomes, recalibrate, and expand only where evidence supports expansion. This approach treats uncertainty as part of management rather than as a reason either for inaction or for unconditional scaling.

Traditional technology-transfer metrics—disclosures, patents, licenses and licensing income—remain useful [6]–[10]. The proposed framework does not reject them; it places them within a broader hierarchy. An invention disclosure is an upstream process event, a patent is a legal asset, a license is a transaction, a payment is a verified commercial event, and a repeat payment is stronger evidence of market persistence. This separation limits overinterpretation and helps align management responses with the actual stage of commercialization.

The results also highlight the importance of negative and null evidence. A positive but statistically uncertain coefficient is not hidden proof of effectiveness, and an uncertain pilot estimate does not automatically prove failure. Appropriate responses may include longer observation, larger samples, better measurement, refined treatment definitions or redesign. This distinction is important in research commercialization because gestation periods vary substantially across scientific fields.

Several policy implications follow. National targets should separate inputs and activities from verified outcomes; new instruments should have an evaluation design before implementation; pre-intervention data should be preserved; comparison organizations should be maintained where feasible; operational definitions of transactions and sales should be standardized; data quality should function as a gate condition; and scaling should depend on additional impact rather than gross reported outcomes. Evaluation findings are useful only when they feed back into mechanism design.

5. Conclusion

The central challenge in research-commercialization policy is not merely to increase research inputs but to determine whether management mechanisms convert those inputs into additional verified market outcomes. Uzbekistan's 2024 regional evidence shows a moderate positive correlation of 0.540 between innovation expenditure and innovative product output, with positive but statistically imprecise regression coefficients. With N = 14, these relationships cannot support causal claims.

The appropriate next step is stronger research design. This paper proposes a prospective pilot involving at least 24 organizations and 600 research developments, eight pre-intervention quarters and four to eight post-intervention quarters. The design combines comparison-group construction, parallel-trend assessment, DiD and event-study methods, while PPML, logit/probit, Kaplan–Meier and Cox approaches address count, binary and time-to-event outcomes. The broader transition is from input-based

accounting toward a mechanism → measurable change → conversion → verified market outcome → impact logic. For emerging innovation systems, this creates a basis for three defensible decisions: scale when credible additional effects are supported, adjust when evidence remains uncertain, and refrain from causal claims when data quality does not permit them.

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