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Resilient outputs, disrupted inputs: Internalised intermediation and the decoupling of university spin-off pipelines during COVID-19

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Resilient outputs, disrupted inputs: Internalised intermediation and the decoupling of university spin-off pipelines during COVID-19

Abstract

Entrepreneurial ecosystem research usually judges resilience by whether venture outputs continue. This paper argues that in staged knowledge-commercialisation systems such judgements can mislead, because inputs, outputs and the intermediaries that connect them can respond differently to the same shock. Using a validated panel of 93 UK universities' invention disclosures, spin-out formation and pre-pandemic commercialisation arrangements (2014/15–2024/25), linked to a register of 2,560 university spin-outs, I examine how university spin-off pipelines responded to COVID-19. Because restriction intensity barely differed across the four UK nations, identification relies on comparisons across pipeline stages within each university and year, and on differences in how universities organised commercialisation before the pandemic. Invention disclosures fell by about 19% at the trough, yet spin-out formation did not decline: spin-outs relative to disclosures rose by about 40% during the shock years, partly continuing a pre-pandemic upward trend. Universities that lost more disclosures formed fewer spin-outs over the following years. Contrary to the view that partner-based, relationally embedded intermediation confers adaptability, conversion rose less where spin-off support was delivered with external partners and more where it was provided in-house, while pre-pandemic ties with industry buffered neither disclosures nor spin-outs. I conceptualise these patterns as stage-specific resilience and propose that under correlated shocks, internalised conversion capacity matters more than access to partners. The findings caution against output-based resilience metrics and inform how universities and policymakers configure technology transfer for future disruptions.

Keywords: Academic spin-offs; Technology transfer offices; Entrepreneurial ecosystems; Resilience; Knowledge commercialisation; COVID-19

JEL classification: I23; L26; M13; O32; O33; O38

1 Introduction

In the 2020/21 academic year, UK universities recorded fewer invention disclosures than in any other year between 2014/15 and 2024/25. In the same year they incorporated more spin-

out companies built on university intellectual property (IP) than in any other year in that period. The inputs to university commercialisation were contracting while one of its most visible outputs was expanding. Anyone judging the health of an entrepreneurial ecosystem by its outputs, such as new ventures formed or capital raised, would read the second fact as evidence of resilience. The first fact points the other way. This paper examines what happened inside the pipeline that links the two, and what that implies for how ecosystem resilience is theorised and measured.

Entrepreneurial ecosystem research has become much more precise about what ecosystems consist of and how their elements produce outputs. Stam and Van de Ven (2021) model productive entrepreneurship as the output of interdependent institutional arrangements and resource endowments, and Wurth et al. (2023) organise the empirical evidence around the mechanisms that link those elements to outputs and wider outcomes. Resilience research builds on this foundation by asking how outputs resist and recover from shocks (Martin & Sunley, 2015; Roundy et al., 2017). Both literatures treat outputs, implicitly, as a contemporaneous reading of the system's condition. That is reasonable where venture formation responds quickly to current conditions. It is less reasonable for the part of an ecosystem that converts scientific knowledge into ventures. There, opportunities pass through a sequence of stages, from disclosure through protection and licensing or equity agreements to incorporation and financing. Different actors perform each stage, and time separates them (Vohora et al., 2004). In such a staged system, outputs at any moment partly reflect inputs that entered years earlier. A shock that disrupts the entry of new inventions need not reduce outputs straight away, and a shock to the actors who convert inventions need not affect inflow. Resilience may therefore be stage-specific, and output-based assessments may mistake the drawdown of accumulated work-in-progress for robustness.

University spin-offs make this argument testable. Each stage of their formation is performed by an identifiable class of actors: academic inventors disclose, technology transfer offices (TTOs) assess, protect and negotiate, and founders and investors incorporate and finance. In the UK, every stage is reported annually through a statutory return. Universities also differ in how they organise the intermediary function. Some run commercialisation through an internal department and others through an exploitation company. Many deliver spin-off support, such as incubation, seed funding, access to venture capital and business advice, jointly with external partners (Fini et al., 2011; Good et al., 2020; Hayter et al., 2018). A long-standing argument in ecosystem and technology transfer research holds that support distributed across

partners, and embedded in dense relationships with industry, provides the redundancy and access needed to adapt (Spigel, 2017; Hayter, 2016). The COVID-19 pandemic tested that argument under unusual conditions, because it hit inventors, intermediaries, partners and investors at the same time.

The study asks: *How did the stages of university spin-off pipelines respond to the COVID-19 shock, and which pre-existing intermediary and relational configurations sustained the conversion of research into ventures?* I assemble a validated panel of 93 UK universities observed annually from 2014/15 to 2024/25. It combines the Higher Education Business and Community Interaction (HE-BCI) survey's records of disclosures, licences and spin-out formation with a register of 2,560 spin-outs and a pre-pandemic survey of each university's commercialisation arrangements. The shock was near-universal and restriction intensity differed little across the four UK nations, so I do not estimate "the effect of COVID-19". Identification instead rests on two comparisons. The first is across pipeline stages within each university and year, which absorbs every university-specific shock, from local restrictions to institutional finances. The second is across pre-determined differences in intermediary configuration. The hypotheses and estimation plan were fixed before any university-level model was estimated.

Three findings emerge. First, the pipeline decoupled. Disclosures fell by about 19% at their 2020/21 trough, but spin-out formation did not decline: spin-outs relative to disclosures rose by about 40% over the shock years, although part of that rise continued an upward pre-pandemic trend. Monthly incorporations in the spin-out register show no dip after the first lockdown. Second, the decoupling had limits: universities that lost more disclosures during the shock formed fewer spin-outs over the shock and post-shock years. Third, contrary to my pre-specified expectations, conversion rose *less* where spin-off support was delivered with external partners and *more* where it was provided in-house. Universities with an arm's-length exploitation company also showed a smaller rise, though less robustly. Neither stocks of protected IP nor pre-pandemic ties with industry buffered any stage of the pipeline.

The paper makes two contributions. First, it adds a temporal, stage-based dimension to the theory of entrepreneurial ecosystem resilience. I introduce *stage-specific resilience*, the observation that continuity of inflow, conversion and output are distinct properties that can diverge, and show that output continuity can coexist with inflow erosion that later propagates. This qualifies the upward-causation mechanism in Wurth et al. (2023), under which ecosystem elements generate outputs, by showing that in staged subsystems upward causation

runs through stocks and lags. It also implies that output-based resilience indicators can overstate resilience. Second, the paper identifies a boundary condition, *correlated disruption*, for the claim that distributed, partner-based and relationally embedded intermediation makes commercialisation adaptable. When a shock strikes all partners at once, internalised conversion capacity that the university can direct appears to matter more than access to partners or ties with industry. This qualifies the debate on whether university-level and local-context support for spin-offs are complements or substitutes (Fini et al., 2011), and it reverses the expectation that social capital buffers ecosystems against shocks.

The findings also matter for practice. Universities and funders that monitor only spin-out counts would have seen the pandemic years as a success while the inflow that sustains future spin-outs was falling. TTOs that rely on partners to deliver spin-off support may need contingency capacity that they control directly. These implications are timely for the UK, where policy has recently focused on the speed and terms of university spin-out formation (Tracey & Williamson, 2023).

Section 2 develops the theory and hypotheses. Section 3 describes the data, measures and identification strategy. Section 4 reports the results, and Section 5 discusses their implications, limitations and directions for future research. Section 6 concludes.

2 Theoretical background and hypotheses

2.1 Entrepreneurial ecosystems and the measurement of resilience

Stam and Van de Ven (2021) give the most explicit account of what an entrepreneurial ecosystem contains. They specify ten elements, grouped into institutional arrangements and resource endowments, among them new knowledge, intermediate services, networks and finance. These elements are interdependent and jointly produce productive entrepreneurship as the ecosystem's output. Their framework turned a metaphor into a measurable model, and its logic underlies index-based comparisons of ecosystems. For this paper, its key assumption is temporal. Elements and outputs are observed in the same period, and the quality of the ecosystem is read from the outputs it currently generates. The framework does not ask how long elements take to produce outputs, or whether outputs at a given time draw on elements that existed earlier.

Wurth et al. (2023) move the field from inventories of elements to mechanisms. Their review of 181 empirical studies organises the evidence around five causal mechanisms:

interdependence among elements; upward causation from elements to ecosystem outputs and, separately, to wider outcomes; downward causation and path dependence; and links between ecosystems. Their account sharpens what counts as explanation. It also exposes the gap this paper addresses. Upward causation is usually examined as a cross-sectional or contemporaneous association between the strength of elements and the volume of outputs. Its time structure, meaning which actor converts what into what, and over what interval, is rarely specified. Roundy and Lyons (2023) make a related point from the other direction. They ask "where are the entrepreneurs?" in ecosystem theory and call for explanations grounded in the actions of identifiable actors rather than in aggregate attributes.

Resilience research inherits these assumptions. Regional resilience is commonly decomposed into resistance to a shock, recovery from it and longer-run reorientation or renewal (Martin & Sunley, 2015). Roundy et al. (2017) argue that ecosystem resilience arises from the interplay between the diversity of participants and the coherence of their activities. Empirically, resilience is usually assessed by tracking an output such as firm births or investment before and after a shock. If outputs are a contemporaneous reading of the system, this is appropriate. If outputs are produced by a staged process that holds work-in-progress, an output that holds up during a shock may reflect conversion of the existing stock rather than robustness of the system. This paper examines that possibility directly.

2.2 The university spin-off pipeline as a staged conversion system

Research on academic entrepreneurship has long described spin-off formation as staged. Vohora et al. (2004) show that university spin-outs move through research, opportunity-framing, pre-organisation, re-orientation and sustainable-returns phases. Each transition requires passing a critical juncture: opportunity recognition, entrepreneurial commitment, a threshold of credibility and a threshold of sustainability. The phases are performed by different people. Academic inventors recognise and disclose opportunities. TTOs assess them, protect the underlying IP and negotiate licences or equity arrangements. Founders, sometimes joined by surrogate entrepreneurs, commit to a venture, and investors confer credibility by funding it. The capabilities of TTOs, including business-development skills, networks and the organisation's approach to equity, shape how many disclosed inventions become companies (Lockett & Wright, 2005; Siegel et al., 2003). So does the work of individual TTO staff (Micozzi et al., 2021).

This staged structure gives the microfoundational perspective a concrete form. Coleman's (1990) scheme explains a macro-level change through three links: macro conditions alter actors' situations, actors respond, and their actions aggregate into a new macro outcome. Felin et al. (2015) emphasise that microfoundational explanation requires specifying the actors and the aggregation, not merely invoking individuals. In a commercialisation pipeline, each observable aggregate is produced by a distinct class of actors. Disclosures aggregate inventors' decisions to report inventions, which depend on access to laboratories and on research time. Licences and spin-out incorporations aggregate the casework of TTOs and the commitments of founders. Investment aggregates investors' decisions. A shock that alters one class of actors' situation should therefore show up first at the stage those actors perform. Because stages hold work-in-progress (inventions disclosed and protected but not yet converted), outputs at any time combine conversions of current inflow with conversions of earlier inflow. I call this approach an *actor-anchored stage decomposition*. It does not observe individual cognition. Instead, it links each aggregate to the actors who produce it and to the shock's distinct effect on their situation.

COVID-19 altered these situations in different ways. For inventors, campus closures cut access to laboratories, and principal investigators in equipment-intensive fields reported the largest reductions in research time, around 30–40% below pre-pandemic levels (Myers et al., 2020). For intermediaries, much of a TTO's work on existing cases, such as assessing disclosures, drafting agreements and negotiating terms, could continue remotely. Siegel and Guerrero (2021) note that lockdowns posed both micro-level and macro-level challenges to commercialising science, but evidence on how the formation pipeline itself responded is scarce. The closest study, Audretsch et al. (2025), examines how existing UK digital university spin-offs coped with the pandemic. It finds that those able to scale while fundraising were more likely to sustain operations. How the stages that create spin-offs responded, and which intermediary arrangements sustained them, remains unexamined.

2.3 Intermediary configuration and relational capital under shocks

Universities organise the intermediary function in different ways, and the literature offers a clear expectation about which arrangements are more adaptable. Ecosystem research emphasises the relational organisation of ecosystems: the ties among entrepreneurs, investors, intermediaries and support organisations through which resources and knowledge move (Spigel, 2017; Rocha et al., 2021). Hayter et al. (2018) find that research on academic

entrepreneurship has focused on individual elements and characteristics. They call for a systemic view in which universities, TTOs, entrepreneurs, investors and support organisations jointly generate ventures. In technology transfer research, the organisational form of the TTO has been linked to licensing strategy and venture formation (Markman et al., 2005). Universities support spin-offs through different incubation models (Clarysse et al., 2005), and much of this support, including incubators, science parks, seed funding and venture capital, is delivered with or through external partners (Good et al., 2020; O'Kane et al., 2021). Fini et al. (2011) show that university-level support mechanisms and local-context mechanisms can complement or substitute for one another in producing spin-offs.

Applied to shocks, the prevailing view implies two expectations. First, arrangements that distribute conversion across actors, through an arm's-length exploitation company or support delivered with partners, provide alternative routes and access to resources outside the university. These should help sustain conversion when internal operations are disrupted. Second, relational capital, the trust and norms embedded in ties (Nahapiet & Ghoshal, 1998), should allow coordination to continue without physical co-presence. Ties with firms provide a flow of problems, collaborators and validation that feeds invention. On this view, relational capital should sustain the inflow stage in particular. The original motivation for this study rested on exactly these expectations, and I state them as hypotheses below.

2.4 Hypotheses

The stage decomposition implies that a shock which mainly disrupts inventors' situations reduces inflow, while conversion can continue by drawing on work-in-progress. The rival view, implicit in output-based resilience assessment, is that a shock reduces all stages roughly proportionally.

> **H1 (stage decoupling).** During the shock, the conversion of invention disclosures into IP-based spin-outs increases, such that spin-out formation declines less than the inflow of disclosures.

If conversion temporarily draws down accumulated work-in-progress, a loss of inflow should eventually reduce outputs.

> **H2 (propagation).** Universities that experienced larger shock-period declines in disclosures subsequently formed fewer IP-based spin-outs, with the association strongest after the shock period.

If work-in-progress buffers outputs, universities with larger stocks of protected IP should sustain spin-out formation better during the shock.

> **H3 (inventory buffering).** Universities with larger pre-shock stocks of protected IP formed more IP-based spin-outs during the shock, relative to their own pre-shock levels.

Following the distributed view of intermediation:

> **H4 (intermediary configuration).** Conversion of disclosures into IP-based spin-outs increased more during the shock where (a) commercialisation was organised through an exploitation company and (b) spin-off support was delivered with external partners.

Following the relational view, and the argument that ties with firms feed the inflow of inventions:

> **H5 (relational capital).** Pre-shock relational capital with firms is associated with smaller shock-period declines in disclosures, but not with the conversion of disclosures into spin-outs.

Fig. 1 summarises the framework.

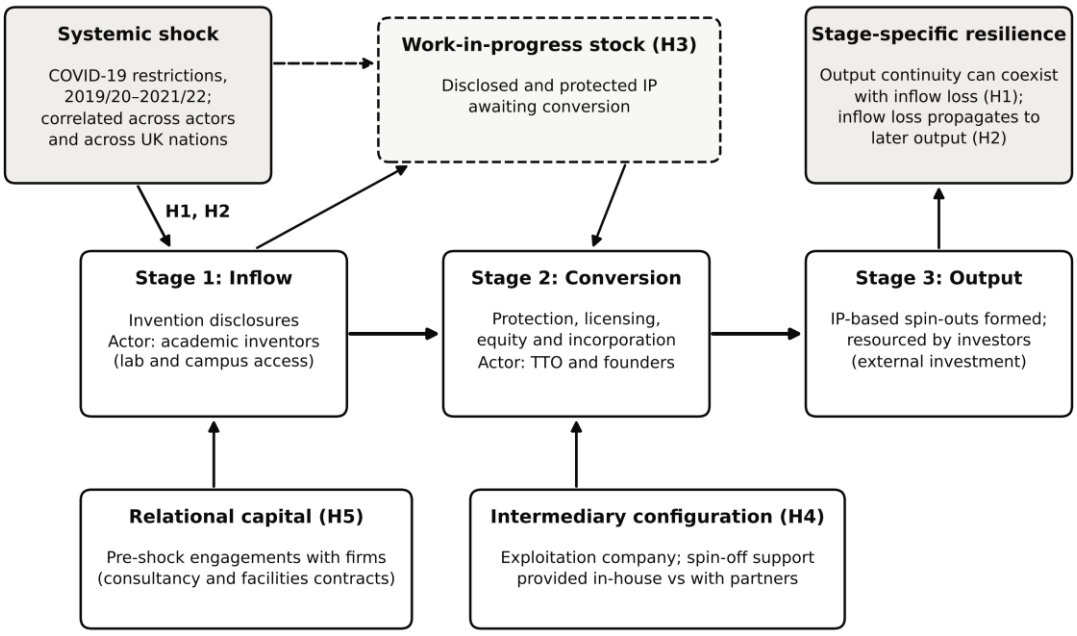


Fig. 1 Conceptual framework: a staged spin-off pipeline under a systemic shock. Each stage is performed by a distinct class of actors. Dashed elements denote work-in-progress that links inflow to later output. H1–H5 identify the relationships tested

3 Data and methods

3.1 Setting and the identification problem

The UK provides an unusually complete record of university commercialisation. UK higher education providers report their knowledge-exchange activity annually through the HE-BCI survey, administered by the Higher Education Statistics Agency (HESA). The survey covers invention disclosures, patents, licences and the formation, survival and investment of spin-outs and start-ups. HESA publishes the returns at provider level as open data under a Creative Commons Attribution licence (HESA, 2026). In 2025 HESA also published a register of individual university spin-outs, compiled from a census of spin-outs founded since 2012/13.

COVID-19 creates a difficult identification problem. Restrictions affected every university at once, and their intensity varied little within the UK. Using the Oxford COVID-19 Government Response Tracker (Hale et al., 2021), I computed mean policy stringency for each UK nation between March 2020 and March 2022. The means were 51.9 for England, 55.0 for Wales, 56.7 for Scotland and 58.4 for Northern Ireland (Online Resource 1, Table S1), and 73 of the 93 universities in the analytical sample are in England. A design that compared universities by exposure to restrictions would therefore rest on almost no exogenous variation, and it would confound ecosystem adaptation with general pandemic effects. I therefore do not estimate the total effect of the pandemic. The estimands are, first, how the pipeline's stages evolved *relative to one another* within the same university and year, and second, how that evolution differed with characteristics fixed before the pandemic. Comparisons within a university-year absorb local restrictions, institutional finances, staffing and any other shock common to a university's activities in that year.

3.2 Data and sample

I use nine HESA tables (Online Resource 1 documents each one): Table 4a (disclosures and patents), Table 4b (licences), Tables 4c and 4d (IP income), Table 4e (spin-outs and start-ups by type), Table 1 (collaborative research income), Table 2a (consultancy and facilities services by type of client), Table A (strategies, approaches and infrastructures, 2015/16–2019/20) and Table 6 (the spin-out register). The HE-BCI tables cover academic years 2014/15 to 2024/25 (April 2026 release); the register was last updated in June 2026. I retained provider-level rows only and excluded HESA's regional total rows. As a validation check, I summed provider-level values by region and year and compared them with HESA's

published totals. The sums reproduce the totals exactly in all 660 region–year–category cells for new spin-outs and start-ups and in all 132 region–year cells for disclosures.

The HE-BCI population expanded from 2019/20, when newly registered providers began reporting. To avoid confounding the shock with changes in composition, I restricted the panel to the 157 providers observed in all eleven years. The analytical sample comprises the 93 of these that recorded at least five invention disclosures between 2014/15 and 2018/19, defined here as commercialisation-active universities. This gives 1,023 university-years. Eleven of the 93 universities formed no IP-based spin-out in any year. Under Poisson estimation with university fixed effects they do not contribute to the spin-out models, so those models draw on 82 universities (902 university-years). Results for all 157 providers are reported as a robustness check.

The register contains 2,560 spin-outs linked to 99 providers, with month and year of incorporation, flags for disciplinary background and current status. Counts of register entries by provider and year correlate at 0.83 with HE-BCI spin-out counts (0.82–0.93 in each year from 2015/16 to 2023/24). Register coverage is incomplete for the most recent cohorts, which are still being added, so I use it only for incorporations up to July 2022.

One data anomaly matters for interpretation. Aggregate counts of consultancy contracts with firms fell by about 29,000 between 2018/19 and 2019/20. That change is almost entirely attributable to a single provider, whose reported contracts fell from 24,344 to 249 in one year, which is consistent with a change in how it reported them. I therefore summarise changes in industry engagement with medians across universities, and I check that results for relational capital do not depend on that provider.

3.3 Measures

Table 1 defines every construct, its measure, its source and the hypothesis it serves. Three outcomes trace the pipeline. *Inflow* is the annual number of invention disclosures. *Output* is the annual number of newly registered IP-based spin-outs, defined as spin-outs with some university ownership plus other formal spin-outs that exploit university IP. Both categories pass through the TTO's protection and transaction processes. *Conversion* is output relative to inflow, which I estimate in a stacked model (described below) rather than as a ratio, so that years with zero values are retained. Staff and student start-ups, which do not require a formal IP transaction, serve as a descriptive comparison for channels that bypass the intermediary.

The moderators were all measured before the shock. *Inflow change* (H2) is the difference between log mean disclosures in 2020/21–2021/22 and in 2016/17–2018/19. *Work-in-progress stock* (H3) is the log of the university's cumulative patent portfolio in 2018/19. *Intermediary configuration* (H4) comes from the 2018/19 Table A return. (a) *Exploitation company* indicates a wholly or majority-owned company responsible for business interactions. (b) *Partner-involved support* counts how many of seven spin-off support mechanisms the university delivered with, or through, an external partner: on-campus incubators, other local incubators, science park accommodation, entrepreneurship training, seed-corn investment, venture capital and business advice. A complementary count records mechanisms provided by the university alone. *Relational capital* (H5) is the log of the mean annual number of consultancy and facilities contracts with small and large firms in 2014/15–2018/19. Each contract is a realised working relationship with a firm. All moderators are standardised except the exploitation-company indicator. Because larger universities have more of everything, every moderator model controls for scale, measured as log mean pre-shock disclosures, interacted with each period.

Table 1 Constructs, measures and sources

Construct	Measure	Source	Role
Inflow	Number of invention disclosures in the year	HE-BCI Table 4a	Outcome (H1, H5)
Output (IP-based spin-outs)	Newly registered spin-outs with some university ownership plus other formal spin-outs exploiting university IP	HE-BCI Table 4e	Outcome (H1–H5)
Conversion	IP-based spin-outs relative to disclosures, estimated as the spin-out-stage × period interaction in a stacked two-stage model	Tables 4a, 4e	H1, H4, H5
Inflow change	log(1 + mean disclosures 2020/21–2021/22) − log(1 + mean disclosures 2016/17–2018/19)	Table 4a	H2
Work-in-progress stock	log(1 + cumulative patent portfolio), 2018/19	Table 4a	H3
Exploitation company	1 if a wholly or majority-owned exploitation company is responsible for business and community interactions, 2018/19 (Q10)	HE-BCI Table A	H4a
Partner-involved support	Number of seven spin-off support mechanisms provided with or by an external partner, 2018/19 (Q16)	Table A	H4b
In-house support	Number of the same seven mechanisms provided by the university alone, 2018/19 (Q16)	Table A	H4 (robustness)
Relational capital	log(1 + mean annual consultancy and facilities contracts with SMEs and other commercial businesses), 2014/15–2018/19	HE-BCI Table 2a	H5
Scale (control)	log(1 + mean annual disclosures), 2014/15–2018/19, interacted with each period	Table 4a	All moderator models
Pre-shock conversion (control)	log(1 + mean IP spin-outs) − log(1 + mean disclosures), 2014/15–2018/19	Tables 4a, 4e	Robustness
Firm-level incorporations	Month and year of incorporation; disciplinary background; multi-university ownership	HESA spin-out register (Table 6)	Exploratory

Construct	Measure	Source	Role
Policy stringency	Mean OxCGRT stringency index by UK nation	Hale et al. (2021)	Context

Note: HE-BCI = Higher Education Business and Community Interaction survey (HESA open data). Continuous moderators are standardised across the 93 universities. The seven Q16 mechanisms are on-campus incubators, other local incubators, science park accommodation, entrepreneurship training, seed-corn investment, venture capital and business advice.

3.4 Estimation

All outcomes are counts with many zeros and skewed distributions, so I estimate Poisson pseudo-maximum-likelihood (PPML) models with high-dimensional fixed effects. These models are consistent under heteroskedasticity and retain zero observations (Santos Silva & Tenreyro, 2006; Correia et al., 2020). Academic year 2019/20, which contains the first lockdown, is the first shock year. The shock period is 2019/20–2021/22, and the post-shock period is 2022/23–2024/25. Event-time coefficients are measured relative to 2018/19.

First, to describe each stage's path within universities, I estimate for university *i* in year *t*:

$$E[y_{it}] = \exp\left(\alpha_i + \sum_{k \neq 2018} \beta_k \, \mathbb{1}[t = k]\right). \qquad (1)$$

The coefficients β_k trace the average within-university change relative to 2018/19. Because no university escaped the shock, they are descriptive and carry no counterfactual interpretation.

Second, to test H1, I stack the two stages, disclosures ($s = D$) and IP-based spin-outs ($s = S$), for each university-year:

$$E[y_{ist}] = \exp\left(\alpha_{is} + \gamma_{it} + \sum_{k \neq 2018} \theta_k \, \mathbb{1}[t = k] \cdot S_s\right), \qquad (2)$$

where S_s indicates the spin-out stage. The university-by-year fixed effects γ_{it} absorb everything that affected a university's commercialisation in a given year, and the university-by-stage effects α_{is} absorb permanent differences in conversion. The coefficients θ_k therefore measure the change in the log ratio of spin-outs to disclosures relative to 2018/19. A pooled version replaces the event-time terms with interactions of S_s with SHOCK and POST indicators.

Third, to test H2–H5, I interact pre-determined university characteristics M_i with the period indicators:

$$E[y_{it}] = \exp\left(\alpha_i + \lambda_{n(i)t} + \delta_1 M_i \cdot \mathrm{SHOCK}_t + \delta_2 M_i \cdot \mathrm{POST}_t + \mathbf{x}_i' \boldsymbol{\phi}_t\right), \qquad (3)$$

where $\lambda_{n(i)t}$ are nation-by-year fixed effects, which absorb UK-nation differences in restrictions and policy, and $\mathbf{x}_i'\boldsymbol{\phi}_t$ are period-specific scale controls. For moderators that concern conversion (H4 and H5), I also estimate the stacked analogue of Eq. (2) with $M_i \cdot S_s \cdot \text{SHOCK}_t$ and $M_i \cdot S_s \cdot \text{POST}_t$:

$$E[y_{ist}] = \exp(\alpha_{is} + \gamma_{it} + \psi_1 M_i S_s \text{SHOCK}_t + \psi_2 M_i S_s \text{POST}_t + \mathbf{x}_i' S_s \boldsymbol{\phi}_t + \pi_1 S_s \text{SHOCK}_t + \pi_2 S_s \text{POST}_t). \quad (4)$$

In Eq. (4), ψ_1 shows whether a configuration was associated with a larger or smaller shock-period change in conversion, holding constant everything that affected the university in that year.

Standard errors are clustered by university, with 93 clusters. The hypotheses, sample definition, variable construction and model specifications were recorded before any university-level model was estimated. At that point only national aggregate series had been inspected, and the plan is archived with the replication files (Online Resource 2). All pre-specified tests are reported regardless of outcome. Analyses added afterwards are labelled exploratory. Robustness checks examine pre-trends with event-study coefficients, adjust for linear stage-specific trends, vary the shock window and the sample, control for pre-shock conversion (to address regression to the mean), and re-estimate with ordinary least squares on log-transformed outcomes (Roth et al., 2023). Estimation used Python 3 with pyfixest 0.60.

4 Results

4.1 Descriptive patterns

Table 2 reports descriptive statistics for the analytical sample. Across the 93 universities, mean annual disclosures fell from 45.6 before the shock to 36.8 during it, then recovered to 41.4. Mean IP-based spin-outs rose from 1.59 to 1.76, then returned to 1.62. In the sample's aggregate series, disclosures fell from 3,929 in 2018/19 to 3,195 in 2020/21, the lowest value in the eleven-year window. IP-based spin-outs rose from 165 to 178, the highest value. Spin-outs per 100 disclosures, which had ranged from 3.1 to 4.2 before the shock, reached 5.6 in 2020/21 and returned to 3.7 by 2024/25 (Online Resource 1, Table S3). External investment received by spin-outs with university ownership, a stock-based measure that covers all active firms, more than doubled across the sector, from £2.27 billion in 2019/20 to £5.04 billion in 2020/21. Industry engagement fell during the shock: the median university's consultancy and

facilities contracts with firms in 2020/21–2021/22 were 17% below their 2016/17–2018/19 level, and 67% of universities recorded a decline.

Table 2 Descriptive statistics, 93 commercialisation-active universities

Panel A. Outcomes by period (university-year means, SD in parentheses)

Variable	Pre-shock 2014/15–2018/19	Shock 2019/20–2021/22	Post 2022/23–2024/25	Medians (pre / shock / post)
Invention disclosures	45.59 (68.36)	36.80 (57.97)	41.43 (58.46)	19.00 / 15.00 / 16.00
IP-based spin-outs (total)	1.59 (2.87)	1.76 (3.17)	1.62 (3.25)	1.00 / 0.00 / 0.00
Spin-outs with university ownership	1.40 (2.69)	1.55 (2.78)	1.38 (2.65)	0.00 / 0.00 / 0.00
Other (formal) spin-outs	0.19 (0.65)	0.22 (0.88)	0.24 (1.07)	0.00 / 0.00 / 0.00
Staff start-ups	0.65 (1.60)	0.63 (1.79)	0.74 (2.05)	0.00 / 0.00 / 0.00
Student start-ups	31.81 (50.19)	33.99 (44.50)	34.51 (38.82)	17.00 / 19.00 / 21.00
Engagements with firms (consultancy + facilities contracts)	636 (2,236)	466 (930)	394 (683)	201 / 175 / 178
External investment received by IP spin-outs (£ thousand)	14,396 (54,433)	49,068 (183,544)	139,104 (1,695,441)	237 / 400 / 975

Panel B. University characteristics measured before the shock

Variable	Mean	SD	Min	Median	Max
Mean annual disclosures, 2014/15–2018/19	45.59	66.51	1.00	20.60	374
Mean annual IP spin-outs, 2014/15–2018/19	1.59	2.54	0.00	0.80	17.20
Mean annual engagements with firms, 2014/15–2018/19	636	2,183	8.60	195	19,956
Cumulative patent portfolio, 2018/19	237	517	0.00	76.00	3,941
Inflow change: log disclosures 2020/21–2021/22 minus 2016/17–2018/19	-0.31	0.80	-2.94	-0.18	1.73
Exploitation company (1 = yes), 2018/19	0.59	0.49	0.00	1.00	1.00
Spin-off support mechanisms with partner involvement (0–7), 2018/19	3.87	1.90	0.00	4.00	7.00
Spin-off support mechanisms provided in-house only (0–7), 2018/19	1.84	1.42	0.00	2.00	6.00
Licensing capability in-house and external (1 = yes), 2018/19	0.40	0.49	0.00	0.00	1.00

Note: 1,023 university-years (Panel A) and 93 universities (Panel B). External investment is the estimated investment received in the year by all active IP-based spin-outs; the post-shock mean and SD are dominated by one university's 2022/23 return, which HESA flags as reporting an increase of over £27 billion.

4.2 Stage decoupling (H1)

Fig. 2(a) and Table 3 trace each stage within universities. Relative to 2018/19, disclosures were 18.7% lower in 2020/21 ($p = 0.010$) and 16.0% lower in 2021/22 ($p = 0.025$), and they returned to pre-shock levels by 2023/24. IP-based spin-out formation shows no shock-period decline: the 2020/21 coefficient corresponds to +7.9% ($p = 0.56$), and no shock-year coefficient approaches significance.

The stacked model compares the two stages within the same university-year (Fig. 2(b); Table 3, columns 3–4). Over the shock period, spin-outs relative to disclosures rose by 0.335 log points ($p = 0.020$), about 40% above their pre-shock level. The increase peaked in 2020/21

and faded after the shock (POST: 0.114, $p = 0.40$). This supports H1: during the shock, spin-out formation declined less than inflow, so conversion rose.

Two qualifications matter. First, conversion was already rising before the pandemic: the pre-shock event-time coefficients climb steadily towards 2018/19. Allowing for a linear stage-specific trend of about 4% a year reduces the shock-period estimate to 0.168 ($p = 0.33$). Compared only with 2017/18–2018/19, the estimate is 0.286 ($p = 0.065$). The data therefore establish that spin-out formation was sustained while inflow fell, but they cannot separate a shock-specific acceleration of conversion from continuation of its earlier trend. Second, the result does not depend on a few large producers or on how the shock is defined (Table 6). It holds for spin-outs with university ownership alone (0.352, $p = 0.023$), when the four largest pre-shock spin-out producers are excluded (0.484, $p < 0.001$), in England alone (0.374, $p = 0.029$), in the full balanced population of 157 providers (0.333, $p = 0.021$), when the shock is restricted to the two full pandemic years (0.414, $p = 0.006$), and under ordinary least squares on log outcomes (0.264, $p = 0.001$).

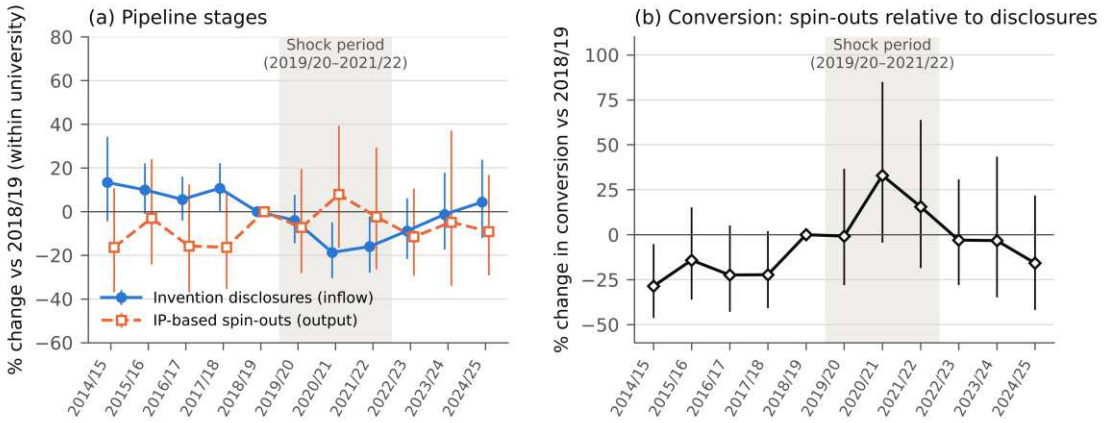


Fig. 2 Pipeline stages within universities, 2014/15–2024/25. (a) Percentage change in invention disclosures and IP-based spin-outs relative to 2018/19, from PPML with university fixed effects (Eq. 1). (b) Percentage change in spin-outs relative to disclosures, from the stacked model with university-by-year and university-by-stage fixed effects (Eq. 2). Bars show 95% confidence intervals with standard errors clustered by university (93 universities)

Table 3 Pipeline stages and conversion within universities (H1)

	(1) Disclosures	(2) IP-based spin-outs	(3) Conversion: spin-outs relative to disclosures
2014/15	0.125 (0.087)	-0.179 (0.144)	-0.337** (0.145)
2015/16	0.095* (0.053)	-0.031 (0.126)	-0.153 (0.150)
2016/17	0.054 (0.049)	-0.171 (0.148)	-0.254 (0.156)
2017/18	0.102** (0.051)	-0.179 (0.131)	-0.252* (0.139)
2018/19 (reference)	0	0	0
2019/20	-0.041 (0.059)	-0.076 (0.130)	-0.008 (0.163)

	(1) Disclosures	(2) IP-based spin-outs	(3) Conversion: spin-outs relative to disclosures
2020/21	-0.207*** (0.080)	0.076 (0.131)	0.285* (0.168)
2021/22	-0.175** (0.078)	-0.025 (0.144)	0.145 (0.178)
2022/23	-0.093 (0.078)	-0.122 (0.114)	-0.030 (0.152)
2023/24	-0.013 (0.090)	-0.050 (0.187)	-0.033 (0.201)
2024/25	0.043 (0.087)	-0.095 (0.128)	-0.172 (0.189)
Pooled: spin-out stage × shock period			0.335** (0.145)
Pooled: spin-out stage × post period			0.114 (0.136)
Fixed effects	University	University	University × stage; university × year
Observations	1,023	902	1,840
Universities	93	82	93

Note: PPML estimates; standard errors clustered by university in parentheses. Columns (1)–(2): year coefficients relative to 2018/19 (Eq. 1). Column (3): spin-out-stage × year coefficients from the stacked model (Eq. 2); the pooled rows replace the year interactions with shock-period (2019/20–2021/22) and post-period (2022/23–2024/25) interactions. Eleven universities never formed an IP-based spin-out and drop out of column (2). *** p < 0.01, ** p < 0.05, * p < 0.10.

The firm-level register corroborates this pattern at monthly resolution (Fig. 3). Between April 2017 and February 2020, 14.4 spin-outs were incorporated per month on average. Between April 2020 and March 2022 the average was 14.6. Incorporations in the months immediately after the first lockdown were at or above their usual level: 19 in March, 14 in April, 17 in May and 11 in June 2020, against a 2017–2019 average of 14.0 for the same months. Firms continued to be formed in the months when campuses were closed.

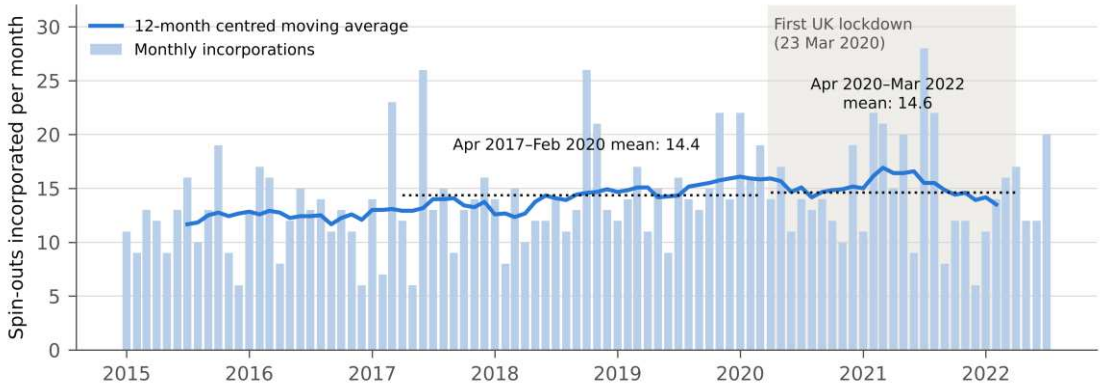


Fig. 3 Monthly incorporations of UK university spin-outs, January 2015–July 2022. Source: HESA spin-out register (Table 6), unique companies. Shading marks the period from the first UK lockdown (23 March 2020) to March 2022. Later months are omitted because the register is incomplete for recent cohorts

4.3 Propagation (H2)

Table 4 (column 1) relates spin-out formation to each university's shock-period loss of disclosures. Universities whose inflow held up better formed relatively more spin-outs after the shock. A one-standard-deviation smaller decline in disclosures (0.81 log points) is

associated with 36% more spin-outs in the post-shock period (0.307, $p = 0.044$), with nation-by-year effects, scale and the pre-shock trend in disclosures held constant. Equivalently, a one-standard-deviation larger loss is associated with about 26% fewer spin-outs. The shock-period association is similar in size but less precise (0.255, $p = 0.13$), and the difference between the two is small and not significant (0.052, $z = 0.50$). Excluding the four largest producers sharpens both estimates (shock period 0.274, $p = 0.032$; post period 0.349, $p = 0.021$). H2 is therefore partly supported. Inflow losses propagated to spin-out formation, but the data do not show that the association was concentrated after the shock period. Event-time estimates, reported in Online Resource 1, also show some movement in the pre-shock coefficients, which counsels caution in reading the association causally.

Table 4 Propagation, inventory, configuration and relational capital: spin-out formation and inflow (H2–H5)

	(1)	(2)	(3)	(4)	(5)	(6)
Hypothesis	H2	H3	H4a	H4b	H5	H5
Dependent variable	IP spin-outs	IP spin-outs	IP spin-outs	IP spin-outs	IP spin-outs	Disclosures
Moderator	Inflow change (z)	Patent stock (z)	Exploitation company	Partner-involved support (z)	Relational capital (z)	Relational capital (z)
Moderator × shock period	0.255 (0.166)	-0.054 (0.154)	-0.345 (0.235)	-0.094 (0.105)	0.095 (0.142)	0.039 (0.109)
Moderator × post period	0.307** (0.152)	0.127 (0.168)	-0.348 (0.264)	0.075 (0.107)	0.227 (0.148)	0.021 (0.129)
Scale × shock period	0.208 (0.146)	0.229 (0.179)	0.237 (0.159)	0.217 (0.154)	0.143 (0.156)	-0.098 (0.092)
Scale × post period	0.313** (0.139)	0.184 (0.161)	0.340** (0.140)	0.258* (0.138)	0.190 (0.141)	-0.207** (0.083)
Pre-shock disclosure trend × shock	-0.023 (0.196)					
Pre-shock disclosure trend × post	-0.016 (0.172)					
Fixed effects	Univ.; nation × year	Univ.; nation × year	Univ.; nation × year	Univ.; nation × year	Univ.; nation × year	Univ.; nation × year
Observations	902	902	902	902	902	1,023

Note: PPML estimates with university and nation-by-year fixed effects; standard errors clustered by university (93 clusters) in parentheses. Moderators are measured before the shock and standardised (z) except the exploitation-company indicator. Main effects of time-invariant moderators are absorbed by university fixed effects. *** p < 0.01, ** p < 0.05, * p < 0.10.

4.4 Inventory buffering (H3)

The stock of protected IP did not predict shock-period spin-out formation once scale was controlled (Table 4, column 2: −0.054, $p = 0.73$). H3 is not supported. Whatever sustained conversion during the shock, it was not simply the size of the patent portfolio.

4.5 Intermediary configuration (H4)

Table 4 (columns 3–4) and Table 5 report the configuration models. Neither configuration was associated with greater conversion during the shock, so H4 is not supported. Both estimates point the other way, with different degrees of robustness.

Universities with an exploitation company show a lower shock-period change in spin-out formation (−0.345, $p = 0.14$) and a smaller shock-period rise in conversion (Table 5, column 1: −0.653, $p = 0.010$). Part of this gap reflects regression to the mean among universities that were already converting at high rates. Controlling for pre-shock conversion reduces the estimate to −0.377 ($p = 0.084$; column 5), and excluding the four largest producers gives −0.343 ($p = 0.092$). Event-time estimates show no pre-shock difference (coefficients between −0.28 and −0.03, all $p > 0.35$) and a divergence from 2019/20 (−1.24, $p < 0.001$) that persists into the post-shock years (Online Resource 1). H4a is not supported. The evidence points in the opposite direction, though it is less robust than for partner support.

The estimates for partner-involved support are robust. A one-standard-deviation increase in the number of support mechanisms delivered with external partners (1.9 mechanisms) is associated with a 0.307 smaller shock-period rise in conversion (Table 5, column 2; $p = 0.035$). This means that conversion rose about 26% less in universities with more partner-involved support. The estimate holds when pre-shock conversion is controlled (−0.257, $p = 0.003$), when exploitation-company status is included jointly (−0.288, $p = 0.048$), and when the four largest producers are excluded (−0.371, $p < 0.001$). The mirror-image measure gives the same answer: a one-standard-deviation increase in the number of mechanisms provided by the university alone is associated with a 0.313 larger rise in conversion ($p = 0.003$; column 7). The event-time estimates in Fig. 4 show why the result is credible. Pre-shock coefficients are close to zero (between −0.05 and +0.02). The divergence opens in 2019/20 (−0.38, $p = 0.042$), persists through 2020/21 (−0.32, $p = 0.072$), and largely closes by 2022/23 (+0.08). It is not significant thereafter (2024/25: −0.33, $p = 0.110$). Disaggregating the seven mechanisms into finance, space and advice does not isolate any single type (Online Resource 1). The association reflects the overall extent to which spin-off support relied on partners. H4b is rejected in a specific way: conversion was sustained more where support was internalised, not where it was distributed.

Table 5 Intermediary configuration, relational capital and conversion: stacked two-stage models (H4–H5)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Exploitation company × spin-out stage × shock	-0.653*** (0.252)		-0.621** (0.249)		-0.377* (0.218)		
Exploitation company × spin-out stage × post	-0.514* (0.295)		-0.498* (0.287)		-0.223 (0.250)		
Partner-involved support (z) × spin-out stage × shock		-0.307** (0.145)	-0.288** (0.146)			-0.257*** (0.086)	
Partner-involved support (z) × spin-out stage × post		-0.148 (0.125)	-0.145 (0.127)			-0.096 (0.094)	
In-house support (z) × spin-out stage × shock							0.313*** (0.103)
In-house support (z) × spin-out stage × post							0.160 (0.104)
Relational capital (z) × spin-out stage × shock				-0.102 (0.192)			
Relational capital (z) × spin-out stage × post				0.066 (0.229)			
Pre-shock conversion (z) × spin-out stage × shock					-1.113*** (0.155)	-1.150*** (0.162)	
Pre-shock conversion (z) × spin-out stage × post					-1.231*** (0.157)	-1.258*** (0.139)	
Scale (z) × spin-out stage × shock	0.370** (0.172)	0.317** (0.155)	0.442*** (0.160)	0.272 (0.187)	-0.349*** (0.132)	-0.381*** (0.119)	0.263* (0.150)
Scale (z) × spin-out stage × post	0.548*** (0.153)	0.480*** (0.132)	0.583*** (0.134)	0.419** (0.172)	-0.240 (0.148)	-0.274** (0.109)	0.452*** (0.134)
Hypothesis	H4a	H4b	H4	H5	H4a	H4b	H4
Fixed effects	Univ. × stage; univ. × year	Univ. × stage; univ. × year	Univ. × stage; univ. × year	Univ. × stage; univ. × year	Univ. × stage; univ. × year	Univ. × stage; univ. × year	Univ. × stage; univ. × year
Observations	1,840	1,840	1,840	1,840	1,840	1,840	1,840

Note: PPML estimates of the stacked model in Eq. (4), with disclosures and IP-based spin-outs as stages; university-by-stage and university-by-year fixed effects; spin-out stage × period main effects included. Coefficients measure the association between the moderator and the change in spin-outs relative to disclosures. Standard errors clustered by university (93 clusters) in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

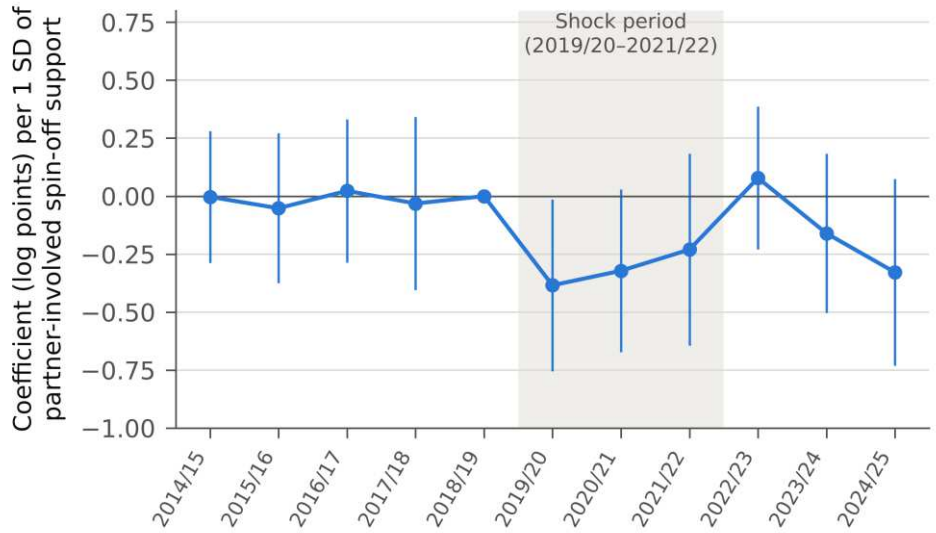


Fig. 4 Partner-involved spin-off support and conversion, event-time estimates. Coefficients on the interaction of standardised partner-involved support (2018/19) with the spin-out stage and year, from the stacked model with university-by-year and university-by-stage fixed effects, spin-out-stage-by-year effects and scale-by-year controls; reference year 2018/19. Bars show 95% confidence intervals clustered by university

4.6 Relational capital (H5)

Pre-shock relational capital with firms did not buffer either stage (Table 4, columns 5–6; Table 5, column 4). Its association with shock-period disclosures is small and imprecise (0.039, $p = 0.72$), as is its association with spin-out formation (0.095, $p = 0.51$) and with conversion (−0.102, $p = 0.59$). The null result holds when relational capital is measured as a percentile rank (0.147, $p = 0.19$), as contracts relative to the scale of inflow (0.036, $p = 0.72$), and when the provider with the reporting anomaly is excluded (0.083, $p = 0.57$). H5 is not supported. Universities with denser pre-pandemic engagement with firms did not maintain their invention inflow any better than others.

4.7 Additional analyses (exploratory)

Three further analyses help interpret the main results. They were not pre-specified. First, laboratory dependence did not reshape the composition of spin-outs. In the register, spin-outs with a background in medicine, health and life sciences had been rising relative to those from the physical sciences, engineering and mathematics before 2018/19. Relative to 2018/19, however, the shock-period coefficients are between −0.10 and +0.01, and none is significant ($p > 0.6$). Second, channels that bypass the intermediary moved differently. Student start-ups rose modestly (+14.5% in 2020/21, $p = 0.069$), while staff start-ups dipped in 2021/22, though their pre-shock coefficients were similarly variable. Third, spin-outs co-owned by

more than one university made up 4.9% of shock-period cohorts against 3.5% of pre-shock cohorts, a difference that is not statistically significant (Fisher's exact $p = 0.21$).

Table 6 Robustness of the main estimates

Specification	Estimate	(SE)	p	N
H1: spin-out stage × shock period (stacked)				
Baseline (Table 3)	0.335**	(0.145)	0.020	1,840
Linear stage-specific trend added	0.168	(0.171)	0.327	1,840
Baseline years 2017/18–2018/19 only	0.286*	(0.155)	0.065	1,302
Shock = 2020/21–2021/22 (2019/20 dropped)	0.414***	(0.150)	0.006	1,666
Spin-outs with university ownership only	0.352**	(0.155)	0.023	1,836
Excluding four largest spin-out producers	0.484***	(0.136)	< 0.001	1,752
England only	0.374**	(0.171)	0.029	1,428
All 157 balanced providers	0.333**	(0.144)	0.021	1,931
OLS on log(1 + y)	0.264***	(0.079)	0.001	
H2: inflow change × post period (IP spin-outs)				
Difference: post minus shock coefficient	0.052	(0.105)	0.619	
Excluding four largest producers	0.349**	(0.152)	0.021	852
OLS on log(1 + y)	0.079*	(0.046)	0.086	
H4b: partner-involved support × spin-out stage × shock				
With pre-shock conversion control	-0.257***	(0.086)	0.003	1,840
Joint with exploitation company	-0.288**	(0.146)	0.048	1,840
Excluding four largest producers	-0.371***	(0.111)	< 0.001	1,752
H4a: exploitation company × spin-out stage × shock				
With pre-shock conversion control	-0.377*	(0.218)	0.084	1,840
H5: relational capital × shock period (disclosures)				
Percentile-rank measure	0.147	(0.112)	0.188	1,023
Contracts relative to inflow scale	0.036	(0.100)	0.717	1,023
Excluding provider with reporting anomaly	0.083	(0.145)	0.566	1,001

Note: PPML unless stated; standard errors clustered by university. The four largest pre-shock spin-out producers are excluded jointly. *** p < 0.01, ** p < 0.05, * p < 0.10.

Table 7 Summary of hypotheses and evidence

Hypothesis	Prediction	Evidence	Assessment
H1 Stage decoupling	Conversion rises; spin-outs decline less than disclosures	Disclosures −18.7% (2020/21); spin-outs unchanged; conversion +0.335 (p = 0.020); trend-adjusted +0.168 (p = 0.33)	Supported (output sustained while inflow fell); acceleration beyond pre-trend not established
H2 Propagation	Larger inflow loss → fewer later spin-outs, strongest after the shock	Post +0.307 (p = 0.044); shock +0.255 (p = 0.13); difference not significant	Partly supported
H3 Inventory buffering	Larger patent stock → more shock-period spin-outs	−0.054 (p = 0.73)	Not supported
H4a Exploitation company	Greater conversion during shock	−0.653 (p = 0.010); −0.377 (p = 0.084) controlling for pre-shock conversion	Not supported: estimates in the opposite direction, less robust
H4b Partner-involved support	Greater conversion during shock	−0.307 (p = 0.035); robust to all checks; in-house support +0.313 (p = 0.003)	Rejected: opposite direction
H5 Relational capital	Buffers disclosures, not conversion	Disclosures +0.039 (p = 0.72); spin-outs +0.095 (p = 0.51)	Not supported

5 Discussion

5.1 Stage-specific resilience

The first contribution concerns how ecosystem resilience is conceived and measured. Judged by spin-out formation, the most common output indicator for university commercialisation, the UK system was highly resilient to COVID-19: formation did not fall, and in 2020/21 it reached its highest level in the period. Judged by its inflow, the same system lost close to a fifth of its invention disclosures. The two readings are reconciled by recognising that a staged pipeline holds work-in-progress. Its outputs are produced by actors, chiefly TTO staff and founders, whose situations the shock altered differently from those of the inventors who supply the inflow. The decoupling was not permanent: universities that lost more inflow formed fewer spin-outs over the following years.

This extends the mechanism-based account of ecosystems in a specific way. Wurth et al. (2023) treat upward causation, from elements to outputs, as a central ecosystem mechanism. The present evidence shows that in the knowledge-conversion subsystem, upward causation operates through a stock with time-consuming stages. The temporal structure of that mechanism determines what an output reveals at any moment. Stam and Van de Ven's (2021) framework, in which new knowledge and intermediate services are elements that jointly produce productive entrepreneurship, can accommodate this if the knowledge element is understood as a flow that intermediaries convert with a lag, rather than as an endowment read off contemporaneous outputs. It also answers Roundy and Lyons's (2023) call to locate the entrepreneurs, and the other actors, in ecosystem explanation without claiming to observe cognition. Anchoring each stage to the class of actors that performs it lets aggregate data show *whose* activity held up and whose did not.

For resilience research, the implication is that resistance measured at outputs can be apparent rather than real. In Martin and Sunley's (2015) terms, the UK spin-off system resisted the shock at its output stage while its inflow stage did not resist at all, and the inflow loss later propagated forward. Roundy et al. (2017) locate ecosystem resilience in the interplay of diversity and coherence. The present findings add that resilience also has a temporal anatomy: different parts of the same ecosystem can be in different phases of resistance and recovery at the same time.

5.2 Internalised intermediation under correlated disruption

The second contribution concerns which intermediary arrangements sustain conversion under a systemic shock. I pre-specified the distributed view: arrangements that spread conversion across an arm's-length company and external partners should adapt better. The evidence rejects that expectation for partner-involved support, and universities with exploitation companies show, if anything, a smaller rise in conversion. Conversion rose more where universities provided spin-off support themselves. The explanation offered here is post hoc, and I present it as a proposition for future testing.

The distributed view assumes that disruption is idiosyncratic, so that when one route is blocked another remains open. COVID-19 was a *correlated* shock: it disrupted the university and its partners together. Incubators and science parks were subject to the same restrictions as campuses. Seed and venture investors initially reprioritised existing portfolios before the later surge in investment (Brown et al., 2020). Partners' own staff faced the same constraints as university staff. When partners are disrupted at the same moment, support that depends on coordinating with them carries additional exposure. Each joint activity requires two disrupted organisations to realign. Support provided in-house can be redirected by the university's own decision, for example by reassigning staff whose transactional work, such as consultancy and facilities services, had contracted to the assessment and formation of ventures. This logic connects to arguments that slack resources under managerial control allow organisations to absorb shocks (Bourgeois, 1981; Williams et al., 2017). It also qualifies the debate on whether university-level and local-context support are complements or substitutes (Fini et al., 2011). Distributed and internalised arrangements may each be the more effective under different kinds of disruption: distributed arrangements when shocks are idiosyncratic, internalised arrangements when they are correlated. This yields a testable proposition:

> *Proposition 1.* The value of distributing commercialisation support across external partners, relative to internalising it, is positive under idiosyncratic shocks and declines, or reverses, as disruption becomes correlated across the university and its partners.

A second, related proposition follows from the timing in Fig. 4, where the disadvantage of partner-involved support was concentrated in the acute years and largely faded by 2022/23:

> *Proposition 2.* The advantage of internalised conversion capacity is greatest in the acute phase of a correlated shock and diminishes as partners recover their capacity.

5.3 Why relational capital did not buffer the pipeline

The null result for relational capital matters because the claim that social capital buffers ecosystems against shocks is among the most widely held in the field. It was also the central expectation of an earlier version of this study. The measure used here records realised working relationships, namely consultancy and facilities contracts with firms. Firms cut such engagements during the shock: the median university's contracts fell by 17%. A tie that stays intact while the partner on the other side retrenches may keep communication going but cannot keep transactions going. Uzzi's (1997) observation that embeddedness can constrain adaptation as well as enable it points in the same direction. Under correlated disruption, the relational resources a university holds may be impaired by the same shock that creates the need for them. *Relational continuity is not commercialisation continuity*: in the UK case, commercialisation continued at the output stage even though relational activity and inflow contracted. The measure captures transactional ties rather than trust, and survey-based measures may yield different results (Section 5.6).

5.4 What the pipeline reveals about the wider ecosystem

What do university spin-off outcomes reveal about the resilience of the wider ecosystem? Three implications follow from the evidence. First, the university commercialisation pipeline is one element of an ecosystem's knowledge and intermediate-services endowment (Audretsch & Belitski, 2017; Stam & Van de Ven, 2021), and its outputs are a lagged signal of that element's condition rather than a current one. Ecosystem indices that combine current spin-out counts with other current indicators therefore mix measures that operate on different time scales. Second, channels within the same institutions moved in different directions. Ventures that pass through the TTO held up because of conversion. Student start-ups, which bypass the TTO, rose modestly, and staff start-ups were volatile. Aggregate counts of "university-linked ventures" therefore mask responses with different causes, which reinforces the case for treating academic entrepreneurship as broader than formal spin-offs (Siegel & Wright, 2015). Third, the boundary condition on distributed support concerns the relationship between intermediaries and the wider ecosystem. Under correlated disruption, the ecosystem's partners were a source of exposure as well as resources. This finding is specific to the kind of shock studied and should not be read as a general case against ecosystem partnerships.

5.5 Implications for practice and policy

For TTOs and university leaders, the findings suggest monitoring the pipeline's stages and stocks, not only its outputs. Disclosure inflow and the stock of cases awaiting conversion are leading indicators: a fall in inflow during 2020/21–2021/22 foreshadowed weaker spin-out formation afterwards. Universities that rely on partners to deliver incubation, seed funding or business advice may benefit from contingency capacity they control directly, such as staff who can be redeployed and arrangements that can be activated without a partner when partners are disrupted. For funders and policymakers, including those implementing the UK review of university spin-outs (Tracey & Williamson, 2023), the evidence cautions against evaluating commercialisation performance on spin-out counts alone during and immediately after disruptions. Those counts can overstate resilience while the inflow that sustains future formation is eroding. Supporting the research activity that generates disclosures, such as continued access to laboratories and research time for bench scientists during disruptions, is part of sustaining commercialisation, not separate from it.

5.6 Limitations and future research

Several limitations qualify the conclusions. First, the analysis uses university-year aggregates. The actor-anchored decomposition links each aggregate to the actors who produce it, but it does not observe their decisions. Founder-level data on prior entrepreneurial experience, and case-level data on TTO processing times, would allow the mechanisms proposed here to be tested directly. Linking the register to Companies House filings would make it possible to study time to first external equity and firm survival, two questions that the public data used here cannot address. Second, HE-BCI data are self-reported. Definitions changed in places: from 2022/23, HESA guidance excludes assigned patents from patent counts, so patents are not used as outcomes. Some providers' reporting also shifts, as the industry-contract anomaly shows. The exact reconciliation with HESA's published totals confirms internal consistency, not the accuracy of each return. Third, the configuration measures come from a single pre-shock survey (2018/19). They record whether support mechanisms were provided with partners, not how intensively. Fourth, conversion was trending upward before the shock, and the data cannot separate a shock-specific acceleration from that trend. The finding that output was sustained while inflow fell does not depend on the distinction, but any claim that the shock *caused* faster conversion would. Fifth, the study covers one country and one shock. Testing Propositions 1 and 2 requires contexts in which

shocks differ in how correlated they are across partners, such as localised disruptions to particular universities, sector-specific funding shocks, or the 2008–2009 financial crisis.

6 Conclusion

University spin-off pipelines in the UK sustained their output during COVID-19 while their inflow fell, and the inflow loss later propagated to output. Conversion held up best where universities provided spin-off support themselves, not where they relied on partners, and pre-pandemic ties with industry did not protect any stage of the pipeline. These findings support a stage-specific view of ecosystem resilience, in which inputs, conversion and outputs are distinct properties. They also identify a boundary condition, correlated disruption, under which internalised intermediation matters more than distributed or relational arrangements. For scholars, the implication is to measure resilience across a pipeline's stages and over time. For universities and policymakers, it is to watch the inflow that future ventures depend on, and to maintain conversion capacity that does not depend on partners being available.

References

Audretsch, D. B., & Belitski, M. (2017). Entrepreneurial ecosystems in cities: Establishing the framework conditions. *The Journal of Technology Transfer, 42*(5), 1030–1051. https://doi.org/10.1007/s10961-016-9473-8

Audretsch, D. B., Belitski, M., Guerrero, M., & Siegel, D. S. (2025). Assessing the impact of the pandemic on digital spin-offs at universities: Theory and evidence from the United Kingdom. *Strategic Entrepreneurship Journal*. https://doi.org/10.1002/sej.1544

Bourgeois, L. J. (1981). On the measurement of organizational slack. *Academy of Management Review, 6*(1), 29–39. https://doi.org/10.5465/amr.1981.4287985

Brown, R., Rocha, A., & Cowling, M. (2020). Financing entrepreneurship in times of crisis: Exploring the impact of COVID-19 on the market for entrepreneurial finance in the United Kingdom. *International Small Business Journal, 38*(5), 380–390. https://doi.org/10.1177/0266242620937464

Clarysse, B., Wright, M., Lockett, A., Van de Velde, E., & Vohora, A. (2005). Spinning out new ventures: A typology of incubation strategies from European research institutions. *Journal of Business Venturing, 20*(2), 183–216.

Coleman, J. S. (1990). *Foundations of social theory*. Harvard University Press.

Correia, S., Guimarães, P., & Zylkin, T. (2020). Fast Poisson estimation with high-dimensional fixed effects. *The Stata Journal, 20*(1), 95–115. https://doi.org/10.1177/1536867X20909691

Felin, T., Foss, N. J., & Ployhart, R. E. (2015). The microfoundations movement in strategy and organization theory. *Academy of Management Annals, 9*(1), 575–632. https://doi.org/10.5465/19416520.2015.1007651

679 Fini, R., Grimaldi, R., Santoni, S., & Sobrero, M. (2011). Complements or substitutes? The role of
680 universities and local context in supporting the creation of academic spin-offs. *Research*
681 *Policy, 40*(8), 1113–1127. https://doi.org/10.1016/j.respol.2011.05.013

682 Good, M., Knockaert, M., & Soppe, B. (2020). A typology of technology transfer ecosystems: How
683 structure affects interactions at the science–market divide. *The Journal of Technology*
684 *Transfer, 45*(5), 1405–1431.

685 Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-
686 Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of
687 pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human*
688 *Behaviour, 5*(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8

689 Hayter, C. S. (2016). Constraining entrepreneurial development: A knowledge-based view of social
690 networks among academic entrepreneurs. *Research Policy, 45*(2), 475–490.

691 Hayter, C. S., Nelson, A. J., Zayed, S., & O'Connor, A. C. (2018). Conceptualizing academic
692 entrepreneurship ecosystems: A review, analysis and extension of the literature. *The Journal*
693 *of Technology Transfer, 43*(4), 1039–1082. https://doi.org/10.1007/s10961-018-9657-5

694 HESA. (2026). *Higher Education Business and Community Interaction (HE-BCI) open data: Tables*
695 *1, 2a, 4a–4e, 6 and A* [Data set]. Higher Education Statistics Agency.
696 https://www.hesa.ac.uk/data-and-analysis/business-community

697 Lockett, A., & Wright, M. (2005). Resources, capabilities, risk capital and the creation of university
698 spin-out companies. *Research Policy, 34*(7), 1043–1057.
699 https://doi.org/10.1016/j.respol.2005.05.006

700 Markman, G. D., Phan, P. H., Balkin, D. B., & Gianiodis, P. T. (2005). Entrepreneurship and
701 university-based technology transfer. *Journal of Business Venturing, 20*(2), 241–263.

702 Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: Conceptualization and
703 explanation. *Journal of Economic Geography, 15*(1), 1–42. https://doi.org/10.1093/jeg/lbu015

704 Micozzi, A., Iacobucci, D., Martelli, I., & Piccaluga, A. (2021). Engines need transmission belts: The
705 importance of people in technology transfer offices. *The Journal of Technology Transfer,*
706 *46*(5), 1551–1583.

707 Myers, K. R., Tham, W. Y., Yin, Y., Cohodes, N., Thursby, J. G., Thursby, M. C., Schiffer, P.,
708 Walsh, J. T., Lakhani, K. R., & Wang, D. (2020). Unequal effects of the COVID-19
709 pandemic on scientists. *Nature Human Behaviour, 4*(9), 880–883.
710 https://doi.org/10.1038/s41562-020-0921-y

711 Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational
712 advantage. *Academy of Management Review, 23*(2), 242–266.
713 https://doi.org/10.5465/amr.1998.533225

714 O'Kane, C., Cunningham, J. A., Menter, M., & Walton, S. (2021). The brokering role of technology
715 transfer offices within entrepreneurial ecosystems: An investigation of macro–meso–micro
716 factors. *The Journal of Technology Transfer, 46*(6), 1814–1844.

717 Rocha, A., Brown, R., & Mawson, S. (2021). Capturing conversations in entrepreneurial ecosystems.
718 *Research Policy, 50*(9), 104317. https://doi.org/10.1016/j.respol.2021.104317

719 Roth, J., Sant'Anna, P. H. C., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-
720 differences? A synthesis of the recent econometrics literature. *Journal of Econometrics,*
721 *235*(2), 2218–2244. https://doi.org/10.1016/j.jeconom.2023.03.008

Roundy, P. T., Brockman, B. K., & Bradshaw, M. (2017). The resilience of entrepreneurial ecosystems. *Journal of Business Venturing Insights, 8*, 99–104. https://doi.org/10.1016/j.jbvi.2017.08.002

Roundy, P. T., & Lyons, T. S. (2023). Where are the entrepreneurs? A call to theorize the micro-foundations and strategic organization of entrepreneurial ecosystems. *Strategic Organization, 21*(2), 447–459.

Santos Silva, J. M. C., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics, 88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

Siegel, D. S., & Guerrero, M. (2021). The impact of quarantines, lockdowns, and 'reopenings' on the commercialization of science: Micro and macro issues. *Journal of Management Studies, 58*(5), 1389–1394.

Siegel, D. S., Waldman, D., & Link, A. (2003). Assessing the impact of organizational practices on the relative productivity of university technology transfer offices: An exploratory study. *Research Policy, 32*(1), 27–48. https://doi.org/10.1016/S0048-7333(01)00196-2

Siegel, D. S., & Wright, M. (2015). Academic entrepreneurship: Time for a rethink? *British Journal of Management, 26*(4), 582–595. https://doi.org/10.1111/1467-8551.12116

Spigel, B. (2017). The relational organization of entrepreneurial ecosystems. *Entrepreneurship Theory and Practice, 41*(1), 49–72. https://doi.org/10.1111/etap.12167

Stam, E., & Van de Ven, A. (2021). Entrepreneurial ecosystem elements. *Small Business Economics, 56*(2), 809–832. https://doi.org/10.1007/s11187-019-00270-6

Tracey, I., & Williamson, A. (2023). *Independent review of university spin-out companies: Final report and recommendations*. Department for Science, Innovation and Technology and HM Treasury.

Uzzi, B. (1997). Social structure and competition in interfirm networks: The paradox of embeddedness. *Administrative Science Quarterly, 42*(1), 35–67. https://doi.org/10.2307/2393808

Vohora, A., Wright, M., & Lockett, A. (2004). Critical junctures in the development of university high-tech spinout companies. *Research Policy, 33*(1), 147–175. https://doi.org/10.1016/S0048-7333(03)00107-0

Williams, T. A., Gruber, D. A., Sutcliffe, K. M., Shepherd, D. A., & Zhao, E. Y. (2017). Organizational response to adversity: Fusing crisis management and resilience research streams. *Academy of Management Annals, 11*(2), 733–769. https://doi.org/10.5465/annals.2015.0134

Wurth, B., Stam, E., & Spigel, B. (2023). Entrepreneurial ecosystem mechanisms. *Foundations and Trends in Entrepreneurship, 19*(3), 224–339. https://doi.org/10.1561/0300000089

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