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Abstract

Almost everything known about equity rounds in young firms comes from the records of professional investors, so the evidence is selected on the presence of an intermediary. We read rounds instead from the share-premium reserve, a compulsory, disclosed and restricted line of the Italian statutory balance sheet, for 3,225 certified innovative SMEs over 2016–2025: 2,991 priced capital increases on 1,330 firms. Firms about to raise grew twice as fast in the preceding year and held identical cash, yet six in ten closed it at a loss; profitability falls and intangible assets rise only after the round. Seven panel estimators place the association across firms and not within them; a taxonomy estimated blind to the event finds the mechanism in all five financial configurations, with incidence differing eightfold; six flexible learners fail to improve on the linear specification. Selection operates on growth, not on profitability, a distinction intermediated samples cannot see.

Keywords: Equity rounds, Share premium, Unlisted firms, Innovative SMEs, Firm growth.

JEL Codes: G32, G24, L26, M41, C23.

1. Introduction

Almost everything known about how young firms raise outside equity comes from the records of professional investors. Greenberg (2013) prices patents from financing rounds, Grilli (2019) studies business angels and local financial markets, Bronzini, Caramellino and Magri (2020) observe venture capitalists at the screening stage, Åstebro, Rafih and Serrano (2022) document who European founders are, and Lezana et al. (2026) trace the sequence of rounds to listing outcomes. All share one property: a round exists in the data when an intermediary reports it. Firms financed by their own

shareholders, by families or by unintermediated investors are absent, so coverage is selected on precisely the variable of interest.

This paper asks a question that requires escaping that filter. Does outside equity arrive at firms that are growing, or at firms whose cash is running out? That is the difference between capital that funds a choice and capital that rescues a position, and it cannot be settled on a sample assembled by the investors whose behaviour is under examination.

The gap is specific rather than general. The literature on small-firm finance has the right population and no dated event: Venturelli and Gualandri (2009), Carpentier, L'Her and Suret (2012) and Kwak (2021) treat equity as a ratio, a preference or the residual of a pecking-order choice. The literature evaluating public certification schemes for innovative firms has the right institutional setting and measures every margin except equity — entry in Accetturo (2022) and Albanese and Bronzini (2026), a broad outcome set in Biancalani, Czarnitzki and Riccaboni (2022), credit access in Ferrucci et al. (2021). And the staged-financing literature has the right object and the wrong sample. No study observes a dated equity event inside the statutory accounts of a complete population of private firms and asks what precedes it.

The originality of what follows lies in the measure. The share-premium reserve records capital contributed above the nominal value of the shares issued; under Italian company law, as under the French rules examined by Le Manh (2025), it is compulsory, disclosed and restricted, and cannot be created by revaluation. An increase in it is a priced capital increase — an equity round — observable for every firm that files, whoever subscribed. Two checks establish that it measures this and not something else: contributions at par respond weakly, and a placebo on the legal reserve, which is fed by retained profit, reverses the sign of the cash-flow coefficient.

The answer is affirmative with a qualification that changes it. Capital follows growth and does not follow a draining balance, but it does not follow profitability: six firms in ten close the preceding year at a loss, and the losses deepen after the round rather than before it, alongside an asset base shifting towards the intangible — the channel through which Brown and Petersen (2011), Booth, Chang and Zhou (2015) and Falato et al. (2022) link intangibility to outside equity. Selection operates on growth alone, and growth and profitability are separate things here.

The contribution is also methodological. Three modules are estimated on one sample: a panel that locates the association across firms and not within them, a taxonomy built blind to the event, and flexible learners fitted to exactly the variation the estimator uses.

The article continues as follows. Section 2 places the question against four literatures that have grown apart and identifies the vacancy between them. Section 3 sets out the source, the definition of the event and the estimation strategy, and states in advance what the design can and cannot deliver. Section 4 asks what precedes an equity round, comparing the year before a round with all other years, tracing the sequence around the event, and reporting seven panel estimators and an instrumental specification. Section 5 partitions the population on financial configuration alone, blind to the event, and asks whether the mechanism belongs to one type of firm or to all of them. Section 6 submits the imposed linear form to six flexible learners fitted to exactly the variation the estimator uses. Section

7 draws the three modules together and sets each result against the existing literature; Sections 8 and 9 state what follows for policy and what the design leaves unresolved; Section 10 concludes. Appendices A to F document the sample and the robustness of the panel module, and Appendices G and H the taxonomy and the validation exercise in detail.

2. Literature review

Four literatures bear on the question asked here, and they have grown apart. One studies how risk capital is supplied to young firms and observes it through the records of professional investors. A second studies how small unlisted firms choose between debt and equity and observes the choice through aggregates or surveys. A third evaluates public certification schemes for innovative firms and observes everything except their equity. A fourth supplies the tools — instruments for firm-level shocks, panel estimators for binary outcomes, flexible learners used as specification tests — and is largely indifferent to the substance. Placing them side by side identifies a specific vacancy rather than a general one: no study observes a dated equity event inside the statutory accounts of a complete population of private firms and asks what precedes it.

Staged financing and how rounds are observed. The theory of staged financing is settled and its empirical counterpart is not. Capital is committed in tranches conditional on realised performance, and the interval between tranches is itself informative: Greenberg (2013) uses Israeli start-ups' financing rounds to price patents, Lezana et al. (2026) relate the sequence of rounds to subsequent listing outcomes, and Kim and Marzocchi (2026) show that prior success and failure shape the ability to raise seed capital. Wunder and Maula (2026) examine what corporate venture investors do to the innovation of the firms they back, and Åstebro, Rafih and Serrano (2022) document how founder characteristics map into European venture financing. For Italy specifically, Grilli (2019) studies how local financial markets and business angels finance innovative start-ups, Bronzini, Caramellino and Magri (2020) examine venture capitalists' late-stage screening with a difference-in-differences design, and a substantial body of work on equity crowdfunding — Borello, De Crescenzo and Pichler (2015), Giudici, Guerini and Rossi-Lamastra (2020), Feola et al. (2021), Policaro (2019), Gennaro et al. (2026) — describes a channel opened to registered innovative start-ups by the same decree that created the register.

What these studies share is the observation window. A round is recorded when an intermediary reports it, so the sample is the set of firms that raised from a professional investor and that the investor, or a platform, chose to disclose. Rounds subscribed by existing owners, by families, or by unintermediated investors are simply absent. Coverage is therefore selected on precisely the variable of interest, and the direction of that selection — towards larger, later, more visible deals — is the direction in which the literature's conclusions would be biased if the unobserved rounds behaved differently. Corsi and Prencipe (2017) and Talaia, Pisoni and Onetti (2016) approach the problem from the firm side, asking what shapes the fund-raising process, but they too rely on the visible subset.

External equity in unlisted firms. The second literature asks the question from the balance sheet but rarely dates the event. Venturelli and Gualandri (2009) ask what determines the need for equity in small firms and identify size, youth and innovation as the candidates; Wieczorek-Kosmala, Błach and Trzęsiok (2020) compare the relevance of equity financing across European SMEs; Kwak (2021) revisits the pecking order for Korean high-technology SMEs; Dwyer and Kotey (2015) examine the role of a junior exchange and of advisers in financing SME growth. Carpentier, L'Her and Suret (2012) study seasoned offerings by small and medium firms, and Brown and Floros (2012) exploit private investment in public equity to link access to private capital to real activity. The pandemic produced a policy-oriented strand — Díez et al. (2022) on targeted equity injections, Panetsidou and Synapis (2025) on equity financing during the downturn — that treats equity as an instrument rather than as an observed outcome.

Across this work equity is a share, a ratio or a stated preference. It is seldom an event with a date, an amount and a price, and never, to our knowledge, an event read from a specific line of the statutory accounts of an entire population. That absence is what makes the share-premium reserve worth the attention: it is a compulsory line, filed by every company, whose increase is by construction the arrival of capital above nominal value.

A small accounting literature bears directly on the line itself. Le Manh (2025) examines how equity-capital management and distributions are governed by accounting standards in France, a jurisdiction whose company law treats the premium account much as Italian law does: the reserve is restricted, its movements are disclosed, and it cannot be created by a revaluation. That is what makes it usable as a measure. An increase in it is not an accounting choice but the recording of cash or assets contributed above par, which distinguishes it from reserves that grow out of retained profit and from revaluation reserves that grow out of nothing at all.

The Italian regime and what has been measured about it. The evaluation literature on Decree-law 179/2012 is large and, on the financial margin, thin. Biancalani, Czarnitzki and Riccaboni (2022) provide a microeconomic evaluation of the Start-up Act; Accetturo (2022) and Albanese and Bronzini (2026) examine whether subsidies and public incentives change firm entry; Santoleri and Russo (2025) study the entrepreneurs the subsidy attracts; Giraudo, Giudici and Grilli (2019) assess the policy's effect on the financing of young innovative companies; Ferrucci et al. (2021) relate financial constraints to the growth and survival of Italian innovative start-ups; Beltrame et al. (2023) examine relationship lending and access to credit in the same population. A parallel strand — Colombelli (2016), Capozza, Salomone and Somma (2018), Antonietti and Gambarotto (2020), Cavallo et al. (2020), Del Bosco, Chierici and Mazzucchelli (2021) — explains where innovative start-ups are created rather than how they are financed. Legal scholarship completes the picture: Giudici and Agstner (2019) and Agstner (2024) describe the corporate-law forms the regime introduced, and Enriques, Giudici and Agstner (2026) ask whether American venture contracts transplant into Germany and Italy.

Two features of this body of work matter here. Registry status is almost always the treatment, which requires an argument about selection into the register that the data rarely support. And the outcomes measured are employment, survival, patents, entry and credit — not the composition of equity. The regime is used below in neither role. It defines the population for which the necessary balance-sheet detail exists, and nothing in the design turns on certification being exogenous.

Cash, intangibles, and why equity rather than debt. Why a firm raises equity rather than borrowing has a well-developed answer that has been tested almost entirely on listed companies. Falato et al. (2022) show that the rise of intangible capital shrinks debt capacity and pushes firms towards cash; Zahid and Islam (2025) and Yang (2026) relate intangible assets to unsecured borrowing and to the cost of debt through collateral value. On the liquidity side, Bates, Kahle and Stulz (2009) established the secular rise in corporate cash, and Brown and Petersen (2011), Booth, Chang and Zhou (2015), He and Wintoki (2016) and Magerakis, Gkillas and Tsagkanos (2022) connect it to research intensity and to the smoothing of innovation spending. Chen and Chen (2012) and Brown and Petersen (2015) question how well investment–cash-flow sensitivities measure constraints at all, while Malamud and Zucchi (2019) formalise the link between liquidity and endogenous growth.

The prediction this yields — that firms whose assets cannot be pledged fund intangible investment with outside equity and hold the proceeds as cash — has not been observed as a sequence in small private firms, because the three ingredients are rarely measured together. Here they are: the round is dated, cash is a filed line, and intangible fixed assets are reported separately from tangible ones.

A related and much smaller strand asks what it means for a firm to grow while losing money. Harris and Li (2021) treat negative operating cash flows as a marker of investment inefficiency; Kei et al. (2025) ask, on Chinese data, whether firms accumulate cash precisely by financing persistent negative cash flows, which is the pattern an outside-equity round would produce. On the Italian population,

Innocenti and Zampi (2019) ask what an innovative start-up needs in order to grow, Rocha and Grilli (2024) study early-stage hiring as a function of initial resources, and Onesti et al. (2022) build a composite index of performance that deliberately does not reduce to profitability. None of these connects the loss to a dated financing event, so whether the loss is the condition that brings the capital in or the consequence of having received it remains an open question — and it is the question the event study below is built to answer.

Identification and functional form. The methodological literatures used below are mature. Leave-one-out and shift-share instruments have a precise recent treatment — Goldsmith-Pinkham, Sorkin and Swift (2020), Borusyak, Hull and Jaravel (2022, 2025), Breuer (2022) — together with pointed warnings about their exclusion restrictions from Jaeger, Ruist and Stuhler (2020) and a formal relaxation by Apfel (2024). Dynamic discrete-choice panels with fixed effects carry the incidental-parameter problem addressed by Carro (2007), Shiu and Hu (2013) and Boneva and Linton (2017). And the use of flexible learners as a check on an imposed functional form, rather than as a prediction exercise, rests on tools whose pitfalls are documented: Hooker, Mentch and Zhou (2021) show that unrestricted permutation forces extrapolation, and Inglis, Parnell and Hurley (2022) set out how importance and interaction effects should be displayed. Applications such as D'Amato, Zhang and Zhu (2024) and Bertomeu et al. (2025) illustrate the measurement use to which these methods are increasingly put.

Table 1. The literature, the gap, and what this study adds

Research theme	Representative studies	Main gap identified	Contribution of this study
Staged financing and the observation of rounds	Greenberg (2013); Grilli (2019); Bronzini, Caramellino & Magri (2020); Āstebro, Rafih & Serrano (2022); Lezana et al. (2026); Kim & Marzocchi (2026); Wunder & Maula (2026)	Rounds are observed through venture capital databases, which record only the deals an intermediary reports. Firms financed by existing owners, family or unintermediated investors are invisible, and coverage is selected on the presence of a professional investor.	Rounds are read from the share-premium reserve in filed accounts: 2,991 increases above one per cent of assets on 1,330 firms and 23,243 years at risk, complete for the whole population and independent of who subscribed.
External equity in unlisted firms	Venturelli & Gualandri (2009); Brown & Floros (2012); Carpentier, L'Her & Suret (2012); Dwyer & Kotey (2015); Wieczorek-Kosmala et al. (2020); Kwak (2021); Diez et al. (2022)	The literature treats equity as the residual of a pecking-order choice and tests it on aggregates or on survey responses. Almost none of it identifies a dated equity event inside the accounts of a private firm.	The event is dated to the financial year and separated from at-par contributions: increases in share capital without premium move the cash-flow coefficient from -0.33 to -0.06 , confirming that the premium identifies priced outside capital.
The Italian innovative-firm regime	Colombelli (2016); Giraudo, Giudici & Grilli (2019); Ferrucci et al. (2021); Biancalani, Czarnitzki & Riccaboni (2022); Accetturo (2022); Santoleri & Russo (2025); Albanese & Bronzini (2026)	Evaluations measure entry, employment, survival, patenting and access to credit, and treat registry status as a binary treatment. What the regime does to the equity margin of the balance sheet has not been measured.	The regime is not used as a treatment at all. It defines a population in which the balance-sheet items needed to observe equity exist, and heterogeneity by configuration is recovered from the accounts rather than from status.
Financing constraints, growth and profitability	Chen & Chen (2012); Brown & Petersen (2015); Löff & Nabavi (2016); Innocenti & Zampi (2019); Beladi, Hu & Yuan (2021); Mitra et al. (2026)	Constraint proxies are built from investment-cash-flow sensitivities whose interpretation is contested, and growth and profitability are usually treated as a single dimension of firm quality.	Selection operates on growth and not on profitability, and the two separate: firms raising equity grow twice as fast and close the preceding year at a loss in 62 per cent of cases against 26 per cent elsewhere.
Cash, intangibles and the choice of equity over debt	Bates, Kahle & Stulz (2009); Brown & Petersen (2011); Booth, Chang & Zhou (2015); He & Wintoki (2016); Falato et al. (2022); Zahid & Islam (2025); Yang (2026)	Intangible capital is shown to shrink debt capacity and to raise precautionary cash, but the two are studied on listed firms and the equity that funds intangible investment is inferred rather than observed.	The event study shows cash flat before the round, rising 6.8 points of assets at it, and intangibles rising 1.6 and 1.7 points one and two years after: the sequence of an investment, not of a rescue.
Identification with local demand instruments	Goldsmith-Pinkham, Sorkin & Swift (2020); Jaeger, Ruist & Stuhler (2020); Borusyak, Hull & Jaravel (2022, 2025); Breuer (2022); Apfel (2024)	Shift-share and leave-one-out designs are well developed for regional labour and trade outcomes; their exclusion restrictions have been interrogated, but the instruments are rarely applied to firm-level financing decisions.	Lagged revenue growth is instrumented with leave-one-out provincial growth. Across firms the first-stage F is 75.2 and the coefficient triples to 0.097; within firms the F falls to 5.5 and the estimate is reported as uninformative.

Research theme	Representative studies	Main gap identified	Contribution of this study
Panel estimation of a binary outcome	Carro (2007); Shiu & Hu (2013); Boneva & Linton (2017)	Dynamic discrete-choice panels with fixed effects face the incidental-parameter problem, and the linear probability model is often used without justifying it against the alternative.	Seven estimators are reported side by side. The across-firm and within-firm answers differ sharply, and the difference is the result rather than a robustness check.
Flexible learners as specification tests	Hooker, Mentch & Zhou (2021); Inglis, Parnell & Hurley (2022); D'Amato, Zhang & Zhu (2024); Bertomeu et al. (2025)	Machine learning enters applied economics mostly as prediction or as a treatment-effect estimator. Its use as a test of the functional form a parametric model has already imposed is uncommon and rarely benchmarked.	Six learners are fitted to the same variation under firm-grouped cross-validation. The best beats the linear model by 1.10 on levels and 1.00 within firms, so the linear form is adequate rather than convenient.

Note. Representative studies are illustrative rather than exhaustive. Entries in the last column refer to results reported in Sections 4 to 6.

Read together, the four strands leave one thing unmeasured. The staged-financing literature has the right object and a sample selected on the presence of an intermediary. The SME-finance literature has the right population and no dated event. The evaluation literature has the right institutional setting and measures every margin except equity. And the methodological literature supplies instruments and learners that applied corporate finance uses for prediction more often than for testing a specification it has already committed to. What follows occupies that vacancy. It reads equity rounds from a compulsory line of the statutory accounts of 3,225 Italian innovative SMEs over 2016–2025, asks what precedes them within the firm and across firms, partitions the population by financial configuration without reference to the rounds, and submits the resulting linear equation to six learners fitted to exactly the variation the panel estimator uses. The answer it reaches — that selection operates on growth and not on profitability, and that losses follow the round rather than preceding it — is available only because the event is observed for every firm rather than for the firms an investor chose to report.

3. Data and methodology

The population is the set of firms enrolled in the special section of the Italian Business Register for innovative small and medium enterprises, the status created alongside the innovative start-up by Decree-law 179/2012 and described in its corporate-law dimension by Giudici and Agstner (2019), Agstner (2024) and Enriques, Giudici and Agstner (2026). Accounts are drawn from AIDA, organised in four blocks — balance-sheet assets, balance-sheet liabilities, income statement and derived ratios — covering calendar years from 2016 to 2025. The blocks are reconciled on the normalised corporate name, since they carry no fiscal code, and incorporation dates are matched from the public register itself, which is complete on that field. The register also supplies the ATECO 2007 activity code, complete for the estimation sample and yielding 68 two-digit divisions and 19 activity sections.

The unit of observation is the firm-year. This is the same unit on which the Italian evaluation literature works — Giraud, Giudici and Grilli (2019), Ferrucci et al. (2021), Biancalani, Czarnitzki and Riccaboni (2022), Accetturo (2022) — but the outcome differs. Those studies take registry status as a treatment and measure entry, employment, survival or credit. Here registry status is not a treatment at all. It defines the population for which the balance-sheet detail required to observe equity exists, and no step of the design turns on certification being exogenous. The consequence is that this paper makes no claim about what the regime does; it makes a claim about what happens inside a population the regime happens to delimit.

The event. The dependent variable is an indicator that the share-premium reserve rose over the previous financial year. That reserve records amounts contributed above the nominal value of the shares issued, and under Italian company law — as under the French rules examined by Le Manh (2025) — it is restricted, disclosed, and cannot be created by revaluation. An increase in it is therefore the recording of capital paid in at a price, which is the accounting counterpart of an equity round. This is the methodological departure from the literature on staged financing. Greenberg (2013), Grilli (2019), Bronzini, Caramellino and Magri (2020), Åstebro, Rafih and Serrano (2022) and Lezana et al. (2026) all observe rounds through the records of professional investors, which means the sample is the set of firms that raised from an intermediary willing to disclose the deal. Reading the round from the accounts inverts the selection: every company that files is observed, whoever subscribed, and the price dimension is preserved because at-par contributions do not touch the premium account. Two checks establish that the item measures what it is taken to measure, and both are reported in the appendix rather than asserted here. Increases in share capital unaccompanied by any premium — contributions at par by existing owners — produce a markedly weaker association with the firm's financial position than premium increases do. And an increase in the legal reserve, which under Italian law is fed by the compulsory appropriation of profit, reverses the sign of the cash-flow coefficient, as it must if the specification separates equity accumulated out of earnings from equity injected from outside. A materiality threshold expressed as a share of lagged total assets removes rounding; the appendix shows the results do not depend on where it is set.

Variables. Seven predictors enter the equation, all lagged one financial year. Revenue growth in logs is the focal regressor, because the hypothesis concerns whether capital follows growth. Cash over total assets and operating cash flow over total assets are the two competing descriptions of the firm's financial position: the first is the stock the firm has accumulated, the second the flow it is generating. Their joint use is deliberate, given the long-standing doubt — set out by Chen and Chen (2012) and by Brown and Petersen (2015) — over how well investment–cash-flow sensitivities identify financing constraints on their own. Intangible fixed assets over total assets capture the part of the balance sheet that cannot be pledged, the mechanism through which Falato et al. (2022), Zahid and Islam (2025) and Yang (2026) link intangibility to shrinking debt capacity and through which Brown and Petersen (2011), Booth, Chang and Zhou (2015) and He and Wintoki (2016) link research intensity to cash. Debt over assets, log total assets and log age complete the set. All continuous variables are winsorised at the first and ninety-ninth percentiles. No variable is standardised in the panel module, so coefficients read in the units of the underlying ratios.

Estimation: seven panel estimators. The outcome is binary and the model is a linear probability model with a full set of controls, estimated seven ways: pooled, pooled with year effects, between, random effects, firm fixed effects, two-way fixed effects, and weighted least squares with total assets as weights. The seven are reported side by side rather than sequentially, because the object is not to find the preferred specification but to locate the dimension of the data in which the association lives. The across-firm estimators use variation between different companies; the fixed-effects estimators use variation within the same company over time; and when the two disagree, that disagreement is the finding and not a robustness failure.

A dynamic specification adds the lagged dependent variable to firm and year effects, since a company that has just raised rarely raises again immediately. That estimator carries the incidental-parameter problem studied by Carro (2007), Shiu and Hu (2013) and Boneva and Linton (2017); with the number of periods available here the resulting bias acts downward on the autoregressive coefficient, and the appendix states the magnitude rather than correcting it, since no coefficient of interest depends on it.

An event study around the first round completes the module. Each firm is compared with itself and with the calendar year, taking the financial year immediately preceding the round as the base, and companies that never raise remain in the sample as untreated controls. Its purpose is narrow and should not be overstated: it separates whether losses precede or follow the round. Because a pre-trend in growth is what the hypothesis predicts rather than what would invalidate it, the event study here describes selection into financing and does not estimate a treatment effect. This is why the interpretation stays at the level of conditional association throughout.

Identification. Lagged revenue growth is measured with error and may itself respond to an anticipated round. It is therefore instrumented with the mean revenue growth of the other innovative SMEs located in the same province in the same year, computed leaving the firm itself out — a local demand shift that moves a company's turnover without operating through its own financing decisions. The design belongs to the shift-share and leave-one-out family, whose properties have been set out by Goldsmith-Pinkham, Sorkin and Swift (2020), Borusyak, Hull and Jaravel (2022, 2025) and Breuer (2022), and whose exclusion restriction has been questioned with some force by Jaeger, Ruist and Stuhler (2020) and formally relaxed by Apfel (2024).

Those warnings are taken literally in two ways. First-stage strength is reported for both dimensions separately, and the instrument is used only where it is strong: once firm and year means are removed the provincial shifter loses most of its power, and the within-firm instrumental estimate is reported in the appendix as uninformative rather than presented as a result. Second, the instrumental estimate is compared with least squares through an exogeneity test whose failure to reject is stated as such, so the two estimates are not claimed to be different when the data do not establish it.

The taxonomy module. A partition of the population is estimated on firm averages over ten balance-sheet dimensions — growth, cash, operating cash flow, operating result, intangible and tangible fixed assets, leverage, size, age and capital turnover — standardised before partitioning. Neither the dependent variable nor any registry characteristic enters. This blindness is the point: the taxonomy is asked whether firms that raise equity form one recognisable type or several, and an answer built from the outcome would be no answer at all.

Six algorithms are compared across a range of cluster counts on eleven validity indices. The indices that measure fit rise or fall monotonically with the number of clusters and therefore cannot select it; the ranking is built on those that a larger partition does not automatically reward, and the number of clusters is fixed where they agree on an interior maximum. Stability is assessed by bootstrap resampling and the dependence of the solution on any single dimension by removing dimensions one at a time. The round equation is then re-estimated inside each group, which tests whether the mechanism belongs to one configuration or holds across all of them.

The validation module. The panel module imposes linearity and additivity. Whether that form is adequate is a separate question from whether the coefficients are identified, and it is answered by fitting six regression learners — linear regression, a linear support vector machine, nearest neighbours, a decision tree, a random forest and gradient boosting — to exactly the same variables and comparing out-of-sample fit. Cross-validation folds are grouped by firm so that no company appears in both training and test sets; without that grouping the persistence of both outcome and predictors within firms inflates every learner, and the flexible ones disproportionately.

The exercise is run twice, on raw levels and on data demeaned by firm and by year. The second is the Frisch–Waugh representation of the two-way fixed-effects estimator, so a learner fitted to those residuals competes with the panel specification on its own variation; running the comparison on levels alone would answer a different question. Hyperparameters are fixed in advance and not tuned on the scoring folds, since tuning the flexible learners on the same folds used to judge them would bias a validation exercise towards the conclusion it is meant to test.

Two diagnostics accompany the comparison. Permutation importance is computed on held-out data, with the caveat documented by Hooker, Mentch and Zhou (2021) that unrestricted permutation forces

the model to extrapolate into regions the data do not occupy, so the measure is read as an ordering rather than as a decomposition. Interaction strength and partial dependence are displayed following the guidance of Inglis, Parnell and Hurley (2022). The use of flexible learners as a check on an imposed specification, rather than as a predictor or a treatment-effect estimator, follows the measurement tradition represented by D'Amato, Zhang and Zhu (2024) and Bertomeu et al. (2025).

What the design can and cannot deliver. Three boundaries follow from the choices above and are carried into the results. The accounts identify that priced capital entered and when, but not who supplied it: a subscription by a venture fund and one by an industrial shareholder are indistinguishable in the reserve, so nothing here speaks to investor type, and the literature surveyed in Section 2 retains its advantage on that margin. The balance-sheet items required to build the measure exist only for the certified population, so no comparison with non-certified firms is available and none is attempted. And the design establishes what precedes an equity round, not what the round causes; the event study is read as selection, the panel coefficients as conditional associations, and the instrument as addressing measurement error and reverse causation in one regressor rather than identifying a causal effect of financing on the firm.

4. What precedes an equity round

The share-premium reserve records money paid into a company above the nominal value of the shares issued. An increase in it is therefore a priced capital increase — an equity round — and unlike commercial deal databases it is observable in the filed accounts of the whole population. Across the 26,584 firm-years of innovative SMEs the item is reported in one hundred per cent of cases and is non-zero in 32.6. In first difference it yields 2,991 increases above one per cent of total assets, spread over 1,330 firms and 23,243 years at risk, with a median of 350 thousand euro and a ninety-fifth percentile of 5.4 million.

The hypothesis was that the round arrives at firms that are growing and not at firms running out of cash. Table 2 compares the characteristics of the year preceding a round with those of all other years.

Table 2. Firms in the year before an equity round

Variable, lagged one year	No round	Year before a round	Difference	t
Revenue growth (log)	0.268	0.500	+0.232	10.3
Cash / assets	0.194	0.195	+0.000	0.1
Operating cash flow / assets	0.065	−0.066	−0.131	−22.8
Operating result / assets	0.030	−0.136	−0.166	−25.9
Share of loss-making years	0.259	0.617	+0.358	31.1
Intangibles / assets	0.185	0.315	+0.129	23.1
Debt / assets	0.529	0.535	+0.006	0.8
ln(total assets)	6.999	7.109	+0.111	3.1
ln(1+age)	1.979	1.589	−0.390	−21.9

Note. Means over the estimation sample, 17,235 observations on 2,905 firms, of which 1,973 years with a round. Variables winsorised at the 1st and 99th percentiles. The t column reports a Welch test on the difference between the two means.

Two columns move in the expected direction and two contradict it. Revenue growth in the preceding year is 0.50 in logs against 0.27, almost double, and is the difference the hypothesis predicted. Cash over assets is instead identical, 0.195 against 0.194, with a t of 0.1: nothing indicates that the round follows a decline in cash. But operating cash flow and the operating result are both negative in firms about to raise, and the share of years closed at a loss rises from 26 to 62 per cent. Firms that raise equity grow their turnover and lose money at the same time.

That combination admits two opposite readings, and telling them apart is the whole empirical content of the hypothesis: if the losses precede the round, equity is a rescue; if they follow it, equity funds a choice. Figure 1 separates the two cases by comparing each treated firm with itself and with the year, taking the financial year immediately before the first round as the base.

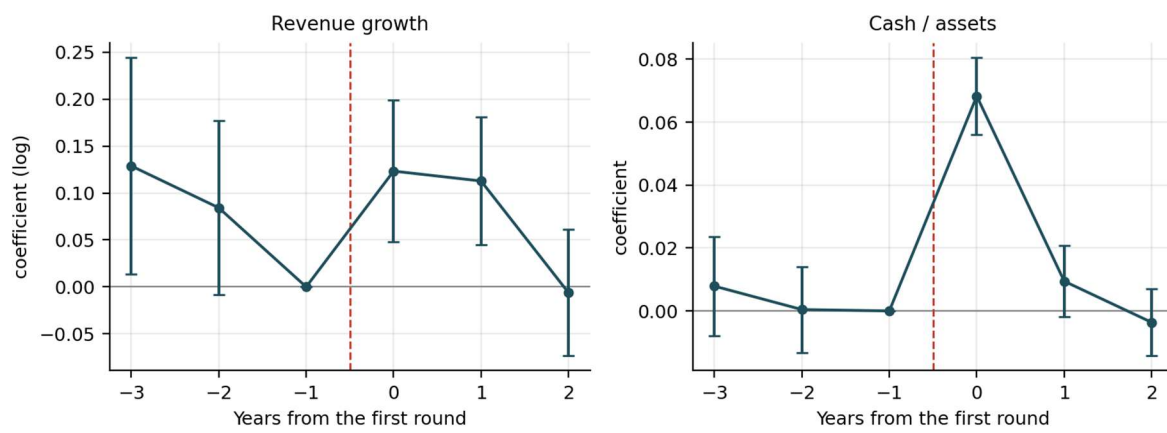


Figure 1. Revenue growth and cash around the first round. Note. Coefficients on relative-time indicators with firm and year fixed effects, firm-clustered standard errors, 95 per cent intervals. Base: $t-1$. The 1,895 never-treated firms remain in the sample as controls. The dashed line marks the round.

Revenue growth is already elevated three and two years before, at 0.129 and 0.084, and stays elevated in the year of the round and the one after. Cash does not move beforehand — 0.008 and 0.000, both indistinguishable from zero — then jumps by 6.8 points of assets in the year of the round, which is the money arriving, and recedes the following year. Both legs of the hypothesis hold: the round follows growth and does not follow a deterioration in cash.

Figure 2 shows where the losses sit in time.

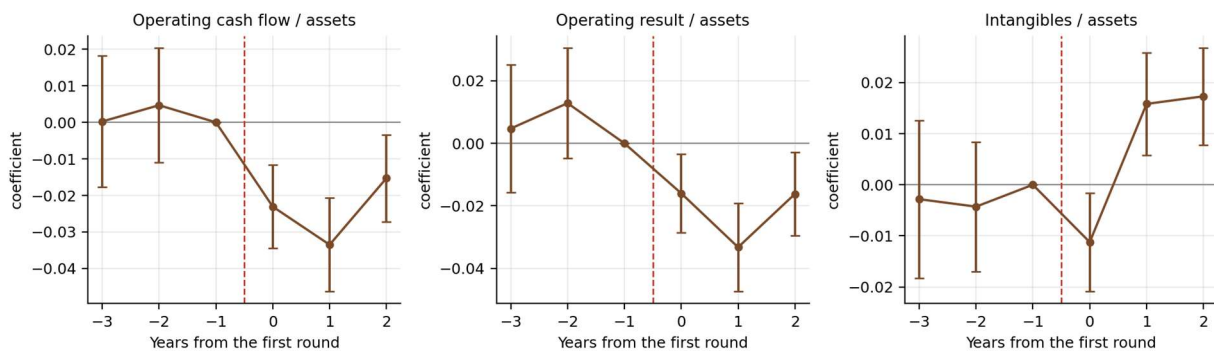


Figure 2. Profitability and asset composition around the first round. Note. As Figure 1. Operating cash flow and the operating result are scaled by total assets; intangibles are total intangible fixed assets over assets.

Before the round, operating cash flow and the operating result are flat: 0.000 and 0.005 for the first, 0.005 and 0.013 for the second, none significant. They fall afterwards and stay below for two years. Intangible fixed assets trace the mirror path: flat before, rising by 1.6 and 1.7 points of assets one and two years after the round. The sequence is that of an investment, not that of a collapse. The losses that Table 2 associated with the round do not precede it: they follow it, and they arrive alongside an asset base shifting towards the intangible.

It remains to establish whether the association between growth and rounds survives controls, and to which dimension of the data it belongs. Table 3 reports seven estimators of the same equation, with the round as a binary dependent variable and every regressor lagged one year.

Table 3. Seven estimators of the equity-round equation

Regressor (t-1)	Pooled	Pooled + year	Between	Random effects	FE firm	FE firm+year	WLS assets
Revenue growth	0.0324*** (0.0039)	0.0328*** (0.0039)	0.0739*** (0.0080)	0.0193*** (0.0038)	0.0034 (0.0040)	0.0028 (0.0044)	0.0174 (0.0130)
Cash / assets	0.0619*** (0.0145)	0.0577*** (0.0148)	0.0725*** (0.0266)	0.0285* (0.0146)	-0.0407* * (0.0194)	-0.0552* * (0.0221)	-0.1458* * (0.0638)
Operating cash flow / assets	-0.3267* ** (0.0185)	-0.3248* ** (0.0186)	-0.5347* ** (0.0234)	-0.2120* ** (0.0178)	0.0102 (0.0226)	0.0165 (0.0250)	0.1199* (0.0662)
Debt / assets	-0.0400* **	-0.0389* **	-0.1364* **	0.0095	0.1250***	0.1285***	0.2316***
Intangibles / assets	0.2216***	0.2174***	0.2017***	0.2041***	0.1225***	0.1106***	0.0383
ln(total assets)	0.0191***	0.0186***	0.0250***	0.0145***	-0.0178* **	-0.0222* **	-0.0507* **
ln(1+age)	-0.0473* **	-0.0478* **	-0.0425* **	-0.0508* **	-0.0021	-0.0299*	-0.0037
Observations	17,179	17,179	2,900	17,179	17,179	17,179	17,179
Firms	2,900	2,900	2,900	2,900	2,900	2,900	2,900

Note. Dependent variable: indicator of an increase in the share-premium reserve above 1% of total assets. Firm-clustered standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. The between model is estimated on firm means.

The structure of the result is sharp. In the across-firm dimension growth matters — 0.032 pooled, 0.074 between — and operating cash flow matters more, negatively, with coefficients between -0.21 and -0.53. Within the firm both disappear: 0.003 and 0.010, neither significant. What does not disappear is the intangible share of assets, positive in six specifications out of seven, and age, negative

wherever it can be identified. Equity goes to a type of firm — young, intangible, growing, loss-making — more than it goes to a particular year in the life of a given firm. Because equity rounds are concentrated in a few industries, the across-firm association could reflect sector composition rather than firm characteristics. Replacing year effects with 19 ATECO section by year effects — 151 cells — moves the growth coefficient from 0.0328 to 0.0332, and adding province effects as well returns 0.0322; operating cash flow goes from −0.326 to −0.298 and the intangible share from 0.217 to 0.201. Within the firm the coefficients are unchanged, since sector is already absorbed by the firm itself. Sector composition therefore accounts for almost none of the association: the relation is not an artefact of equity being raised more often in some industries than in others. Ninety-six of the 151 sector-year cells hold fewer than twenty observations, which is why the sector dimension is used at section rather than division level.

Revenue growth is, however, measured with error and may itself be a consequence of an anticipated round. Table 4 instruments it with the mean revenue growth of the other innovative SMEs in the same province and year, computed leaving the firm out: a local demand shift that moves turnover without passing through the financial decisions of the individual company.

Table 4. Instrumental-variable estimates

	Pooled OLS	2SLS pooled	2SLS within firm
Revenue growth (t−1)	0.0324*** (0.0039)	0.0974** (0.0412)	0.0738 (0.1342)
First-stage coefficient	—	0.2617***	0.0788**
First-stage F	—	75.2	5.5
Wu–Hausman (p)	—	0.151	0.652
Observations	17,179	17,179	17,179

Note. Instrument: leave-one-out mean revenue growth in the province and year. Controls as in Table 3. Firm-clustered standard errors. The within-firm column removes firm and year effects before instrumenting.

In the across-firm dimension the instrument is strong, with a first-stage F of 75.2, and the instrumented coefficient is 0.097 against 0.032 by least squares: three times as large, significant at five per cent. The Wu–Hausman test does not reject exogeneity, with a p of 0.151, so the two estimates are not statistically distinguishable and the correct reading is that attenuation from measurement error is plausible but not demonstrated. Within the firm the instrument loses power, with an F of 5.5, and the estimate is uninformative; it is reported in the appendix and supports no conclusion.

The instrument could be narrowed further, since provincial growth still contains national sector dynamics. Recomputing the leave-one-out mean within ATECO section by province by year leaves the point estimate almost unchanged, 0.094 against 0.097, but halves the first-stage F from 75.2 to 31.0 and costs statistical significance, because the median cell falls to fifteen firms and one cell in five holds fewer than five. Absorbing sector by year effects and instrumenting with the narrower cell drives the first-stage F to zero: once national sector dynamics are removed, the cell mean carries no

independent variation. That is informative rather than disappointing, and it is the mechanism Jaeger, Ruist and Stuhler (2020) describe. The provincial instrument is therefore retained, with the narrower version reported here as a robustness check that changes the estimate's precision and not its magnitude.

Everything estimated so far asks whether a firm raises, not how much it raises. These are two margins and the data carry both, since the amount is observed whenever a round occurs. A second equation, fitted to the 1,973 round-years with the same seven regressors, completes the model.

Table 5. The amount raised, conditional on a round

Regressor (t-1)	ln(amount)	ln(amount), sector × year	Amount / lagged assets
Revenue growth	0.0826*** (0.0300)	0.0816*** (0.0316)	0.1291*** (0.0331)
Cash / assets	0.8224*** (0.1795)	0.6682*** (0.1883)	0.4956*** (0.1824)
Operating cash flow / assets	-0.9357*** (0.1304)	-0.9832*** (0.1388)	-0.8678*** (0.1598)
Debt / assets	0.1348 (0.1097)	0.1005 (0.1148)	0.1642 (0.1214)
Intangibles / assets	-0.1472 (0.1389)	-0.2547* (0.1463)	-0.4808*** (0.1260)
ln(total assets)	0.6597*** (0.0228)	0.6602*** (0.0238)	-0.3075*** (0.0287)
ln(1+age)	-0.0773 (0.0476)	-0.0748 (0.0495)	0.0063. (0.0348)
Observations	1,973	1,973	1,973
Firms	1,051	1,051	1,051
R ²	0.361	0.398	0.204

Note. Second part of a two-part model, estimated on the round-years of the estimation sample. The first two columns include year and sector-by-year effects respectively; the third scales the amount by lagged total assets and is winsorised at the 1st and 99th percentiles. Firm-clustered standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.10. Median amount raised: 437 thousand euro.

Growth predicts both margins. A round is more likely after a year of fast growth, and it is also larger: the elasticity of the amount to lagged revenue growth is 0.083, and 0.129 once the amount is scaled by lagged assets, both significant at one per cent and both unchanged by sector-by-year effects. Under firm fixed effects the coefficient falls to 0.037 and loses significance, exactly as in the first part, so the intensive margin too is a property of firm type rather than of firm circumstance.

Two regressors behave differently across the margins, and the contrast is the reason for estimating them separately. The intangible share of assets is the most robust predictor of whether a round occurs, positive in six of the seven estimators of Table 3; conditional on raising, it turns negative, -0.48 on the amount scaled by assets. Intangibility governs whether a firm must use outside equity, not how

much it takes — the size of the round follows the scale of the firm, with an elasticity to total assets of 0.66. Cash holdings run the other way, weak in the first part and strongly positive in the second, 0.82. Operating cash flow is the one regressor that works the same way on both margins, negative and strong throughout. A single equation reports the average of two different objects.

Both margins so far treat rounds as independent events. They are not. Half the firms that raise once raise again — 531 of 1,051 — and the median interval between the first and the second is a single year. That makes a third question available, and it is the one staged financing actually poses: whether the next tranche responds to what the firm did with the last one, or was effectively settled when the first was agreed. A discrete-time hazard of the second round, estimated on 2,080 risk-years from 919 firms with duration dummies, answers it.

Table 6. Hazard of a second round

Regressor	Logit	Linear probability
Cumulative operating result between rounds	−0.2403*** (0.0410)	−0.0424*** (0.0068)
Cumulative revenue growth between rounds	0.2201*** (0.0613)	0.0431*** (0.0109)
ln(amount of the first round)	0.0052 (0.0523)	−0.0008 (0.0088)
Intangibles / assets	0.5742** (0.2650)	0.0920* (0.0485)
Cash / assets	−0.4787 (0.3009)	−0.0751 (0.0521)
ln(total assets)	0.0598 (0.0617)	0.0120 (0.0102)
ln(1+age)	−0.2589*** (0.0801)	−0.0492*** (0.0154)
Risk-years	2,080	2,080
Firms	919	919
Second rounds observed	531	531

Note. Discrete-time hazard estimated from the year after the first round until the second round or the end of the firm's filing record. Cumulative variables are summed from the year after the first round to the current year; the operating result is scaled by total assets at the first round. Duration dummies included; firm-clustered standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Raw hazard by year since the first round: 0.317, 0.245, 0.204, 0.203, 0.121.

The size of the first round carries no information about the second. Its coefficient is 0.005 with a z of 0.10 in the logit and −0.001 in the linear model, as close to zero as an estimate can be. What does carry information is what happened in between: cumulative revenue growth raises the hazard and the cumulative operating result lowers it, both at one per cent and both robust across the two estimators. Capital arrives in tranches conditioned on realised outcomes rather than on a schedule fixed at the outset, which is the empirical content of staged financing, and here it is tested rather than assumed.

The negative sign on the accumulated operating result completes what precedes rather than contradicting it. The event study showed that losses follow the first round; the hazard shows that those same losses precede the second. Selection into the first round runs on growth, and the timing of the rounds that follow is governed by the consumption of the previous tranche. Duration dependence is negative and steep — the hazard falls from 0.32 in the first year to 0.12 in the fifth — so the firms that return, return quickly. Age enters negatively here as it does everywhere else, and the intangible share positively, which is the one regressor that operates on all three margins in the same direction.

Hypothesis H1 is confirmed in its testable form, with one qualification that changes how it reads. Risk capital arrives at firms that are growing, and it does not arrive at firms whose cash is draining away: on this the data are clear and concordant across the cross-sectional comparison, the event study, the instrumental estimates and both margins of the two-part model. It does not, however, arrive at firms that are «doing well» in the accounting sense, because six in ten close the preceding year at a loss. Selection operates on growth and not on profitability, and in this population the two are separate. The hazard of a second round adds the dynamic counterpart: what brings a firm back is not how much it raised before but what it did with it. The consequence is that the filed accounts of small Italian firms contain a financing margin — measurable, dated and complete — that the literature on risk capital has never observed at this scale, and that behaves as the theory of staged financing predicts, on a population that theory has never had available.

5. The taxonomy and what it does to the hypothesis

The panel module showed that equity rounds concentrate in a type of firm rather than in a particular year of a given firm's life: revenue growth and operating cash flow matter across firms and vanish within them. That leaves open a question the equation cannot settle on its own, because it is a question about the population and not about the coefficients — whether a type exists at all, and if it does, whether it is one type or several. A partition estimated on balance-sheet configurations alone, blind to the dependent variable and to registry status, answers it without building the answer into the question.

Ten dimensions are used, computed as firm averages over the years the firm enters the panel estimation sample and standardised: revenue growth, cash over assets, operating cash flow over assets, operating result over assets, intangible and tangible fixed assets over assets, debt over assets, log total assets, age and capital turnover. All ten are reported by 2,876 of the 2,905 firms, ninety-nine per cent. Six algorithms — K-means, fuzzy C-means, Ward's hierarchical method, a Gaussian mixture, a random-forest proximity embedding and DBSCAN — are scored on eleven validity indices for every number of clusters from two to twelve.

The fit indices are monotone in the number of clusters by construction: R^2 rises from 0.16 to 0.54 and the information criteria fall without ever reversing. Neither can therefore identify the algorithm or the value of k , and the ranking must be built on the indices that an increase in k does not automatically

reward. Algorithms are ranked within each k on silhouette, Calinski–Harabasz, Dunn, Pearson gamma, minimum separation, maximum diameter and concentration, and the ranks are then averaged.

Table 7. Algorithm ranking, mean rank within k

Algorithm	Mean rank
K-means	2.123
Fuzzy C-means	2.688
Hierarchical (Ward)	2.825
Random forest (proximity)	3.240
Model-based (GMM)	4.188
Density-based (DBSCAN)	5.643

Note. Mean of the ranks on seven indices that are not monotone in k , computed separately for each number of clusters and then averaged over the eleven values of k . Rank 1 is best. DBSCAN yields an admissible partition for only two values of the radius, both reported in the full grid in the appendix.

K-means wins at 2.12, ahead of fuzzy C-means at 2.69 and Ward at 2.83; the Gaussian mixture comes fifth at 4.19 and DBSCAN last. The gap between the first three is modest and the choice is not dramatic, but the direction is clear: on ten standardised accounting dimensions, spherical partitions separate better than density-based ones, because the space of accounting ratios contains no empty regions for a density procedure to exploit. DBSCAN indeed labels almost everything as noise or as a single block, with a negative silhouette in both admissible configurations.

With the algorithm settled, k remains, and for that the indices with an interior maximum are needed.

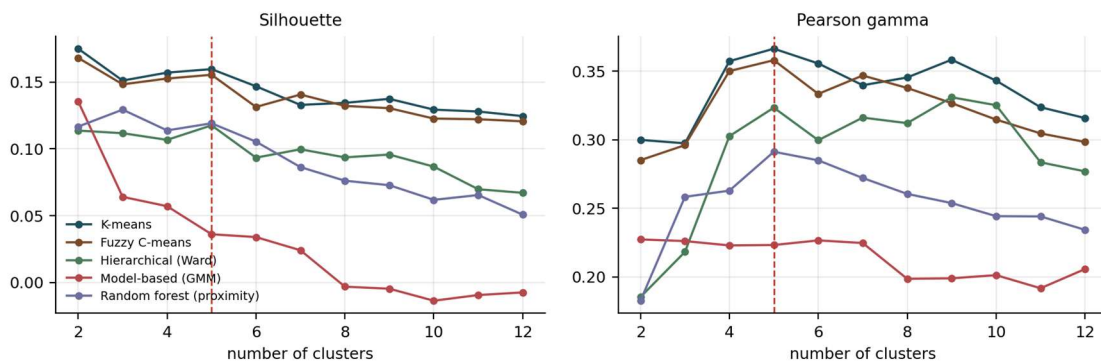


Figure 3. Silhouette and Pearson gamma by algorithm and number of clusters. Note. The vertical line marks the retained solution. DBSCAN is omitted from the plot because it is defined for only two values of k .

The Pearson gamma of K-means has a clear maximum at five clusters, 0.3664 against 0.3573 at four and 0.3556 at six, and the silhouette has a local maximum at the same point, 0.1595, after descending from the degenerate two-group case. The two-cluster solution has a higher silhouette, 0.1748, but places fifty-four per cent of the firms in a single group and has a Pearson gamma of 0.2999: it separates little and describes less. Five is where the two indices agree, and it is the retained partition.

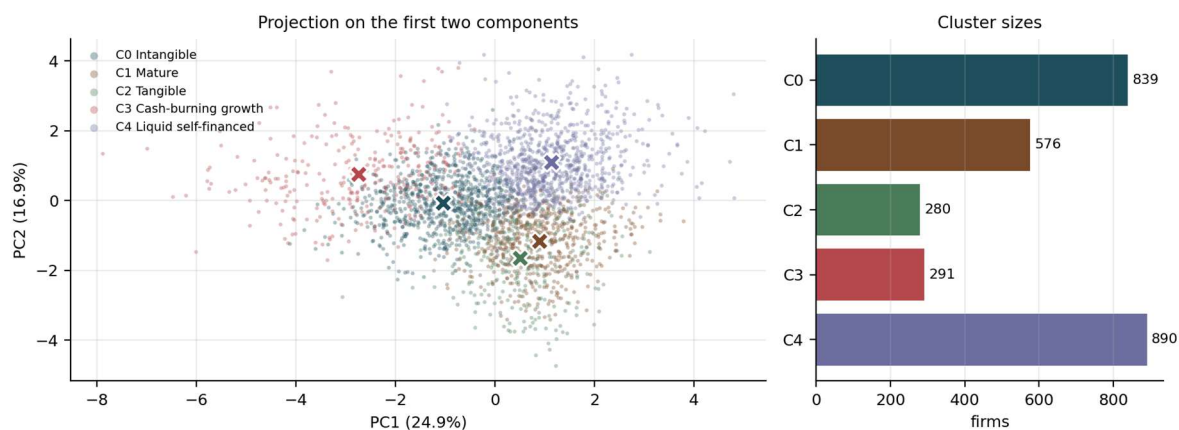


Figure 4. The five clusters in the plane of the first two principal components. Note. Crosses mark the centroids. The first two components account for 24.9 and 16.9 per cent of total variance. The first contrasts profitability and capital turnover with intangibles; the second contrasts cash with size, age and tangible assets.

Read in original units the five groups are unambiguous. The first, 839 firms, holds 43.6 per cent of assets in intangible fixed assets, has a median age of five years and a capital turnover of 0.40: a firm whose balance sheet is almost entirely intangible capital. The second, 576 firms, is seventeen years old, has the largest assets and a positive operating result: the mature SME that entered the register halfway through its life. The third, 280 firms, carries 36.7 per cent in tangible fixed assets. The fourth, 291 firms, grows at 42 per cent a year, holds 25.9 per cent of assets in cash and burns 28.7 per cent of assets a year in negative operating cash flow, with an operating result of -0.397 . The fifth, 890 firms, has the highest cash, the lowest leverage, the highest turnover and a positive result: it finances itself.

Table 8. Cluster centroids in original units, and stability

Dimension	C0 Intang.	C1 Mature	C2 Tangible	C3 Cash-burning	C4 Liquid
Revenue growth	0.187	0.082	0.201	0.422	0.241
Cash / assets	0.107	0.143	0.097	0.259	0.307
Operating cash flow / assets	0.030	0.081	0.073	-0.287	0.116
Operating result / assets	-0.049	0.061	0.034	-0.397	0.101
Intangibles / assets	0.436	0.117	0.098	0.303	0.102
Tangibles / assets	0.038	0.071	0.367	0.051	0.050
Debt / assets	0.560	0.530	0.595	0.555	0.447
ln(total assets)	6.904	8.355	7.599	6.921	6.332
Age (years)	5.430	16.858	9.108	4.942	6.005
Capital turnover	0.398	0.814	0.579	0.490	1.102
Firms	839	576	280	291	890
Bootstrap Jaccard	0.882	0.803	0.771	0.889	0.868

Note. Means of firm averages. The bootstrap Jaccard is the mean over fifty resamples of the maximum overlap between each cluster and the resampled partition; the conventional stability threshold is 0.75.

All five groups clear the conventional stability threshold, between 0.771 and 0.889, which is unusual and follows from the dimensions being few and strong. The taxonomy is not an artefact of the sample.

A partition built on financial ratios could be a sector classification in disguise, and the data allow the objection to be tested directly. Matched against the 19 ATECO activity sections, the five clusters return an adjusted Rand index of 0.039 and a corrected Cramér's V of 0.174; against the 68 two-digit divisions, 0.038 and 0.238. The chi-square is large because the sample is, but the overlap is negligible. The substantive reading is clearer than the coefficients: information and communication services are the modal section in four of the five clusters, with shares between 38 and 52 per cent, and that single section — 1,323 firms, the largest in the population — contains all five configurations, 32.4 per cent of it in the intangible cluster and 35.9 per cent in the self-financed one. The one cluster with a sector tilt is the tangible group, where manufacturing rises to 43.2 per cent against 9 to 27 elsewhere, which is what tangible fixed assets should imply. Four of the five configurations cut across industries.

The point that bears on the hypothesis comes now. If the link between growth and equity rounds were a property of one type of firm, the equation estimated within clusters should switch on in one and off in the others.

Table 9. The equity-round equation estimated within each cluster

Cluster	Obs.	Firms	Rounds %	Revenue growth	Op. cash flow / assets	Intangibles / assets
C0 Intangible	4504	839	18.0	0.0182 (0.0063)	-0.2475 (0.0389)	0.1012 (0.0300)
C1 Mature	4222	576	4.8	0.0390 (0.0141)	-0.1773 (0.0579)	0.0773 (0.0303)
C2 Tangible	1713	280	6.8	0.0391 (0.0127)	-0.4025 (0.0844)	0.1357 (0.0676)
C3 Cash-burning growth	1445	291	37.5	0.0361 (0.0122)	-0.1004 (0.0457)	0.1841 (0.0779)
C4 Liquid self-financed	5319	890	5.5	0.0215 (0.0056)	-0.1448 (0.0247)	0.2425 (0.0374)

Note. Pooled estimates with the same seven regressors as Table 3 and firm-clustered standard errors in parentheses. Rounds % is the share of years at risk with an increase in the share-premium reserve above one per cent of assets.

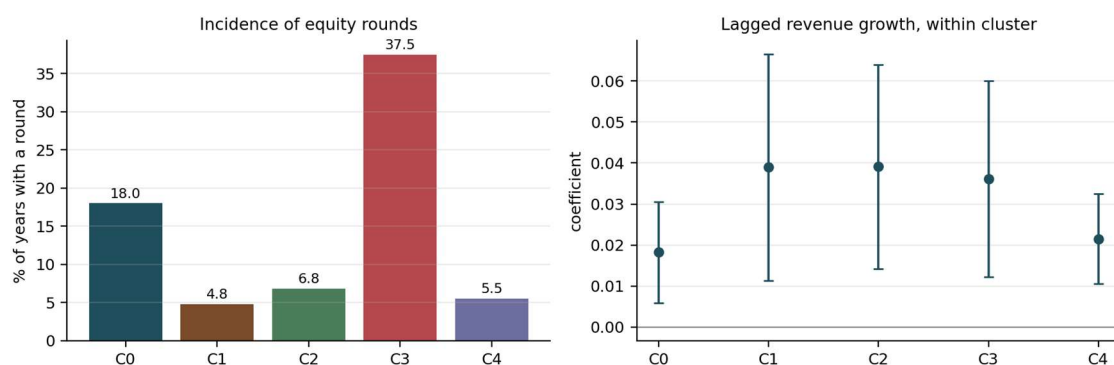


Figure 5. Incidence of rounds and the growth coefficient within clusters. Note. On the right, 95 per cent intervals on the coefficient of lagged revenue growth.

The growth coefficient is positive and significant in all five groups, with t statistics between 2.77 and 3.82, and operating cash flow is negative in all five. The mechanism behind the hypothesis does not belong to a configuration: it holds everywhere. The Wald test of equality across the five coefficients nonetheless rejects, with a chi-square of 30.9 and p below 0.001, and the magnitude varies by a factor of two, from 0.018 in the intangible cluster to 0.039 in the mature and the tangible ones. Growth matters more where rounds are rare.

What varies spectacularly is the incidence, not the coefficient. Thirty-seven and a half per cent of the years in the cash-burning growth cluster contain a round, against 18.0 per cent in the intangible cluster and under seven per cent in the other three — eight times the frequency between the most active group and the most inert. The taxonomy recovers from the accounts alone, without ever seeing the share-premium reserve, the population that raises risk capital, and it splits that population into two types the single equation conflated: a small core that burns cash and raises continuously, and a group three times larger, intangible and not deeply loss-making, that raises at an intermediate frequency. Growth is the selection criterion everywhere; the financial configuration decides how often the criterion is applied.

6. Is the linear equation adequate?

The panel module imposed a linear and additive equation on a binary outcome, and the clustering module showed that the coefficient it estimates is common to five very different financial configurations. Neither exercise can tell whether the form itself is a good approximation. That question is answered by fitting flexible learners to exactly the same variables and asking how much predictive content the linear specification leaves on the table. The purpose here is validation and not prediction: a large gap would mean the panel coefficients describe a surface they cannot represent, while a small one means the linear reading is safe.

Six learners are compared — linear regression, a linear support vector machine, k -nearest neighbours, a decision tree, a random forest and gradient boosting — under five-fold cross-validation grouped by firm, so that no firm ever appears in both the training and the test fold and the comparison is not inflated by within-firm persistence. The exercise is run twice. Once on raw levels, which is the variation a pooled or between estimator uses, and once on data demeaned by firm and by year, which

is exactly the variation the two-way fixed-effects estimator uses. Running it only on levels would answer a different question from the one the panel module asks.

Table 10. Six learners on raw levels, firm-grouped cross-validation

Learner	R ² out-of-sample	RMSE	MAE	AUC	Spearman	Ratio to linear
Linear regression	0.0981	0.3024	0.1865	0.7661	0.2935	1.00
Linear SVM	-0.1293	0.3383	0.1145	0.5774	0.0853	-1.32
K-nearest neighbours	0.0931	0.3032	0.1770	0.7532	0.2798	0.95
Decision tree	0.0810	0.3052	0.1805	0.7495	0.2752	0.83
Random forest	0.0949	0.3029	0.1822	0.7663	0.2937	0.97
Gradient boosting	0.1077	0.3008	0.1798	0.7747	0.3030	1.10

Note. 17,235 observations on 2,905 firms; five folds grouped by firm. The dependent variable is the binary round indicator, so the linear learner is a linear probability model and R² is computed out of sample against the observed zero–one outcome. The last column is the ratio of each learner's R² to that of linear regression.

On levels the linear probability model reaches an out-of-sample R² of 0.0981 and an AUC of 0.766. Gradient boosting, the best of the flexible learners, reaches 0.1077 and 0.775. The ratio is 1.10: allowing arbitrary non-linearity and arbitrary interaction in seven predictors recovers ten per cent more predictive content than a straight line through them. The random forest does slightly worse than the linear model at 0.0949, nearest neighbours at 0.0931 and the decision tree lowest among the usable learners at 0.0810. The linear support vector machine is the only genuine failure, at –0.129, and the reason is mechanical rather than substantive: its epsilon-insensitive loss is designed for a continuous target and collapses towards predicting the majority class on an outcome that takes only two values, which its AUC of 0.577 confirms.

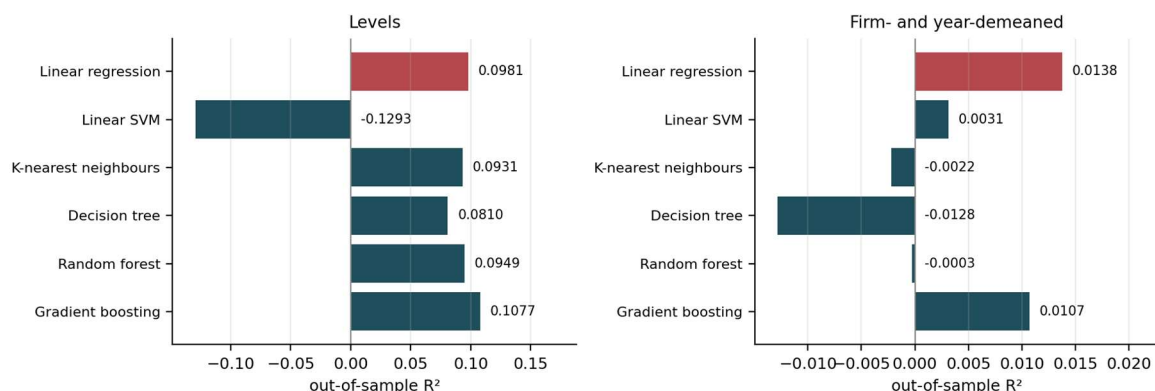


Figure 6. Out-of-sample R² by learner and by sample. Note. The linear learner is marked in a different colour. Negative values indicate a learner predicting worse than the sample mean.

The demeaned exercise is the stricter of the two, and its result is stronger.

Table 11. Six learners on firm- and year-demeaned data

Learner	R ² out-of-sample	RMSE	MAE	AUC	Spearman	Ratio to linear
Linear regression	0.0138	0.2490	0.1370	0.6094	0.1613	1.00
Linear SVM	0.0031	0.2503	0.1318	0.6599	0.2066	0.23
K-nearest neighbours	-0.0022	0.2510	0.1443	0.5753	0.1098	-0.16
Decision tree	-0.0128	0.2523	0.1444	0.5878	0.1187	-0.93
Random forest	-0.0003	0.2508	0.1433	0.6087	0.1464	-0.02
Gradient boosting	0.0107	0.2494	0.1369	0.6123	0.1557	0.78

Note. Both the dependent variable and the predictors are demeaned by firm and by year before fitting, reproducing the variation used by the two-way fixed-effects estimator. Same folds as Table 10.

Once firm and year means are removed, linear regression is the best of the six. Its R^2 of 0.0138 is small in absolute terms, which the panel module already showed — within the firm almost nothing predicts a round — but no flexible learner improves on it. Gradient boosting falls to 0.0107, the random forest to -0.0003 , the decision tree to -0.0128 . The ratio of best to linear is 1.00. There is no non-linear structure left in the within-firm variation for a flexible method to find; what little signal exists there, the linear equation already extracts.

Taken together the two tables settle the functional-form question in favour of the specification actually used. A useful benchmark is that the same procedures applied to accounting levels in related work routinely return ratios of three to five, and the maturity-matching study on this same source reported 1.27. A ratio of 1.10 on levels and 1.00 within the firm places this equation at the safe end of that range. The linearity imposed in the panel module is adequate rather than merely convenient.

One objection survives that exercise. The dependent variable takes two values, so an out-of-sample R^2 computed against a zero–one outcome is bounded in ways that make its level hard to read, and a learner built for continuous targets can fail for reasons that have nothing to do with functional form. The second part of the model supplies a continuous target on the same seven predictors, and repeating the comparison on it removes the ambiguity.

Table 12. Six learners on the amount raised, firm-grouped cross-validation

Learner	R ² out-of-sample	RMSE	Spearman	Ratio to linear
Linear regression	0.3617	1.2372	0.5949	1.00
Linear SVM	0.3578	1.2410	0.5943	0.99
K-nearest neighbours	0.3052	1.2908	0.5478	0.84
Decision tree	0.2988	1.2967	0.5376	0.83
Random forest	0.3452	1.2531	0.5723	0.95
Gradient boosting	0.3059	1.2902	0.5439	0.85

Note. Dependent variable: log of the amount raised, 1,973 round-years on 1,051 firms, standard deviation 1.549. Same folds, same predictors and same fixed hyperparameters as Tables 10 and 11. On data demeaned by firm and by year the ordering is unchanged: linear regression 0.0448, linear

SVM 0.0429, random forest 0.0375, nearest neighbours 0.0309, gradient boosting -0.0669 , decision tree -0.0579 .

On a continuous target the linear specification is not merely competitive but best, on levels and on demeaned data alike, and the R^2 is now interpretable in the ordinary way: the seven predictors account for thirty-six per cent of the out-of-sample variance in the log amount raised. Every flexible learner falls below the line, by between five and seventeen per cent, and the ordering is the same in RMSE and in rank correlation. The linear support vector machine, which failed on the binary target, performs at 0.358 against 0.362 — its earlier collapse was an artefact of an outcome taking two values and not a statement about the model or the data. Whatever curvature gradient boosting recovered on the probability margin does not exist on the intensive one.

Two diagnostics explain why, and both matter for how the panel coefficients should be read.

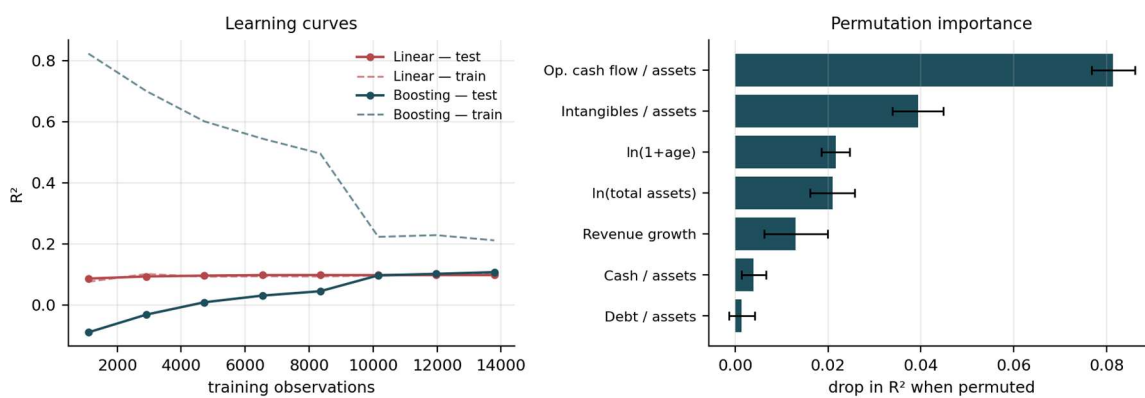


Figure 7. Learning curves and permutation importance. Note. Left: mean training and test R^2 across the five firm-grouped folds at eight training-set sizes. Right: drop in held-out R^2 when each predictor is permuted, twenty repetitions, bars showing one standard deviation. Both computed on the binary target.

The learning curves show that the small gap is not an artefact of sample size. The boosting test score plateaus early and rises by little over the last two thirds of the data, while its training score falls towards the test score — the signature of a model that has stopped memorising. The linear curve is flat almost from the start, which means additional observations will not help it; but since it is not being outperformed, what it is missing is not information either.

Permutation importance, computed on held-out data so that it measures contribution to genuine prediction rather than in-sample fit, orders the predictors in a way that confirms the panel reading. Operating cash flow accounts for 44.8 per cent of the total drop in R^2 , intangible assets for 21.6, age for 11.9 and size for 11.5. Revenue growth, which is the focal regressor of the hypothesis, accounts for 7.2 per cent. This is not evidence against the hypothesis, and it is important not to read it as such: a variable can matter per unit and matter little for prediction when its coefficient is modest relative to the dispersion of the outcome. What the ranking says is that if the object were to predict which firm raises capital next year, one would look first at whether it is burning cash and how intangible its balance sheet is. The question here is a different one.

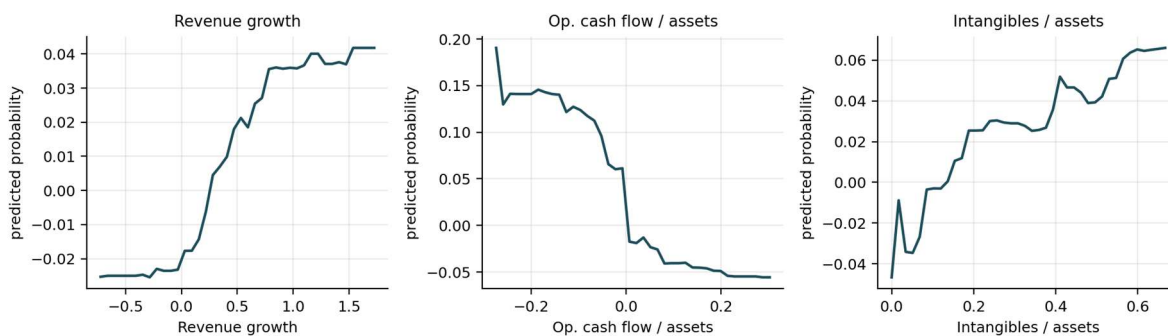


Figure 8. Partial dependence on the three leading predictors. Note. Averaged partial dependence from the gradient-boosting fit on levels, over the full sample.

The partial-dependence profiles are the visual form of the same conclusion. Revenue growth enters close to monotonically and with mild curvature; operating cash flow declines steeply over the negative range and flattens once it turns positive, which is the one genuine departure from linearity in the system; intangible intensity rises steadily. None of the three shows the reversals or thresholds that would invalidate a linear reading, and the flattening in cash flow is a saturation rather than a sign change.

Interaction strength completes the picture. Friedman's H^2 is highest for intangible assets with age, at 0.097, followed by revenue growth with operating cash flow at 0.053 and revenue growth with leverage at 0.050. All ten leading pairs sit below 0.10, so interactions are second-order: a purely additive surface would show parallel contours, and the curvature present is visible but slight. The additivity the panel equation assumes is therefore not contradicted, and the two per cent of predictive content that separates gradient boosting from the linear model on the binary margin is spread thinly across several weak interactions rather than concentrated in one that the specification omits.

7. Discussion

The three modules were built to answer different questions and they converge on the same account of the phenomenon. Outside equity in this population arrives at firms that are growing, does not arrive at firms whose cash is draining away, and is followed rather than preceded by losses and by a shift of the asset base towards the intangible. The panel module establishes the sequence, the taxonomy establishes that it is not the property of a single kind of firm, and the validation module establishes that the linear equation used to state it is an adequate description of the surface it sits on. Convergence across three procedures that share only the sample is worth more than any one of them, because the failure modes differ: a spurious panel association would not survive a partition built without seeing the outcome, and a badly specified functional form would leave predictive content for a flexible learner to pick up.

Where the result qualifies the hypothesis as it was written is instructive. Risk capital does not arrive at firms that are «doing well» in the accounting sense. It arrives at firms that are growing and losing money at the same time, which is a different statement and a more useful one. Growth and profitability are routinely bundled into a single notion of firm quality — the composite measurement approach of Onesti et al. (2022) is an explicit example, and Innocenti and Zampi (2019) ask what a start-up needs to grow without separating the two margins. In this population the two come apart, and the financing margin tracks only one of them.

The sharpest finding is also the least comfortable. Growth and cash flow predict an equity round across firms and predict nothing within the firm. This is not a robustness failure to be managed in a footnote; it is a statement about what kind of object the financing margin is. Equity goes to a type of company — young, intangible, growing, unprofitable — more than it goes to a particular year in the life of a given company.

The pecking-order tradition on which much SME-finance work rests carries the opposite implicit structure. When Venturelli and Gualandri (2009) ask what determines the need for equity, or Kwak (2021) revisits the ordering for high-technology SMEs, or Carpentier, L'Her and Suret (2012) study seasoned offerings by smaller firms, the object is a decision that a firm takes when its own position changes. A within-firm test of that logic on these data would return nothing and would be read as a null. What the two dimensions together show is that the null would be an artefact of the question rather than of the phenomenon: the selection happens once, at the level of what the firm is, and the timing within that type is governed by something these seven predictors do not contain.

This has a direct consequence for how the evaluation literature on Decree-law 179/2012 should read financing outcomes. Studies that use registry status as a treatment and measure firm-level responses — Giraudo, Giudici and Grilli (2019), Ferrucci et al. (2021), Biancalani, Czarnitzki and Riccaboni (2022), Accetturo (2022) — are looking for within-firm movement. On the equity margin there may be very little to find, not because the regime is inert but because the margin itself is a cross-sectional property.

The partition was estimated blind to the event, which is what makes its agreement with the panel module informative rather than circular. Its contribution is a distinction the single equation could not draw. The mechanism is universal — the growth coefficient is positive in every configuration — while the incidence is not, differing roughly eightfold between the configuration that grows fastest while burning cash and the configurations that finance themselves. A pooled equation reports one number that is the average of two populations behaving at very different frequencies.

This is also where the design reaches something the investor-record literature cannot. Grilli (2019) on business angels and local financial markets, Bronzini, Caramellino and Magri (2020) on venture screening, and Åstebro, Rafih and Serrano (2022) on European founder teams all describe the firms that professional capital reaches. The base rate among configurations that professional capital does not reach is not measurable from those sources at all, because the absence of a record and the absence of a round are indistinguishable there. Reading the event from the accounts separates them.

One detail of the partition deserves emphasis because it cuts against an expectation. Revenue growth turns out to be nearly redundant for the taxonomy: removing it barely changes the solution, while tangibility, profitability, age and cash flow carry it. Growth, in other words, separates years within a firm more than it separates firms from one another — which is exactly the pattern the panel module found from the opposite direction, and which the Italian literature's habit of treating growth as a defining firm characteristic does not anticipate.

The validation module answers a question of form, not of identification, and the distinction matters for how its result should be used. A best-to-linear ratio close to one, on the demeaned data that reproduce the estimator's own variation, licenses reading the panel coefficients as a description of the conditional expectation. It licenses nothing about causality, and the paper's estimand remains a conditional association throughout.

Two by-products are worth carrying beyond this paper. The first is procedural: cross-validation folds must be grouped by firm, because outcome and predictors are both persistent within companies and ungrouped folds let a flexible learner recover that persistence and present it as structure. Applied corporate finance uses firm panels constantly and reports grouping rarely. The second is interpretive. The focal regressor of the hypothesis ranks low in permutation importance, well behind cash flow and intangibility, and it would be easy — and wrong — to report that as evidence against the hypothesis. Importance for prediction and importance per unit are different quantities, and Hooker, Mentch and Zhou (2021) give the technical reason why the first should not be read as the second. The presentation conventions of Inglis, Parnell and Hurley (2022) are followed for the same reason.

Table 13. Results by method, and their standing relative to the existing literature

Method	Result obtained	What the literature holds	Status	What follows
Panel	Revenue growth in the year before a round is roughly double that of other years, and cash over assets is identical.	Staged financing predicts that capital follows realised performance (Greenberg, 2013; Lezana et al., 2026; Kim & Marzocchi, 2026).	Confirmatory	The prediction survives on a population observed without an intermediary filter, which is where it had never been tested.
Panel	Six firms in ten close the year before the round at a loss, against roughly one in four elsewhere.	Equity is commonly read as selecting firm quality, with growth and profitability treated as one dimension (Innocenti & Zampi, 2019; Onesti et al., 2022).	Counterfactual	Selection operates on growth and not on profitability. The two must be separated in any measure of start-up quality built for financing questions.
Panel	Cash and profitability are flat before the round; profitability falls and intangible assets rise after it.	Intangible capital shrinks debt capacity and pushes firms towards outside equity and cash (Brown & Petersen, 2011; Booth et al., 2015; Falato et al., 2022).	Confirmatory	The channel is observed as a dated sequence in private firms rather than inferred from listed-firm cross-sections.
Panel	Growth and cash flow predict the round across firms and predict nothing within the firm.	The pecking-order tradition treats the debt-equity choice as a firm-level decision responding to the firm's own changing position (Venturelli & Gualandri, 2009; Carpentier et al., 2012; Kwak, 2021).	Oppositional	The margin is a property of firm type rather than of firm circumstance. A within-firm test of pecking-order logic would have concluded that nothing is there.
Panel	The local-demand instrument is strong across firms and collapses once firm and year means are removed.	Shift-share and leave-one-out designs are powerful but their exclusion restrictions and power are fragile (Jaeger et al., 2020; Borusyak et al., 2022; Apfel, 2024).	Confirmatory	The warning is not hypothetical. Reporting first-stage strength by dimension, not only overall, should be standard in firm-level applications.

Method	Result obtained	What the literature holds	Status	What follows
Panel	At-par capital increases respond weakly, and the legal-reserve placebo reverses the sign of the cash-flow coefficient.	No prior study uses the share-premium line as a financing event, so no validation protocol exists (cf. Le Manh, 2025, on the accounting regime).	Innovative	The measure separates outside capital from equity accumulated out of profit, which is the condition for the whole design to mean anything.
Clustering	Five financial configurations, all stable to bootstrap resampling, recovered without seeing the event.	Italian taxonomies of innovative firms partition on location, knowledge base and sector rather than on financial configuration (Colombelli, 2016; Antonietti & Gambarotto, 2020; Cavallo et al., 2020).	Innovative	A financial taxonomy of the certified population exists and is reproducible, and it is orthogonal to the geographic one the literature uses.
Clustering	The growth coefficient is positive and significant inside every one of the five groups.	Financing behaviour is often argued to be heterogeneous across firm types, with mechanisms switching on in some and off in others.	Confirmatory	The mechanism is general within this population. Heterogeneity in this setting is about how often it operates, not whether it does.
Clustering	The share of years containing a round differs roughly eightfold between the most and the least active configuration.	The literature observes which firms raise from investor records, which cannot measure the base rate of a configuration that investors do not reach.	Innovative	Incidence, not elasticity, is where financial configuration matters. A single pooled equation conflates two populations with very different frequencies.
Clustering	Revenue growth is nearly redundant for the partition; tangibility, profitability, age and cash flow carry it.	Growth is treated as a defining dimension of start-up type in much of the Italian evaluation literature (Innocenti & Zampi, 2019; Rocha & Grilli, 2024).	Counterfactual	Growth separates years within a firm more than it separates firms, which is consistent with the panel result and reinforces it from an independent direction.
ML regression	The best flexible learner improves on the linear model by about a tenth on levels and not at all on demeaned data.	Flexible learners applied to accounting levels routinely improve substantially on linear specifications, including in prior work on this data source.	Confirmatory	The linear probability model is adequate rather than convenient. The panel coefficients describe a surface they can represent.
ML regression	Cross-validation folds grouped by firm are necessary; without grouping, persistence inflates every learner.	Grouped validation is standard in prediction work but rarely reported in applied corporate finance, where firm panels are the norm.	Innovative	A specification test that does not group by firm will find non-linearity that is persistence. This should be stated wherever the protocol is used.
ML regression	The focal regressor accounts for a small share of permutation importance, well behind cash flow and intangibility.	Permutation importance is widely read as a measure of a variable's substantive weight, a reading Hooker et al. (2021) show to be unsafe.	Counterfactual	Importance for prediction and importance per unit are different quantities. The finding is not evidence against the hypothesis and must not be reported as if it were.
ML regression	All leading interaction pairs fall below the conventional threshold; the strongest is intangibility with age.	Additivity is almost always imposed in panel financing equations and almost never tested.	Confirmatory	Additivity survives here. The one interaction worth adding has an economic reading and is recorded rather than silently omitted.

Note. Confirmatory: the result reproduces a claim the literature makes, on a population or a measure where it had not been tested. Counterfactual: the result reverses an expectation the literature's framing generates, without contradicting a claim it has tested. Oppositional: the result contradicts a claim the literature has tested. Innovative: no comparable claim exists, so the result has no counterpart to agree or disagree with. Magnitudes and test statistics are reported in Sections 4 to 6; the wording here is deliberately qualitative so that the table can be read against the literature rather than against the tables.

For research, the immediate implication is a measurement one. The share-premium reserve is a compulsory, disclosed and restricted line in every filed set of accounts in Italy and in jurisdictions with comparable rules, such as the French regime examined by Le Manh (2025). Any question about outside equity in private firms that has so far been answered on intermediated samples can be re-asked on complete populations, and the direction in which the answers would move is knowable only

by doing it. The finding that selection runs on growth rather than profitability is a first instance of what that re-asking can produce.

For policy, the implication is narrower than it may appear, and the paper is careful not to overstate it. Nothing here identifies an effect of certification, because certification is not used as a treatment. What the design does show is that the equity margin of certified innovative SMEs is observable, dated and complete, which means the schemes evaluated by Accetturo (2022), Santoleri and Russo (2025) and Albanese and Bronzini (2026) can in future be assessed against an outcome that has so far been out of reach. If the object of a start-up policy is to bring risk capital to firms that cannot borrow against their assets, then whether risk capital actually arrived is now a question with an answer in the accounts.

Three limits bound all of this and are restated rather than relegated. The reserve identifies that priced capital entered and when, but not who supplied it, so nothing here speaks to investor type and the intermediated literature retains its advantage on that margin. The balance-sheet detail exists only for the certified population, so no comparison with non-certified firms is available. And the design establishes what precedes a round, not what a round causes: the pre-trend in growth that confirms the hypothesis is precisely what forbids reading the post-round movements as its consequences.

8. Policy implications

The first implication is about measurement rather than about any particular scheme. Evaluations of Decree-law 179/2012 have had to work with outcomes that public registers and commercial databases happen to record: entry and survival in Accetturo (2022) and Albanese and Bronzini (2026), the composition of applicants in Santoleri and Russo (2025), a broad set of firm outcomes in Biancalani, Czarnitzki and Riccaboni (2022), access to credit in Ferrucci et al. (2021). The equity margin has been the exception, available only for firms that raised from a professional investor willing to disclose the deal — the constraint that also binds Grilli (2019) and Giraudo, Giudici and Grilli (2019). The share-premium reserve removes it. Whether risk capital actually arrived, in what year and at what scale, is now a question answerable from filed accounts for every company in the population, and any future assessment of the regime can use it as an outcome.

The second concerns what such an assessment should expect to find. Growth, not profitability, is what precedes an equity round, and six firms in ten that raise closed the preceding year at a loss. A scheme judged on whether supported firms become profitable would therefore be judged on the wrong margin: in this population the firms that attract capital are precisely those that are expanding while losing money. This matters for instrument design as much as for evaluation. Measures that condition eligibility or renewal on profitability — or on any composite of quality that bundles growth and earnings together — would screen out the firms the equity market itself selects.

The third is institutional. The result that the financing margin is a property of firm type rather than of firm circumstance implies that instruments acting on the firm's current position, such as the targeted equity injections discussed by Díez et al. (2022), operate on a dimension where these data show little movement. Instruments that change which firms exist, or which firms are visible to investors, act on

the dimension where the variation actually lives. The corporate-law reforms described by Giudici and Agstner (2019), Agstner (2024) and Enriques, Giudici and Agstner (2026), and the opening of equity crowdfunding to registered firms analysed by Policaro (2019), belong to that second category, and this evidence gives a reason to prefer them.

A fourth implication is administrative and cheap. Because the measure rests on a compulsory, restricted and disclosed line of the statutory accounts — the same accounting logic Le Manh (2025) documents for France — it requires no new reporting obligation, no survey and no agreement with data vendors. The information already exists in the filings that firms are required to deposit. What is needed is that evaluation practice start reading it, and that public agencies publishing firm-level registers include the fiscal code consistently, so that register and accounts can be linked without recourse to name matching.

9. Limitations

The design establishes what precedes an equity round, not what a round causes. The pre-trend in revenue growth that confirms the hypothesis is precisely what forbids reading the post-round movements in profitability and intangible assets as consequences of the capital injection. The event study describes selection into financing, and the panel coefficients are conditional associations. An estimate of the effect of the round would require exogenous variation in the supply of capital, which these data do not contain.

The reserve identifies that priced capital entered and when, but not who supplied it. A subscription by a venture fund, by a business angel, by a crowdfunding platform or by an industrial shareholder are indistinguishable in the accounts. On investor type the intermediated literature retains a real advantage, and studies such as Greenberg (2013), Åstebro, Rafih and Serrano (2022) and Bronzini, Caramellino and Magri (2020) answer questions this measure cannot reach. The two sources are complements rather than substitutes, and linking them at firm level is the obvious next step.

The balance-sheet items required to build the measure exist only for the certified population, because the abbreviated filings of smaller uncertified firms do not carry them at comparable coverage. There is therefore no control group, and nothing here establishes whether the same margin behaves the same way outside the register. Any extension to the wider population of unlisted firms depends on an extraction that supplies share capital, share premium, equity and retained results for firms that are not certified.

Two econometric limits are inherited. The instrument is a leave-one-out local demand shifter, and the concerns raised by Jaeger, Ruist and Stuhler (2020) about exclusion in this family, together with the formal treatment in Apfel (2024) and the guidance of Borusyak, Hull and Jaravel (2022), apply here in full; the instrument is used only in the dimension where it is strong, and the within-firm estimate is reported as uninformative rather than as a result. The dynamic specification carries the incidental-parameter problem addressed by Carro (2007) and Boneva and Linton (2017); its magnitude is stated and no conclusion rests on the autoregressive coefficient.

A further limit concerns the taxonomy. The partition is estimated on firm averages, so each company carries one configuration for the whole period; a firm that moves from burning cash to financing itself is classified once, and the within-cluster comparison is conservative as a result. The within-cluster estimates are also pooled rather than fixed-effects, because inside a single group the residual variation left after removing firm means is too thin to identify seven coefficients, so that part of the evidence is cross-sectional by construction.

Finally, the two flexible-learner diagnostics have known interpretive limits. Permutation importance forces extrapolation into regions the data do not occupy, as Hooker, Mentch and Zhou (2021) show, so it is read as an ordering and never as a decomposition of substantive weight; display conventions follow Inglis, Parnell and Hurley (2022). And the validation module answers a question of functional form only. A linear specification can approximate the conditional expectation well, as it does here, and still fail to recover a causal parameter — a distinction the results section keeps and that any use of these coefficients should keep too.

10. Conclusions

This paper set out to test a simple proposition: that outside equity arrives at firms that are growing rather than at firms running out of cash. The proposition is confirmed, with one qualification that changes what it means. Capital does follow growth, and it does not follow a deteriorating cash position — on that the cross-sectional comparison, the event study and the instrumental estimates agree. But it does not follow profitability. The majority of firms that raise close the preceding year at a loss, and the losses deepen after the round rather than before it, alongside an asset base shifting towards the intangible. The sequence is that of an investment being funded, not of a firm being rescued. Selection operates on growth alone, and in this population growth and profitability are separate things.

The route to that answer is the second contribution, and possibly the more durable one. Equity rounds in private firms have been observed through the records of professional investors, which means through a sample selected on the presence of an intermediary. Reading the round from the share-premium reserve inverts that selection: every company that files accounts is observed, whoever subscribed. The measure survives the checks that matter — contributions at par respond weakly, and a placebo on a reserve fed by retained profit reverses the sign — so it is separating outside capital from equity accumulated out of earnings, which is the condition for anything else to follow.

Three procedures were applied to one sample and they converge. The panel module locates the association in the dimension across firms and finds nothing within them, which says that the financing margin is a property of firm type rather than of firm circumstance. A partition of the population estimated without seeing the event recovers five stable financial configurations, shows the mechanism operating inside every one of them, and reveals that what differs across them is not the strength of the relationship but how often a round occurs — a distinction a single equation cannot draw. Six flexible learners fitted to exactly the variation the estimator uses fail to improve on the linear specification once firm and year means are removed, which licenses reading the coefficients as a description of the surface rather than as a convenient approximation to something more complicated.

What remains open is causality and counterparty. The design says what precedes a round, not what a round produces, and the pre-trend that confirms the hypothesis is what forbids the causal reading. The accounts record that priced capital entered and when, but not who supplied it. Both gaps have obvious routes forward: exogenous variation in capital supply for the first, and a firm-level link between filed accounts and investor records for the second.

The wider point is that a compulsory line of a statutory balance sheet turned out to contain a financing margin that a large literature has studied only where an intermediary chose to report it. Questions answered on intermediated samples can be re-asked on complete populations, and the direction in which those answers move is knowable only by asking them.

11. Declarations

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Conflict of interest statement. The authors declare that they have no conflict of interest. None of the authors has any financial or personal relationship with any organisation or individual that could have appeared to influence the work reported in this manuscript. No author holds an interest, position or consultancy in any of the firms observed in the data, and none has received payment, sponsorship or benefit from any party with a stake in the findings. The research received no specific grant from any funding agency in the public, commercial or not-for-profit sectors, and was carried out with institutional support alone. The data provider had no role in the design of the study, in the collection, analysis or interpretation of the data, in the writing of the manuscript, or in the decision to submit it for publication.

Data availability statement. The financial data analysed in this study were obtained from the AIDA database (Analisi Informatizzata delle Aziende Italiane), distributed by Bureau van Dijk, a Moody's Analytics company, and available at <https://www.moody's.com/web/en/us/capabilities/company-reference-data/orbis/aida-orbis-for-italy.html>. AIDA contains the filed annual accounts, registry details and sector classification of Italian limited companies, with up to ten years of history. Access is by institutional subscription, and the authors accessed it under their institution's licence.

Because AIDA is a proprietary, licensed database, the underlying firm-level accounts cannot be redistributed by the authors. Researchers with a subscription can reproduce the extraction from the variable definitions and selection criteria set out in Appendix A of the manuscript, which specify the four balance-sheet and income-statement blocks, the reporting years and the reconciliation procedure applied. The registry information — incorporation dates, entry into the special section, declared requirements, ATECO 2007 activity codes and ownership prevalence indicators — comes from the public register of innovative start-ups and innovative SMEs maintained by the Italian Chambers of Commerce, available without restriction at <https://startup.registroimprese.it>. Descriptive material on the regime is published by the Ministry of Enterprise and Made in Italy at <https://www.mimit.gov.it/it/impresa/piccole-e-medie-imprese/pmi-innovative>. The code used to construct the panel, define the event, estimate the three modules and produce every table and figure, together with the derived and de-identified analysis dataset, is available from the corresponding author on reasonable request and will be provided to referees at any point in the review process.

Authorship contribution form. Conceptualization, A.L., M.d.M., V.N., M.G.T. and A.V.P.; data curation, A.L., M.d.M., V.N., M.G.T. and A.V.P.; formal analysis, A.L., M.d.M., V.N., M.G.T. and A.V.P.; investigation, A.L., M.d.M., V.N., M.G.T. and A.V.P.; methodology, A.L., M.d.M., V.N., M.G.T. and A.V.P.; project administration, A.L., M.d.M., V.N., M.G.T. and A.V.P.; resources, A.L., M.d.M., V.N., M.G.T. and A.V.P.; software, A.L., M.d.M., V.N., M.G.T. and A.V.P.; supervision, A.L., M.d.M., V.N., M.G.T. and A.V.P.; validation, A.L., M.d.M., V.N., M.G.T. and A.V.P.; visualization, A.L., M.d.M., V.N., M.G.T. and A.V.P.; writing—original draft, A.L., M.d.M., V.N., M.G.T. and A.V.P.; writing—review and editing, A.L., M.d.M., V.N., M.G.T. and A.V.P.

Appendix A. Sample construction

The accounts come from twenty AIDA extractions on innovative SMEs, organised in four blocks — balance-sheet assets, balance-sheet liabilities, income statement, ratios — for five bands of about 730 firms each, with calendar years from 2016 to 2025. The blocks carry no fiscal code and were reconciled on the normalised corporate name, stripping legal form, punctuation and liquidation wording. The reconciliation produces 3,228 keys against 3,225 firms with at least one filed set of accounts, so residual collisions number three.

Incorporation dates come from the register of innovative SMEs, 3,224 firms with the Business Register date complete at one hundred per cent, matched on the same key: 96.2 per cent of the firms in the panel receive an age. Province and the ISTAT municipality code come from the corporate block and cover one hundred per cent. The same register supplies the ATECO 2007 activity code, which covers 96.2 per cent of the firms in the panel and all of the estimation sample, and yields 68 two-digit divisions and 19 activity sections. The final panel has 26,584 firm-years with total assets reported on 3,225 firms; the estimation sample, which requires one contiguous lagged year on every regressor, has 17,179 observations on 2,900 firms.

Sector codes are matched from the same register and on the same key as the incorporation date, so the 124 firms without a sector are exactly those without an age and were already excluded by any specification containing it: coverage on the estimation sample is complete. Those firms have higher median revenue and headcount than the matched ones, but indistinguishable total assets and an indistinguishable round incidence, 0.122 against 0.129.

The event is defined as an increase in the share-premium reserve over the previous year, with contiguous years, above one per cent of lagged total assets. The threshold excludes rounding and is not binding: Table D1 shows the results do not depend on it. It yields 2,991 rounds on 1,330 firms, recording €4,218.8 million of capital, whose size distribution is reported below.

Table A1. The distribution of round sizes

Threshold	Rounds below	% of rounds	% of capital
€50,000	286	9.6	0.2
€100,000	568	19.0	0.7
€250,000	1,201	40.2	3.3
€500,000	1,754	58.6	8.2
€1,000,000	2,192	73.3	15.8
€2,000,000	2,523	84.4	27.1
€5,000,000	2,815	94.1	49.0
€10,000,000	2,925	97.8	66.9

Note. All 2,991 material rounds on 1,330 firms, 2016–2025. Median €383,004; tenth percentile €52,050; twenty-fifth €139,770; seventy-fifth €1,098,408; ninetieth €3,161,157; ninety-ninth €14,943,095.

The distribution is heavily skewed, and the skew bears on what an intermediated sample can observe. Seventy-three per cent of rounds fall below one million euro and together carry 15.8 per cent of the capital; at the other end, 176 rounds — 5.9 per cent of the events — carry 51 per cent. Whatever coverage floor a commercial deal database applies, the part of the margin beyond its reach consists of small and numerous operations rather than large ones. Reading the event from the accounts therefore adds few euros to what is already observable elsewhere: it adds events. That is the relevant addition, because a theory of financing decisions requires decisions rather than amounts, and because the timing structure exploited in the hazard of a second round — 531 repeat rounds at a median interval of one year — cannot be recovered from a source selected on deal size.

Appendix B. Full event-study coefficients

Table B1 reports the coefficients plotted in Figures 1 and 2. The base is the financial year immediately preceding the firm's first material round; the 1,895 firms that never raise remain in the sample as untreated controls.

Table B1. Event study around the first round, coefficients and standard errors

Event time	Revenue growth	Cash / assets	Op. cash flow / assets	Op. result / assets	Intangibles / assets
t – 3	0.1288** (0.0590)	0.0079 (0.0081)	0.0002 (0.0092)	0.0047 (0.0104)	–0.0028 (0.0079)
t – 2	0.0842* (0.0474)	0.0004 (0.0070)	0.0047 (0.0080)	0.0128 (0.0090)	–0.0043 (0.0065)
t – 1 (base)	0	0	0	0	0
t = 0	0.1233*** (0.0386)	0.0683*** (0.0063)	–0.0231*** (0.0058)	–0.0160** (0.0064)	–0.0112** (0.0049)
t + 1	0.1128***	0.0094	–0.0335***	–0.0332***	0.0158***

Event time	Revenue growth	Cash / assets	Op. cash flow / assets	Op. result / assets	Intangibles / assets
	(0.0348)	(0.0057)	(0.0065)	(0.0072)	(0.0051)
t + 2	−0.0062 (0.0343)	−0.0036 (0.0054)	−0.0153** (0.0061)	−0.0162** (0.0068)	0.0173*** (0.0048)
Observations	20,866	26,512	26,512	26,584	26,512

Note. Firm and year fixed effects; firm-clustered standard errors. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. The window stops at t+2 because beyond that point the number of firms observed falls below half.

The joint test on the two pre-round indicators is the check that matters for the hypothesis. For cash over assets both are indistinguishable from zero, as they are for operating cash flow and for the operating result: there is no anticipated deterioration. For revenue growth both are positive, and the one at three years is significant, which is precisely the pre-trend the hypothesis predicts and which in a causal design would instead be a problem. The event study here describes a selection rather than estimating a treatment effect, and should be read that way.

Appendix C. Within-firm instrumental variables

Removing firm and year effects before instrumenting, the first-stage coefficient falls from 0.262 to 0.079 and the F from 75.2 to 5.5, below every conventional relevance threshold. The second-stage estimate is 0.074 with a standard error of 0.134. It is uninformative and is not used: once firm and year means are removed, variation in provincial demand does not contain enough signal to identify the growth of an individual company. The instrumental conclusion in the main text holds for the across-firm dimension and not for the within-firm one, and is stated as such.

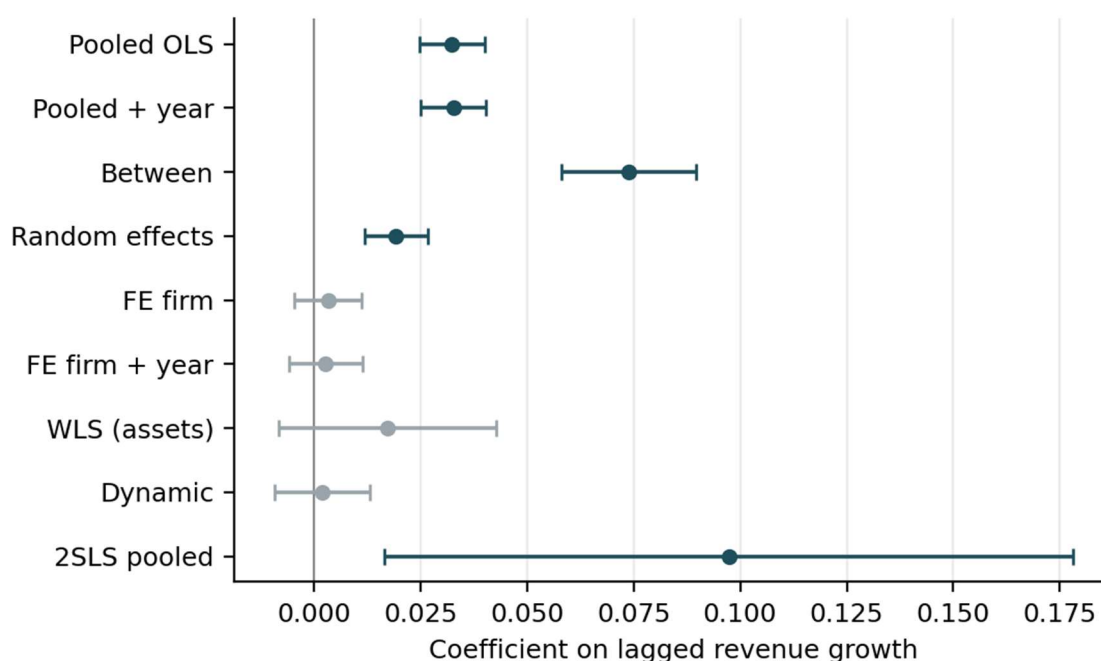


Figure C1. The coefficient on revenue growth across the nine estimators. Note. 95 per cent bars. Solid colour marks estimates significant at 5 per cent. The distance between the cross-sectional group and the within-firm group is the main result of Table 3.

Appendix D. Robustness to the definition of the event

Table D1. Alternative definitions of the event, and a placebo

Definition of the event	Events	N	Pooled: growth	Pooled: op. cash flow
Increase > 1% of assets (baseline)	1,973	17,235	0.0323 (0.0039)	−0.3275 (0.0185)
Any increase	2,081	17,235	0.0333 (0.0039)	−0.3336 (0.0187)
Increase > 5% of assets	1,789	17,235	0.0293 (0.0038)	−0.3142 (0.0181)
Share capital only, no premium	1,402	17,235	0.0089 (0.0031)	−0.0581 (0.0136)
Placebo: increase in the legal reserve	5,632	17,235	0.0433 (0.0042)	+0.6230 (0.0206)

Note. Pooled coefficients with firm-clustered standard errors in parentheses. Controls as in Table 3.

The first three rows show that the materiality threshold does not matter: moving from any increase to an increase above five per cent of assets shifts the coefficients in the third decimal. The fourth row isolates increases in share capital alone without any premium, which are at-par contributions by existing owners rather than priced rounds: the operating cash flow coefficient falls from −0.33 to −0.06, one sixth, confirming that the share-premium item does identify the entry of new capital and not a generic strengthening of equity.

The last row is the placebo. The legal reserve is fed by the compulsory appropriation of profit, so an increase in it should be associated with positive rather than negative cash flow. The coefficient is +0.62, opposite in sign to the main equation and twice the magnitude. The specification distinguishes equity accumulated out of profits from the injection of outside capital, which is the minimum condition for the rest of the work to mean anything.

Appendix E. Dynamic specification

Rounds are not independent over time: a firm that has just raised rarely raises again the following year. Table E1 adds the lag of the dependent variable to firm and year fixed effects.

Table E1. Dynamic model, firm and year fixed effects

Regressor (t−1)	Coefficient	Standard error	t
Round in the previous year	−0.1211	0.0153	−7.93
Revenue growth	0.0019	0.0057	0.33
Cash / assets	−0.0247	0.0258	−0.96
Operating cash flow / assets	0.0122	0.0309	0.40
Debt / assets	0.1223	0.0281	4.35
Intangibles / assets	0.1391	0.0352	3.96
ln(total assets)	−0.0198	0.0087	−2.26
ln(1+age)	−0.0479	0.0233	−2.05
Observations	14,279		

Note. Firm-clustered standard errors. Least squares with a lagged dependent variable and fixed effects is subject to Nickell bias, which with eleven periods is of the order of one ninth and acts downward on the autoregressive coefficient.

The autoregressive coefficient is -0.121 : after a round the probability of another round the following year falls by twelve points, consistent with financing that arrives in spaced stages. The other coefficients are unchanged relative to the fixed-effects column of Table 3: growth and cash flow remain null within the firm, the intangible share and debt remain positive. The dynamics absorb the persistence of the event without altering the substance.

Appendix F. What this exercise does not establish

Three limits should be recorded before the result is used. The first is that the share-premium reserve captures the entry of priced capital but does not identify its source: an increase subscribed by a venture capital fund and one subscribed by an industrial shareholder are indistinguishable in the accounts. The second is that the sample is that of innovative SMEs, and a control population with the same balance-sheet items does not exist in the available extractions: nothing here says whether the same margin behaves the same way in non-certified firms. The third is that the event study describes selection and does not estimate a causal effect of the round, because the pre-trend in growth — which for the hypothesis is the result — prevents reading the subsequent movements as consequences of the capital injection.

Appendix G. The clustering module in detail

The ten dimensions are firm averages computed over the years that enter the estimation sample of the panel module, after the winsorisation at the 1st and 99th percentiles applied there, and standardised to zero mean and unit variance before partitioning. All ten are reported by 2,876 of the 2,905 firms, so the loss is one per cent and introduces no appreciable selection. No dimension is the dependent variable of the panel module, and the share-premium reserve appears neither in level nor in difference: the partition is blind to the object of the paper, which is the condition under which the comparison in Table 9 means anything.

The table below reports the six algorithms over eleven values of k on eleven indices. Three regularities are visible reading down the columns. R^2 rises and the information criteria fall monotonically for every algorithm, so none of the three can identify k . Silhouette and Pearson gamma have interior maxima for K-means and fuzzy C-means but not for the Gaussian mixture, whose silhouette turns negative beyond eight components: a mixture that describes the density well can partition the space badly, and the two properties should not be conflated. The Herfindahl index falls mechanically with k and serves only to flag degenerate solutions, such as those of DBSCAN, where it exceeds 0.63.

Table G1. Six algorithms, eleven values of k , eleven validity indices

Algorithm	k	R^2	AIC	BIC	Silhou.	C-H	Dunn	Max diam.	Min separ.	Pearson	Entropy	HHI
Density-based (DBSCAN)	2	0.0017	14	199	-0.2515	2	0.0281	17.3126	0.4858	-0.0719	0.0482	0.9855

Algorithm	k	R ²	AIC	BIC	Silhou.	C–H	Dunn	Max diam.	Min separ.	Pearson	Entropy	HHI
Density-based (DBSCAN)	4	0.0256	-644	-340	-0.2516	19	0.0235	17.3126	0.4066	-0.1768	0.5911	0.6395
Fuzzy C-means	2	0.1615	-5.025	-4.900	0.1680	554	0.0286	17.3126	0.4950	0.2851	0.6735	0.5195
Fuzzy C-means	3	0.2571	-8.487	-8.302	0.1482	497	0.0281	17.3126	0.4858	0.2961	1.0967	0.3346
Fuzzy C-means	4	0.3247	-11.208	-10.963	0.1525	460	0.0244	17.3126	0.4230	0.3501	1.3346	0.2730
Fuzzy C-means	5	0.3746	-13.399	-13.095	0.1553	430	0.0244	17.3126	0.4230	0.3580	1.5292	0.2307
Fuzzy C-means	6	0.3971	-14.429	-14.065	0.1313	378	0.0361	17.3126	0.6248	0.3334	1.7384	0.1823
Fuzzy C-means	7	0.4437	-16.727	-16.303	0.1406	381	0.0280	17.3126	0.4845	0.3468	1.8829	0.1594
Fuzzy C-means	8	0.4696	-18.075	-17.592	0.1320	363	0.0355	13.6577	0.4845	0.3377	2.0249	0.1374
Fuzzy C-means	9	0.4869	-19.009	-18.466	0.1304	340	0.0361	13.4312	0.4845	0.3267	2.1476	0.1213
Fuzzy C-means	10	0.5022	-19.858	-19.256	0.1226	321	0.0380	12.7640	0.4845	0.3147	2.2668	0.1065
Fuzzy C-means	11	0.5143	-20.550	-19.888	0.1221	303	0.0424	12.4111	0.5268	0.3046	2.3659	0.0963
Fuzzy C-means	12	0.5245	-21.138	-20.417	0.1205	287	0.0354	12.4111	0.4395	0.2984	2.4440	0.0896
Hierarchical (Ward)	2	0.1152	-3.477	-3.351	0.1136	374	0.0399	17.3126	0.6912	0.1854	0.6889	0.5042
Hierarchical (Ward)	3	0.1961	-6.216	-6.032	0.1117	350	0.0376	17.3126	0.6509	0.2183	1.0032	0.4013
Hierarchical (Ward)	4	0.2651	-8.776	-8.531	0.1067	345	0.0376	17.3126	0.6509	0.3026	1.3119	0.2887
Hierarchical (Ward)	5	0.3151	-10.785	-10.481	0.1175	330	0.0376	17.3126	0.6509	0.3234	1.4534	0.2658
Hierarchical (Ward)	6	0.3512	-12.321	-11.957	0.0934	311	0.0376	17.3126	0.6509	0.2997	1.7060	0.1946
Hierarchical (Ward)	7	0.3803	-13.618	-13.195	0.0996	293	0.0486	13.3992	0.6509	0.3162	1.7956	0.1859
Hierarchical (Ward)	8	0.4080	-14.913	-14.430	0.0936	282	0.0486	13.3992	0.6509	0.3121	1.9390	0.1639
Hierarchical (Ward)	9	0.4282	-15.894	-15.351	0.0957	268	0.0486	13.3992	0.6509	0.3310	2.0051	0.1546
Hierarchical (Ward)	10	0.4442	-16.692	-16.090	0.0866	255	0.0486	13.3992	0.6509	0.3252	2.1038	0.1432
Hierarchical (Ward)	11	0.4576	-17.373	-16.711	0.0698	242	0.0486	13.3992	0.6509	0.2836	2.2848	0.1090
Hierarchical (Ward)	12	0.4697	-18.003	-17.282	0.0671	231	0.0486	13.3992	0.6509	0.2770	2.3772	0.1000
K-means	2	0.1625	-5.059	-4.933	0.1748	558	0.0361	17.3126	0.6248	0.2999	0.6553	0.5373
K-means	3	0.2576	-8.503	-8.318	0.1510	498	0.0351	16.7552	0.5874	0.2974	1.0930	0.3370
K-means	4	0.3256	-11.249	-11.004	0.1570	462	0.0244	17.3126	0.4230	0.3573	1.3138	0.2811
K-means	5	0.3753	-13.430	-13.125	0.1595	431	0.0244	17.3126	0.4230	0.3664	1.5047	0.2403
K-means	6	0.4165	-15.374	-15.010	0.1467	410	0.0280	17.3126	0.4845	0.3556	1.7143	0.1909
K-means	7	0.4454	-16.815	-16.391	0.1328	384	0.0280	17.3126	0.4845	0.3397	1.8992	0.1557
K-means	8	0.4708	-18.142	-17.659	0.1343	365	0.0397	12.1965	0.4845	0.3454	2.0070	0.1417
K-means	9	0.4915	-19.266	-18.723	0.1373	346	0.0399	12.1446	0.4845	0.3583	2.0809	0.1349
K-means	10	0.5069	-20.135	-19.532	0.1293	327	0.0498	12.1446	0.6042	0.3431	2.2064	0.1178
K-means	11	0.5227	-21.051	-20.389	0.1279	314	0.0434	11.1541	0.4845	0.3237	2.3234	0.1024
K-means	12	0.5352	-21.791	-21.070	0.1244	300	0.0443	12.1965	0.5402	0.3158	2.4156	0.0937
Model-based (GMM)	2	0.1277	-3.887	-3.762	0.1354	421	0.0339	17.3126	0.5875	0.2274	0.6889	0.5042
Model-based (GMM)	3	0.1278	-3.870	-3.685	0.0641	210	0.0342	17.3126	0.5929	0.2262	1.0398	0.3698
Model-based (GMM)	4	0.1874	-5.885	-5.641	0.0571	221	0.0268	17.3126	0.4636	0.2230	1.3696	0.2581
Model-based (GMM)	5	0.2009	-6.348	-6.044	0.0361	180	0.0244	17.3126	0.4230	0.2233	1.5434	0.2238
Model-based (GMM)	6	0.2309	-7.430	-7.066	0.0340	172	0.0268	17.3126	0.4636	0.2267	1.7474	0.1811
Model-based (GMM)	7	0.2413	-7.801	-7.378	0.0241	152	0.0244	17.3126	0.4230	0.2248	1.8834	0.1605
Model-based (GMM)	8	0.2600	-8.498	-8.015	-0.0031	144	0.0244	17.3126	0.4230	0.1987	2.0313	0.1356
Model-based (GMM)	9	0.2680	-8.792	-8.249	-0.0046	131	0.0254	17.3126	0.4395	0.1990	2.1406	0.1228
Model-based (GMM)	10	0.2800	-9.247	-8.645	-0.0136	124	0.0254	17.3126	0.4395	0.2014	2.2178	0.1166
Model-based (GMM)	11	0.2973	-9.924	-9.262	-0.0093	121	0.0293	17.3126	0.5080	0.1918	2.3430	0.1001
Model-based (GMM)	12	0.3128	-10.547	-9.825	-0.0074	119	0.0304	17.3126	0.5268	0.2058	2.4132	0.0949
Random forest (proximity)	2	0.1073	-3.223	-3.098	0.1166	346	0.0351	17.3126	0.6080	0.1827	0.6862	0.5069
Random forest (proximity)	3	0.2187	-7.037	-6.853	0.1293	402	0.0320	17.3126	0.5541	0.2584	1.0940	0.3363
Random forest (proximity)	4	0.2735	-9.106	-8.862	0.1137	360	0.0320	17.3126	0.5541	0.2629	1.3431	0.2695
Random forest (proximity)	5	0.3313	-11.471	-11.166	0.1190	356	0.0320	17.3126	0.5541	0.2913	1.5845	0.2096
Random forest (proximity)	6	0.3638	-12.886	-12.522	0.1053	328	0.0242	16.7711	0.4066	0.2850	1.7783	0.1710
Random forest (proximity)	7	0.3920	-14.168	-13.745	0.0863	308	0.0350	16.7711	0.5864	0.2721	1.9370	0.1454
Random forest (proximity)	8	0.4003	-14.544	-14.061	0.0761	273	0.0334	17.3126	0.5785	0.2605	2.0734	0.1265
Random forest (proximity)	9	0.4180	-15.384	-14.841	0.0728	257	0.0341	14.9105	0.5080	0.2539	2.1947	0.1117
Random forest (proximity)	10	0.4311	-16.021	-15.419	0.0618	241	0.0295	14.9105	0.4395	0.2443	2.2952	0.1014
Random forest (proximity)	11	0.4457	-16.747	-16.085	0.0654	230	0.0254	17.3126	0.4395	0.2441	2.3855	0.0932
Random forest (proximity)	12	0.4531	-17.117	-16.395	0.0507	216	0.0328	17.3126	0.5679	0.2344	2.4695	0.0859

Note. Computed on 2,876 firms and ten standardised dimensions. AIC and BIC derive from the Gaussian likelihood of the partition and fall by construction as k rises, so they discriminate between

algorithms at a given k rather than between values of k . Fuzzy C-means uses a fuzzifier of 1.25: at the conventional value of 2 the centroids collapse onto the global mean in ten dimensions and the solution degenerates to two groups for every k .

Table G2. K-means indices by number of clusters

k	R²	Silhouette	Pearson gamma	Dunn	C-H	HHI
2	0.1625	0.1748	0.2999	0.0361	558	0.5373
3	0.2576	0.1510	0.2974	0.0351	498	0.3370
4	0.3256	0.1570	0.3573	0.0244	462	0.2811
5	0.3753	0.1595	0.3664	0.0244	431	0.2403
6	0.4165	0.1467	0.3556	0.0280	410	0.1909
7	0.4454	0.1328	0.3397	0.0280	384	0.1557
8	0.4708	0.1343	0.3454	0.0397	365	0.1417
9	0.4915	0.1373	0.3583	0.0399	346	0.1349
10	0.5069	0.1293	0.3431	0.0498	327	0.1178
11	0.5227	0.1279	0.3237	0.0434	314	0.1024
12	0.5352	0.1244	0.3158	0.0443	300	0.0937

Note. The retained solution is $k = 5$.

Pearson gamma peaks at five and the silhouette has a local maximum at the same point. The two- and three-group solutions have higher silhouettes but far greater concentration, 0.537 and 0.337 against 0.240, and describe a coarse split between profitable and unprofitable firms that Figure 4 shows to be insufficient. Beyond six clusters every non-monotone index deteriorates steadily.

Removing one dimension at a time and re-estimating the five-group solution, the adjusted Rand index against the baseline partition measures how necessary that dimension was.

Table G3. Adjusted Rand index after removing one dimension at a time

Dimension removed	ARI against the baseline partition
Revenue growth	0.9339
Debt / assets	0.8966
ln(total assets)	0.7697
Cash / assets	0.6701
Capital turnover	0.6616
Intangibles / assets	0.6267
Operating cash flow / assets	0.5210
Age (years)	0.5146
Operating result / assets	0.5140
Tangibles / assets	0.4991

Note. High values indicate a redundant dimension; low values indicate a load-bearing one.

Revenue growth and leverage are close to redundant, at 0.934 and 0.897: the partition reconstructs them from the others. Load-bearing instead are tangible assets, the operating result, age and operating cash flow, all between 0.499 and 0.521. This is consistent with the reading of Table 9: growth is not what distinguishes the groups from one another, which is why its coefficient stays positive in all five.

The configuration separates firms by how they finance themselves and how far they are into the life cycle, not by how fast they grow.

Table G4. Loadings on the first two components

Dimension	PC1	PC2
Revenue growth	-0.045	0.231
Cash / assets	0.172	0.540
Operating cash flow / assets	0.522	-0.033
Operating result / assets	0.566	-0.033
Intangibles / assets	-0.406	0.000
Tangibles / assets	0.093	-0.399
Debt / assets	-0.171	-0.228
ln(total assets)	0.047	-0.478
Age (years)	0.223	-0.419
Capital turnover	0.347	0.195

Note. Computed on the standardised dimensions. Together the two components account for 41.8 per cent of total variance.

The first component contrasts the operating result, operating cash flow and capital turnover with intangible fixed assets: an axis running from the firm that converts capital into revenue to the firm whose capital is still intangible. The second contrasts cash with size, age and tangible assets: a life-cycle axis. Revenue growth loads almost nothing on the first, 0.045, and little on the second, 0.231, which explains why the cash-burning growth cluster does not detach in the projection despite being the most extreme group in the data on other dimensions.

Three. The partition is estimated on firm averages and therefore assigns each firm a fixed configuration for the whole period: a firm that moves from the loss-making cluster to the self-financed one is classified once, and Table 9 is conservative as a result. The within-cluster estimates are pooled rather than fixed-effects, because inside a cluster the residual variation after removing firm means is too thin to identify seven coefficients on the 1,445 observations of the smallest group; the correct reading is therefore cross-sectional, as it is for the rest of the panel module. And the taxonomy is built on innovative SMEs alone, because the balance-sheet items that feed it do not exist in the extractions for the other two populations: nothing here says whether the same five configurations are found among non-certified firms.

Appendix H. The validation module in detail

The estimation sample is the one used throughout: 17,235 firm-years on 2,905 innovative SMEs, with seven predictors lagged one year and the binary round indicator as the outcome. Folds are constructed with grouped five-fold cross-validation on the firm identifier, so that all observations of a firm fall in the same fold. This matters more than it may appear: with ungrouped folds the same firm appears on both sides of the split, and because both the outcome and the predictors are persistent within firms, every learner — and the flexible ones disproportionately — reports an inflated score. Grouping

removes that channel and is the reason the numbers here are lower than a naive cross-validation would produce.

Hyperparameters are fixed in advance and are deliberately not tuned on the test folds: forty neighbours with distance weighting; a tree of depth six with at least sixty observations per leaf; three hundred and fifty trees in the forest with at least eight per leaf; and boosting with three hundred and fifty iterations, a learning rate of 0.06, twenty-four leaves and an L2 penalty of one. Tuning each learner on the same folds used to score it would bias the comparison towards the most flexible method, which is the opposite of what a validation exercise should do. The linear learner and the support vector machine are preceded by standardisation; the tree-based learners are scale-invariant and are not.

In the second exercise both the outcome and each predictor are demeaned by firm and then by year before fitting. This is the Frisch–Waugh representation of the two-way fixed-effects estimator, so a learner fitted to these residuals is competing with the panel specification on exactly its own variation. The absolute R^2 values are consequently much smaller than on levels — the fixed effects have absorbed most of the variance — and only the ratios between learners are interpretable. The relevant comparison is therefore within a column of Table 11 and not between Tables 10 and 11.

Table H1. Learning-curve values, levels

Training observations	Linear, train	Linear, test	Boosting, train	Boosting, test
1,103	0.0756	0.0861	0.8224	-0.0900
2,915	0.1010	0.0929	0.6998	-0.0319
4,727	0.0920	0.0956	0.6007	0.0085
6,539	0.0934	0.0974	0.5442	0.0302
8,351	0.0927	0.0975	0.4954	0.0446
10,163	0.0961	0.0973	0.2226	0.0965
11,975	0.1001	0.0974	0.2282	0.1015
13,788	0.0995	0.0975	0.2112	0.1070

Note. Means across the five firm-grouped folds. Training sizes run from eight per cent to the full training portion of each fold.

Two readings follow. The boosting training score starts far above its test score and converges downwards, so the residual gap at the full sample is variance rather than bias that more data would remove. The linear training and test scores are close to each other throughout, which is what a correctly specified low-variance model looks like. If the linear form were badly wrong, its test curve would sit well below the boosting test curve and the distance would persist as the sample grows; it does not.

Table H2. Permutation importance, levels, held-out fold

Predictor	Drop in R ²	SD	Share of total (%)
Op. cash flow / assets	0.0814	0.0046	44.8
Intangibles / assets	0.0393	0.0055	21.6
ln(1+age)	0.0216	0.0031	11.9
ln(total assets)	0.0209	0.0048	11.5
Revenue growth	0.0130	0.0068	7.2
Cash / assets	0.0040	0.0027	2.2
Debt / assets	0.0014	0.0027	0.8

Note. Twenty permutations per predictor on the held-out fold of the first split. Shares are computed over positive drops.

The standard deviations are small relative to the distance between operating cash flow and everything else, so the ordering is not a sampling artefact. Debt over assets is the only predictor whose importance is indistinguishable from zero, at 0.0014 with a standard deviation of 0.0027 — consistent with the panel module, where its coefficient was significant within the firm but small across firms.

Table H3. Friedman H² by pair, ten strongest

Pair	H ²
Intangibles / assets × ln(1+age)	0.0972
Revenue growth × Op. cash flow / assets	0.0530
Revenue growth × Debt / assets	0.0498
ln(total assets) × ln(1+age)	0.0492
Revenue growth × ln(total assets)	0.0468
Intangibles / assets × ln(total assets)	0.0455
Op. cash flow / assets × ln(total assets)	0.0430
Revenue growth × ln(1+age)	0.0420
Cash / assets × Debt / assets	0.0404
Cash / assets × Intangibles / assets	0.0375

Note. Computed on four hundred held-out observations from the gradient-boosting fit. H² is the share of the joint partial-dependence variance not explained by the two univariate profiles.

The strongest pair, intangible assets with age, at 0.097, has an economic reading: the intangible share means something different in a firm of three years and in one of seventeen, and the panel equation, which enters both linearly and additively, cannot express that. It is the one interaction worth reporting, and it accounts for a small part of the ten per cent gap. Adding it explicitly to the linear specification would be defensible; leaving it out costs little, and the appendix records the choice rather than concealing it.

Three. The outcome is binary and the learners are regression rather than classification methods, so R^2 is computed against a zero–one target and its level is not comparable with the same statistic on a continuous dependent variable; only the ratios between learners on the same target carry information, which is how they are used. The linear support vector machine is inappropriate for this target and is retained in the tables for completeness of the comparison rather than as an informative competitor. And the exercise validates the functional form of the equation, not its identification: a linear specification can be perfectly adequate as an approximation of the conditional expectation and still fail to recover a causal parameter, which is why the panel module states its estimand as a conditional association and the event study is described as selection rather than as treatment.

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