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Daina KLEPONĖ

ECONOMIC IMPACT OF BALTIC REGION STARTUPS ECOSYSTEMS

DOCTORAL DISSERTATION

SOCIAL SCIENCES,
ECONOMICS (S 004)

Vilnius, 2026

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Abstract

Since the 1990s, a distinct innovation-driven and high-growth activity, organised around venture-capital-financed startups and their surrounding ecosystems, has diffused globally. Despite strong policy and investor attention, the field still lacks a consistent, operational definition of a "startup," and empirical evidence on startups' net economic contribution remains fragmented. Consequently, policy ambition for startup-tailored instruments has advanced faster than empirical clarity, complicating the design, targeting, and evaluation of ecosystem interventions. This dissertation develops and empirically substantiates an integrated conceptual model for assessing the enabling environment and macroeconomic impact of startup ecosystems. The research proceeds in two stages. First, it constructs a structured theoretical framework for defining startups and refines the definition using empirically validated characteristics. Second, it operationalises ecosystem inputs, firm-level outputs, and macro-level outcomes in an empirically testable framework grounded in entrepreneurial ecosystem theory, endogenous growth theory, and Schumpeterian creative destruction. The empirical core focuses on the Baltic startup ecosystems (Lithuania, Latvia, and Estonia) using extensive firm-level accounting data (2014–2024) for startups and comparable non-startups within the same industries, complemented by ecosystem and macro indicators from international organisations. Methods include comparative performance analysis, panel econometrics for growth and productivity determinants (including total factor productivity estimation), and machine-learning techniques (principal component analysis and k-means) for indicator reduction, ecosystem typologies, and composite index construction. A key contribution is the construction of a startup ecosystem maturity proxy (V index) based on venture capital activity metrics and the estimation of its association with selected macroeconomic indicators via regression models. The dissertation provides an empirically grounded basis for startup identification, cross-country ecosystem assessment, and a more rigorous evaluation of whether and how startup ecosystem development translates into measurable economy-wide outcomes.

Reziumė

Nuo 1990-ųjų globaliai išplitusi išskirtinė inovacijomis ir dideliu augimo potencialu grįsta, rizikos kapitalo finansuojama ir „startuoliu“ vadinama ekonominė veikla susilaukia vis daugiau politikos formuotojų ir investuotojų dėmesio. Tačiau startuoliams skirtų paramos priemonių politika vystosi greičiau nei empirinės įžvalgos apie startuolių veiklą, o tai apsunkina duomenimis grįstų intervencijų į ekosistemą kūrimą, taikymą ir poveikio vertinimą. Ir Europos politikos formavimo, ir akademinėje aplinkoje vis dar trūksta nuoseklaus, vieningai taikomo „startuolio“ apibrėžimo, o empiriniai įrodymai apie grynąjį startuolių indėlį į ekonomiką išlieka fragmentiški. Šioje disertacijoje sukuriamas ir empiriškai pagrindžiamas integruotas koncepcinis modelis, skirtas vertinti startuolių ekosistemas įgalinančią aplinką ir pačių ekosistemų makroekonominį poveikį. Tyrimas vykdomas dviem etapais. Pirma, sudaroma struktūruota teorinė startuolių charakteristikų sistema ir apibrėžimas patikslinamas empiriškai patvirtintais kriterijais. Antra, operaciškai apibrėžiamos ekosistemos „įvestys“, įmonių lygmens „išvestys“ ir makrolygmens „rezultatai“, sukuriant empiriškai patikrinamą modelį, paremtą antreprenerinių ekosistemų ir endogeninio augimo teorijomis bei šumpeteriškąja kūrybinės destrukcijos samprata. Empirinė analizė daugiausia orientuota į Baltijos šalių (Lietuvos, Latvijos ir Estijos) startuolių ekosistemas, naudojant išsamius 2014–2024 m. įmonių lygmens apskaitos duomenis ir startuolius lyginant su kitų įmonių grupe. Papildomai pasitelkiami tarptautinių organizacijų ekosistemos ir makrolygmens rodikliai. Taikomi metodai apima lyginamąją veiklos analizę, panelinius ekonometrinius modelius augimo ir bendrojo gamybos veiksnių produktyvumo determinantams įvertinti, bei mašininio mokymosi metodus (pagrindinių komponenčių analizę ir k-means algoritmą) rodiklių redukcijai, ekosistemų tipologijoms ir sudėtiniam indeksui sudaryti. Svarbus disertacijos indėlis – startuolių ekosistemos brandos aproksimacijos (V indekso), pagrįstos rizikos kapitalo aktyvumo rodikliais, sukūrimas ir jo sąsajos su pasirinktais makroekonominiais rodikliais įvertinimas regresiniais modeliais. Disertacija suteikia empiriškai pagrįstą pagrindą startuolių identifikavimui, tarptautiniam startuolių ekosistemų palyginimui ir vertinimui, bei jų poveikio ekonomikai vertinimui.

Notations

Abbreviations

- 2SLS – two-stage least squares (liet. *dviejų pakopų mažiausių kvadratų metodas*); an instrumental variables estimation method used when regressors are endogenous.
- CAGR – compound annual growth rate (liet. *sudėtinis metinis augimo tempas*); the constant yearly growth rate that would take an initial value to its final value over a period.
- CEO – Chief Executive Officer (liet. *generalinis direktorius)*; top manager responsible for overall management and decisions in a company.
- EE – Estonia (liet. *Estija*); country code.
- EIS – European Innovation Scoreboard (liet. *Europos inovacijų švieslentė*); EU tool comparing innovation performance across countries.
- EU – European Union (liet. *Europos Sąjunga*)*;* political and economic union of European countries.
- EUROSTAT – statistical office of the European Union (liet. *Europos sąjungos statistikos tarnyba)*; providing official EU statistics.

- FDI – foreign direct investment (liet. *tiesioginės užsienio investicijos*); cross-border investment where an investor has significant influence or control over a foreign enterprise.
- FE – fixed effects (liet. *fiksuotieji efektai*); econometric approach controlling for time-invariant unobserved heterogeneity (for example, country or firm dummies).
- GAM – generalised additive model (liet. *apibendrintasis adityvusis modelis*); flexible regression model allowing non-linear relationships via smooth functions.
- GDP – gross domestic product (liet. *bendrasis vidaus produktas*); total value of goods and services produced in an economy.
- GCI – Gloval Competitiveness Index (liet. *pasaulinis konkurencingumo indeksas*); composite index measuring countries' competitiveness across many pillars.
- GLM – generalised linear model (liet. *apibendrintasis tiesinis modelis*)*;* a family of regression models that extends ordinary least squares to non-normal errors and link functions.
- HICP – harmonised index of consumer prices (liet. *suderintasis vartotojų kainų indeksas*)*;* EU harmonised inflation measure produced by Eurostat.
- ICT – information and communication technology (liet. *informacinės ir ryšių technologijos*); digital technologies and systems used to create, store, process, and exchange information.
- IE – innovation ecosystem (liet. *inovacijų ekosistema*).
- IoT – Internet of Things (liet. *daiktų internetas*)*;* a network of physical devices connected to the internet that collect and exchange data
- IPO – initial public offering (liet. *pirminis viešas akcijų siūlymas*)*;* when a company first offers its shares to the public on a stock exchange.
- NIS – national innovation system (liet. *nacionalinė inovacijų sistema*)*;* the network of institutions and policies that shape innovation in a country.
- OECD – Organisation for Economic Co-operation and Development (liet. *Ekonominio bendradarbiavimo ir plėtros organizacija*) (liet. *paprastųjų mažiausių kvadratų metodas*)*;* an international organisation of mainly high-income countries.
- OLS – ordinary least squares (liet. *paprastųjų mažiausių kvadratų metodas*)*;* standard linear regression estimation method.
- PCA – principal component analysis (liet. *pagrindinių komponenčių analizė*)*;* a dimensionality-reduction technique that transforms correlated variables into uncorrelated components.

- PC1 – first principal component (liet. *pirmoji pagrindinė komponentė*)*;* the PCA component explaining the largest share of total variance.
- PLM – panel linear model (liet. *panelinių duomenų tiesinis modelis*); regression model for panel (longitudinal) data.
- PSM – propensity score matching (liet. *polinkio balo atitikimo metodas*); a causal inference method that matches treated and control units with similar treatment probabilities.
- R&D – research and development (liet. *moksliniai tyrimai ir eksperimentinė plėtra*)*;* creative and systematic work to increase knowledge and develop new applications.
- SME – small and medium-sized enterprises (liet. *mažos ir vidutinės įmonės*)*;* firms below specific employment and turnover or balance-sheet thresholds.
- ST – startup (liet. *startuolis*); newly created, innovative firm with scalable business model and high growth ambitions.
- STEM – science, technology, engineering and mathematics fields (liet. *gamtos mokslai, technologijos, inžinerija ir matematika*).
- TFP – total factor productivity (liet. *bendrasis veiksnių produktyvumas*)*;* part of output not explained by measured inputs, capturing efficiency and technology.
- TW – two-way fixed effects (liet. *dvipusiai fiksuotieji efektai*)*;* model with fixed effects for two dimensions (for example, firm and year or country and year).
- VC – venture capital (liet. *rizikos kapitalas*)*;* equity financing for high-growth startups, usually provided by specialised funds.
- VIF – variance inflation factor (liet. *sklaidos infliacijos faktorius*); measure of multicollinearity in regression models.
- YoY – year-on-year (liet. *metai su metais pokytis*)*;* comparison of a variable with its value in the same period of the previous year

Definitions

- Business angels (liet. *verslo angelai*) – high-net-worth individuals who invest their own money directly into early-stage startups.
- High growth (liet. *spartus augimas*) – OECD definition of enterprises with average annualised growth greater than a threshold (often 10% or 20%) over a given period.

- High-potential entrepreneurship (liet. *didelio potencialo verslumas*) – entrepreneurial activity with strong expected growth, innovation and job-creation potential.
- High-tech (liet. *aukštosios technologijos*) – high-technology sectors or companies with intensive R&D and advanced technological content.
- K-means clustering (liet. *k-vidurkių klasterizavimas*) – an unsupervised machine-learning algorithm that partitions observations into clusters based on similarity.
- Knowledge-intensive/knowledge-intensive services (liet. *žinioms imlūs sektoriai / žinioms imlios paslaugos*) – sectors where value creation relies heavily on knowledge, expertise and highly skilled labour, such as IT, R&D, and consulting.
- Leverage (liet. *finansinis svertas*) – use of debt relative to equity in financing.
- RESET test (liet. *RESET testas, Ramsey regresijos specifikacijos klaidos testas*) – Ramsey regression equation specification error test; diagnostic for functional form misspecification in regression.
- Scaleup (liet. *sparčiai augantis startuolis*) – a startup that has moved into a fast-growth phase, scaling revenues, markets and team.
- Startup exit (liet. *pasitraukimas iš startuolio investicijos*) – an event where investors or founders realise returns, for example, through acquisition, merger, IPO, or secondary sale.

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Introduction

Problem Formulation

Economic growth is fundamentally driven by the generation of new ideas (Bloom et al., 2020), which catalyse technological advancement and enable economies to address emerging challenges through new forms of entrepreneurship. This activity is often organised around startups: young, innovation-intensive, venture capital-financed firms designed for rapid scaling in global markets. Despite their prominence, no consensus exists on a clear, operational definition of startups among policymakers or in academia. Beyond definitional ambiguity, there is also no clear empirical consensus on the net economic impact of startup ecosystems: whether, under what conditions, and to what extent they contribute to productivity, innovation, and economic growth compared with other SMEs. Some scholars even warn that startups evolving into global "superstar" firms or monopolistic platforms may alter market structures and weaken democratic and competitive institutions, shifting entrepreneurship away from traditional small firms towards dominant technology giants (Kuratko & Audretsch, 2022).

Relevance of the Dissertation

Despite definitional ambiguity, policymakers and investors treat startups as a key engine of future growth, assuming they scale rapidly, create jobs, and strengthen competitiveness through novel technologies and business models. The EU's own strategy recognises that thriving startup ecosystems drive productivity, investment, and quality job creation (European Commission, 2025), yet around 60% of global startups remain US-based compared to only 8% in the EU. The IMF has identified the failure to develop startups into "superstar" firms as a key driver of the EU's poor productivity growth (Arnold et al., 2024), and Draghi (2024) observed that Europe largely missed the digital revolution, a gap explained by its tech sector's underperformance. This finding has prompted a policy push for startup-tailored instruments: in 2023, the European Commission announced a EUR 1.6 billion package for scaling breakthrough technologies, while the European Innovation Council alone commands over EUR 10 billion under Horizon Europe. The dissertation is relevant both academically and practically. Academic research on startups remains fragmented, with limited systematic quantitative studies examining startup ecosystem development and macroeconomic impact. Practically, this fragmentation weakens the evidence base for designing and evaluating support instruments. The dissertation, therefore, develops and delivers a conceptual framework that integrates startup definition criteria, enabling-environment indicators, and macroeconomic impact measures into a single empirically testable model, with practical policy recommendations.

Research Object

The object of the dissertation is the startup ecosystem.

Aim of the Dissertation

The dissertation aims to develop an integrated conceptual and methodological framework grounded in an empirically validated startup definition, operationalising startup ecosystem maturity and enabling empirical analysis of its relationship with macroeconomic outcomes.

Tasks of the Dissertation

The following tasks were addressed to achieve the aim:

1. To systematise and theoretically substantiate the concept of a startup by integrating empirically validated startup characteristics into a coherent definitional framework.
2. To design an integrated methodological framework for assessing the maturity of the startup ecosystem and its macroeconomic implications.
3. To operationalise startup ecosystem maturity by identifying key developmental dimensions and constructing an indicator set suitable for empirical testing.
4. To evaluate the empirical performance and practical relevance of the proposed framework through its application to the startup ecosystems of the Baltic region (Lithuania, Latvia, and Estonia) and European countries.

Research Methodology

The research follows a two-stage design: conceptual model development and empirical validation in the context of the Baltic and European countries. Logical analysis and synthesis are employed to construct the conceptual framework, define startup identification criteria, identify the enabling environment dimensions influencing startup development, and establish the relationship between startup ecosystems and macroeconomic outcomes. The theoretical foundation is based on Stam's (2015) integrative entrepreneurial ecosystem model, while firm-level total factor productivity is estimated using a Cobb–Douglas production function. The empirical analysis applies quantitative methods using firm-level financial accounting data, as well as ecosystem- and macro-level indicators. Comparative analysis, econometric modelling, and machine learning techniques are employed. Ecosystem maturity is proxied by the V index, a composite indicator capturing venture capital activity, which is subsequently linked to macroeconomic outcomes to assess ecosystem-level impact. All computations are performed using the RStudio environment.

Scientific Novelty of the Dissertation

The scientific novelty of this dissertation lies in the development and empirical substantiation of an integrated approach for evaluating startup ecosystems that connect micro-level firm dynamics with macro-level economic outcomes, and is expressed in the following respects:

– The dissertation introduces a new empirically grounded definition of a startup, addressing one of the key gaps in both theory and practice: the lack of a consistent basis for distinguishing startups from non-startup firms.

- A structured indicator framework integrating ecosystem-level conditions, firm-level development drivers, and macroeconomic outcomes is constructed. The study further establishes a model application methodology and indicator system enabling empirical operationalisation.
- The key novelty of the work lies in the development and operationalisation of a composite startup ecosystem maturity index, which enables systematic quantification of ecosystem development and its linkage to macroeconomic performance through econometric modelling.
- The empirical scope of startup research is extended, enabling a systematic comparative assessment of startups and non-startup firms complementing the literature with a robust empirical foundation.

Practical Value of the Research Findings

For policymakers, the findings provide an empirical basis for moving beyond direct financial instruments towards targeted, evaluable ecosystem policies. Given persistent debate about whether startups represent "true" innovation and their high failure rates driven by market and product uncertainty, evidence-based intervention design is essential. The proposed model enables a systematic cross-country comparison, supporting strategic benchmarking, identification of structural bottlenecks, and policy scenario formulation, while implementation guidelines are provided in the recommendations chapter. For investors, the model enables comparing ecosystems by maturity, thereby supporting decisions on investment intensity and the forecasting of returns.

Defended Statements

Based on the results of the present investigation, the following statements are formulated as the official hypotheses to be defended:

1. Startups constitute an empirically distinguishable firm category within the same industry.
2. Distinct patterns of startups' growth, productivity, financial performance, and survival are shaped by determinants that differ from those affecting other early-stage SMEs.
3. The startup enabling environment can be comprehensively assessed using a structured indicator system.

4. Startup ecosystem maturity can be proxied by the V index derived from venture capital activity indicators.
5. The proposed conceptual model, operationalised through an integrated startup ecosystem maturity index, enables an empirical assessment of the macroeconomic impact of the startup ecosystem.

Approval of the Research Findings

The findings of the dissertation research were disseminated in two publications in the scientific journals indexed in Scopus: Kleponė & Okunevičiūtė Neverauskienė (2025); Okunevičiūtė Neverauskienė & Klepone (2024). The author has made two presentations at two scientific conferences:

– 23 February 2024. Forum For Institutional Thought Institutions and Survival "Challenges for Sustainability", Bialystok, Poland.
– 26 June 2025. 13th International Conference on Applied Economics Contemporary Issues in Economy, Olsztyn, Poland.

Dissertation results were presented at academic seminars at the Universitat Autònoma de Barcelona (Barcelona, Spain) and the Universitat Rovira i Virgili (Reus, Spain).

Structure of the Dissertation

The dissertation consists of an introduction, three chapters, general conclusions, recommendations, references, a list of the author's publications, a summary in Lithuanian and five annexes. The total scope of the dissertation is 157 pages. It includes 36 figures, 39 tables, and 239 references.

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1

Role of Startups in Economic Development

This chapter reviews and synthesises scientific literature on the concept of a startup and its role in economic development. It examines how startups are defined and distinguished from other early-stage firms, how startup ecosystems are positioned within broader innovation ecosystem frameworks, and which internal and external factors shape startup emergence and scaling. The chapter also summarises existing evidence on startups' economic impact, particularly through innovation, productivity, job creation, and growth, while highlighting methodological challenges such as heterogeneity and the speed and volatility of startup growth trajectories. The main research results of this chapter are published in the author's publication (Okunevičiūtė Neverauskienė & Klepone, 2024), and findings of the research were presented at the International Forum for Institutional Thought Institutions and Survival "Challenges for Sustainability" in Bialystok, Poland.

1.1. Startup Concept

The most important methodological question is how to distinguish startups (ST) from other SME for the purpose of defining the scope of the research. It is difficult to define a startup as an empirical phenomenon; moreover, the existing definitions overlap and contradict one another. Before 1980, the term “startup” referred to the early stages of any firm’s development. Later, a “startup” became a description of a particular kind of firm or working practice in selected economic regions in the 1980s, e.g., semiconductor firms in Silicon Valley (Angel, 1989) or “fast-growing electronic startup” (Florida, 1991). Government funding agencies prioritise startups focused on developing innovative technologies, products, or business models that have the potential to create new markets or disrupt traditional industries, and policymakers around the world are constantly searching for efficient and specific support models. However, no common agreement exists in the public sector at the European level or among academia on which forms of business are attributed to STs.

Age and innovation potential are the most common criteria used to distinguish STs. Some countries and support programmes also use other criteria related to the specificities of STs, such as financing or growth speed. However, even criteria with consensus, such as age, are not treated the same way across countries, as the age of an ST varies from three to ten years. A similar diversity of opinion and debate exists in academia, where the taxonomic approach to ST categories involves trials to distinguish STs based on different criteria such as their business model, industry, type of funding, and stage of development.

To examine the evolution of the term “startup” within the economic and business research context, a literature survey was conducted using the keywords “startup” and “born global” in the Web of Science and Scopus databases. The search was limited to academic journal articles published from 1990 onward, within the subject categories Business, Management, Accounting, Economics, Econometrics, and Finance. The analysis reveals several distinct phases in the development of these research domains. The term “born global” initially dominated the literature in the 1990s and early 2000s, reflecting early interest in internationalisation and global market-entry strategies (Fig. 1.1).

However, from around 2015 onward, the use of the term “startup” has expanded exponentially, surpassing “born global” in frequency. Approximately half of all publications related to STs were produced in the most recent four-year period (2020–2023), indicating a sharp increase in academic attention. This surge aligns with major economic and technological shifts: a noticeable increase around 2000 coincides with the dotcom and internet revolution, followed by another wave of growth after the 2008 financial crisis, and a further acceleration during the COVID-19 pandemic, reflecting intensified digital transformation and entrepreneurial activity.

It is difficult to define whether an ST is an empirical phenomenon, an economic sector, a characteristic of the firm or a kind of work, since the definition of “startup” is used both as a discourse object and as a research objective of the “new, modern, and innovative form of work” (Cockayne, 2019). The criteria used to define an ST are diverse, often encompassing a combination of different contextual factors such as industry vertical, the firm's age, development stage, business model, level of innovation, early internationalisation, strategic approach, organisational culture, growth characteristics, sources of funding, or exposure to high financial risk.

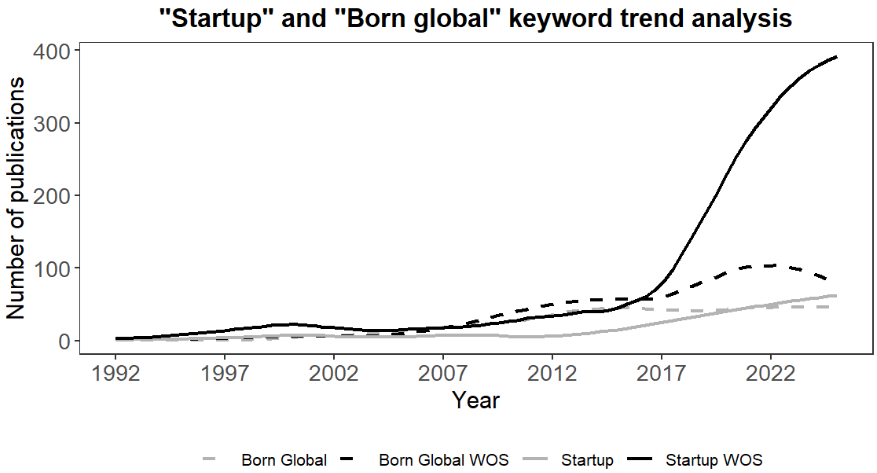

Fig. 1.1. Usage of "Startup" and "Born global" keyword trend analysis in Scopus and Web of Science (WOS) databases. Source: compiled by the author

These definitions are also marked by significant differences in viewpoints and, in certain instances, outright contradictory assertions. To better understand those complexities, an organised framework by offering three perspectives, i.e., structural (foundational), strategic (functional), and operational (output), is suggested to simplify the broad spectrum of varying definitions found in literature and practice, see Table 1.1. This table synthesises how the academic literature defines startups, grouping commonly used definitional criteria into structural, strategic, and operational dimensions. For each criterion, it presents the startup-specific interpretation most frequently emphasised by scholars and lists common terminology. The table, therefore, illustrates the diversity of definitional approaches and the resulting lack of consensus on what constitutes a "startup"

Structural (foundational) perspective. The foundational aspects align with how STs are often categorised at a fundamental level by their technological focus, their basic status as an innovative venture, or their early development stage in the lifecycle, with terms such as "high-tech" and "startup" commonly used. From the perspective of an industry subsector or industry verticals (technology used), STs are firms that operate in specific high-value-added sectors such as IT, financial technologies, biotechnology and others. Silicon Valley or the San Francisco area is in many ways the archetypal example of STs and knowledge-based regional economies. The industry taxonomy approach categorises STs by the industry in which they operate.

Table 1.1. Conceptual framework for the startup definition criteria in academic literature. Source: compiled by the author

Dimension (terms used)	**Criterion**	**Startup-specific interpretation**	**Source**
Structural (“Hitech”, “Startup”)	Industry vertical	Operation in high-value-added sectors	Felgueiras et al. (2020); Kühnemann et al. (2020); Savin et al. (2023)
	Firm’s age and size	Young (up to 10 years old) with limited size (number of employees)	Czarnitzki & Delanote (2013); Haltiwanger (2022); Vandresse et al. (2023)
	Stage of development	Early development stage	Bayard et al. (2018); Reisdorfer-Leite et al. (2020)
Strategic (“Born global”, “Born to run”, “International new venture”, “Scaleup”)	Business models	Early internationalisation	Phillips McDougall et al. (1994); Knight & Cavusgil (2004); Brynjolfsson et al. (2017); Mathews & Zander (2023)
	Level of innovation	High (both product and process)	Cockayne (2019); Andersson et al. (2014); Nummela et al. (2004); Manotti et al. (2021); Weber et al. (2022)
	Organisational culture	High degree of entrepreneurship	Ries (2011); Dessyana & Dwi Riyanti (2017)
Operational (“Gazelle”, “High-growth tech”, “Unicorn”, “Blitzscaled ventures”)	Growth	Scalable growth	Birch (1979); Stampfl et al. (2013); De Haas, Sterk, Horen, et al. (2022a)
	Survival	Low	Calvino et al. (2018); Rannikko et al. (2019)
	Financial risk	High	Mattsson & Andersson (2019)
	Sources of funding	Specific	Manigart & Struyf (1997); Coleman et al. (2016); Frid et al. (2016); Gabrielsson & Manek Kirpalani (2004)

The difficulties for the robust industry-based classification stem from different challenges: multidisciplinary ST teams, expert bias of the founders who attribute their firms to a certain industry in the official databases (Savin et al., 2023), and limitations of the economic classification systems, used by national statistic organisations (Kühnemann et al., 2020). For example, recent research by Felgueiras et al. (2020) using ST data from Crunchbase identified 46 subindustries.

An ST, as a product of the innovation ecosystem and it's own lifecycle, follows development path, similar to its product lifecycle which begins with an idea, then develops through the phase of middle of life, and ends with an exit strategy (IPO), according to Reisdorfer-Leite et al. (2020). STs are mostly defined as younger than 10 years old (Haltiwanger, 2022), yet Bayard et al. (2018) showed a long tail for STs that begin operations only several years after their initial registration. Czarnitzki and Delanote (2013) suggested using several ST firm characteristics, e.g., R&D expenses that should represent at least 15% of its total operating expenses, being less than 6 years old, and having fewer than 250 employees. A similar approach is proposed by the latest Vandresse et al. (2023) study, where the need for the EU to have a common ST definition is identified, and three possible scenarios are suggested, based on the ST structural characteristics:

– Scenario A: firms up to 5 years old, with less than 50 employees, and less than EUR 5 million in turnover;
– Scenario B: firms up to 10 years old, with less than 250 employees and less than EUR 50 million in turnover;
– Scenario C: firms up to 10 years old and have less than 250 employees, with no turnover limit.

Strategic (functional) perspective. IT investments have brought a new potential for small firms to grow their productivity and profitability and have influenced modern organisational changes related to new business models, operational processes, employee competencies, and skills (Brynjolfsson et al., 2017). From the perspective of strategy, STs are distinguished from other early-stage SMEs by their market approach (early internationalisation), innovation, scalable business models and distinctive organisational culture. Followers of this approach commonly use terms: "born global", "born to run", "international new venture" or "scaleup". The term "international new venture" was first used by Phillips McDougall et al. (1994), who identified a new type of international firm that exhibited distinct characteristics and had a strategy to expand into many international markets shortly after inception, despite limited resources, knowledge, and international experience, as well as increased risks and responsibilities. Later, Knight and Cavusgil (2004) introduced "born global" as firms that "seek superior international business performance from the application of knowledge-based resources to the sale of outputs in multiple countries". STs are firms that create, employ or market innovative products, processes, technologies, or business models (Cockayne, 2019). Successful startups quickly achieve international growth shortly after their inception due to innovative products (Andersson et al., 2014; Nummela et al., 2004) or value proposition (Manotti et al., 2021). They employ innovative models (Weber et al., 2022) and their proactive high-risk appetite development strategies create value beyond the boundaries of the home market (Mathews & Zander, 2023). From an organisational culture perspective, STs are characterised as having flatter organisational structures with a low number of hierarchical levels, a higher degree of informality, entrepreneurial, creative and disruptive working patterns, and high work commitment of the founders (Dessyana & Dwi Riyanti, 2017).

Operational (output) perspective. From an operational perspective, STs are defined by their growth, survival or market value characteristics with the reflecting terms, such as “gazelle”, “high growth firm”, “unicorn”, “blitz scaled ventures”. Terms like “unicorn” and “gazelle” refer to STs that achieve significant valuation or scalability. ST scalability refers to the ability of an ST to grow its business rapidly and efficiently in response to increasing demand or new opportunities, while maintaining or even increasing profitability (De Haas et al., 2022). Scalability is often a critical factor in the success of an ST, particularly for those seeking investment from VC or other sources of funding (Stampfl et al., 2013). The term “gazelles” to refer to high-growth firms was popularised by American economist Birch (1979). OECD (2021) provided the recent definition of the “high growth” firm:

> *“All enterprises with average annual growth greater than 20% per annum, over a three-year period, and with ten or more employees at the beginning of the observation period. Growth is thus measured by the number of employees and by turnover”.*

According to the OECD, “gazelles” are characterised by the same growth and size criteria but have a defined age limit of up to five years, represent less than 1% (by employment) or 2% (by turnover) of the total population of enterprises, and grow faster in terms of turnover than of employment.

STs are usually attributed to a high-risk business with low survival rates (Mattsson & Andersson, 2019). In scientific discourse, numerous empirical investigations have been conducted to elucidate the formula for ST survival. These studies meticulously examine various factors and conditions that contribute to the longevity and resilience of newly established SMEs. Calvino et al. (2018) scrutinised the OECD data from 10 countries to find out that firms’ survival rates were somewhat homogeneous between different countries: 60% after 3 years, 50% after 5 years, and 40% after 7 years. The fact that the biggest ST failure occurs during the first year and high growth might have a reducing effect resonates with a finding by Rannikko et al. (2019), who investigated the new technology-based enterprises that survived more than 8 years. The authors revealed that among the surviving companies, only very few experienced high growths during their first 7 years. According to Ries (2011), not all "born global" are STs, as these entities are characterised by their ability to create a new product or service under conditions of extreme uncertainty.

Because of the highly innovative products, low survival and high financial risk, ST funding sources are specific and basically different from non-technology SMEs: personal savings of the entrepreneurs themselves (Gabrielsson & Manek Kirpalani, 2004), occasionally supplemented with capital or loans from family or friends (Manigart & Struyf, 1997; Coleman et al., 2016) or the specific players of the business investment market (business angels and venture capital firms (Frid et al., 2016)).

This chapter clarified the concept of a "startup" by synthesising how academic literature operationalises the term across structural, strategic, and operational dimensions (e.g., industry vertical, the firm's age and size, development stage, internationalisation, innovation intensity, entrepreneurial culture, scalability, survival, financial risk, and funding patterns). The academic literature review demonstrates that the definition of a startup remains conceptually fragmented and context-dependent: studies frequently use overlapping labels (e.g., "high-tech," "born global," "gazelle," "unicorn") and apply heterogeneous criteria, which limits comparability across empirical studies. Accordingly, this chapter adopts a pragmatic, literature-grounded definition of startups as young and relatively small firms, often operating in high-value-added sectors that pursue innovation-driven and scalable growth trajectories, frequently supported by distinctive financing structures and elevated risk profiles.

Building on these definitional criteria, the next chapter shifts focus from "what a startup is" to "what a startup does" in the economy. Specifically, it analyses startups through the perspective of economic growth theory, examining the mechanisms by which startup activity may contribute to productivity dynamics, innovation diffusion, structural change, and overall economic performance.

1.2. Startup From the Perspective of Economic Growth Theories

The ST concept is closely linked to broader economic theories through ST's role in technological advancement and the creative destruction of markets. Over time, economic growth models have evolved from classical approaches focused on capital accumulation and labour to modern endogenous models that emphasise technological innovation and knowledge as key drivers of economic growth. Classical theory representatives, associated with economists Adam Smith and David

Ricard, who developed their theory around the "Malthusian Law of Population Growth", emphasised capital accumulation and labour as growth factors, are sometimes called "pessimistic" (Harris, 2007). Cobb and Douglas (1928) suggested a production function which has since then become a fundamental tool used for analysing the relationship between input and output in various production processes. Until now, the Cobb–Douglas production function has been widely used in production process estimation, production efficiency analysis, economic growth prediction, and background policy recommendations:

$$Y = AL^{\alpha}K^{\beta}, \quad (1.1)$$

where Y represents the output; A is a constant representing the productivity of the total factor; L is the input of labour; K is the input of capital; α and β are the output elasticities of labour and capital.

Term A, which now stands for total factor productivity, was interpreted as a measure that captures the effects of technological change, among other factors.

In neoclassical growth theory, Solow (1957) showed that most long-term output growth stems from technological change rather than capital accumulation:

$$Y = f(L, K, T), \quad (1.2)$$

where T is a level of technology.

Here, technology acts as an exogenous factor, enhancing the efficiency with which labour and capital are converted into output, independent of labour and capital input. For the ST, the importance of technology becomes paramount as it allows small firms to offset diminishing returns to capital and compete with established businesses by leveraging innovative practices and processes. Later, in his Human Capital Theory, Becker (1962) posited that skills, knowledge, and experience constitute a form of capital, and investment in human capital, such as education and training, can enhance productivity and foster innovation. The model by Nelson and Phelps (1965) introduced the interaction between human capital and technology as a crucial determinant of economic growth. It emphasised technological diffusion and provided a framework for understanding how STs in less developed regions can adopt technologies from wealthier nations to spur rapid growth.

The endogenous growth theory, developed by Romer (1990), argues that economic growth is primarily driven by internal factors such as human capital, education, R&D, and innovation. This contrasts with earlier models that treated technological progress as an external or exogenous factor. For STs, this theory underscores the idea that innovation and human capital development are not just byproducts of growth but its direct contributors. Romer's endogenous growth model posits that technological progress is driven by market incentives, with STs acting as catalysts for new ideas and technologies. In the same year, Mankiw et al. (1990)

augmented the model with a human capital term. An additional key determinant of "human capital" was added to the form of the function:

$$Y = f(L, K, T, HC), \tag{1.3}$$

where HC is human capital.

This adjustment highlights that economic growth can come from investing in human capital, which produces increasing returns to scale, unlike the neoclassical view that the marginal product of capital is declining. For STs, this implies that investing in skills, education, and team expertise is directly correlated with productivity and output. STs, especially in knowledge-intensive sectors, gain a competitive edge through the quality and skill of their teams, leading to innovative business models and processes.

ST founders are the "Schumpeterian entrepreneurs" archetypes of Schumpeter and Stiglitz (2010), characterised by their drive to innovate and disrupt, who contribute to job creation, productivity, and competitiveness (Block et al., 2017). The term "disruptive industries" was first used by Bower and Christensen (1995): an ST often leverages new technologies or business models to challenge established firms, and this disruptive change creates major opportunities for the firm's growth (Christensen & Euchner, 2011). Disruptive innovations often lead to the destruction of old industries and the creation of new ones, and the process is a dynamic, ever-changing economic landscape (Becker & Knudsen, 2002). Schumpeter believed that economic development is characterised by cycles of the waves of innovation and that innovation-driven monopolies are a natural part of the economic landscape. During the peak of the innovation wave, even new firms may gain a temporary monopolistic position in the market due to their technological leadership, which is basically happening today in disruptive industries dominated by the high-tech STs (Kuratko & Audretsch, 2022). Schumpeterian theory provided a different perspective on economic growth compared to traditional economics, which assumed static equilibrium and perfect competition. STs innovate through their connection to the surrounding environment because this environment provides them with their disruptive potential.

This chapter positioned startups within the main concepts of economic growth theory, showing that their economic impact stems from their capacity to generate, commercialise, and diffuse innovation. Moving from classical and neoclassical models, where technological progress is largely exogenous, to endogenous and Schumpeterian perspectives, where knowledge, human capital, and creative destruction drive long-run growth, startups emerge as a key form of economic activity, which can translate new ideas into productivity gains and structural change. However, these growth effects do not arise by default. Literature consistently implies that startups' innovative and disruptive potential depends on the conditions that shape their ability to access resources, build capabilities, and scale.

Accordingly, the next chapter shifts the focus from startups as engines of economic growth to the enabling environment that allows such growth mechanisms to operate. From the perspective of the innovation ecosystem (IE), it conceptualises startup ecosystem development as the outcome of interacting endogenous and exogenous determinants.

1.3. Factors of Startup Ecosystem Development

This chapter conceptualises the startup enabling environment by situating startups within national innovation ecosystems. As startups are simultaneously shaped by and contribute to these systems, their emergence, growth, and productivity depend on a combination of internal firm-level capabilities and external ecosystem and macro-economic conditions. Building on the literature, the chapter therefore structures the determinants of startup ecosystem development into two groups: endogenous factors (startup-internal characteristics and capabilities) and exogenous factors (macro-economic and ecosystem-level conditions that startups can leverage but cannot directly control).

STs function within complex dynamic innovation ecosystems (IE), which determine their growth patterns. An IE analogy to the biological ecosystems is used as the interactive economic network comprising various entities and institutions engaged in R&D and innovation (Mazzucato, 2013). The evaluated ST ecosystem should be seen as an integrative part of the national innovation ecosystem and ST companies as its products and the actors (Spender et al., 2017).The term of national innovation ecosystem (NIS) was first used by Lundvall (2016), who defined NIS as all parts and aspects of the economic and institutional structure that affect learning, as well as search and research – the production, the marketing, and the financial systems are subsystems, in which learning takes place. Motoyama and Knowlton (2017) used a social networking approach to analyse NIS connections across multiple layers of entrepreneurs and support organisations and highlighted the importance of clear inter-organisational collaboration and strategic structuring of resources. Suseno and Standing (2018) saw NIS from a holistic, open-systems perspective, emphasising five key policy areas: investment in human capital and access to professionals, infrastructure, public–private partnerships, support for financing and commercialisation, and an innovative corporate culture. Building further, Granstrand and Holgersson (2020) conceptualised the most recent definition of NIS as a dynamic constellation of actors, activities, artefacts, institutions, and interrelationships that collectively shape the emergence of innovation. In this view, artefacts encompass tangible and intangible products, services, technologies, and other inputs and outputs, while actors may engage in cooperative or competitive relationships with or without a parent organisation.

The IE structure functions as a key element that drives expansion. The "quadruple helix" model by Ziakis et al. (2022) demonstrates how government, industry, and academia work together to advance innovation through their combined efforts. Government support for entrepreneurship development exists alongside university-based talent supply and research innovation. Large corporations offer their expertise and market entry opportunities to ST and civil society organisations working to establish social responsibility and impact standards. The combined forces of these different elements form an adaptable system that maintains continuous innovation and growth through their synergistic relationships. The performance of high-tech industries depends on specific economic conditions, scientific research, technological advancements, and government support, according to Wei et al. (2023), which requires an ST to explore different success paths. Academic studies show that various IE elements form interconnected relationships and create dynamic capabilities to produce economic and social value to STs as they operate within these ecosystems (Stam, 2015). Guerrero and Siegel (2024) claimed that an ST's ability to innovate and scale depends on the presence of supportive policies, infrastructure, and access to resources. Filho et al. (2024) developed a performance-assessment tool that translates IE indicators into direct measures of ST competitiveness. These metrics explicitly connect the health of an ST surrounding IE and its capacity to access and mobilise resources, with its ability to compete internationally.

The research of Hannigan et al. (2022) demonstrates that IE enable STs to handle market uncertainties through technological and business model innovations, which support their performance in unstable markets and stable markets with lower profits. According to Noelia and Rosalia (2020), to overcome the natural obstacles faced by STs due to the challenges related to their business model, e.g., high cost of innovation or lack of managerial and commercial experience, firms usually rely on their ecosystem. Some of the important structural IE factors, such as regulation and policy, can either hinder or support an ST's ability to innovate and thrive, as demonstrated by Cozzolino and Geiger (2024), who emphasised the need for different ST-entry scenarios based on the degree of disruption brought by innovation and the impact of regulation. Oghazi et al. (2022) emphasised that disruptive innovation and technological advancement, particularly by an ST, lead to new value creation in the IE. At the same time, STs, understanding their role in transforming IE, strategise how to leverage technological advances and value propositions to drive change and position themselves advantageously within it. STs function differently within IE based on their stage of development. Marcon and Ribeiro (2021) showed that in the early stages, an ST interacts most intensively with non-market-oriented actors, whereas in the later, market-ready phase, its interactions shift towards market-oriented actors.

The growth and competitive success of STs depend on their ability to recognise and utilise structural elements, interaction patterns, and support systems within their ecosystems. Based on an academic literature review, the most frequently examined determinants that influence ST growth can be broadly categorised into two main groups: intrinsic to an ST and originating externally. Endogenous determinants capture startup-internal resources and capabilities, such as the firm's age and size, founder/team human capital, ownership and capital structure, innovation capability, business model scalability, and financing strategy. Exogenous determinants reflect conditions outside the startup's direct control, including macro-economic dynamics and ecosystem-level structures. By integrating these determinants and their measurable indicators, the chapter provides an analytical framework for explaining how ecosystems shape startup formation, survival, and scaling.

1.3.1. Endogenous Determinants

Endogenous ST growth and productivity determinants, which are related to the internal ST firm characteristics, can be subdivided into two categories: structural and functional (Table 1.2).

Table 1.2. Startup internal characteristics and capabilities as endogenous growth determinants. Source: compiled by the author

Category	Determinant	Indicative mechanism	Sources
Structural	Industry/sector positioning	Initial industry selection; sector-specific risk exposure and bankruptcy vulnerability	Martínez-Fierro (2020); Cantamessa et al. (2018)
Structural	Firm's size	Resource base and scaling capacity; growth rates differ by size; productivity differences over time	Somya & Saripalle (2023); Y.-R. Li (2009); Geroski, Mata & Portugal (2010); De Haas, Sterk & Van Horen (2022)
Structural	Firm's age	Experience accumulation and learning versus potential rigidity effects	De La Fuente (2011); Añón Higón et al. (2022); Alon et al. (2017); Douch et al. (2023); Galego et al. (2018)

End of Table 1.2

Category	Determinant	Indicative mechanism	Sources
Structural	R&D and intellectual property	R&D intensity; patents as signals for subsidies and investors	de Rassenfosse (2012); Colombo et al. (2023); Leiponen & Byma (2009)
Structural	Founder/team human capital	Managerial and sector experience; innovation experience; ownership concentration linked to acquisitions and strategy	Gompers et al. (2020); Cassar (2014); Lin et al. (2023)
Structural	Ownership and capital structure	Shareholder composition and funding mix shape strategy, investment, and growth direction	Giaretta & Chesini (2021); Bloch et al. (2023); Chung et al. (2022)
Functional	Innovation capability	Product and process innovation underpin early growth; risk of "killer acquisitions" for innovative entrants	Andersson et al. (2014); Aminova & Marchi (2021); Cunningham et al. (2021)
Functional	Internationalisation and partnerships	Early internationalisation and strategic partnerships build capabilities for complex markets	Hagen & Zucchella (2014); Sapienza et al. (2006)
Functional	Organisational culture and entrepreneurship	Entrepreneurial culture linked to financial performance and TFP; tensions in startup work culture; overconfidence dynamics	Pisar & Mazo (2020); Erken et al. (2018); Cockayne (2019); Szerb & Vörös (2021)
Functional	Business model scalability	Scalability drivers: technology, cost/revenue structure, adaptability, network effects, user orientation	Stampfl et al. (2013)
Functional	Financing strategy and constraints	Debt vs equity preferences; leverage-performance trade-offs; constraints affect innovation and survival	Robb & Robinson (2014); Mattsson & Andersson (2019); Gomezel (2022); Ling Ng et al. (2024); De Haas, Sterk & Van Horen (2022); Fuertes-Callén et al. (2022)

Endogenous structural (foundational) attributes, such as age, size, profile of founders, business model, ownership structure, and possession of intellectual property rights, stand out as significant intrinsic determinants that influence ST's growth and likelihood of survival.

An ST business model is related to the initial selection of the industry sector. While Martínez-Fierro (2020) found that ST's growth is industry-agnostic, Cantamessa et al. (2018) showed that vulnerability to bankruptcy varies across sectors, suggesting that sector-specific risks significantly influence ST endurance and success.

The size and age of a firm can influence a range of business aspects, from the ability to attract investment to the agility with which it can adapt to market changes and are critical factors to consider when evaluating potential success (Fuertes-Callén et al., 2022). A small ST size could be an advantage for growth, as shown by Somya and Saripalle (2023), who found that the larger firms grow at a decreasing rate compared to small firms. But the firm's size also correlates with resources available for innovation, market reach, and the capacity for risk-taking, which are all pivotal in determining an ST's strategy and scalability of the business model. The firm's size and age are positively associated with SME growth in the studies by Li (2009) and Geroski et al. (2010), who identified a positive relationship between founding conditions, specific to the firm's size in early life, and subsequent survival. De Haas et al. (2022) showed that large STs that continue to grow throughout time achieve higher productivity levels. However, the relationship between the ST's age and productivity remains a topic of ongoing academic investigation. The research by De La Fuente (2011) and Añón Higón et al. (2022) supports age as a positive factor because it enables skill development and accumulation of experience, yet Alon et al. (2017), Douch et al. (2023), and Galego et al. (2018) discovered a negative relationship between the firm's age and productivity growth.

According to de Rassenfosse (2012), R&D activities often require vast financial resources and having patents creates better access to state subsidies, also helping to attract investors (Colombo et al., 2023). However, Leiponen and Byma (2009) found that most STs prefer other means to protect their intellectual property, such as speed to market or trade secrets, and that only R&D intensive and science-based SMEs, most with university cooperation, were likely to identify patents as the most important method of appropriating innovation returns.

Personal experience, relationships, and knowledge of the firm's founder or founding team are therefore crucial to the successful development of an ST. Gompers et al. (2020) showed that VC funds, especially investing in early-stage ST, consider the management team as the most important factor for deal selection. According to Cassar (2014), previous founders' experience in the sector is more important for ST success than previous ST founding experience. Lin et al. (2023) revealed that firms in high-tech industries led by CEOs with hands-on innovation experience engage in more technology acquisitions and high ownership concentration.

According to Giaretta and Chesini (2021), the ownership structure of an ST determines its future growth direction. The capital structure STs can differ by industry. Business models that scale well attract investors who provide essential resources for rapid business expansion. The research by Bloch et al. (2023) revealed that firms investing in R&D through technical activities, management, and marketing investments experience increased productivity. Research shows that ownership structure, combined with the accumulation of intangible and organisational assets, leads to better productivity and growth opportunities. The funding sources and shareholder composition of STs determine their strategic choices. According to Chung et al. (2022), STs that receive funding from their CEOs and family members show different operational patterns than businesses backed by outside investors. Research shows that capital provider types and their investment proportions impact business operations.

Endogenous functional determinants. Successful STs quickly achieve international growth shortly after their inception due to innovative products (Andersson et al., 2014) or value proposition (Manotti et al., 2021). Growth cycles with waves of different innovation and resource reconfigurations are a distinctive feature characterising high-tech STs. Hagen and Zucchella (2014) examined key factors for the waves of innovation: openness of the managerial team related to the learning potential of the organisation, early strategic orientation to grow internationally, and strategic partnerships, enabling them to enter complex markets. Aminova and Marchi (2021) emphasised the importance of both product and process innovation at the small and young firms; however, sometimes, STs created innovation or knowledge might become a target of "killer acquisitions" as admitted by Cunningham et al. (2021), which is the phenomenon when the competing firms acquire new product-developing STs targeting possible future competition for the acquirer's product portfolio.

According to Scheffran et al. (2012), ST ecosystems have developed a new generation of entrepreneurs who base their work on financial success and social responsibility goals. They employ innovative business models (Weber et al., 2022) and their proactive high-risk appetite development strategies create value beyond the boundaries of the home market (Mathews & Zander, 2023). The business model of "transformational business" emerged because of this development, which unites social value creation with economic value generation in its fundamental operations. The ecosystem itself drives this cultural transformation because, as Filippelli et al. (2025) discovered, it forces STs to work towards economic success and sustainability goals.

The clear relationship between organisational culture and financial performance was confirmed by Pisar and Mazo (2020), and between a strong entrepreneurial culture and TFP growth by Erken et al. (2018). Cockayne (2019) pointed to a group of potentially conflicting features of ST organisational culture, focused on informality, flexibility, and horizontality on one end and stress, hard work, taking initiative, and individual responsibility on the other. Entrepreneurs tend to overestimate their skills in different phases of the ST process, and this overconfidence influences growth expectations through perceived competitive advantages, as revealed by Szerb and Vörös (2021). However, as growth expectations decrease significantly over time, perceived skills remain inflated, with other entrepreneurial expectations becoming more realistic and their impact growing with experience.

The specific culture of ST firms is also linked to the strategies of early internationalisation aspirations. Sapienza et al. (2006) argued that early internationalisation increases the scalability of the growth (by creating new capabilities), but at the same time might decrease firms' survival probabilities. So, a proper ST firm management strategy, as emphasised by Miller (2001), becomes very important: the basic principles of current innovation management and organisational capability, architecture for innovation, and current "best practices" that enable innovation. The scalability of business models is often defined as a primary driver of the growth of firms. Stampfl et al. (2013) suggested an explorative model to estimate the scalability of the business model based on five growth factors in the early stage of firm development: technology, cost and revenue structure, adaptability, network effects, and user orientation.

The financial condition of a company and its capital structure are the essential elements that determine its success. The main sources of ST capital can be segmented into three parts: owners' equity or debt, insiders' equity or debt, and outsiders' equity (VC and government) or loans (bank loans and credit lines). Robb and Robinson (2014) researched almost five thousand young firms from Kauffman Firm Survey data and revealed that newly founded firms heavily rely on external debt financing: owner-backed bank loans, business bank loans, and business credit lines. Based on the research results, the average amount of bank financing outperforms the average amount of insider-financed debt by seven times. Even for newly established firms that rely on insider debt, the average amount of outside debt was twice as high as insiders' debt.

From the firm's financing perspective, STs are attributed to the higher risk businesses (Mattsson & Andersson, 2019) and, for this reason, their funding sources are basically different. STs usually lack access to formal capital markets and rely on investments or loans from their internal network (Gabrielsson & Manek Kirpalani, 2004) or other financing sources such as government grants. Different authors, i.e., Manigart and Struyf (1997), distinguished ST categories by the source of funding: personal savings of the entrepreneurs, occasionally supplemented with capital or loans from family or friends (Coleman et al., 2016), or specific players of the business investment market: business angels and VC firms (Frid et al., 2016).

Financial constraints are a primary factor in ST growth and productivity. Gomezel (2022) proved that external funding creates positive effects on innovation outcomes, especially when companies implement product and organisational changes, and Ling Ng et al. (2024) showed a negative influence of the external funding restrictions. External funding choices depend on the firm's size (as larger businesses use more external funding) and profitability levels because more profitable firms use less debt, according to the study of Newman et al. (2012). The high establishment expenses of high-tech businesses result in elevated leverage levels and extended debt repayment periods (Derrien et al., 2021). The research by Hyun and Lee (2022) shows that debt financing leads to better sales results. However, the use of debt for business expansion brings both growth opportunities and elevated risk levels. De Haas et al. (2022) demonstrated that STs with excessive debt levels face the lowest chances of survival during a 12-year period, and Fuertes-Callén et al. (2022) indicated an extreme increase in bankruptcy risk for unprofitable one-year-old STs.

ST financing patterns transform as businesses progress through their development stages. The study by Yang et al. (2023) demonstrates that new businesses face restricted access to funding through patents during their initial development phase, but they gain access to multiple funding options as they grow. According to Rajaiya (2023), young innovative companies often select equity funding instead of debt because they want to maintain their ability to innovate. This finding was confirmed by Neville and Lucey (2022), who showed that STs with previous entrepreneurial experience prefer equity funding and that established businesses depend more on their internal funds while transitioning from equity to debt financing, yet their bank relationships do not lead to substantial improvements.

The interplay between leverage, financing preferences, the firm's age, and innovation underscores the complex financial environment the ST must navigate. Dvouletý and Blažková (2021) demonstrated that STs total factor productivity (TFP) depends on the combination of age, size, capital structure, and equity. The IT industry research conducted by Nakatani (2023) shows that TFP levels are highest among large and young companies and improve when they use leverage and intangible assets. According to Sung et al. (2022), profit growth follows productivity. Moreover, Honjo et al. (2024) demonstrated that high entrepreneurial activity could reduce some adverse effects stemming from financial limitations.

1.3.2. Exogenous Determinants

Exogenous ST development determinants, which are outside their immediate control, can be categorised into macro-economic, encompassing general economic conditions and market dynamics, and into ecosystem-related, which include local industry networks and support systems (Table 1.3).

Macro-economic determinants. The growth and development of STs are influenced by a complex interplay of economic policies, investment strategies, taxation, prevailing ownership structures, and market-specific factors. Goldschlag and Miranda (2020) investigated US high- and low-technology firms' employment trends and found significant changes. Since 1987, SMEs have dominated in the employment of high technology firms, and their share in the total employment has been growing. The introduction of new products and services in the early 2000's has changed the allocation of labour and capital and brought structural changes to global economies, with a clear shift in production moving away from manufacturing to the services and IT areas. According to the opportunity cost theory of productivity growth, aggregate disturbances in the economy have a positive effect on economic growth. Audretsch and Acs (1994) claimed that during periods of great technological change, there is an increase in the rate of SMEs, especially in the technology-oriented sector, due to increased unemployment and decreased opportunity costs of starting a business.

Table 1.3. Exogenous (macro-economic and ecosystem-level) determinants, frequently linked to startup growth and productivity. Source: compiled by the author

Category	Determinant	Indicative mechanism	Sources
Macro-economic	Technological change and labour reallocation	Periods of high technological change may increase new firm formation; structural shifts towards services/ICT affect opportunities	Audretsch & Acs (1994); Goldschlag & Miranda (2020)
Macro-economic	Globalisation and market concentration	Rise of dominant "superstar" firms associated with declining business dynamism and startup job creation	Haltiwanger (2022)
Macro-economic	Exit markets (M&A) and incentives	Acquisition prospects can increase entrepreneurial and investment attractiveness by providing exit options	Buenstorf (2016)
Macro-economic	Policy, taxation, and institutions	Targeted fiscal incentives (e.g., capital gains); institutional quality (property rights, corruption control); regulation affecting diffusion and dynamics	Edwards & Todtenhaupt (2020); H. Li et al. (2020); Amoroso & Martino (2020)
Macro-economic	Public investment and countercyclical support	State investment and subsidies can shape innovation and investment, especially in downturns and emerging markets	Mazzucato (2012); Jeng & Wells (2000b); Zarrouk et al. (2021)

End of Table 1.3

Category	Determinant	Indicative mechanism	Sources
Macro-economic	Subsidies and programme design	Grants/loans affect R&D and performance; evidence mixed; complementary mentoring/networking increases effectiveness	Varaku & Sickles (2023); Hottenrott & Richstein (2020); Acemoglu et al. (2018); Heller (2024); Autio & Rannikko (2016)
Ecosystem-level	Human capital and skills	Education/STEM skills enhance technology adoption and productivity; effects vary with labour regulation and skill mix	Ramírez et al. (2020); Cammeraat et al. (2024); Fedotenkov et al. (2024)
Ecosystem-level	Market access and market size	Access to customers and export markets supports growth; incumbents may outperform on commercialisation	Arora et al. (2024); Kerner & Kitsing (2023); Almuzel et al. (2024); Kuebart et al. (2025)
Ecosystem-level	Infrastructure (digital and physical) and regulation	Digitalisation and connectivity can raise TFP (often via reallocation); infrastructure requires integrated physical and institutional development	Edquist et al. (2021); Bartelsman et al. (2017); Díaz-Santamaría & Bulchand-Gidumal (2021)
Ecosystem-level	Knowledge spillovers and geography	Universities and dense regions may enable spillovers; benefits depend on mechanisms, social capital and firm stage	Romer (1992a); Audretsch & Keilbach (2007); Bandera & Thomas (2019); Gauger et al. (2021)
Ecosystem-level	Venture capital availability	VC/angel finance supports scaling where conventional funding is limited; selection and governance constraints	Cavallo et al. (2018); Lerner & Nanda (2020); Bonini & Capizzi (2019); Xu (2022)

However, Haltiwanger (2022) distinguishes one more concerning negative effect of globalisation in innovation-intensive sectors in the US. His study shows a significant decline in the rate of new business launches and a decreasing share of the economic activity of young companies. This downturn, which has accelerated post-2000, is linked to the rise of dominant “superstar” firms in the high-tech industry. Unlike the 1990s, which saw a shift towards smaller, younger firms, the 21st century has seen the opposite. There has been a notable decrease in the number of STs that create jobs, alongside a rise in self-employed ventures. Another notable trend is related to the phenomenon when established companies frequently acquire innovative STs: in the ecosystems, these incumbents play an indirect but crucial role in the innovation process. They offer a vital exit strategy for ST founders and investors, enabling them to profitably divest their ventures. The knowledge that a successful ST can potentially be sold to a larger, established firm increases the ST's appeal. According to Buenstorf (2016), the anticipation of a lucrative exit through acquisition makes the entrepreneurial and investment risks more attractive to prospective entrepreneurs.

Several studies investigating exogenous ST growth determinants from a macroeconomic perspective are particularly addressing the role of policy, investment, market dynamics, and competitiveness. Availability of funding, government policies, market demand, and competition are significant exogenous factors, according to Pandya et al. (2023). Khader et al. (2014) pointed out that lending rates are as important to the new business formation. Charaia et al. (2020) emphasised qualitative, sector-specific FDI strategies, and Edwards and Todtenhaupt (2020) indicated targeted fiscal policies, highlighting how capital gains tax incentives can enhance capital flow into an STs. Good institutions, which uphold property rights, reduce corruption, and encourage investment, enhance the potential for long-term growth. According to Li et al. (2020), a strong institutional environment can provide an ST with stability, resources, and incentives needed for growth and innovation. These components collectively contribute to the overall productivity growth by creating an ecosystem that fosters innovation, education, efficiency, infrastructure development, and stable institutional frameworks. Amoroso and Martino (2020) explored how regulatory frameworks in labour, capital, and product markets affect technology diffusion and firm dynamics. Contrary to the belief that fewer regulations always promote productivity growth, their findings reveal a complex relationship, where deregulation's impact varies depending on business dynamism and the regulatory environment.

Mazzucato's (2012) emphasis on the role of public-sector investment in fostering innovation highlights the importance of a supportive innovation ecosystem that includes both public and private sector players. Government policies and subsidies can have a strong impact by setting the regulatory stage and by galvanising investment during downturns (Jeng & Wells, 2000), especially in emerging markets, according to Zarrouk et al. (2021). Structural policies influencing the creation of a certain ST type entering the economy might have an important macroeconomic impact (De Haas et al., 2022). The study by Komninos et al. (2024) emphasises the role of supportive policies, access to financing, and a favourable regulatory environment in enhancing the positive impact of entrepreneurships on employment.

Public subsidies function as a common policy instrument that governments use to promote ST development. Different types of public support, including grants, tax benefits, and subsidised financial assistance, help solve market problems that stem from information gaps and high ST business risks, or to help them, especially in the early stages, with, e.g., physical resources (Dourado Freire et al., 2023). Research by Varaku and Sickles (2023) indicates that public subsidies create positive effects on ST performance because they drive higher R&D spending and generate better revenue and job creation. Hottenrott and Richstein (2020) found a positive correlation between grants and subsidised loans and tangible investments accessed by firms and growth of revenue and employment. However, grants had a higher impact on the additional investments of firms in R&D activities than loans, and STs that received both types of financing outperformed other groups that received just one type in terms of employment, revenue, and innovation performance. Research findings on the effectiveness of public subsidies remain controversial among experts. For example, Acemoglu et al. (2018) argued that it is worth encouraging the death of less productive firms, because it frees skilled labour resources, which could be better used by the IE. Heller (2024) indicated that innovation subsidies create new ideas, but their effectiveness in producing valuable patents and enduring business expansion remains uncertain. The way in which subsidy programmes are designed and executed determines their ability to succeed.

The combination of targeted financial support with mentorship and networking services in subsidy programmes leads to better results, according to Autio and Rannikko (2016). Beyond initial funding support, Clayton (2024) pointed out policy measures, which also focus on the ST sustainability and are context-specific (Pardo-del-Val et al., 2025). Venâncio and Jorge (2022) discussed the role of public investment in helping STs create more external financing opportunities by increasing credibility and attracting external equity investors, especially during economic slowdowns or recession periods. The competitiveness of STs in developing economies is shaped by a complex set of factors beyond just macroeconomic policies, and, as Satyanarayana et al. (2021) indicated, a closer look at the ecosystem level should be taken.

Ecosystem-level startup growth and productivity determinants. The literature on entrepreneurial ecosystems shows that ST growth and productivity depend on five key ecosystem-level factors, which include human capital, market access, infrastructure access, knowledge spillovers, and venture capital funding availability. These factors work together to create the overall dynamic nature and competitive advantage of ST ecosystems.

Education plays a vital role in spreading new technologies throughout the economy and enhancing the workforce's ability to assimilate and utilise these technologies effectively. The economy depends on education to spread and absorb new technologies throughout its system. For example, Ramírez et al. (2020) showed that human capital serves as a fundamental factor that drives STs' expansion and productivity growth through technology adoption. Plesca and Summerfield (2023) discovered that productivity levels increase by 3% when overeducation rates rise by 1%, while this effect becomes stronger in industries that use many intangible assets. Employee education determines a firm's operational success. Fedotenkov et al. (2024) showed that employment protection laws affect labour productivity differently based on worker education levels and create negative impacts in sectors employing skilled workers, because such rules make it harder for firms to adjust or reallocate highly qualified staff to their most productive uses. Cammeraat et al. (2024) revealed that adult STEM skills create a positive relationship with productivity levels.

ST firms need market access to achieve both growth and maintain their business operations. The research by Arora et al. (2024) demonstrated that STs excel at developing new technologies, yet incumbent companies excel at commercialisation, which results in deep tech sector inefficiencies when these two functions do not align. The ability of an IE to produce exportable goods represents a vital operational element. Digital service STs that export their products to foreign markets and receive foreign ownership generate substantial national export value, according to Kerner and Kitsing (2023). Early ST internationalisation is also a source of organisational learning (Ferrante & Freo, 2019) for sustainable growth (Vekic, 2020). The market perspective stands as the essential factor for entrepreneurial ecosystems, according to Almuzel et al. (2024), while market size emerges as the leading criterion. The research by Kuebart et al. (2025) demonstrates that better market access enables firms to generate higher revenues and achieve better product quality and increased profits.

STs need digital infrastructure with high-speed internet access to join the digital economy and expand their customer base worldwide. The ST ecosystem depends on physical infrastructure elements, such as transport, telecommunications, and energy systems, as well as institutional and regulatory structures. For example, Edquist et al. (2021) determined that IoT connections per inhabitant increase by 10% and boost TFP by 0.23%. Zhu and Yu (2023) explored the links between firms' TFP and the government digitalisation level and established a positive relationship in Chinese companies. However, Bartelsman et al. (2017) found no significant effect of broadband access on within-firm productivity, but a positive effect at the aggregate level, which may indicate positive effects from reallocation (i.e., more productive firms relative to less productive firms), firm entry and exit, or knowledge spillovers across firms. Wen and Zhan (2023) claimed that increasing the investment in innovation due to the new type of infrastructure, capital flow can be stimulated to firms with high market value and high productivity. The physical network infrastructure and communication systems form a part of the necessary infrastructure, but the complete system requires a solid institutional and regulatory structure. Díaz-Santamaría and Bulchand-Gidumal (2021) demonstrated that infrastructure development needs an integrated strategy because both physical and non-physical elements create an environment which supports successful ST ecosystems.

The geographical location of the ST could be attributed to the growth/success determinants due to the phenomenon of the knowledge spillover, the term introduced by Romer (1992). The knowledge spillover theory of entrepreneurship demonstrates that new businesses emerge to convert unused knowledge that existing organisations and research centres have developed but failed to exploit (Audretsch et al., 2025). This theory extends to the original model by establishing an ecosystem framework, which shows that both intrapreneurship and entrepreneurship play essential roles in converting uncommercialised knowledge into marketable innovations. Audretsch and Keilbach (2007) argued that entrepreneurs can be more successful in regions where a higher level of knowledge spillover is promoted by universities and research institutions. Later, Changoluisa (2023) showed that new companies located in densely populated areas tend to exhibit improved performance during their early stages, typically up to 7 years.

However, Guckenbiehl et al. (2021) admitted that there is no clear answer to how STs benefit from knowledge spillovers and what mechanisms they use to integrate knowledge into their innovation process. According to Bandera and Thomas (2019), merely being in such an environment does not guarantee that an ST will utilise this social capital, and the impact also depends on the ST's development stage (Gauger et al., 2021). For example, the research by Lee and Kim (2024) investigates how human capital generates productivity growth and argues that strategic knowledge spillover initiatives can help late market entrants reach high innovation levels despite their delayed entry.

Knowledge spillovers also raise the question of the endogenous or exogenous nature of the productivity increase due to human capital influence. Does it increase due to internal effects of the firm or due to the benefits of operating in a highly digitalised industry? The strength of these effects depends on the specific industry sector, according to Foster-McGregor and Pöschl (2016), who discovered that labour shifts between high- and medium-tech industries produce beneficial knowledge transfer to the destination sector. Akhvlediani and Cieślik (2020) demonstrated the positive effect of knowledge transfer between entities on economic convergence, especially beneficial for the countries and firms below the averages, according to Nguyen-Huu (2024).

Investing in technological STs is specific not only due to the higher risks related to innovative products and services and non-linear growth patterns, but also due to the greater uncertainty related to the valuation of specific STs' assets, such as human capital of the founder team or entrepreneurial idea (Balcerzak et al., 2023; Zinecker et al., 2022). Research by Davis and Zhao (2019) confirmed that ST entrepreneurs select VC financing options when the risk is medium and high. Therefore, VC serves as a vital financial resource that supports ST development and expansion for businesses that cannot access conventional funding channels. VC is a type of private equity investment by wealthy individuals or by public or private companies.

According to Cavallo et al. (2018), venture capitalists and angel investors play a prominent role in the development of an ST, promoting entrepreneurialism and economic growth. The availability of VC stands as a fundamental factor that determines how STs emerge, survive and expand their operations. The research by Croce et al. (2019) demonstrates that STs with funding from privately owned VC firms experience better outcomes related to job creation and innovation (Pradhan et al., 2018). According to research by Lerner and Nanda (2020), of the 4,109 initial public offerings of 1995–2018, 56% of ST firms survived as they were backed by VC. However, the authors emphasised some limiting factors, including only 0.5% of the firms in the US that received VC financing:

- A narrow band of technological innovations that meet the requirements of institutional VC investors.
- A small number of VC investors who can afford to invest in radical technological change.
- Issues of corporate governance within VC firms.

The entrepreneurial finance sector continues to depend on VC firms, according to Bonini and Capizzi (2019), even though alternative funding options have appeared. However, the research by Xu (2022) demonstrates that VC investments sometimes create negative effects on future business value expansion. The competition for STs among VCs with different skill levels leads to STs often partnering with less established VCs, according to Khanna and Mathews (2022), and the ownership structure of VC firms determines how the innovation ecosystem will develop (Li et al., 2023). For example, Xie et al. (2024) showed that the presence of VC reduces corporate financialisation, with this effect being more pronounced in privately-owned VCs and STs with weaker corporate governance.

The chapter demonstrated that startup ecosystems operate as multi-actor innovation systems in which firms' growth trajectories are enabled or constrained by interdependent resources, institutions, and networks. The literature indicates that startup outcomes reflect an interaction between endogenous determinants (e.g., founder human capital, innovation capability, business model scalability, and financing strategy) and exogenous determinants (e.g., policy and institutional quality, public support instruments, human capital and infrastructure at the ecosystem level, knowledge spillovers, and venture capital availability). Consequently, startup ecosystem development should be understood not as a single policy lever or market condition, but as a coordinated configuration of complementary factors that jointly shape startup formation, survival, and scaling.

The next chapter extends this perspective by moving from determinants to outcomes: it examines the socio-economic impact of startup ecosystems, focusing on how ecosystem maturity translates into measurable effects.

1.4. Socio-Economic Impact of Startup Ecosystem

This chapter examines the socio-economic impact of startup ecosystems by shifting the focus from ecosystem inputs (enablers and determinants) to ecosystem outputs and outcomes. Building on the entrepreneurial ecosystem approach, the chapter conceptualises ecosystem value creation as a systemic process in which productive entrepreneurship translates ecosystem conditions into measurable macroeconomic effects. In this view, startups matter not only as individual firms, but also as a collective mechanism through which innovation, employment, and productivity gains diffuse across the wider economy.

ST ecosystems generate economic value that spreads throughout the economy while surpassing the achievements of individual ST. According to Romer (1990), endogenous factors, such as R&D, innovation, human capital, and knowledge spillover, drive sustained productivity growth. Extending this theoretical foundation, Stam (2015) conceptualises the entrepreneurial ecosystem as a system of framework and systemic conditions that enable productive entrepreneurship and, in turn, generate aggregate value creation at the macro level. The economic value of ST ecosystems emerges through three main channels that support productive entrepreneurship through enhancing growth and employment opportunities, driving innovation and productivity. Stam's (2015) model demonstrates how specific entrepreneurial outputs emerge from ecosystem systemic conditions, which produce new economic value through their outcomes (Fig. 1.2).

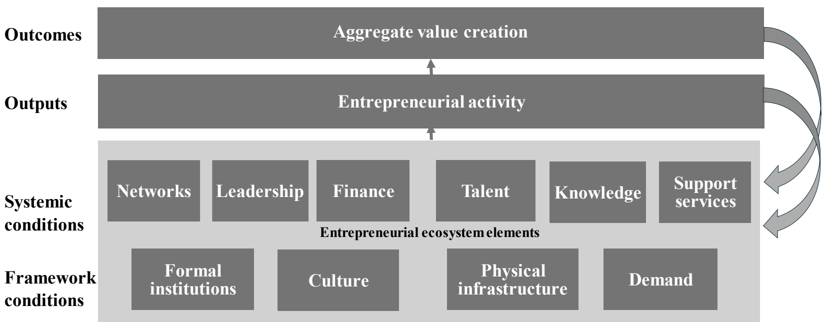

Fig. 1.2. Entrepreneurial ecosystem approach. Retrieved from Stam (2015)

Multiple evaluation methods are needed to assess entrepreneurial ecosystems because success appears in different performance areas. STs drive economic expansion through job development and financial growth, while using technology to increase productivity and develop human capital and create an environment that supports long-term innovation and business competitiveness. The financial market has developed into a sophisticated network of diverse elements because STs struggle to obtain funding through conventional channels. Table 1.4 synthesises the main channels through which startups and startup ecosystems are argued to influence economic development in academic literature.

Table 1.4. Startup ecosystem impact channels and expected macroeconomic outcomes in academic literature. Source: compiled by the author

Impact channel	**Macro-level outcomes**	**Key sources**
Economic growth and firm dynamics	Contribution to aggregate output growth through entry, scaling and reallocation; growth is non-linear and concentrated in a small subset of high-growth firms	Audretsch et al. (2014); Coad & Hölzl (2009); Wiklund et al. (2009); Coad et al. (2014); Hagen & Zucchella (2014); Halabisky (2006)
Job creation and labour-market dynamism	Young and innovative firms contribute disproportionately to net job creation; effects vary across cohorts and over time	Decker et al. (2014); Calvino et al. (2018); Davidsson et al. (2006); Ouimet & Zarutskie (2014); Dinopoulos et al. (2023); Garcia-Tapial & Cardenete (2023); Croce, Martí & Reverte (2019)
Innovation, productivity and technology diffusion	Acceleration of technological adoption and diffusion; potential productivity gains with heterogeneous firm-level effects; implications for TFP dynamics	Chen & Liu (2023); OECD (2023); Fernald et al. (2023); Syverson (2017); Gal et al. (2019); Brynjolfsson et al. (2017); De Haas, Sterk & Van Horen (2022); Alon et al. (2018); Douch et al. (2023)
Financial market development and entrepreneurial finance	Expansion and specialisation of entrepreneurial finance; adaptation of financing instruments and theory to high-risk, intangible-asset firms	Manigart & Struyf (1997); Robb & Robinson (2014); Mattsson & Andersson (2019); Frid et al. (2016); Myers (1984); Rajaiya (2023); Neville & Lucey (2022); Hyun & Lee (2022); Yang et al. (2023); Edwards & Todtenhaupt (2020)
Human capital formation and skills upgrading	Acceleration of experiential learning via dense networks of founders, mentors, and investors; upgrading of technical and managerial skills	Almeida & Miguel-Oliveira (2022); Harada (2004); Lai & Vonortas (2019); Filippelli et al. (2025)

End of Table 1.4

Impact channel	Macro-level outcomes	Key sources
Entrepreneurial culture and competitiveness	Normalisation of experimentation and risk-taking; networked learning; high-potential entrepreneurship as a catalyst for broader ecosystem ambition	Ferreira et al. (2017); Ziakis et al. (2022); Martínez-Fierro (2020); Stam (2015)
Trade and high-tech exports	Linkages between ecosystem innovation capacity, R&D and high-tech export performance; GDP–export relationship is context-dependent	Nitescu, Murgu & Bunea (2024); Sojoodi & Baghbanpour (2023)

It maps each impact channel to the most frequently discussed macro-level outcomes (e.g., growth, employment, innovation, productivity, finance, and trade), highlighting the mechanisms through which ecosystem activity may translate into economy-wide effects. The selected sources provide the theoretical and empirical foundations for the impact pathways later operationalised in the dissertation's macro-level assessment framework.

1.4.1. Economic Growth

The innovative nature of STs, underpinned by human capital and knowledge, is not just a feature of their operation but a fundamental component of their growth potential. Audretsch et al. (2014) provided a structured framework to understand an academic approach to a firm's growth. A foundational perspective in this field is Gibrat's Law, which posits that firm growth is a stochastic process independent of the initial size. Some empirical studies have found evidence supporting Gibrat's Law; others, including recent work by Serrasqueiro et al. (2023) and Ferrucci et al. (2021), have presented contrary findings. The ST growth is a multidimensional process. Although quantitative metrics, such as increases in sales or employment, are frequently used, as noted by Coad and Hölzl (2009), qualitative factors are equally vital for long-term success. As Wiklund et al. (2009) argued, qualitative growth involves building a robust, adaptable, and respected firm, creating value in ways that are not always immediately quantifiable but are crucial for sustainable economic impact. However, quantitative measures remain prevalent, with changes in employee numbers or revenue being the most common indicators, aligning with the definition of high-growth firms (OECD, 2021).

However, it is crucial to recognise that high growth is a relatively rare event. Research by Coad et al. (2014) indicates that firms in the high-technology or knowledge-intensive services sectors do not inherently have a higher probability of experiencing strong growth compared to companies in other industries. Furthermore, as Hagen and Zucchella (2014) demonstrated in their study of "born global" firms, early internationalisation follows a non-linear path that is intrinsically linked with survival, underscoring the principle that while many STs may be founded with global ambitions, only a select few are destined for sustained growth and significant economic contribution: "Many companies can be born global, but only some are born to run". Halabisky (2006) also underscored a potential trade-off between rapid growth and long-term survival: over time, survival rates of hyper-growth firms declined, which is associated with rapid growth.

The creation of new jobs represents the main way through which ecosystems influence macroeconomic results. Several authors emphasised the significant ST impact on job creation. A thriving ST ecosystem directly generates new employment opportunities as one of its most visible economic advantages. Decker et al. (2014) showed that innovative STs are the main job creators in the US, but at the same time, the authors admitted that: "The contribution of STs and young businesses to jobs and productivity is a noisy and complex process". According to the presented data, STs create about 20% of the total jobs, and high-growth firms create around 50% of the total jobs in the US. The study by Calvino et al. (2018) is based on data from OECD countries and explores ST survival rates at the beginning of the decade after the inception, which revealed that there was a small share of successful STs that "disproportionally contribute" to job creation.

The changes in revenue or sales are most likely, but not necessarily highly correlated with changes in employment. As Davidsson et al. (2006) claimed, sales and employment growth indicators can represent different phases of ST growth processes, mainly because sales are an intermediary variable that responds to changes in supply and demand conditions, and the employment decision is made by the entrepreneur. For example, faster employee growth (in comparison with revenue growth) can signal the entrepreneur's decision to face a new level of demand. STs also disproportionately employ and hire young employees: around 27% of employees in firms aged 1 to 5 years are between 25 and 34 years old, a percentage that exceeds 18% of mature companies and young employees in young firms earn higher wages than young employees in older firms (Ouimet & Zarutskie, 2014). New ST significantly contribute to job creation, particularly in innovative, technology, and service sectors, fostering a dynamic labour market and reducing unemployment, according to Dinopoulos et al. (2023). Research by Garcia-Tapial and Cardenete (2023) demonstrates that scaleup ST businesses create substantial effects on GDP and employment. They scale up their workforce even further during the first 12 years of their existence (thus diverging even more from other firm types in terms of employee numbers). Croce et al. (2019) demonstrated that VC investments, which could be used as a proxy for a vital ST ecosystem, create positive effects on employment patterns even when the economy faces financial challenges. The research also shows that private VC investments generate more employment opportunities than government-backed funds.

The direct link between GDP expansion and high-tech export growth remains complex to understand. The research by Nitescu et al. (2024) demonstrates that R&D investments, together with GDP performance, create positive effects on high-tech export development. The study by Sojoodi and Baghbanpour (2023) demonstrates that high-technology exports create GDP growth in particular developing and developed countries.

1.4.2. Financial Market Development

The distinctive risk profiles, intangible assets and fast growth potential of STs require adjustments in financial theory for the corporate finance models that were developed for established businesses. STs transform financial markets through their active participation as transformative agents in market development. The modern financial system undergoes transformation through the development of new financial tools, specialised investment networks, and regulatory framework adjustments, which redefine its operational structure.

In traditional industries, corporate financing theories apply consistently across both small and large firms, as demonstrated by Cassar and Holmes (2003), who also provided empirical evidence linking asset structure, profitability, and growth with a firm's capital structure and financing strategies. But in innovative industries, the effects can vary. Financial constraints affect hi-tech and low-tech firms differently: for low-tech firms, they might positively induce cost-saving practices and increase efficiency, while in high-tech firms, they will decrease product innovation levels (Bonanno et al., 2023). For example, Zhu and Kim (2023) revealed how equity and credit markets affect innovation differently in high-tech and low-tech industries: equity markets have a diminishing impact on innovation in high-tech sectors, while credit markets are a primary driver of innovation in non-high-technology industries. The high-risk and high-growth characteristics of STs in technology sectors prove that established financing theories do not apply universally, which indicates a fundamental transformation in capital distribution for innovation promotion.

STs face different funding opportunities because their high-risk business models create a separate financial system for their operations. The financial restrictions of STs, according to Manigart and Struyf (1997), establish them as separate from conventional businesses. The financing needs of STs differ from traditional businesses because they do not receive the same level of bank loans and trade credit support that, according to Robb and Robinson (2014), can reach seven times higher than insider-financed debt.

The combination of low survival rates and insufficient tangible assets makes traditional lenders view STs as risky investments, according to Mattsson and Andersson (2019). STs face restricted access to conventional capital markets because of their high-risk profile, so they must seek funding through alternative sources. STs obtain funding through personal savings, family and friend capital, government grants, and business investment market participants who include business angels and VC firms, according to Frid et al. (2016). The funding needs of STs have led to the development of a specialised network of early-stage investors who operate outside traditional financial markets, thus expanding the scope of available funding options.

The financing patterns of STs require financial theorists to reassess the Pecking Order Theory as one of the established financial models. Myers (1984) developed the Pecking Order theory, which describes how firms select their funding sources by using internal funds first, then debt, and finally issuing new equity. The theory works well for established companies, but it becomes more complicated when applied to ST businesses. The research conducted by Serrasqueiro et al. (2023) demonstrates that SMEs, including STs, use external debt financing after they exhaust their internal funding sources, which supports the theory. The natural characteristics of STs create disruptions to the typical funding sequence described by the Pecking Order Theory. Rajaiya (2023) discovered that innovative companies with high levels of innovation tend to avoid debt financing because they either lack the ability or show a reduced willingness to take on debt. The financing choices of STs depend on more than capital costs, e.g., Neville and Lucey (2022) found that experienced STs prefer equity funding because of investor value and flexible funding requirements. The complex nature of ST financing decisions proves that the Pecking Order Theory needs revision because it fails to capture the full complexity of ST funding choices. Financial market development receives its main driving force from the financial limitations that startups encounter.

The financial barriers that STs must overcome create substantial market development opportunities for financial markets. STs face high external financing requirements because they maintain mostly intangible assets in their business operations (Albert & Caggese, 2019; Ferrucci et al., 2021). The market has developed new financial tools and approaches because STs need to manage their unique risk-return characteristics. For example, Hyun and Lee (2022) suggested complex portfolio financing methods, which use equity funding during ST development before transitioning to debt financing when the company demonstrates its growth potential. New funding options through patent-backed financing were noted by Yang et al. (2023), and changing capital gains tax policies by Edwards and Todtenhaupt (2020), who show how the market adapts to these changes.

1.4.3. Tech Adoption and Productivity

The positive effects of IE stem from its ability to accelerate technological progress and improve knowledge sharing and implementation of production technology, according to Chen and Liu (2023). OECD (2023) highlighted the complex and uncertain landscape of the productivity developments of the current decades. Fernald et al. (2023) attributed this slowdown primarily to decreased TFP growth, addressing the impact on the global trends, the 2007 financial crisis, the COVID-19 pandemic and decreasing returns from innovations, particularly in ICT industries. For example, manufacturing and ICT sectors are seen as major struggling sectors of the UK economy, which is also maintained by Coyle and Mei (2023).

There is no single factor to blame. The increase of nonstandard jobs (Capriati et al., 2024), the combination of the decline in capital contribution, the reduced spillovers of intangible capital, trade slowdown, and the decrease in allocative efficiency, among others, collectively explain much of the observed slowdown (Goldin et al., 2024). The economic value produced by STs remains a complex matter that generates different opinions from experts. The essential connection between technology and human capital and productivity stands out as a key solution to the Solow Paradox, according to Brynjolfsson and Hitt (1994). The Solow Paradox is a term coined by Solow (1987) to describe the puzzling situation where technology advances quickly, yet productivity levels remain stagnant.

Several studies established a link between the adoption of digital technologies and the increase in firm productivity (Syverson, 2017). Acemoglu et al. (2014) linked faster labour productivity growth in IT-related industries after the 1990s with diminishing output and declining employment levels. Cesaratto et al. (2003) examined the long-term impact of technological change on employment, challenging the idea that innovation automatically leads to investment or employment growth. The authors emphasised an aligning role and importance of demand growth, which can come from export growth or expansionary macroeconomic policies, and the fact that technical change does not guarantee economic growth or full employment. That is, the study by Malik and Mitra (2023) revealed a slightly negative TFP growth impact on employment levels in lower-income countries. Zamparelli (2024) explored the relationship between wage share and labour productivity growth through the lens of induced innovation and endogenous growth theories, and these findings suggest that labour productivity growth positively correlates with the wage share under certain technological conditions; the same positive effect for labour productivity was examined by Banday and Erdem (2024) for the OECD countries.

While it is widely agreed that technology enhances a firm's productivity, quantifying this benefit presents challenges due to its varied effects. Brynjolfsson et al. (2017) challenged traditional measures of TFP inputs and output reasoning by new technologies, such as the disproportionate impact of artificial intelligence or machine learning on intangible assets. They maintained that an unexplained investors' trust in companies of new technologies is reflected in high market values of the firms developing these technologies. Given that STs are young companies fundamentally driven by technology, how do these core aspects influence their productivity levels?

Another important question related to digital technologies and productivity: How does the impact of adopting technology vary among firms based on their age, existing productivity levels, or the industries in which they operate? In the study of Gal et al. (2019), the authors have shown that productivity benefits of the adoption of technology at the industry level could be significant, not related to the size of the firm and that already high productivity firms are gaining more. Also, that technology adoption is sector-specific: manufacturing sector firm gains were higher than those of firms from the service sector. The fact that higher productivity level firms gained more from digital adoption was related to a reversed causality effect: the firms with higher productivity have more resources to invest in digital technologies. The research by Knott and Vieregger (2018) presents an opposing view, which states that R&D productivity rises when companies expand their size. Research indicates that big corporations outperform STs in R&D investment returns because they can better utilise their resources, but STs lead the way in creating new concepts through an innovative combination of existing ideas.

There are not as many studies on ST productivity, and some scholars provide mixed evidence on ST benefits for national economies. For example, De Haas et al. (2022) found that large STs are relatively productive, and, importantly, this productivity premium is very persistent over time. Alon et al. (2018) stated that the ST deficit and subsequent ageing of the US business sector have had a considerable impact on aggregate productivity and found a robust relationship between labour productivity growth and the firm's age: the relationship between the firm's age and productivity growth is downward sloping, but the magnitude decreases significantly after 5 years. The same evidence for decreasing TFP was received lately by Douch et al. (2023), who researched UK firms and earlier, by Galego et al. (2018), who revealed an increasing contribution of the labour factor and a decrease in the capital in mature-stage family firms.

1.4.4. Enhancing Human Capital

ST ecosystems demonstrate their ability to drive innovation and economic expansion through the way endogenous growth theory explains these phenomena. According to Romer (1992), technology functions as a "non-rival" resource which enables different actors to access and use it without reducing its availability. The concept applies specifically to ST ecosystems because they use open-source technologies, shared knowledge platforms, and collaborative development models. ST ecosystems function as essential drivers of human capital development because they transform workforce skills, knowledge, and abilities through their operations.

Almeida and Miguel-Oliveira (2022) demonstrated that high-quality entrepreneurship clusters in California and Massachusetts form their own distinct convergence group, indicating ongoing spatial separation between knowledge and capital centres. Human capital in these dynamic environments goes beyond conventional measures of formal education because it encompasses practical skills and tacit knowledge. Research by Harada (2004) on Japanese firms demonstrated that practical experience of managers proved more vital for productivity than their educational background or gender, which indicates that STs value experiential learning above formal qualifications. The research results contradict traditional educational standards by demonstrating that practical experience is the most crucial factor for ST success.

The fundamental ST characteristics, including their unpredictable nature and limited resources, require specific characteristics of human capital. The founders, together with their initial team members, need to demonstrate flexibility and speed in learning because they work in an environment of continuous change. The demanding nature of IE, according to Filippelli et al. (2025), forces firms and founders to develop competencies. The success or failure of ST depends heavily on what founders know and on how well they connect with others. The development of human capital for STs requires a complete training in both technical competencies and essential soft skills, including communication and leadership abilities, and networking capabilities.

Lai and Vonortas (2019) claimed that high-growth firms, STs, and university graduates, together with risk finance investments, lead to higher human capital development and knowledge production within the ST ecosystem. The dense ST environment with mentors and investors creates an active learning space which enables people to learn new skills through multiple educational practices. The combination of structured training and mentorship in incubators and accelerators and peer-to-peer learning at informal networking events enables participants to gain new knowledge and skills, which include handling economic goals alongside sustainability targets.

1.4.5. Cultivation of an Entrepreneurial Culture

ST ecosystems play a vital role in developing an entrepreneurial culture that extends beyond their influence on human capital development. The entire ecosystem operates under a distinct set of values and norms that support innovation and growth through its unique entrepreneurial culture. The main characteristic of this culture involves accepting high risks and celebrating experimental approaches. ST ecosystems differ from traditional corporate settings because they treat failure as an essential learning experience instead of a negative event. Schumpeter's highlighted importance of entrepreneurial activities and innovation was empirically proved by Ferreira et al. (2017), who identified a positive effect of total early-stage entrepreneurial activity on a national Global Competitiveness Index.

The entrepreneurial culture of ST firms demonstrates two essential characteristics through its emphasis on teamwork and its strong network connections. The framework developed by Ziakis et al. (2022) demonstrates that stakeholder connectivity is a critical factor for ST success. The network structure between entrepreneurs and their investors and mentors allows them to exchange knowledge, resources, and professional connections. The collaborative nature of the ecosystem improves operational efficiency and establishes a unified community that shares common goals and improves the potential of high-potential entrepreneurs. And vice versa, high-potential entrepreneurship plays a vital role in developing the entrepreneurial culture which exists within the ecosystem. High-potential entrepreneurship, according to Martínez-Fierro (2020), produces stronger effects on entrepreneurial ecosystems than general entrepreneurship. These high-growth companies generate most of the new jobs and economic expansion while serving as examples to other entrepreneurs who become inspired to pursue their own ambitious business goals. The influence of high-potential entrepreneurship and sustainable economic development is contingent on the economic development stage, suggesting that fostering entrepreneurship requires context-specific strategies tailored to each country's development level.

The chapter showed that startup ecosystems create macroeconomic value through multiple, interrelated channels. First, ecosystems support economic growth via firm entry, scaling, and resource reallocation, although high growth remains concentrated in a relatively small subset of firms. Second, startups and scaleups contribute disproportionately to employment dynamics, influencing both job creation and labour-market composition. Third, ecosystems can accelerate innovation, technology diffusion, and productivity improvements with heterogeneous effects across sectors and firm cohorts. Fourth, the distinctive risk profiles and intangible asset bases of startups reshape financial markets by fostering specialised instruments and investment networks. Finally, ecosystems strengthen human capital and entrepreneurial culture through learning, mentoring, and network effects, which reinforce longer-term competitiveness.

1.5. Conclusions of the First Chapter and Formulation of the Dissertation Tasks

1. The literature analysis demonstrates that the concept of a startup remains immature and lacks a unified definition. Existing studies apply

heterogeneous criteria and frequently use overlapping terms (e.g., “high-tech firms”, “born global”, “gazelles”, and “scaleups”), which results in conceptual ambiguity and limited comparability across empirical contexts. Startups are defined in various ways, using structural (e.g., age, size, and industry sector), strategy, or business models (e.g., innovation orientation and early internationalisation) or operational attributes (e.g., scalability, growth intensity, risk profile and funding patterns). Because these dimensions are not consistently combined, the startup construct often becomes context-dependent and sensitive to data availability and research purpose.

2. The synthesis indicates that the most relevant characterisation of startups is not limited to “new and small firms” but emphasises their innovation-driven, scalable growth orientation, frequently combined with early market expansion (including internationalisations) and distinctive financing structures. The literature consistently shows that startup performance reflects an interaction between internal firm-level factors (e.g., founder/team human capital, business model scalability, innovation capability, financing strategy, ownership, and capital structure) and external conditions (e.g., market access, institutions and regulation, public support instruments, human capital at ecosystem level, knowledge spillovers, infrastructure, and venture capital availability). This interactional perspective supports the treatment of startup ecosystems as dynamic innovation systems rather than as isolated firm populations.
3. From the perspective of economic growth theory, startups contribute to macroeconomic performance through identifiable channels. In endogenous growth theory and Schumpeterian frameworks, startups operate as engines of technological change and creative destruction. The macroeconomic contribution of startups is expressed through channels such as (i) productivity growth via innovation and diffusion, (ii) employment dynamics through firm entry and scaling, (iii) resource reallocation and structural transformation, (iv) human capital formation and entrepreneurial culture, and (v) financial market development through specialised entrepreneurial finance. The reviewed evidence also indicates that these benefits are typically concentrated in a limited share of high-performing firms, reinforcing the importance of ecosystem conditions that enable survival and scaling.
4. The literature provides a foundation for a measurement-driven framework but highlights the need for a structured indicator set. Although the determinants and impact channels are well documented, the empirical evidence base remains methodologically fragmented. A substantial share of

studies relies on qualitative case analyses, survey instruments, or expert-based assessments, while quantitative work often employs partial proxies or context-specific datasets that limit cross-country comparability. This combination constrains the ability to systematically link ecosystem conditions to measurable startup performance and, subsequently, to macroeconomic outcomes. Consequently, a methodological gap persists, and there is a need for an integrated framework that connects ecosystem determinants to standardised, indicator-based measurement and to macroeconomic results.

5. Based on these conclusions, the literature review enables the formulation of the dissertation's subsequent research tasks. The dissertation, therefore, proceeds by developing a structured indicator system to operationalise the enabling environment and key impact channels and by empirically testing the proposed framework in a relevant regional setting. To achieve the dissertation objective, the following tasks are formulated:
   5.1. To empirically test and validate the startup characteristics derived from the literature-based definition framework, and to confirm their ability to distinguish startups from non-startup firms.
   5.2. To develop a methodological framework for assessing the enabling environment of the startup ecosystem and its macroeconomic impact.
   5.3. To identify key dimensions of startup ecosystem development and to construct a coherent set of indicators for assessing (a) enabling conditions and (b) macroeconomic impact, based on the literature review.
   5.4. To verify the practical applicability of the proposed assessment model by applying it to the startup ecosystems of the Baltic region and European countries.

2

Methodology for Assessing the Enabling Environment and Macroeconomic Impact of the Startup Ecosystem

This chapter presents the methodological approach used to achieve the dissertation objective: to develop and empirically substantiate a conceptual model for assessing the enabling environment and macroeconomic impact of startup ecosystems, using the Baltic region countries as the empirical setting. The main research results of this chapter are published in the author's publication (Kleponė & Okunevičiūtė Neverauskienė, 2025), and findings of the research were presented at the 13th International Conference on Applied Economics Contemporary Issues in Economy in Olsztyn, Poland.

2.1. Research Framework

The research design follows the sequential logic (Fig. 2.1). First, a conceptual model is constructed through systematic literature analysis and synthesis of definitional and ecosystem approaches. Second, it is operationalised through a structured indicator system linking country–year enabling conditions, firm–year startup dynamics, ecosystem maturity proxied by the V index, and macroeconomic outcomes. Third, the model is empirically examined through firm-level and macro-level analysis.

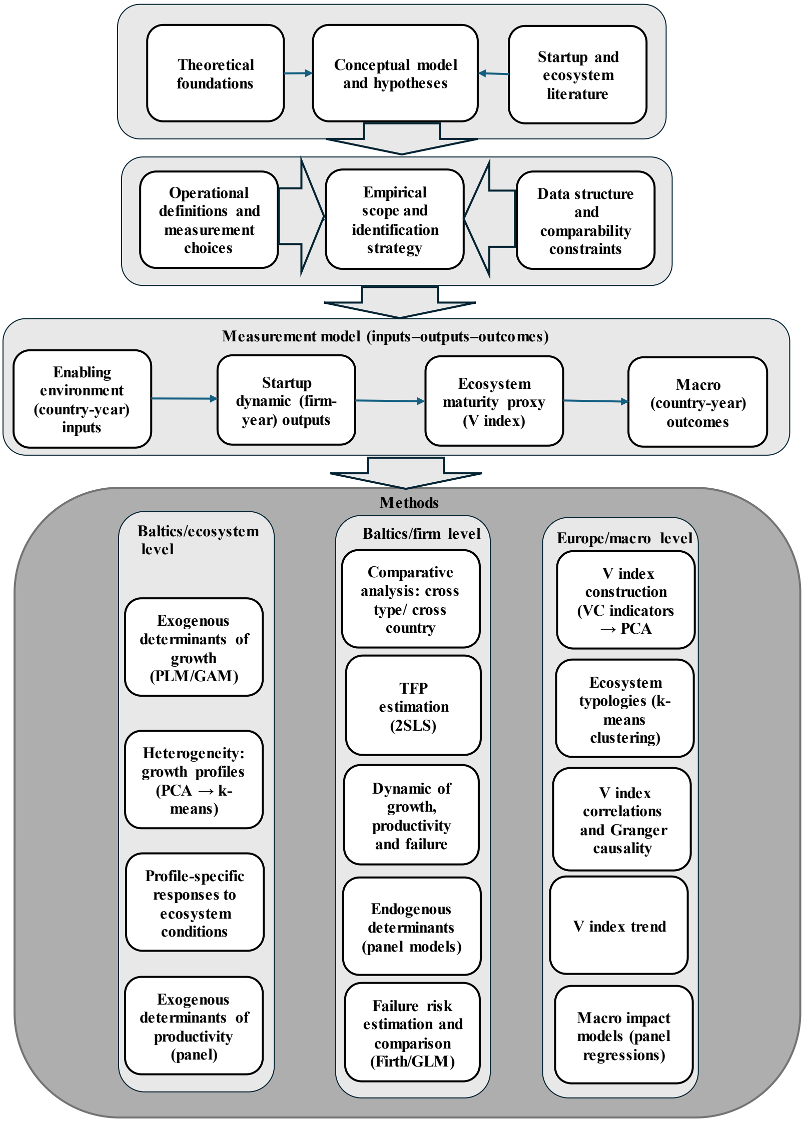

Fig. 2.1. Research framework linking ecosystem inputs to startup dynamics, ecosystem maturity (V index), and macroeconomic outcomes, with Baltic firm-level validation and Europe-wide macro benchmarking

Fourth, the empirical strategy is implemented in two connected settings: firm-level validation is conducted on the Baltic startup ecosystems (Lithuania, Latvia, and Estonia) using matched comparisons, lifecycle analysis, productivity estimation, and determinant models; macroeconomic impact is assessed in a broader European panel to ensure sufficient cross-country variation and to benchmark the Baltic region against the European baseline. Finally, interaction specifications are used to identify whether the transmission from ecosystem maturity to macroeconomic outcomes differs systematically in the Baltic region, thereby distinguishing general European patterns from region-specific effects.

2.2. Conceptual Model

The conceptual model is developed through logical analysis and synthesis of scientific literature on startup definition criteria, endogenous and exogenous startup development drivers, and mechanisms linking startups to macroeconomic performance. The outcome of this stage is an integrated conceptual model specifying:

- Startup concept (identification logic): based on literature-defined criteria and empirically testable characteristics.
- Enabling-environment structure (external ecosystem conditions alongside internal firm-level capabilities).
- Impact pathway linking enabling conditions to startup performance and to macroeconomic outcomes.

Given the dissertation's objective to assess startup ecosystem enabling conditions and macroeconomic effects, the startup concept in this study is anchored primarily in operational outcomes linked to growth and productivity, while acknowledging that innovation orientation and early internationalisation often function as enabling features of such outcomes.

This choice is justified on three grounds. First, ecosystem performance and socio-economic contribution are ultimately observable through outcomes that can be quantified and compared across countries and time (e.g., employment growth, revenue dynamics, productivity, and failure). Second, operational criteria allow the startup construct to be aligned with economic growth theory, where the key transmission mechanisms operate through innovation-driven scaling and productivity improvements. Third, operationalisation enables the construction of a coherent set of indicators that can be applied empirically to evaluate both the enabling environment and the macroeconomic impact of startup ecosystems.

Building on Romer (1990), endogenous growth theory, which emphasises technological advancement, knowledge accumulation, and human capital as internal drivers of economic development, this study integrates the perspective of Stam's (2015) entrepreneurial ecosystem framework and systemic conditions (Fig. 1.2) to analyse how ST ecosystems contribute to aggregate economic value creation. By combining these foundations, the dissertation specifies a causal logic in which ecosystem inputs condition startup performance and startup ecosystem maturity, which then aggregate into macroeconomic outcomes, while feedback mechanisms reinforce ecosystem evolution over time. Before designing the model to ensure theory alignment with empirical evidence, the connection between theoretical constructs and observable variables was established. The research objectives and empirical strategy were developed through a collaborative process between the insights of the academic literature and the limitations of available data.

The proposed conceptual model (Fig. 2.2) distinguishes three linked analytical layers, with an explicit ecosystem maturity mechanism connecting inputs to macroeconomic outcomes. The input layer (external development drivers) captures the innovation ecosystem enabling environment as a set of external conditions that shape startup development. In the model, these conditions are represented by measurable indicators of aggregate demand, public investment and support, access to markets, human capital, knowledge spillovers, and venture capital availability.

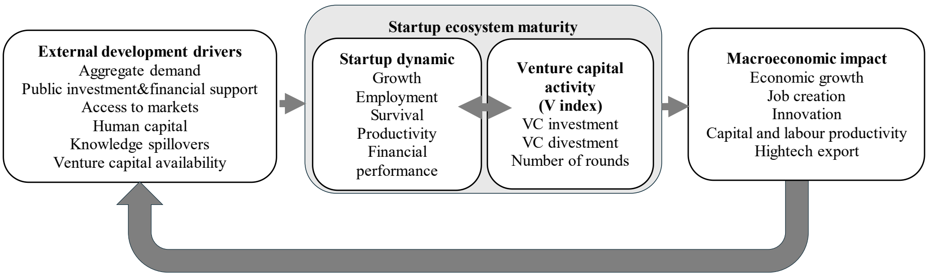

Fig. 2.2. Conceptual model linking the startup ecosystem to economic development.
Source: created by the author

The central layer conceptualises startup ecosystem maturity as the degree to which the enabling environment (external growth drivers) is conducive to scalable startup dynamics (growth, employment, survival, productivity, and financial performance). In this model, ecosystem maturity is proxied by the V index, a composite measure constructed from venture capital activity metrics. The V index captures key maturity attributes of the ecosystem-deep risk capital, selection quality, and exit-based recycling through indicators reflecting investment intensity, the prevalence of follow-on financing, and divestment/exit activity. The link between startup dynamics and venture capital activity, represented by the V index, is modelled as bidirectional and reinforcing. Stronger startup performance improves the ecosystem's attractiveness to investors, increasing deal flow and supporting higher V index values; in turn, a more active venture capital (as reflected by the V index) enables scaling, capability building, and market expansion, thereby strengthening startup ecosystem maturity.

The aggregate outcomes (macroeconomic impact) layer captures economy-wide effects associated with the startup ecosystem, measured through economic growth and job creation, innovation outcomes, capital and labour productivity, and high-tech export performance. These impacts reflect the combined activity of startups and the broader ecosystem, conditional on ecosystem maturity. The model incorporates a feedback loop whereby favourable macroeconomic outcomes strengthen the enabling environment over time (e.g., through increased demand, improved public support capacity, upgraded human capital, stronger spillovers, and deeper capital markets.

This theory-based model provides the foundation for the dissertation's subsequent methodological chapters, which operationalise the constructs through indicators and implement econometric tests to validate the proposed relationships empirically.

2.3. Indicator System for Empirical Testing

While the preceding chapters establish how startup ecosystems connect enabling conditions to startup performance and macroeconomic outcomes, empirical testing requires that each component of the model be represented by observable variables that are comparable across countries and time. Accordingly, this chapter presents the indicator system used in the dissertation for three conceptual model elements. Most prior research on startup ecosystems is qualitative, survey-based, or expert-assessment oriented, and quantitative studies often rely on heterogeneous proxies.

Therefore, this dissertation operationalises the determinants using a harmonised set of secondary indicators selected for theoretical consistency and cross-country comparability. The cited references justify the inclusion of each determinant and inform the determinant–indicator mapping; they are not presented as evidence that the same indicators were used in each study.

External growth factors that constitute the enabling environment are defined by the selected set of indicators in Table 2.1.

Table 2.1. Indicators for external growth drivers (startup ecosystem enabling environment). Source: created by the author

Category	**Determinant**	**Indicator (abbreviation), explanation**	**Sources motivating indicator selection**
Macro-economic	Aggregate demand and growth conditions	GDP growth (GDP GR), average annual growth, %	Komninos et al. (2024); Satyanarayana et al. (2021)
Macro-economic	Public investment and countercyclical support; subsidies and programme design	Financial support (FS), composite indicator of: R&D expenditures public sector (% of GDP); direct government funding and government tax support for business R&D (% of GDP); venture capital expenditures (% of GDP).	Mazzucato (2012); Jeng & Wells (2000b); Zarrouk et al. (2021); Varaku & Sickles (2023); Hottenrott & Richstein (2020); Acemoglu et al. (2018); Heller (2024); Autio & Rannikko (2016)
Ecosystem-level	Human capital and skills	Human capital (HC1), composite indicator of: enterprises providing training to develop or upgrade ICT skills of their personnel (% of total); employed ICT specialists (% of total).	Ramírez et al. (2020); Cammeraat et al. (2024); Fedotenkov et al. (2024)
Ecosystem-level	Market access and market size	Access to the markets (AM), composite indicator of: medium and high-tech product exports (% of total); knowledge-intensive services exports (% of total); Sales of new or improved products (% of turnover).	Arora et al. (2024); Kerner & Kitsing (2023); Almuzel et al. (2024); Kuebart et al. (2025)
Ecosystem-level	Knowledge spillovers and geography	Knowledge spillover (KS), composite indicator of innovative SMEs collaborating with others (% of total); public–private co-publications per million population; Job-to-job mobility of human resources in science & technology (% of total)	Romer (1992a); Audretsch & Keilbach (2007); Bandera & Thomas (2019); Gauger et al. (2021)
Ecosystem-level	Venture capital availability	Venture capital investment (VC), % of GDP	Cavallo et al. (2018); Lerner & Nanda (2020); Bonini & Capizzi (2019); Xu (2022)

The initial pool of indicators for external growth drivers was broader than those retained in the final specification. In the first stage, innovation ecosystem indicators were assembled from Eurostat; however, across the candidate model specifications, these variables were either statistically insignificant or exhibited problematic multicollinearity. Accordingly, they were replaced with theoretically aligned and more parsimonious sub-indices from the European Innovation Scoreboard (EIS) dataset. EIS indicators are extensively used by authors, e.g., Micol et al. (2024), Nawrocki and Jonek-Kowalska (2024). Descriptive summary, observation periods, and data sources for the retained indicators are reported in Annex A, Table A.2.

Startup dynamics indicators capture firm-level outcomes through which ecosystem conditions become economically meaningful. Because outcomes, such as growth, productivity, and failure rate, are not directly observed as single raw variables in most datasets, they are operationalised as measures derived from firm-level structural and financial information. Table presents the underlying (input) indicators used to compute growth (employment and turnover growth rates), productivity (labour productivity and total factor productivity), and survival outcomes (failure rate).

Table 2.2. Measurement of startup dynamics and startup ecosystem maturity: firm-level indicators and V index. Source: created by the author

Determinant	Indicator/abbreviation / explanation	Sources motivating indicator selection
Firm's size	Turnover (TRN), annual, EUR	Somya & Saripalle (2023); Y.-R. Li (2009); Geroski, Mata & Portugal (2010); De Haas, Sterk & Van Horen (2022)
	Total assets (TA), annual, EUR	
	Employees (EMPL), annual average, count	
Firm's age	Age, years at observation	De La Fuente (2011); Añón Higón et al. (2022); Alon et al. (2017); Douch et al. (2023); Galego et al. (2018)
Ownership and capital structure/Financing strategy and constraints	Equity (EQT), annual, EUR	Giaretta & Chesini (2021); Bloch et al. (2023); Chung et al. (2022); Robb & Robinson (2014); Mattsson & Andersson (2019); Gomezel (2022); Ling Ng et al. (2024); De Haas, Sterk & Van Horen (2022); Fuertes-Callén et al. (2022)
	Earnings before interest and taxes (EBIT), annual, EUR	
	Total liabilities (LBL), annual, EUR	
	Total assets (TA), annual, EUR	
V index	Composite index of venture capital investment (VC INV), venture capital divestment (VC DIV), EUR; venture capital investment rounds (VC INV COM), venture capital divestment rounds (VC DIV COM), number of companies	Cavallo et al. (2018); Lerner & Nanda (2020); Bonini & Capizzi (2019); Xu (2022)

In addition, the table reports the V index, a composite indicator of startup ecosystem maturity based on venture capital activity, including venture capital investment and divestment values and the number of investment and divestment rounds. These derived indicators constitute the startup dynamics variables used in subsequent econometric analyses, descriptive summary is reported in Annex A, Table A.1 and Table A3.

In the proposed model, the second layer captures startup ecosystem maturity, operationalised through the interaction between startup dynamics and venture capital activity, which functions as a catalytic mechanism enabling scaling and capital recycling. In the empirical operationalisation, startup ecosystem maturity is proxied by the composite V index, which is constructed exclusively from venture capital market components: VC investment, VC divestment, the number of investment and divestment rounds and is used to quantify startup ecosystem maturity (financing depth and capital-recycling capacity) in a comparable manner across countries and time. The V index complements firm-level startup dynamics by capturing ecosystem-level investment capacity, deal-flow intensity, and exit-related recycling dynamics that are not observable from firm accounts alone.

In the initial macroeconomic impact models, several variables intended to capture the relationship between startup ecosystems and entrepreneurial dynamism were tested, including the size of newly born enterprises, survival rates of new enterprises, and indicators from Eurostat high-growth enterprise statistics. However, these specifications did not yield robust or statistically significant relationships and were, therefore, excluded from the final models. The retained macro-level variables reflect the best balance of theoretical relevance, statistical performance, and acceptable multicollinearity. Macroeconomic impact indicators used to assess whether startup ecosystem maturity translates into broader economic effects are defined in Table 2.3. Descriptive statistics for these macro-level indicators and the component indicators used to construct the V index are reported in Annex A, Table A.3.

Table 2.3. Indicators for macroeconomic impact. Source: created by the author

Impact channel	Macro-level outcomes	Indicator/abbreviation /explanation	Sources motivating indicator selection
Innovation	Acceleration of technological adoption and diffusion	Research and development in the ICT sector (BERD), % from GDP	Chen & Liu (2023); Syverson (2017); Gal et al. (2019); Brynjolfsson et al. (2017)
Productivity	Potential productivity gains with	Labour productivity growth in knowledge-intensive sectors (PRO L): change from previous period, %	Fernald et al. (2023); De Haas, Sterk & Van Horen (2022);

End of Table 2.3

Impact channel	Macro-level outcomes	Indicator/abbreviation /explanation	Sources motivating indicator selection
	heterogeneous firm-level effects	Capital productivity growth in the ICT sector, (PRO C): gross value added per unit of net fixed assets; % change on the previous period	Alon et al. (2018); Douch et al. (2023)
High-tech exports	Linkages between ecosystem innovation capacity, R&D and high-tech export performance	Hitech products export, (HT EXP): annual share of total exports, %	Nitescu, Murgu & Bunea (2024); Sojoodi & Baghbanpour (2023)

2.4. Empirical Research Strategy

The dissertation adopts a mixed-method quantitative design that integrates two complementary analytical levels:

- Micro level (firm level) assessment of startup performance and behaviour relative to a comparative group of non-startup firms within the same industry. This level is used to test whether startups represent an empirically distinct firm category and to identify determinants of growth, productivity, financial performance, and survival.
- Macro level (ecosystem and economy level) assessment of startup ecosystem maturity and its association with macroeconomic indicators. This level is used to evaluate whether more mature startup ecosystems are linked to measurable economy-wide outcomes.

This integrated design ensures that ecosystem-level conclusions are grounded in firm-level dynamics and that firm-level results are interpreted within the broader enabling environment. The firm-level empirical setting comprises the Baltic region countries – Lithuania, Latvia, and Estonia – allowing both within-country assessment and cross-country comparison.

For the macroeconomic impact assessment, the empirical setting is broadened to the full sample of European countries to increase cross-sectional variation in ecosystem maturity and macroeconomic performance, thereby improving identification and statistical power. This broader European panel enables the analysis to benchmark the Baltic countries against a wider distribution of ecosystem development levels and to test whether the association between startup ecosystem maturity (proxied by the V index) and macroeconomic outcomes is systematic beyond the Baltic context, strengthening the external validity of the macro-level results.

The empirical analysis applies complementary quantitative techniques aligned with the dissertation tasks:

1. Comparative evaluation: startups versus non-startups. To establish whether startups constitute an empirically distinct firm category, the study conducts comparative analyses of performance patterns between startups and non-startup firms within the same industries. Comparisons focus on growth and productivity dynamics, financial performance and failure risk evaluation.
2. Econometric modelling of determinants: to explain startup growth and productivity, and to isolate key drivers. The modelling strategy is designed to quantify how endogenous (firm-level) and exogenous (innovation ecosystem conditions captured by enabling-environment indicators) determinants affect startup growth and productivity. In addition, a macro-level econometric analysis is applied to test the relationship between startup ecosystem maturity (proxied by the V index) and selected macroeconomic outcomes, assessing whether ecosystem development is associated with broader economic effects.
3. Machine-learning methods: to identify latent structure in the indicator set and to classify observations into meaningful groups. Principal Component Analysis (PCA) and k-means clustering were applied in two separate contexts:
   - For the Baltic countries firm-level data, PCA was used to extract startup growth-profile components, which were then used in k-means clustering to identify distinct startup scaling trajectories.
   - For the European startup ecosystem macro-level analysis, PCA was used to construct the V index as a composite proxy of startup ecosystem maturity, after which k-means clustering was applied to group European countries into maturity clusters and benchmark the Baltic states.

All statistical procedures, including data preparation, descriptive and comparative analysis, econometric estimation, PCA, clustering, and index construction, were implemented in R 4.4.1 using RStudio version 2024.12.1.563 software.

2.5. Empirical Setting: Baltic Startup Ecosystems

According to Bottazzi and Peri (2003), innovation spillovers typically occur within a 300-kilometre geographical radius. This finding, along with considerations for data availability, motivated the selection of the Baltic countries of Lithuania, Latvia and Estonia as the research region, given their close geographical proximity, similar structural economic development, and shared historical background.

Within the EU, Lithuania (LT), Latvia (LV), and Estonia (EE) are characterised by their geographic proximity and interconnected economies and are not only similar with their population sizes (2.38 million in LT, 1.9 million in LV and 1.3 million in EE), but also a pattern of major economic data indicators reflects a shared economic trajectory likely influenced by regional trends and possibly similar economic policies or external factors impacting this Baltic countries region (Table 2.4).

Table 2.4. Key innovation and economic performance indicators of the Baltic countries, mean values of the period 2014–2024. Source: compiled by the author based on Eurostat and EIS data

Country	**HC**	**GII**	**GDP GR, %**	**HT EXP, %**	**ICT EX, %**	**EMPL, %**	**EIS performance group**
Estonia	43.2	50.6	1.7	13.4	33.6	36.8	Strong
Latvia	35.4	42.8	2.9	10.1	32.9	37.1	Emerging
Lithuania	39.4	40.7	3.6	7.6	12.0	35.7	Moderate

Note. HC – Human capital (EIS index); GII – Global Innovation Index; GDP GR, % – GDP growth rate, %; HT EXP, % – High tech exports, %; ICT EXP, % – ICT services exports, %; EMPL, % – Employment in high tech sector, %; EIS performance group – European Innovation Scoreboard performance group

The Baltic countries were among the first in the EU to establish separate ST definitions that stem from their unique policy structures. The Estonian Aliens Act (Riigi Teataja, EE, 2017) supports immigration through its requirement for STs to demonstrate innovative business models that can be replicated and show potential for worldwide expansion. The Latvian Startup Law (Saeima, 2017) demands that STs operate as capital companies while showing scalable innovation to access a complete ecosystem backing. The amendment of the Lithuanian SME Development Law (XIII-2212) (Seimas, 2019) defines STs as micro- or small enterprises with less than five years of operation while placing them under the existing SME policy framework.

However, despite their proximity, these countries exhibit distinct patterns in VC funding and innovation performance. The different ST definitions lead to inconsistent regulations that make cross-border business operations more challenging, but enable each country to create specific innovation policies, which are reflected by the divergent patterns of the VC market during 2020–2024 (Table 2.5).

The three countries followed the same global market trends through boom-bust cycles, but their intensity of decline, recovery pace, and market position developed differently. The regional ST ecosystem has reached maturity because Lithuania leads in size, while Estonia benefits from established markets, and Latvia shows growing strength.

Table 2.5. Annual VC investment in Baltic countries (2020–2024), EUR million. Source: compiled by the author based on KPMG, 2024; Dealroom, 2025

Year	Estonia	Latvia	Lithuania	Total Baltic	YoY change
2020	68	42	95	205	–
2021	185	120	295	600	193%
2022	220	150	330	700	17%
2023	52	45	110	207	–70%
2024	44	38	55	137	–34%
Total (2020–2024)	569	395	885	1,849	
Average	113.8	79.0	177.0	369.8	

2.6. Data Collection and Preparation

The empirical analysis combines two data blocks:

Firm-level data: accounting and performance data of startups and a comparative group of non-startup firms operating within the same industries. These data enable the construction of operational, financial, productivity, growth, and survival-related measures for comparative analysis.

Macro and ecosystem indicators: indicators obtained from international organisations and harmonised cross-country sources. These indicators capture enabling environment conditions and macroeconomic outcomes relevant to innovation-driven growth in small, open economies.

Fig. 2.3 summarises the data sources used in the empirical analysis and illustrates how information is combined across analytical levels. Macro-level indicators are compiled from international statistical and innovation databases, while micro-level variables are derived from firm-level financial and administrative records in Lithuania, Latvia, and Estonia, complemented by startup ecosystem platforms. Together, these sources provide the integrated dataset required to link the enabling environment, startup dynamics, and macroeconomic outcomes.

Startup firm identification. In the academic field, STs are often distinguished from other new SMEs as a "venture-capital-backed firm with fast growth ambitions" (Breschi et al., 2018). Adopting this approach and following Crnogaj and

Rus (2023) the obtained identifiers (firm registry codes) for ST companies from national ST promotion institutions in LT and LV (“Startup Lithuania”, “Startin.lv”) and the Dealroom database (for EE) are matched with financial statement data of firms, also used by El-Dardiry and Vogt (2023) and for this dissertation extracted from the open sources of the national registry systems: “Lithuanian Registry Centre”, “Lithuanian State Social Insurance Fund (SODRA)”, “Estonian Open Government Data Portal”, and “Latvian Open Data Portal”.

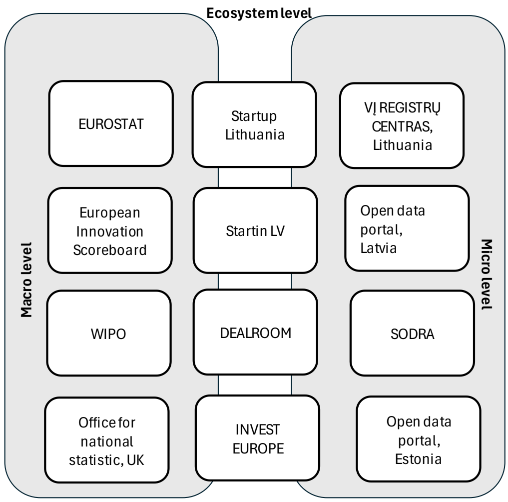

Fig. 2.3. Research data sources. Source: created by the author

The firm-level dataset includes all firms that meet the official ST identification criteria in each country and for which financial records are available. This allows the analysis to capture the overall performance of the ecosystem, including less visible firms, and to avoid sampling bias that would arise if only selected companies were included. This approach maximises coverage of the actual policy-relevant startup population, but it also implies that the operational definition of a “startup” partly reflects country-specific criteria. To account for this institutional heterogeneity, the analyses are conducted both separately for each country and in pooled panel regressions in which country (and, where relevant, time) fixed effects are applied. A related constraint is that data availability starts in different year periods, reflecting the timing of digitalisation and the opening of firm-level registers. As a result, the panel is unbalanced, with different time spans for EE, LV, and LT. This is handled econometrically by using methods that allow for an unbalanced panel and by including year dummies to control for common time shocks.

Comparative group identification. For the comparative group, non-startup firms classified under NACE Rev. 2 code 62 (computer programming, consultancy, and related activities) were selected for Lithuania and Estonia, as detailed NACE classification data are not available for Latvia. Propensity score matching (PSM) is employed exclusively in the analysis of short-run firm failure, where the main objective is to compare the probability of failure between startups and non-startup firms that are as similar as possible in terms of their pre-failure financial and structural characteristics.

For both main (ST) and comparative (HT) groups, only firm legal types registered as "OÜ" in Estonia, "UAB" in Lithuania, and "SIA" in Latvia are included in the analysis, as these private limited company forms represent the predominant legal structure for ST in the Baltic countries. This legal form is most used for VC investment, providing the necessary flexibility in ownership, share distribution, and liability structure required to attract external financing and scale innovative ventures. The firm's age is calculated using the "registration date" and "date when the financial statement was presented". After closer inspection, only firms with 2 or more employees were included in the analysis to exclude entities registered for non-business purposes, self-employment, or those not yet engaged in active operations, following Bayard et al. (2018), who showed a long tail of ST operations that begins only several years after initial registration.

As a result, the final sample comprises an unbalanced panel dataset containing 1645 unique ST firms and, as a comparative group, 3568 non-startup firms (HT), including a subset of STs classified only under NACE code 62 (ST 62) for more direct comparison with the comparative group (Table 2.6).

Table 2.6. Research data. Source: compiled by the author

Country	Type	Observations	Unique firms	Year range
Estonia	HT	5543	1824	2019–2024
	ST	1932	483	
	ST 62	657	209	
Lithuania	HT	10146	1744	2014–2024
	ST	7176	892	
	ST 62	1996	275	
Latvia	ST	1245	270	2014–2024
All	ST	10353	1645	2014–2024

Estimated variables (firm-level indicators). To operationalise startup performance and enable a consistent comparison with the non-startup benchmark group, the study constructs a set of firm-level indicators from financial statement data. These variables are estimated to capture the core dimensions emphasised in literature as distinguishing startup dynamics: profitability, productivity, financial structure/risk, and scaling intensity. Specifically, profitability is measured using return on assets (ROA), return on equity (ROE) and the EBIT margin, which reflect operating performance relative to the firm's asset base, equity base, and turnover.

Financial structure and risk exposure are captured through leverage indicators, debt-to-equity (DTE) and debt-to-assets (DTA), which proxy reliance on external financing and balance-sheet vulnerability. To measure efficiency and scaling, the analysis estimates annual labour productivity as turnover per employee, and several growth metrics: annual turnover growth, annual employment growth, and turnover CAGR. These growth indicators are included because startup trajectories are typically non-linear and concentrated in a subset of rapidly scaling firms.

All indicators are computed directly from accounting items (EBIT, total assets, equity, liabilities, turnover, and employment) using the formulas specified in Annex B, Table B. 1, which also reports the descriptive statistics (median and interquartile range) for startups and comparator firms by country.

2.7. Methods of Comparative Evaluation

The comparative evaluation methods are used to assess whether startups exhibit systematically different economic characteristics than non-startup firms. The comparative design combines sectoral profiling with firm-level performance benchmarking and focuses on three dimensions:

- How startups are distributed across technology-related subsectors.
- How their growth, productivity, and financial performance differ from the comparator group over the firm's lifecycle.
- How heterogeneous startup scaling dynamics can be summarised through distinct growth profiles (constructed via PCA-based k-means clustering).
- Whether startups display distinct short-run failure risk.

Together, these methods provide an empirical basis for identifying startup-specific dynamics prior to the subsequent econometric modelling of endogenous and ecosystem-level determinants.

Technology subsector. To capture the more fine-grained and emerging technological niches that are not adequately reflected in standard industrial classifications, firm-level ST founders' self-reported description of economic activity and technological focus information was extracted from the "Startup Lithuania" database (2023 edition). After basic cleaning (removal of obvious duplicates and non-informative terms), the remaining text was processed to identify distinct technology-related subsectors. Keyword co-occurrence analysis was carried out using the software "VOSviewer", which groups frequently co-occurring terms into clusters representing technological domains.

Comparative firm performance over the firm lifecycle. To assess how startups differ from the comparator group in terms of growth, productivity, and financial performance over the firm lifecycle, the analysis benchmarks ST against non-startup firms using a consistent set of performance indicators (turnover and employment growth, productivity measures, and financial/leverage metrics). Because firm outcomes vary systematically by development stage, the comparison is implemented using age-group classifications, ensuring that observed differences are not driven solely by firms being at different points in their lifecycle. Although startups are typically described as young firms, and in Lithuania, a startup is formally defined as a company up to five years old, the present research includes ST of all ages to capture the full development trajectory and to evaluate whether startup-specific patterns persist beyond the early years. Firms are, therefore, classified into six age categories based on age in the year of observation:

- Up to 3 years old.
- Up to 5 years old.
- Up to 7 years old.
- Up to 10 years old.
- Up to 15 years old.
- More than 15 years old.

The age group classification follows the most applied categorisation schemes used by EU member states and the OECD for analysing firm dynamics and growth stages. For productivity comparisons, both labour productivity and total factor productivity (TFP) are examined, as TFP is particularly informative for startups because it better reflects efficiency and technology/capability effects beyond scale or labour intensity; the TFP estimation procedure is described in Subsection 0 below.

Growth profiles. Before estimating exogenous growth determinants, startups were classified into homogeneous growth profiles to account for heterogeneity in scaling dynamics and to improve the interpretability of subsequent econometric results. Following Signore (2016), a PCA-based k-means clustering procedure was applied using standardised (z-score) measures of compound annual growth rate (CAGR), the firm's age, and the firm's size. Principal components were retained based on the Kaiser criterion (eigenvalue > 1), complemented by scree/elbow diagnostics, and firm-level component scores were computed. These component scores were then clustered using k-means with multiple random starts; the number of clusters was selected using elbow diagnostics. The resulting time-invariant Growth Profile categorical variable was used in the subsequent econometric modelling.

Firm failure risk. Because ST identifiers (firm registry codes) were received only for 2023, the analysis defines a 2023 baseline cohort and evaluates the activity status of each firm in 2024. The time window is restricted to 2023–2024 to ensure consistent labelling and comparability with non-ST firms. This restriction avoids misclassification of firms that may have been identified as ST prior to 2023 but had already failed and, therefore, are absent in the 2023 registries. Activity in 2024 is assessed to define failure and coded as 1 if the firm was active and reported positive turnover in 2023, but recorded zero turnover in 2024, and 0 otherwise. This variable is used to estimate the short-run probability of firm failure for STs and comparison group firms (HT).

2.8. Estimation of Total Factor Productivity

The choice of methodology is rooted in past research that underscores the nuances of innovation spillovers, resource allocation, and structural econometric issues related to endogeneity. Restuccia and Rogerson (2017) highlighted that productivity efficiency is based on two main factors: technology and resource misallocation. Although technology tends to be relatively homogeneous between firms within similar industries and levels of development, resource misallocation, differences in how firms allocate labour and capital, remain a significant source of productivity variation between firms, even within the same country.

This distinction between technology and resource allocation reinforces the need to account for firm-specific productivity factors when estimating TFP. STs are characterised by high proliferation of distinct technologies, working processes, and growth potential, and they also experience different scale effects and learning curves compared to more established or traditional SMEs. To mitigate these issues, Jimichi et al. (2023) introduced industry dummy variables into the Cobb–Douglas model to control for industry-specific factors that might affect a firm's sales independently of its number of employees and total assets. To address these critical factors and improve the clarity and interpretability of the results, in this research, each country is analysed separately, acknowledging also that data periods vary between LT, LV, and EE and that each country has a unique competitive and regulatory environment that may significantly impact productivity.

For the TFP estimation, the firm's turnover and total assets values were deflated to constant prices using the Harmonised Index of Consumer Prices (HICP). For additional robustness of ST and non-ST comparison, TFP is also estimated for NACE 62 economic activity code startups (ST 62). Productivity estimation by analysing large-scale financial statement data was also performed by Ikeda et al. (2010). To control for unobserved productivity shocks, van Beveren (2012) suggested the selection of instrumental variables and the two-stage least squares (2SLS) method. Following Schatzer et al. (2019) and Wang (2023), the linearised form of the Cobb–Douglas production function that incorporates two inputs is used:

$$\ln(\mathrm{TRN}_{i,t}) = \ln(\mathrm{TFP}_{i,t}) + \alpha\ln(\mathrm{EMPL}_{i,t}) + \beta\ln(\mathrm{TA}_{i,t}) + \varepsilon_{i,t}. \quad (2.1)$$

As a proxy for output, following Bosch-Badia (2010), annual turnover is used. For STs, the most suitable proxy for materials and investment differs from traditional SMEs as STs often have unique cost structures, with a greater focus on intangible assets, innovation, and human capital, rather than physical goods and materials. Many STs do not have detailed cost data on intermediate inputs, especially in early years, and focus on turnover growth rather than detailed breakdowns of value added. Wooldridge (2009) suggested using lagged values of inputs as instruments in TFP estimation. Instrumental variables represented by one-period lagged capital and labour regressors in the sectoral Cobb–Douglas to address endogeneity problems in TFP estimation were used as well by Marrocu & Paci (2013). By including the firm's identification code as a fixed effect, the model controls for factors unique to each firm (such as management quality, firm culture, or persistent technological capabilities) that could influence TFP. Including a year as a fixed effect ensures that the model's estimates for capital and labour inputs are not biased by external, time-variant factors.

In the first stage, to address potential endogeneity of capital (TA) and labour (EMPL), variables are regressed on their respective lags as instruments:

$$\ln(\mathrm{EMPL})_{i,t} = \alpha + \alpha_1\ln(\mathrm{TA})_{i,t-1} + \alpha_2\ln(\mathrm{EMPL})_{i,t-1} + \gamma_i + \delta_t + \varepsilon_{i,t}; \quad (2.2)$$

$$\ln(\mathrm{TA})_{i,t} = \beta + \beta_1\ln(\mathrm{TA})_{i,t-1} + \beta_2\ln(\mathrm{EMPL})_{i,t-1} + \gamma_i + \delta_t + \nu_{i,t}. \quad (2.3)$$

In the second stage, output (turnover) is regressed on the instrumented inputs (the fitted values from the first stage), yielding the structural productivity relationship:

$$\ln(\mathrm{TRN}_{i,t}) = \beta + \beta_1\ln\left(\widehat{\mathrm{TA}_{i,t}}\right) + \beta_2\ln\left(\widehat{\mathrm{EMPL}_{i,t}}\right) + \gamma_i + \delta_t + u_{i,t}\,. \quad (2.4)$$

TFP is computed using the actual inputs and estimated coefficients from the second stage of the 2SLS regression, following a Cobb–Douglas specification to retain variability coming from firm effects ($\hat{\gamma}_i$), time effects ($\hat{\delta}_t$), and the idiosyncratic component ($\hat{u}_{i,t}$):

$$\ln\left(\mathrm{TFP}_{i,t}\right) = \ln\left(\mathrm{TRN}_{i,t}\right) - \widehat{\beta_1}\ln\left(\mathrm{TA}_{i,t}\right) - \widehat{\beta_2}\ln\left(\mathrm{EMPL}_{i,t}\right), \quad (2.5)$$

where α, β – intercept terms; α_1, α_2, β_1 and β_2 – coefficients; $\widehat{\beta_1}$ and $\widehat{\beta_2}$ – estimated output elasticities for capital and labour from the 2SLS model; γ_i – firm-specific fixed effect; δ_t – time fixed effect; and $\varepsilon_{i,t}$,$\nu_{i,t}$, $u_{i,t}$ – first and second stage error terms.

By instrumenting inputs and accounting for firm and time fixed effects, the estimated TFP captures the efficiency component of production that is not explained by observable capital and labour inputs.

2.9. Econometric Modelling of Endogenous and Exogenous Determinants of Startup Performance

Based on the literature review, the key endogenous (firm structural, operational, and financial characteristics) and exogenous (macroeconomic and ecosystem-related) determinants were identified and used as independent variables to assess their effects on startups' turnover growth and total factor productivity. The analysis of startup failure risk focuses on endogenous determinants only, as firm exit in the observed window is most directly linked to firm-specific financial and operational sustainability, and comparable ecosystem-level measures are not consistently observable at the firm level.

2.9.1. Endogenous Growth and Failure Determinants

Firm-level (internal) growth determinants for STs are estimated and assessed if they differ from non-startups using two unbalanced panels (only ST and both ST and HT, only NACE 62 code firms). For the estimation of the second dataset, for all regressors, ST interaction terms are added. As firm-level financial accounting and estimated variables exhibit high skewness and include negative values, they are modified using the inverse hyperbolic sine transformation (Aïhounton & Henningsen, 2021):

$$\mathrm{arcsinh}(x) = \ln\left(x + \sqrt{(x^2 + 1)}\right), \tag{2.6}$$

where X is a transformed variable.

Two models are used. Firm-fixed effects (FE) to different out-time-invariant, firm-specific heterogeneity (e.g., founding team and business model):

$$\mathrm{TRN\ GR}_{i,t} = \alpha_i + \beta X_{i,t} + \theta\left(X_{i,t} \times \mathrm{TypeST}_i\right) + \varepsilon_{i,t} \tag{2.7}$$

and two-way fixed effects (TW) with both firm and year fixed effects – to additionally absorb common macro shocks:

$$\text{TRN GR}_{i,t} = \alpha_i + \tau_t + \beta X_{i,t} + \theta(X_{i,t} \times \text{TypeST}_i) + \varepsilon_{i,t}, \quad (2.8)$$

where TRN $GR_{i,t}$ is turnover growth of firm i in year t; α_i is firm-fixed effect capturing time-invariant firm characteristics; τ_t is year fixed effect (TW only) capturing economy-wide shocks common to all firms in year t; $X_{i,t}$ is firm-level variables (ROA, DTE, DTA, EBIT margin, EMPL GR, Age); β is vector of coefficients for an ST and HT (in case of mixed dataset); $TypeST_i$ is ST indicator (1 if startup, 0 otherwise); θ is vector of coefficients on the interaction $X_{i,t}\times TypeST_i$ and measures how the effect of each X differs for startups; $\varepsilon_{i,t}$ is idiosyncratic error term.

Within the TW model, variables perfectly collinear with time and a firm (e.g., Age) are not identified. For startups (TypeST=1), the coefficient is β + θ.

Firm failure risk determinants. To analyse differences in failure risk between STs and non-startup firms, the control group of non-startups (HT) using propensity score matching (PSM) was created (Dehejia, 2005). STs were defined as the treated group and HT as the control group. Propensity scores were estimated using a logistic regression including the firm's size, performance, capital structure and age: number of employees (EMPL), turnover (TRN), earnings before interest and taxes (EBIT), total assets (TA), equity (EQT), liabilities (LBL), return on equity (ROE), return on assets (ROA), debt-to-equity ratio (DTE), debt-to-assets ratio (DTA), and the firm's age (Age). Based on these propensity scores, 1:1 nearest-neighbour matching without replacement was implemented, using the propensity score estimated from a logistic regression as the distance measure and imposing a calliper of 0.2.

After PSM, firm failure risk is modelled using Firth penalised logistic regression on both the unmatched and matched samples. Firth's method, following Heinze and Schemper (2002), is chosen to reduce small-sample bias and to mitigate potential separation arising from rare failures and strong group differences between STs and non-startups using firm-level panel data. Explanatory variables capture the firm's profitability, leverage, operational scale and include turnover growth (TRN GR), size (TRN), return on assets (ROA), return on equity (ROE), EBIT margin, debt-to-equity ratio (DTE), debt-to-asset ratio (DTA), employment (EMPL), and the firm's type (TypeST) and age (Age):

$$\text{logit}\left(P(\text{Failure}_{i,t+1} = 1)\right) = \beta_0 + \beta_1 \text{TRN}_{i,t} + \beta_2 \text{TRN GR}_{i,t} + \beta_3 \text{ROA}_{i,t} + \beta_4 \text{ROE}_{i,t} + \beta_5 \text{EBIT MRG}_{i,t} + \beta_6 \text{DTE}_{i,t} + \beta_7 \text{DTA}_{i,t} + \beta_8 \text{EMPL}_{i,t} + \beta_9 \text{TypeST}_i + \beta_{10} \text{Age}_{i,t}, \quad (2.9)$$

where $Failure_{i,t+1}$ is a binary indicator equal to 1 if the firm i was active in year t but had zero turnover in year $t + 1$, and 0 otherwise; $TRN_{i,t}$ is turnover; TRN $GR_{i,t}$ is turnover growth rate; $ROA_{i,t}$ and $ROE_{i,t}$ represent return on assets and return on equity; EBIT $MRG_{i,t}$ is the operating profit margin; $DTE_{i,t}$ and $DTA_{i,t}$ measure financial leverage (debt-to-equity and debt-to-assets ratios); $EMPL_{i,t}$ is the firm's employment size; $TypeST_i$ is categorical variable distinguishing startups from non-startups; $Age_{i,t}$ is the firm's age; $\varepsilon_{i,t}$ is an error term assumed to follow a logistic distribution.

2.9.2. Exogenous Growth Determinants

To ensure correct functional form and avoid biased inference due to model misspecification, the baseline OLS specification was first formally tested. The Ramsey (1969) RESET test indicated non-linearity, motivating a more flexible estimation strategy.

Therefore, a semiparametric Partial Linear Model (PLM) was estimated within a Generalised Additive Models (GAM) framework, applying the double-residual method to the unbalanced panel dataset (Robinson, 1988). The estimation proceeded in multiple steps; first, the general PLM specification was defined as follows:

$$\mathrm{TRN\ GR}_{(i,c,t)} = \beta Z_{c,t} + \gamma \mathrm{GrowthProfile}_i + s_1(\mathrm{GDP\ GR}_{c,t}) + s_2(\mathrm{FS}_{c,t}) + s_3(\mathrm{HC1}_{c,t}) + s_4(\mathrm{AGE}_{(i,c,t)}) + \varepsilon_{(i,c,t)}, \tag{2.10}$$

where $Z_{c,t}$ is a vector of linear (parametric) ecosystem regressors measured at the country–year level and common to all firms operating in country c in year t. In this specification, $Z_{c,t}$ includes: $AM_{c,t}$ is the access-to-market indicator, capturing the extent of market reach/openness relevant for scaling; $VC_{c,t}$ is the access-to-finance/venture capital indicator (ecosystem financing condition); $KS_{c,t}$ is the knowledge spillovers indicator, capturing the knowledge-generation and diffusion environment. $AGE_{i,c,t}$ is the firm's age (in years) for the firm *i* in the country *c* and year *t*, capturing lifecycle effects in startup growth dynamics. The coefficient vector β measures the marginal linear association between these ecosystem conditions and startup turnover growth. Growth $Profile_i$ is a time-invariant categorical factor that assigns each startup to a growth-type group identified in the comparative analysis. The coefficient γ captures systematic differences in turnover growth between different startup Growth Profile categories.

The following variables enter the model through unknown smooth functions s_j, allowing flexible non-linear effects:

- $GDP\ GR_{c,t}$ is the annual GDP growth rate in the country *c* and year *t*, capturing the macroeconomic cycle and aggregate demand conditions.
- $FS_{c,t}$ is the availability of external finance beyond the VC indicator in the country *c* and year *t*.
- $HC1_{c,t}$ is a human capital indicator in the country c and year t, reflecting the supply/quality of skills relevant for entrepreneurial scaling.

– $\varepsilon_{i,c,t}$ is the idiosyncratic error term capturing unobserved firm-year influences on turnover growth.

Then GAM is fit for the dependent variable using only the non-linear covariates. The smooth functions s_j are estimated, yielding a fitted conditional mean:

$$E(\text{TRN GR}_{i,c,t} | \text{GDP GR}_{c,t}, \text{FS}_{c,t}, \text{HC1}_{c,t}, \text{AGE}_{i,c,t}) = s_1(\text{GDP GRc},_t) + s_2(\text{FS}_{c,t}) + s_3(\text{HC1}_{c,t}) + s_4(\text{AGE}_{i,c,t}). \quad (2.11)$$

This fitted conditional mean is then subtracted from TRN $\text{Gr}_{i,c,t}$ to obtain the residualised outcome for the subsequent linear stage without the non-linear effects:

$$\text{TRN GR}^{(res)}_{(i,c,t)} = \text{TRN GR}_{(i,c,t)}\hat{E}(\text{TRN GR}_{(i,c,t)} | \text{GDP GR}_{c,t}, \text{FS}_{c,t}, \text{HC1}_{c,t}, \text{AGE}_{(i,c,t)}). \quad (2.12)$$

In the second step, each linear regressor is regressed on the non-linear covariates, using GAM smooths:

$$Z_{k,c,t} = s_1(\text{GDP GR}_{c,t}) + s_2(\text{FS}_{c,t}) + s_3(\text{HC1}_{c,t}) + r_{k,c,t}, \quad (2.13)$$

where $Z_{k,c,t}$ is the k[th] element of the linear regressor vector $Z_{c,t}$.

The residuals of all linear variables are extracted.

$$Z^{resid}_{k,c,t} = Z_{k,c,t} - \hat{E}(Z_{k,c,t} | \text{GDP GR}_{c,t}, \text{FS}_{c,t}, \text{HC1}_{c,t}), \quad (2.14)$$

where $\hat{E}\ (Z_{k,c,t} | \text{GDP GR}_{c,t}, \text{FS}_{c,t}, \text{HC1}_{c,t})$ is predicted values obtained from the GAM.

After residualising both TRN GR and the linear predictors, an OLS regression is performed using heteroskedasticity and cluster-robust standard errors, clustering at the country–year level to account for correlation of residuals across firms exposed to the same macroeconomic conditions, following Cameron et al. (2006):

$$\text{TRN GR}^{resid}_{i,c,t} = \beta_0 + \beta_1 \text{AM}^{resid}_{c,t} + \beta_2 \text{VC}^{resid}_{c,t} + \beta_3 \text{KS}^{resid}_{c,t} + \gamma \text{Growth Profile}_i + \eta_{i,c,t}, \quad (2.15)$$

where $\eta_{i,c,t}$ is the error term in the residualised (linear stage) regression.

In the last step, the full GAM model integrating non-linear, linear, and categorical variables is estimated:

$$\text{TRN GR}_{i,c,t} = s_1(\text{GDP GR}_{c,t}) + s_2(\text{FS}_{c,t}) + s_3(\text{HC1}_{c,t}) + s_4(\text{AGE}_{i,c,t}) + \beta_1 \text{AMc},_t + \beta_2 \text{VC}_{c,t} + \beta_3 \text{KS}_{c,t} + \gamma \text{Growth Profile}_i + \varepsilon_{i,c,t}. \quad (2.16)$$

This estimation strategy separates non-linear and linear components using Robinson's double-residual procedure: the linear effects are estimated in the revisualised OLS stage with heteroskedasticity-robust standard errors clustered at the country–year level, and the final specification is represented as a GAM that integrates the smooth terms, parametric ecosystem effects, and the categorical Growth Profile factor.

2.9.3. Determinants of Total Factor Productivity

For the ST-endogenous (firm-level) TFP determinants, the estimation panel OLS FE model to control for unobserved heterogeneity is used. Variables that include zero or negative values are transformed by applying the inverse hyperbolic sine transformation. The explanatory variables include factor (dummy) variables for the firm's size and age. ST firm size classes are defined by the number of employees, following OECD and EUROSTAT practice:

- Micro: up to 10.
- Small: 10–49.
- Medium: 50–249.
- Large: more than 250.

In addition to these structural controls, the specification incorporates continuous measures capturing firm dynamics and financial structure, including turnover growth (TRN GR), return on assets (ROA), leverage (DTE), and EBIT margin (EBIT MRG). Accordingly, total productivity is modelled as:

$$\ln(\mathrm{TFP}_{i,t}) = \alpha_i + \sum_j \beta_{1j}\mathrm{Size}_{i,j,t} + \sum_k \beta_{2k}\mathrm{Age}_{i,k,t} + \beta_3(\mathrm{TRN\ GR}_{i,t}) + \beta_4\ln(\mathrm{ROA}_{i,t}) + \beta_5\ln(\mathrm{DTE}_{i,t}) + \beta_6\ln(\mathrm{EBIT\ MRG}_{i,t}) + u_{i,t}\,. \quad (2.17)$$

For the estimation of exogenous (macro-level) determinants of startup TFP, a pooled OLS model is employed in which TFP is regressed on venture capital activity (VC), GDP growth (GDP GR), labour-market dynamism in the science and technology sector (JOB M), innovation activity (INO ACT) and high-technology exports (HT EXP):

$$\ln(\mathrm{TFP}_{i,c,t}) = \beta_0 + \beta_1\mathrm{VC}_{c,t} + \beta_2\,\mathrm{GDP\ GR}_{c,t} + \beta_3\mathrm{JOB\ M}_{c,t} + \beta_4\mathrm{INO\ ACT}_{c,t} + \beta_5\mathrm{HT\ EXP}_{c,t} + \sum_j \beta_{6k}\mathrm{Age}_{i,k,t} + u_{i,t}\,, \quad (2.18)$$

where ln $(\mathrm{TFP}_{i,t})$ is the dependent variable, proxy for TFP estimated with the 2SLS method, for the firm *i* in the country *c* and year *t*; $\mathrm{Size}_{i,j,t}$ is a dummy variable for the firm's size *j* category; $\mathrm{Age}_{i,k,t}$ is a dummy variable for the *k* age group; α_i is firm-fixed effects (controls for time-invariant unobserved heterogeneity across firms); β_0 is the baseline productivity level; $u_{i,t}$ – is the idiosyncratic error term.

Standard errors are computed using a cluster-robust (heteroskedasticity-consistent) estimator and clustered at the country–year level to account for correlated disturbances among firms exposed to the same macroeconomic and ecosystem conditions.

2.10. Methods of Startup Ecosystems Macroeconomic Impact Assessment

Direct assessment of ecosystem performance is often elusive, necessitating the use of proxy indicators that can effectively represent the output of an ecosystem. An ST ecosystem reaches maturity when it demonstrates productive entrepreneurship as its core output. Nicotra (2018) suggested a share of VC-backed STs within a specific territory to be used as a standard assumption-based indicator for productive entrepreneurship. Sophisticated investors, who invest in ST through VC, demonstrate their confidence in the ecosystem's ability to produce high growth and innovative opportunities. The amount of VC investment functions as a fundamental indicator to measure entrepreneurial activity because it indicates the ecosystem's development level and maturity.

But relying on a single indicator, such as VC funding amounts alone, focusing solely on the input side of the ecosystem without capturing the output and recycling of capital (outcome-based), is incomplete. A mature ecosystem requires successful ST exit mechanisms, which enable the investment cycle to continue after VC funding. Jeng and Wells (2000) determined that an Initial Public Offering (IPO) creates the most powerful force for market development and found that broader economic indicators, such as GDP or market capitalisation growth, were insignificant determinants of VC activity.

To capture both assumption-based and outcome-based measures of a productive entrepreneurial environment, the composite VC index, which encompasses amounts and number of rounds of VC investment and divestment and represents the maturity of the ST ecosystem, is estimated. The selection of VC activity indicators as the proxy for ST ecosystem maturity also aligns with the market-established benchmark methods of leading ecosystem assessment frameworks:

- Startup Genome establishes its rankings and maturity typology through funding and exits by defining ecosystem value as the sum of ST valuations, including unicorn valuations and post-money exit valuations, to identify more developed ecosystems based on large exit numbers and funding volume (Startup Genome, 2025).
- The Global Tech Ecosystem Index 2025 uses VC investments and enterprise value creation to rank ecosystems and perform systematic exit tracking (Dealroom, 2025).
- The global index and analytics of Startup Blink utilise funding and valuations alongside unicorns and exits as fundamental elements to track exit value through funding as one of its core inputs (Startup Blink, 2025).

– Pitch Book evaluates locations based on the size and development level of their VC hubs through an assessment of VC activity together with exit performance metrics (PitchBook, 2023).

V index construction. The ST ecosystems' maturity V index is developed by combining VC invested/divested values of European countries with the number of rounds, after performing normalisation and smoothing the data across multiple years to minimise noise. Because the INVEST EUROPE dataset reports LT, LV, and EE pooled as a single unit, subsequent analyses treat the "Baltics" as one panel entity and compare it with other European countries.

VC metrics present cyclical patterns while showing concentration in mega deals and sector-specific biases and underrepresenting early-stage activities in shallow data markets. These problems are addressed through per-capita scaling and multi-year rolling windows, as well as investment/divestment values triangulation with the number of rounds. Euro-denominated series are deflated to constant prices using the HICP, with the number of rounds representing variables normalised per 1 million of population. Each component is standardised using the z-score method.

The V index is constructed using PCA, a dimensionality reduction technique that identifies the most important sources of variation in a set of related variables. The selection of the principal components for inclusion in the index is guided by the Kaiser criterion value. Consequently, the V index is defined using the calculated scores from Principal Component 1 (PC1). To validate the internal consistency of this single-component structure, Cronbach's alpha is computed.

For comparative assessment, European countries are grouped using the composite V index. Following the literature, 4 economic development indicators (X) are regressed on the V index, its lagged values, and a set of control variables (Z):

– Labour productivity (PRO L) controlling for employment in knowledge-intensive sectors (EMPL) and GDP growth (GDP GR).
– Capital productivity (PRO C) incorporating controls for employment (EMPL), business R&D expenditure (BERD), and GDP growth (GDP GR).
– High-tech exports (HT EXP) with controls for business R&D (BERD) and ICT export share (ICT EXP).
– Innovation (BERD) controlling human capital (HC) and public consumption (PUB CON).

Before econometric modelling, the correlation matrix (type Pearson) between the V index, covariates and dependent variables is inspected to evaluate construct validity. Bivariate Granger causality tests are run for each country in both directions (V index ↔ X) at a pre-specified lag order appropriate to the data frequency. This step probes temporal ordering, whether past V index values improve the prediction of each outcome (X) beyond the outcome's own history (and vice versa).

Econometric modelling. To investigate the V index effects on the economic outcomes, a panel data regression analysis is conducted. To capture the dynamic effects of VC activity, a one-year lag (V 1l) and a two-year lag (V l2) of the V index are also included. An OLS model is initially estimated as a baseline:

$$X_{(c,t)} = \alpha + \beta_0 V_{(c,t)} + \beta_1 V_{(c,t-1)} + \beta_2 V_{(c,t-2)} + \Sigma_{(j\in S_X)} \gamma_j Z_{(c,t,j)} + \varepsilon_{(c,t)}. \quad (2.19)$$

Variance Inflation Factor (VIF) for the inspection of the levels of multicollinearity among the regressors is estimated. The primary model's specification employs FE and Random Effects (RE) estimators. FE choice is theoretically driven by the need to control for time-invariant, country-specific unobserved characteristics (e.g., institutional quality and long-term economic structure) that could be correlated with the V index:

$$X_{(c,t)} = \alpha + \beta_0 V_{(c,t)} + \beta_1 V_{(c,t-1)} + \beta_2 V_{(c,t-2)} + \Sigma_{(j\in S_X)} \gamma_j Z_{(c,t,j)} + \mu_c + \varepsilon_{(c,t)}. \quad (2.20)$$

The RE estimator is considered for its potential for greater statistical efficiency: if the assumption that the unobserved country-specific effects are random and uncorrelated with the independent variables, the RE model utilises both within-country and between-country variation, which can lead to more precise coefficient estimates:

$$X_{(c,t)} = \alpha + \beta_0 V_{(c,t)} + \beta_1 V_{(c,t-1)} + \beta_2 V_{(c,t-2)} + \Sigma_{(j\in S_X)} \gamma_j \cdot Z_{(c,t,j)} + u_c + v_t + e_{(c,t)}. \quad (2.21)$$

To formally test this assumption for the model selection between the FE and RE specifications, a Hausman test is conducted. To further enhance the model, two extensions are implemented. First, a two-way FE model (TW) is estimated to account for both country-specific and time-specific effects, providing resilience against period-specific shocks common to all countries.

$$X_{(c,t)} = \alpha + \beta_0 V_{(c,t)} + \beta_1 V_{(c,t-1)} + \beta_2 V_{(c,t-2)} + \Sigma_{(j\in S_X)} \gamma_j Z_{(c,t,j)} + \mu_c + \tau_t + \varepsilon_{(c,t)}. \quad (2.22)$$

Second, the model is specified with interaction terms between the independent variables and a dummy variable for the Baltic region to test whether the observed relationships differed significantly for this specific geographical subgroup:

$$X_{(c,t)} = \alpha + \Sigma_{(j\in S_X)} \gamma_j Z_{(c,t,j)} + D_c\big[\delta_0 V_{(c,t)} + \delta_1 V_{(c,t-1)} + \delta_2 V_{(c,t-2)}\big) + \Sigma_{(j\in S_X)}\, \theta_j Z_{(c,t,j)}] + \mu_c + \tau_t + \varepsilon_{(c,t)}, \quad (2.23)$$

where $X_{c,t}$ is dependent variable for the country c in year t; $V_{c,t}$ is $V_{(c,t-1)}$, $V_{(c,t-2)}$: regressor and its lags; $Z_{c,t,j}$ is the j^{th} control, varying by country and year; S_X is the set of controls used for X; γ_j is coefficient on control j; α is intercept; $\varepsilon_{c,t}$ is error term; μ_c is the country-fixed effect (a time-invariant, unobserved heterogeneity for country c, can be correlated with regressors); u_c is the country-random effect (a time-invariant component, assumed uncorrelated with regressors); v_t is year-random effect (a common shock in year t, assumed uncorrelated with regressors); $e_{c,t}$ is idiosyncratic error (a country–year specific noise); τ_t year fixed effect (a full set of year dummies capturing shocks common to all countries in the year t (allowed to be correlated with regressors); D_c is 1 only for the region "Baltic," 0 for all others.

The core independent variable of interest is the V index, measured contemporaneously and with two lags: one year (V l1) and 2 years (V l2), while controlling for various macroeconomic factors, including employment at knowledge intensive sector (EMPL), GDP growth (GDP GR), business expenditure on R&D at ICT sector (BERD), human capital index (HC), public consumption (PUB CON) and ICT exports (ICT EXP).

2.11. Conclusions of the Second Chapter

This chapter operationalises the dissertation objective by translating the literature-based conceptual framework into an empirically implementable research design.

1. The chapter establishes a comparative empirical strategy to verify whether startups constitute an empirically distinct firm category. Startup distinctiveness is evaluated through multiple performance dimensions: growth (turnover and employment), productivity (labour productivity and TFP), financial performance, leverage, and failure risk, and is supplemented by age-group analysis and growth-profile classification to account for heterogeneity in scaling trajectories.
2. A multi-layer assessment framework is specified that links (i) enabling-environment conditions, (ii) startup dynamics (growth, productivity, survival, and financial structure), and (iii) macroeconomic outcomes. Econometric modelling is applied to estimate how endogenous (firm-level) and exogenous (ecosystem and macro-level) determinants influence startup growth and productivity, while failure risk is modelled using endogenous determinants and a matched control group. A macro-level econometric component is additionally defined to examine whether ecosystem maturity is associated with broader economic performance.

3. Based on the literature review, data availability and empirical feasibility, the chapter defines the final indicator set for each model layer. Two productivity measures are incorporated – labour productivity and TFP to capture both scale-related efficiency and deeper capability/technology-related performance. The indicator system is documented through tables defining variables, formulas, data sources, and descriptive statistics (with full summaries and sources reported in the Annexes).

3

Empirical Validation of the Startup Ecosystem Model: Development Factors and Macroeconomic Impact

This chapter empirically validates the proposed conceptual model by linking startup ecosystem enabling conditions to firm-level startup dynamics and, in turn, to macroeconomic outcomes. Using the methodology developed in the previous chapter, it compares startup growth, productivity, and survival with matched non-startup firms to test whether startups constitute an empirically distinct category in the Baltic region. The framework is verified in two complementary settings: a micro-level firm analysis for Lithuania, Latvia, and Estonia, and a macro-level assessment that benchmarks the Baltic region against a broader European panel using an ecosystem maturity proxy to evaluate how startup ecosystems relate to productivity, innovation, and export outcomes. The main research results of this chapter are published in the author's publications (Okunevičiūtė Neverauskienė & Klepone, 2024; Kleponė & Okunevičiūtė Neverauskienė, 2025).

3.1. Distinctive Startup Characteristics

This chapter presents the results of the comparative analysis used to identify distinctive startup characteristics by benchmarking startup against non-startup firms across matched lifecycle stages in Lithuania, Latvia, and Estonia. The analysis begins by profiling firm populations according to industry classification, technology subsectors, age, and size, thereby establishing a consistent basis for cross-group and cross-country comparison. It then evaluates differences in growth and productivity dynamics, combining descriptive comparisons of labour productivity, turnover growth (average annual growth and CAGR), and wage/salary levels with an econometric estimation of total factor productivity (TFP) to capture efficiency differences beyond scale and labour intensity.

The chapter further assesses whether startups exhibit distinct patterns of financial performance and risk, comparing EBIT margins, profitability (ROA, ROE), capital structure (debt-to-equity and debt-to-assets), and short-run failure rates relative to the comparator group. All comparisons are reported within lifecycle stages to separate development-stage effects from country effects, followed by an assessment of cross-country differences.

Unless stated otherwise, results are reported using medians and distributional summaries to reduce sensitivity to outliers and skewness. Medians are used for comparison instead of means to reduce the influence of extreme values and skewed distributions typical for firm-level financial data, which indicate high variability and heterogeneity across firms. Medians are reported together with interquartile ranges (IQR), 25th–75th percentiles. This combination provides a robust measure of central tendency and dispersion for skewed firm-level data and reduces the influence of extreme values and outliers. Where relevant, additional percentiles (e.g., 5th–95th) and boxplots are used to illustrate the presence and magnitude of extreme observations. The chapter concludes by presenting startup growth profiles, derived from the firm's age, size, and turnover growth, to summarise heterogeneity in scaling trajectories and to support subsequent determinant modelling.

3.1.1. Structural and Demographic Characteristics

Industry classification. In the absence of firm-level R&D expenditure data, ST innovativeness was approximated using NACE Rev. 2 industry classifications. Analysis of economic activity codes for LT and EE reveals that 69% of LT STs (615 of 892) and 68% of EE STs (328 of 483) are active within high technology and knowledge-intensive services sectors. Knowledge-intensive services dominate, accounting for 64% of LT and 63% of EE STs. The sectoral concentration is particularly high in NACE 62–64 codes, encompassing publishing activities, motion picture, video and sound production, broadcasting, telecommunications, computer programming, and consultancy and information service activities. the top 4 NACE codes for ST in EE and LT are presented in Table 3.1.

Table 3.1. Top 4 NACE classification codes representing the predominant economic activities of startups in Estonia and Lithuania. Source: compiled by the author

Country	NACE code	Number of unique firms
EE	62	214
LT	62	252
EE	63	70
LT	63	48
EE	64	11
LT	64	66
EE	72	29
LT	72	46

These findings suggest a strong orientation of Baltic STs towards digital technologies and ICT-related domains, which aligns with prior evidence of regional specialisation in software and knowledge-intensive industries (OECD, 2022).

Technology subsector. Complementing this classification, retrieved data from the "Startup Lithuania" database show that STs self-identify across 287 technology-based subsectors, reflecting a broad technological diversification within the national ST ecosystem (Fig. 3.1). This empirical finding also underscores the limitations of conventional industrial classification systems such as NACE Rev.2, which were primarily designed for traditional manufacturing-based economies and emphasised as well by Felgueiras et al. (2020) and Kühnemann et al. (2020), who identified 46 subindustries by analysing data from the Crunchbase.

Age. Across all three countries, ST firms are younger than HT firms within the comparative NACE code 62 groups, with an average age ranging between 4 and 6 years. The youngest ST firms are observed in EE and LV, where their median age is 4 years compared to 8 years for HT firms in EE. In LT, ST firms are significantly older, with a median age of 6 years, while HT firms maintain a median age of 8 years. Annex A, Table A.1 presents the median values of collected firm-level indicators for STs and HT firms in EE, LT, and LV.

Size. Older LT STs are also bigger in terms of employee numbers. Fig. 3.2 shows the distribution of the number of employees (5th–95th percentile) at the compared group of firms. The results indicate that LT STs exhibit the largest employment scale, with a median of 8.7 employees, compared to 5 for EE and LV. In contrast, non-startup firms (HT) in both EE and LT maintain smaller median employment levels (3 and 4 employees, respectively). The interquartile ranges further show a greater dispersion in LT ST employment, suggesting higher variability and possibly a broader scaling potential among STs (Fig. 3.2).

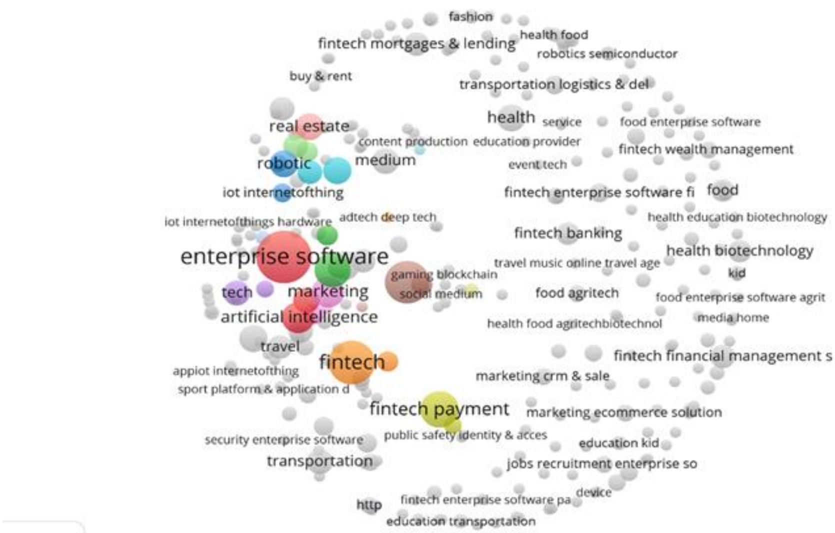

Fig. 3.1. Textual analysis of the startup economic activities. Source: compiled by the author based on 2023 "Startup Lithuania" data; the analysis performed using the VOS viewer software

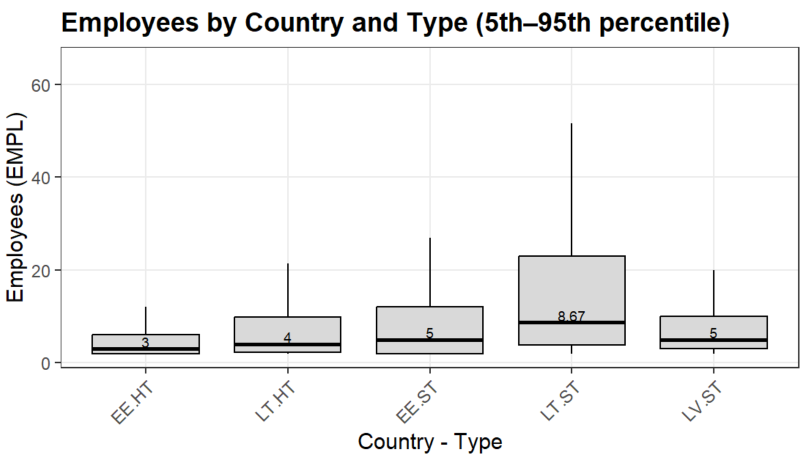

Fig. 3.2. Average annual number of employees among startups (ST) and non-startup firms (HT) across Lithuania (LT), Estonia (EE), and Latvia (LV). Source: calculated by the author

Fig. 3.3 presents median employment by the firm's age group, revealing that STs exhibit faster employment growth with age, reaching around 20 employees after 15 years, while HT firms remain smaller and grow more slowly. STs tend to expand employment more rapidly as they mature, consistent with theories of high-growth, innovation-driven entrepreneurship.

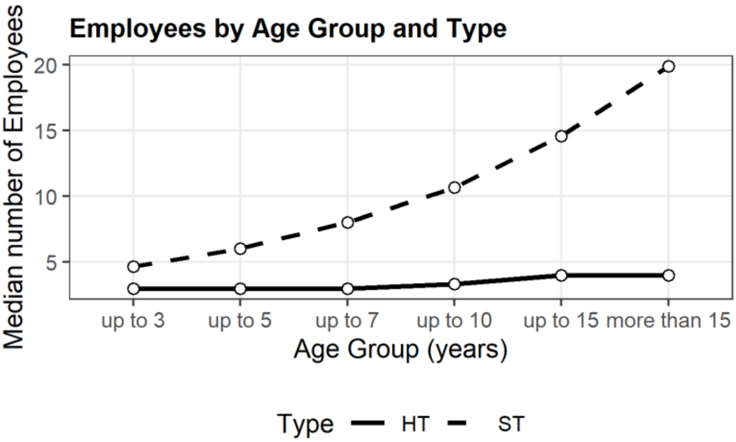

Fig. 3.3. Average annual number of employees by age group among startups (ST) and non-startup (HT) firms, all countries. Source: calculated by the author

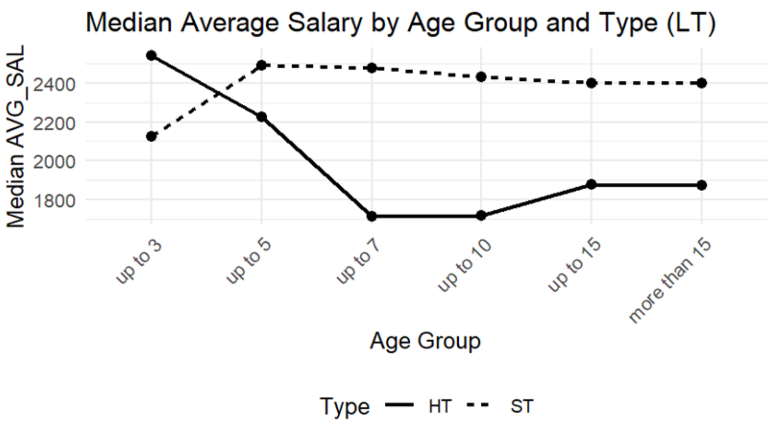

Fig. 3.4. Median average monthly salary by age group and firm type of startups (ST) and non-startup firms (HT), Lithuania. Source: calculated by the author

Salaries. Data on salaries were available only for LT firms. ST employment tends to offer relatively higher pay levels; LT STs exhibit higher median average monthly salaries (EUR 2375) compared to non-startup HT firms (EUR 1977). This pattern indicates that STs maintain a consistent salary advantage across all age groups except up to 3 years, and their salaries stay above those of non-startup firms over time. In contrast, HT firms display a decline in salaries as the firm's age increases (Fig. 3.4). This finding is consistent with the Ouimet and Zarutskie (2014), who showed that, e.g., young employees in young firms earn higher wages than young employees in older firms.

3.1.2. Growth Dynamic

Overall, STs exhibit significantly higher turnover growth rates and greater dispersion than their non-startup counterparts in both countries, EE and LT (Fig. 3.5). Median turnover growth among LV STs reaches 34.1%, followed by LT STs with 20.5%, whereas all EE STs show a much lower median growth of 0.7% (but EE NACE 62 ST fraction growth is at 18.5%, which is similar to LT ST NACE 62 ST high growth (21.9%), see Annex B, Table B. 1. The small median of all EE ST could be explained by slow growth of other than NACE 62 code firms among STs in EE. HT firms in LT and EE display more moderate and stable growth levels of 7.6% in EE and 5.9% in LT HT firms, with narrower interquartile ranges.

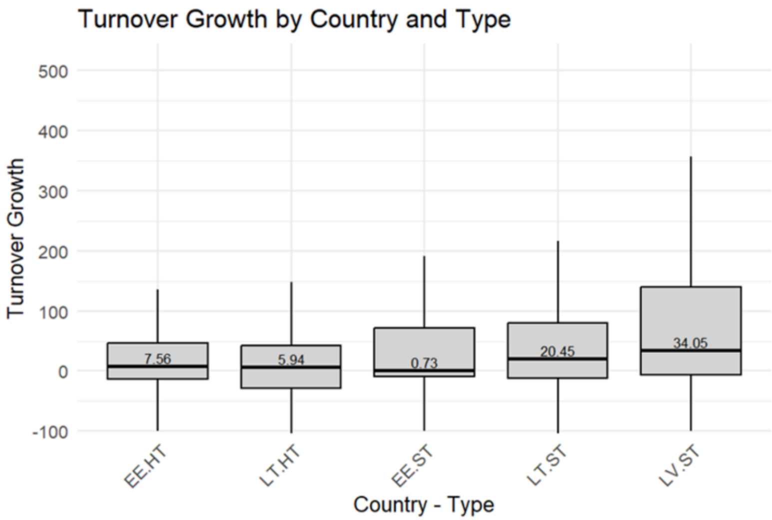

Fig. 3.5. Annual turnover growth (%) of startups (ST) and non-startup (HT) firms across Lithuania (LT), Estonia (EE), and Latvia (LV).
Source: calculated by the author

The wider variability among ST indicates heterogeneous growth patterns, where a subset of high-growth firms drives aggregate performance, consistent with the "gazelle" concept. Both for STs and the comparative HT group, the median of average annual turnover growth exhibits a sharp decline with the firm's age (Fig. 3.6), consistent with the typical early growth followed by stabilisation observed in studies on firm lifecycles.

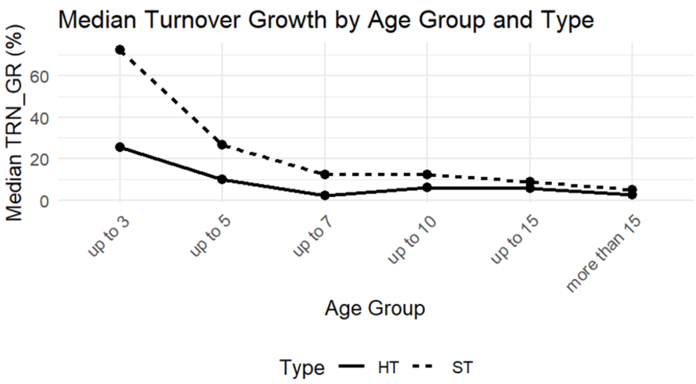

Fig. 3.6. Median annual turnover growth (%) by age group for startups (ST) and non-startup firms, all countries. Source: calculated by the author

STs show substantially higher growth rates in their initial years**,** with the median turnover growth exceeding 60% among firms up to three years old, compared to HT firms. This early advantage converges with non-startup performance as firms mature, with both groups reaching similar growth rates beyond 10 years of operation. Different growth patterns illustrate the initial dynamism and early-stage scaling is typical for STs and reveal that this advantage disappears approximately after 10 years.

To distinguish between short-term fluctuations and volatile early-stage growth, which is often driven by rapid market entry, the more consistent growth indicator CAGR was estimated and compared. CAGR represents more sustained, long-term growth performance. STs demonstrate consistently higher median CAGR values across all age categories, particularly during their early development phase (up to 5 years), where turnover grows at median rates close to 40% annually (Fig. 3.7). The broader interquartile range for STs indicates greater variation in CAGR performance, reflecting the heterogeneous entrepreneurial ecosystems where both high-growth and stagnating firms coexist. In contrast, HT firms display more stable, but low CAGR levels, typically around 1%.

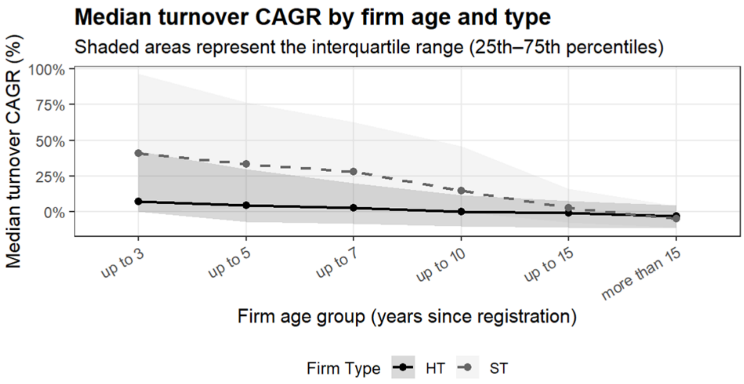

Fig. 3.7. Median turnover CAGR (%) of startups (ST) and non-startup (HT) firms, all countries. Source: calculated by the author

3.1.3. Productivity Dynamic

Labour productivity. Although their turnover growth trend declines and stabilises after approximately 7 years of operation, STs exhibit a clear upward trajectory in labour productivity as they age, indicating that efficiency gains accompany the firm's maturation. Fig. 3.8 displays labour productivity differences by country and the firm's type. Among non-startup firms, EE HT firms have the highest median productivity (0.66), followed by LT HT firms (0.44). In the ST group, EE STs reach a median of 0.55 (and 0.60 for NACE 62), LT STs 0.59 (0.56 for NACE 62), and LV STs 0.26 (Annex B, Table B. 1). These values indicate modest but consistent productivity differences across both countries and sectoral dimensions.

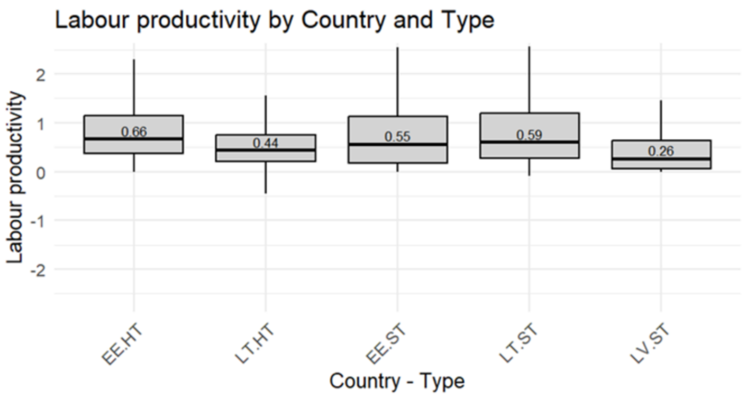

Fig. 3.8. Labour productivity of startups (ST) and non-startup (HT)firms across Lithuania (LT), Estonia (EE), and Latvia (LV). Monetary values are denominated in EUR 100,000. Source: calculated by the author

Age group analysis revealed that ST labour productivity levels increase steadily, reaching close to 800 thousand EUR turnover per employee among STs older than 15 years, while HT firms remain relatively stable around EUR 400–500 thousand throughout the firm's age distribution (Fig. 3.9). This divergence suggests that STs, although initially less productive, can achieve stronger output efficiency over time and their productivity improvements continue through operational efficiency, learning effects, and process optimisation.

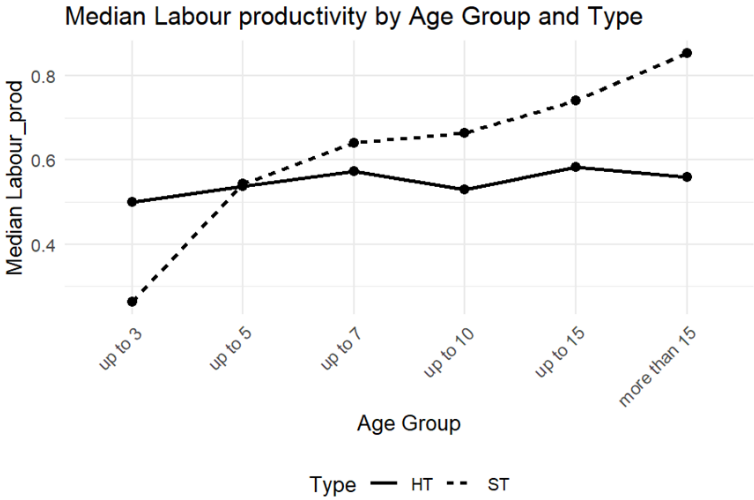

Fig. 3.9. Labour productivity by age and firm type of startups (ST) and non-startup (HT) firms, all countries. Monetary values are denominated in EUR 100,000.
Source: calculated by the author

Total factor productivity (TFP). Econometric modelling was conducted in the RStudio environment: panel instrumental 2SLS models were estimated using the package "ivreg". The first-stage results indicated that the instruments used – lagged values of natural logarithm of total assets (lnTA) and natural logarithm of number of employees (lnEMPL) – are statistically strong and relevant predictors of the endogenous regressors. Weak instrument tests consistently show that lnTA and lnEMPL are strong instruments in all cases (Annex C, Table C.1). The strength of the instruments was confirmed by high first-stage F-statistics; in all cases, the result exceeded the threshold of 10, indicating that weak instrument bias is unlikely to be a concern. Wu–Hausman test showed a significant result for all cases (except EE HT, where it was marginal (0.13) as well, indicating that the OLS FE model would be inconsistent, and there is a strong endogeneity problem in the data that necessitates the use of 2SLS. Thus, the 2SLS method is more reliable in this context, especially due to the importance of correcting for endogeneity, which is critical when assessing the productivity of dynamic sectors like ST and HT.

Capital and labour elasticities. For all LT STs, both highly significant capital (0.67) and labour (0.62) indicate a balanced input response and reflect scalable growth. In NACE 62 STs, labour shows even stronger elasticity (0.72), suggesting that employment growth plays a key role in driving output. Capital elasticity (0.54) remains high as well, though slightly reduced, reflecting relatively equal input contributions. A similar trend is observed among LT HT firms; elasticities remain robust (0.69 for capital and 0.50 for labour). LV STs show a capital elasticity of 0.69, significant at the 10% level, and a non-significant labour coefficient (0.38). This suggests a stronger reliance on capital investments rather than employment for scaling turnover, and it might reflect less labour-intensive business models.

For all EE STs, neither labour nor capital has a statistically significant coefficient, and the estimates (–0.08 and 1.28, respectively) have large standard errors. This suggests high variability or potential noise measurement in firms' inputs. Within NACE 62 STs in EE, the capital elasticity (1.10) is large and marginally significant, while labour has virtually no effect (0.16), which could suggest the presence of capital-heavy business models, which may contribute to lower realised turnover levels, or structural problems in this subsector in EE. This result is especially interesting when the same NACE 62 code HT firms in EE show a very strong and significant labour elasticity (0.88), pointing to the human capital-driven nature of the EE tech sector, where employment is the primary determinant of revenue generation. The capital elasticity remains negative but non-significant, consistent with labour-intense productivity structures in knowledge-intensive sectors. A closer examination of the EE NACE 62 STs revealed that several firms reported exceptionally high total asset values. Upon reviewing available balance sheets, these assets were identified as cryptocurrency holdings, which likely distort capital elasticity estimates. Due to data limitations, it was not possible to verify all balance sheets in this category, meaning that other similar cases may exist, potentially influencing the aggregate elasticity results.

LT firms in general exhibit strong and consistent elasticities to both capital and labour, highlighting their balanced input–output structure. EE STs show greater volatility, with obvious problems in the NACE 62 sector, while at the same time EE HT firms demonstrate labour-driven growth. This is not the case in LV, where STs seem more dependent on capital accumulation with less sensitivity to employment growth.

Observed and predicted TFP. To isolate every type of specific baseline TFP, net of input effects and firm-year heterogeneity, the intercepts from the 2SLS regression to reflect structural productivity in the absence of observable inputs and controls are compared with the actual TFP means, which still embed firm-specific and year effects. This comparison allows for distinguishing between underlying productivity baselines and realised output levels, as a foundation for further analysis of TFP determinants. For all STs, the highest actual average mean TFP is observed in EE (5.50) with a predicted baseline of 11.67, followed by LT (actual 3.14, baseline 2.87) and LV (actual 2.78, baseline 3.30) (Table 3.2).

Table 3.2. Comparison of estimated TFP mean and baseline productivity (as type-specific intercept) of startups (STs) and non-startup (HT) firms across Lithuania (LT), Estonia (EE), and Latvia (LV) and for the NACE 62 ST cohort. Source: calculated by the author

Country, type	Estimated ln of TFP, mean	Type-specific intercept
LT, all ST	3.14	2.87
LV, all ST	2.78	3.30
EE, all ST	5.50	11.67
EE, HT	11.85	12.47
LT, HT	3.39	3.08
EE, NACE 62 ST	–2.01	–2.11
LT, NACE 62 ST	4.57	5.15

Predicted TFP intercepts from the 2SLS model vary significantly by country, suggesting country-specific baseline TFP levels for STs after controlling for firm-level and year characteristics. For LT, all STs and HT firms estimated TFP means were higher than baseline levels, which suggests that the manual TFP proxy (based on turnover adjusted by capital and labour inputs) is relatively consistent with the fixed effects 2SLS model, with only moderate differences.

However, a notable exception emerges for LT NACE 62 STs, where the estimated mean TFP (4.57) is lower than the intercept (5.15) from the fixed-effects model. This reversal implies that transitory firm-level shocks or temporary revenue variations – such as exceptional sales periods or one-time client wins – may have led to underestimation of the structural TFP in the manual calculation. Alternatively, the higher intercept may reflect latent productivity capabilities that are not fully captured through the observed turnover. HT firms in EE have a mean TFP of 11.85 (predicted intercept 12.47), and LT HT mean TFP is 3.39 (predicted intercept 3.08). The comparison suggests that, on average, HT firms in EE tend to have higher TFP than in LT, which doesn't align with the findings for all NACE 62 STs in EE and LT and can be explained with the negative metrics of NACE 62 STs in EE (–2.01 mean and –2.11 predicted intercept): a concern hinting at structurally weak productivity foundations in ST firms within this subsector in EE, which could be seen from the descriptive statistic as well (median of TRN of EE

NACE 62 STs was only 2.74, while median of TA was 3.4 in comparison with LT medians for NACE 62 STs, which was 4.18 for TRN and 2.56 for TA) (Annex A, Table B. 1).

TFP dynamics across the firm's lifecycle reveal a distinguishing age-related trend between STs and HT firms. For STs, TFP gains are concentrated in early stages of development, TFP rises sharply between the ages of 3 and 5 years, peaking in the 5 to 7-year age window (Fig. 3.10). Beyond this point, TFP is rather stable, then declines marginally in older age. This pattern may suggest that younger STs gain productivity quickly in early phases, likely due to learning effects, innovation bursts, or rapid scaling, but that gains stabilise or decline as firms mature and face scaling or market limitations. TFP of HT firms is relatively flat up to the age of 5 years and begins to decline steadily with age. Unlike STs, HT firms do not exhibit an early productivity spike, suggesting more stable but less dynamic growth trajectories.

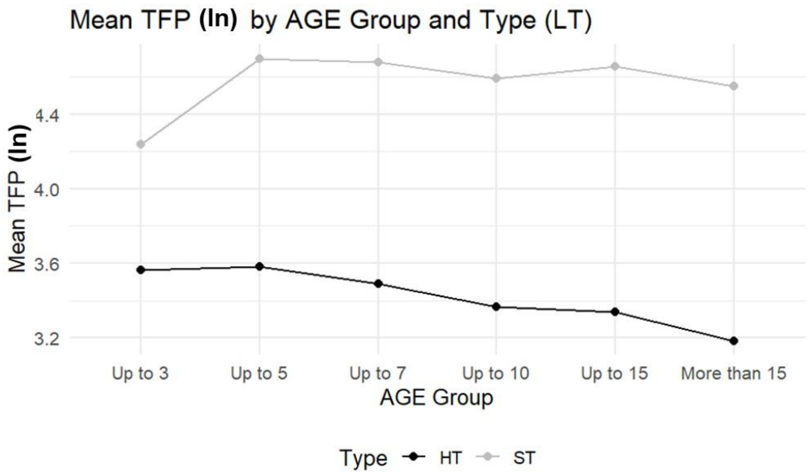

Fig. 3.10. Total factor productivity (TFP) across different age groups for NACE 62 type STs and HT firms in Lithuania. Source: calculated by the author

3.1.4. Financial Performance Dynamic

EBIT margin. The EBIT margin results reveal modest profitability differences across countries and firm types. Among HT firms, EE and LT HT firms exhibit a median EBIT margin of 0.07, while STs show lower and more volatile results. EE STs display the widest dispersion and a median EBIT margin around zero, suggesting high variability in financial performance. LT STs show slightly higher median profitability (0.04), followed by LV STs at 0.02 (Fig. 3.11).

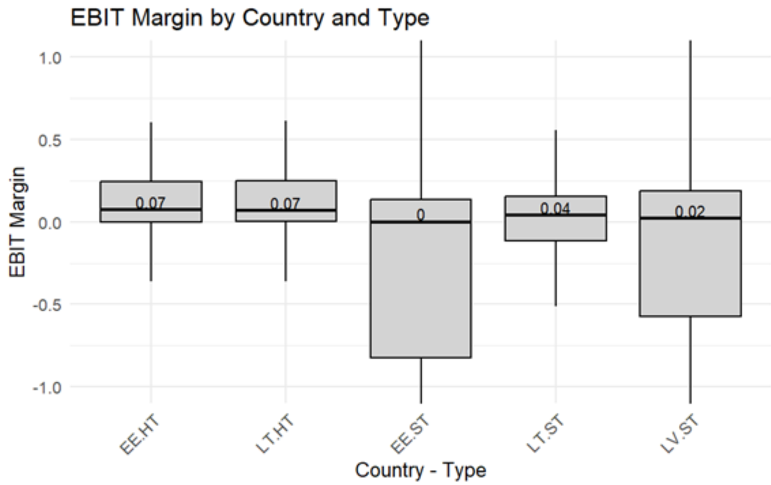

Fig. 3.11. EBIT margin (ratio) of startups (ST) and non-startup (HT) firms across Lithuania (LT), Estonia (EE), and Latvia (LV). Source: calculated by the author

STs initially operate at negative or near-zero margins during their first three years, but their EBIT margins increase steadily with age and approach the levels of non-startup firms after approximately seven to ten years (Fig. 3.12).

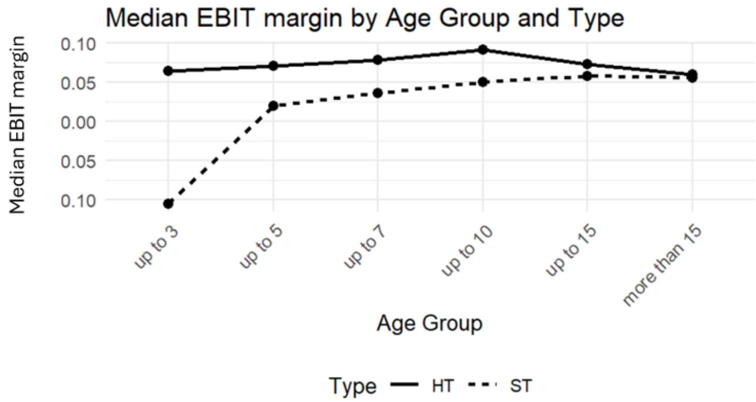

Fig. 3.12. EBIT margin dynamics by age group and firm type of startups (ST) and non-startup (HT) firms, all countries. Source: calculated by the author

This pattern aligns with the earlier findings on labour productivity and salary dynamics, indicating that as ST mature, they not only achieve higher efficiency and pay levels but also move towards financial stabilisation and improved profitability.

Profitability measures. The analysis of return on assets (ROA) and return on equity (ROE) reveals clear cross-country and firm type differences in firms' financial performance. Among HT firms, EE and LT demonstrate similar and relatively high profitability, with median ROE values of 0.27 and 0.31, and median ROA values of 0.14 and 0.13, respectively. However, STs in both countries show lower median profitability and wider dispersion (Fig. 3.13 and Fig. 3.14).

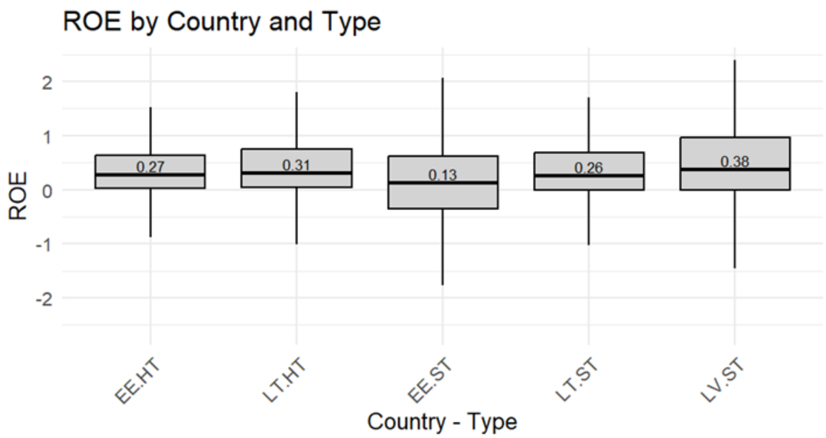

Fig. 3.13. ROE ratio of startups (ST) and non-startup (HT) firms across Lithuania, Estonia, and Latvia. Source: calculated by the author

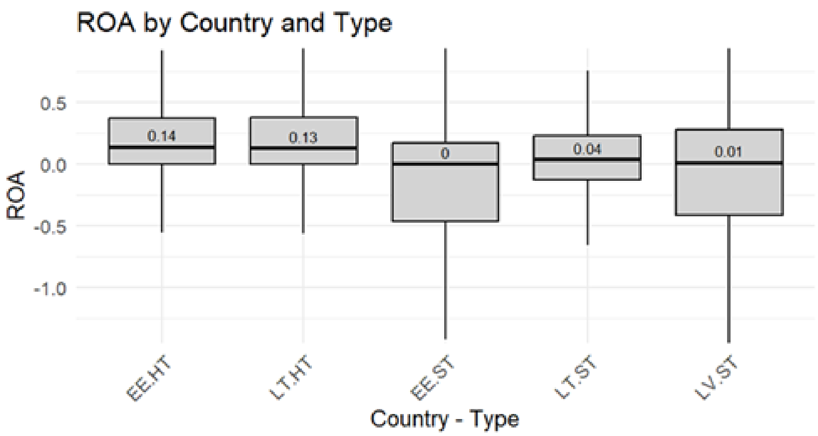

Fig. 3.14. ROA ratio of startups (ST) and non-startup (HT) firms across Lithuania, Estonia, and Latvia. Source: calculated by the author

EE STs report the lowest returns (ROE is 0.13; ROA is 0), while LT STs achieve moderate profitability (ROE is 0.26; ROA is 0.04). LV STs stand out with a comparatively higher ROE (0.38), although their ROA remains low (0.01), suggesting higher leverage or capital intensity; in both EE and LT, STs reported higher total assets and equity levels compared to HT firms, suggesting that STs operate with relatively stronger capital bases or investment intensity despite their lower short-term profitability.

Both HT firms and STs display a declining trend in ROE as they mature (Fig. 3.15), which is related to a rapid increase in equity levels, particularly in the age groups up to 5 and 7 years in all three countries, as STs demonstrate, reflecting growing investor confidence and capital inflows associated with scaling and commercialisation phases.

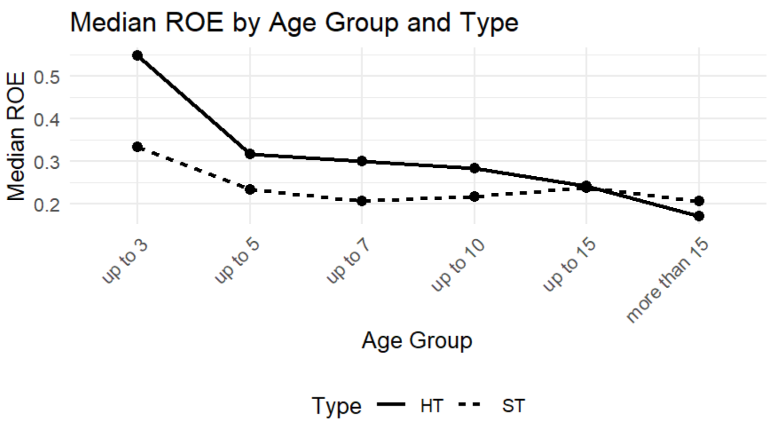

Fig. 3.15. ROE ratio dynamics by age group and firm type of startups (ST) and non-startup (HT) firms, all countries. Source: calculated by the author

This confirms the statement by Rajaiya (2023) that with age, young innovative companies increase equity funding because they want to maintain their ability to innovate.

Capital structure. Among HT firms, LT shows higher leverage (DTA is 0.38; DTE is 0.34) compared to EE, where both ratios are lower (DTA is 0.22; DTE is 0.25). STs generally operate with higher leverage and greater variation in capital structure.

EE STs show moderate levels (DTA is 0.28; DTE is 0.31), while LT STs display higher median ratios (DTA is 0.54; DTE is 0.43), reflecting stronger reliance on external funding during early growth. LV STs stand out with the highest DTA (0.66), but a moderate DTE (0.28) as having the lowest total assets among the region STs (Fig. 3.16 and Fig. 3.17).

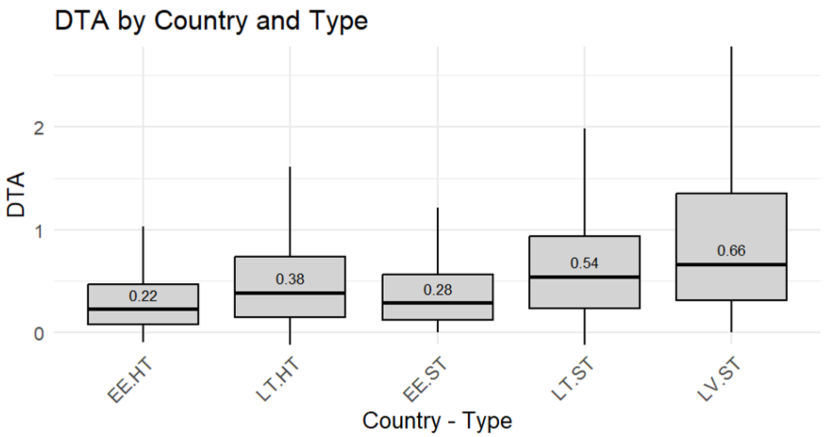

Fig. 3.16. Debt-to-assets ratio of startups (ST) and non-startup (HT) firms across Lithuania (LT), Estonia (EE), and Latvia (LV). Source: calculated by the author

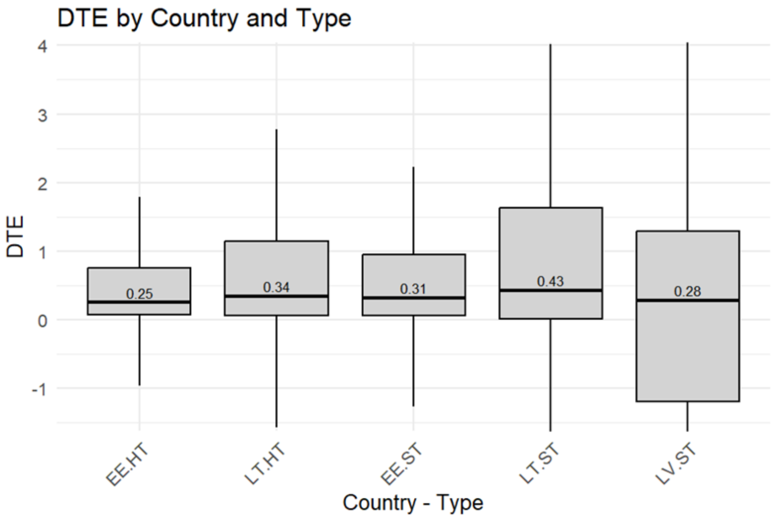

Fig. 3.17. Debt-to-equity ratio of startups (ST) and non-startup (HT) firms across Lithuania (LT), Estonia (EE), and Latvia (LV). Source: calculated by the author

Both STs and HT firms exhibit a clear upward trend in DTE ratios over time. However, for STs, DTE rises sharply in the age groups up to 5 and 7 years, indicating increasing access to or dependence on debt financing as firms expand and scale operations (Fig. 3.18).

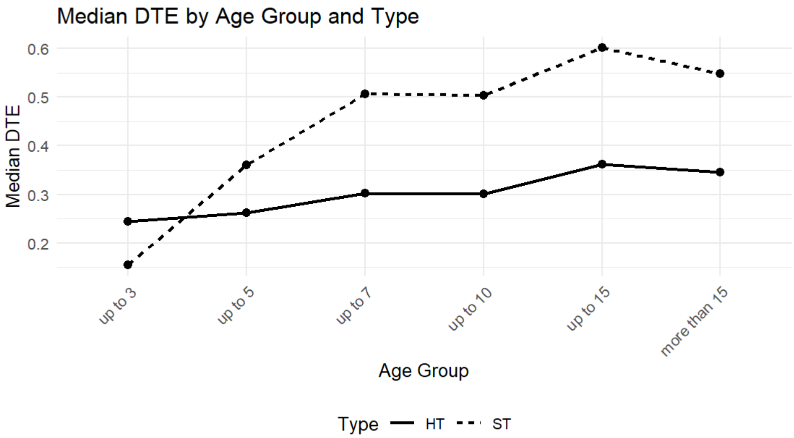

Fig. 3.18. Debt-to-equity ratio by age group and firm type of startups (ST) and non-startup (HT) firms, all countries. Source: calculated by the author

The ratio continues to increase gradually up to 15 years before slightly declining in the oldest group, reflecting a stabilisation of capital structures as firms reach maturity. In contrast, non-startup firms show a more modest and steady increase in leverage with age, consistent with their more established financing profiles.

The findings illustrate that STs tend to increase their leverage rapidly during the early expansion phase, using external debt to support growth and product development. Following the profitability result, these findings are in line with the statement by Newman et al. (2012), who claimed that more profitable firms have less debt. As they mature, capital structures become more balanced, aligning with the rising equity and total assets; however, throughout their entire lifecycle, STs rely more heavily on debt financing than non-startup firms, reflecting their persistent dependence on external capital to sustain growth and operational expansion. While their leverage gradually stabilises with firm maturity, startups remain more debt-oriented compared to established HT firms, highlighting structural differences in financing strategies between the two groups.

3.1.5. Firm Failure Risk

Different survival patterns between STs and non-startup firms become evident through their failure (exit) age distribution data. The failure rate of STs reaches its highest point between 3 and 5 years after the ST inception, when 10–12% of businesses stop operating (Fig. 3.19). The high number of ST failures during their first five years indicates their typical exposure to risks during market entry and initial development stages when financial stability, market acceptance, and business model sustainability become essential. The fact that the biggest ST failure occurs during the first years and high growth might have a reducing effect, resonates with a finding by Rannikko et al. (2019).

Non-startup firms demonstrate a different exit pattern through their flat failure distribution, which shows lower failure rates of 6–7% during the first few years and a steady decline in failure rates after that period. The failure rates of STs and non-startup firms decrease at a steady pace after their firms reach 7 years of age, which indicates that firms that survive their initial years develop better operational stability and resistance to failure.

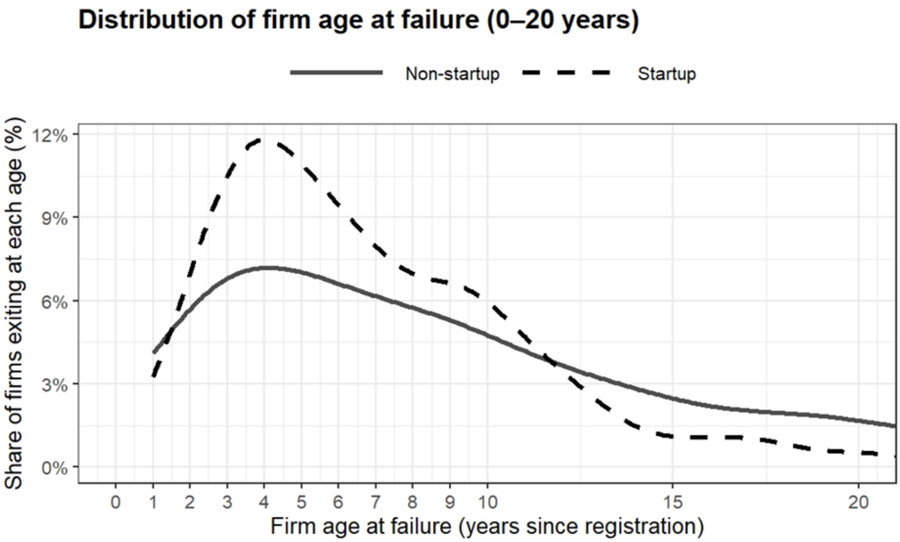

Fig. 3.19. Distribution of the firm's age at failure (exit) by firm type (period 2023–2024), all countries. Source: calculated by the author

3.1.6. Growth Profiles

Principal component analysis (PCA) was applied to three ST firm-level variables: TRN CAGR (compound annual growth rate of turnover), the firm's age and size as the natural logarithm of annual turnover (ln TRN). Together, principal component 1 (PC1) and principal component 2 (PC2) captured 72% of the variance, and PC1 clearly met the Kaiser criterion (eigenvalue > 1) (Table 3.3).

Squared loadings by variable sum to 1, indicating the three orthogonal components fully reconstruct each variable's variance. Substantively, PC1 (size) and PC2 (growth) contain the primary structure (Table 3.4).

Table 3.3. Importance of PCA components. Source: calculated by the author

Importance of components	PC1	PC2	PC3
Standard deviation	1.08	1.00	0.90
Proportion of variance	0.39	0.33	0.27
Cumulative proportion	0.39	0.72	1.00

Table 3.4. PCA component loadings: correlations/weights of variables on principal components. Source: calculated by the author

Variable	PC1	PC2	PC3
TRN CAGR	0.31	0.95	0.04
Age	–0.67	0.19	0.71
ln TRN	–0.67	0.25	–0.70

Building on the PCA results, the first two principal components (PC1 is maturity/size and PC2 is growth), which together captured 72% of total variance, were retained, and K-means clustering was applied to the PC scores. The number of clusters (k) was chosen by the elbow criterion (within-cluster sum of squares vs k), which indicated a clear elbow at k is 5 (Fig. 3.20).

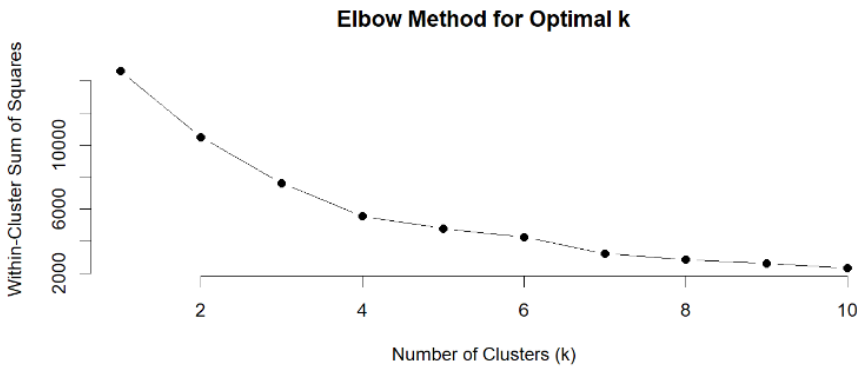

Fig. 3.20. Scree plot visualisation. Source: created by the author

The resulting partition categorises STs into five growth profiles. Means of the original (unstandardised) variables within each cluster are reported in Table 3.5.

Table 3.5. K-means clustering on principal components result, means of variables, all STs. Source: calculated by the author

Growth profile	Unique firms	Observa-tions	Profile definition	CAGR, %	Age, years	Size, ln TRN
1	707	1779	Small, young, fast growth	81	3.31	10.90
2	234	1219	Big, mature, low growth	20	15.93	15.41
3	685	2677	Small, mature, moderate growth	49	7.22	13.59
4	5	35	Big, young, extreme growth	18614	4	15.55
5	14	43	Small, young, very fast growth	2645	2.12	9.90

3.2. Factors Enabling Startup Development

This chapter reports results from the determinants analysis for the ST-enabling environment. The empirical results are organised by outcome and by type of determinant, and econometric methods combine parametric and semiparametric approaches. Determinants of ST failure are estimated with generalised linear models (GLM). Growth outcomes are linked to firm-internal factors using regression specifications tailored to growth metrics, with attention to distributional skew typical of young firms. Determinants of TFP within firms are examined with models that isolate firm-specific contributions, controlling for time and sectoral heterogeneity. Semiparametric partial linear panel models (PLM) capture potentially non-linear effects on ST growth of exogenous IE conditions: market access, human capital, venture capital availability or access to finance.

Results are presented for the ST population as a whole and by ST growth profiles. Across sections, estimates are reported with standard errors and effect sizes, alongside specification notes and diagnostics to facilitate comparison of magnitudes and robustness. Econometric modelling was conducted in the RStudio environment: panel regressions employed the package “plm”, semiparametric partial linear models (PLM) were estimated with “mgcv”, propensity score matching (PSM) was implemented using the “matchit” package, and for Firth, the logistic regression package “logistf” was used.

3.2.1. Determinants of Failure

The original sample contained 4,283 startup and 5,387 non-startup (HT) firm observations. After PSM matching, the analysis sample comprised 3,755 startup and

3,755 non-startup observations; 528 startups and 1,632 non-startup observations without suitable matches were discarded. As some variables used in the outcome model contained missing values (notably, TRN GR and EBIT margin), the Firth logistic regression was estimated on the 7243 complete cases of the unmatched and 5558 on the matched samples. Balance checks from the PSM procedure indicated that standardised differences for the matching covariates are reduced to acceptable levels in the matched sample, suggesting good covariate balance between STs and their matched non-startup counterparts.

Because the dependent variable (Failure) is rare (7.7% in the unmatched sample and 9.9% in the matched sample) and unbalanced, a Firth bias-reduced logistic regression was estimated to correct for potential quasi-separation (Equation 2.9). The interaction term TypeST was included to capture potential differences in the determinants of firm failure between STs and HT firms (Annex D, Table D.1).

The unmatched model uses the full sample of STs and HT firms, whereas the second model uses only the PSM-matched sample of STs and comparable non-startups. In the full-sample Firth model, being a startup (TypeST) is associated with significantly higher odds of the firm's failure (OR is 1.27, $p < 0.01$). Older firms are significantly less likely to experience failure: each additional year of age reduces the odds by about 3% (OR is 0.97, $p < 0.001$). Higher return on assets (ROA) is also associated with lower failure risk (OR is 0.92, $p < 0.01$). Other financial variables are not statistically significant. Overall model fit is modest (AIC is 4085; McFadden R-squared is 0.02).

In the Firth model after PSM, which compares STs only with PSM matched non-startups (HT), same patterns remain. STs still exhibit significantly higher failure risk – TypeST OR (odds ratio) is 1.26, even after conditioning on a broad set of firm characteristics. Age continues to have a protective effect (OR is 0.97, $p < 0.01$), and the negative association with ROA becomes stronger (OR is 0.86, $p < 0.01$). In the matched sample, higher leverage (DTE) emerges as a significant risk factor (OR is 1.01, $p < 0.01$), while the effects of other covariates remain small or statistically insignificant.

This indicates that the higher risk of failure among STs is not solely driven by differences in size, profitability or balance-sheet structure; it persists even when STs are compared to observationally similar non-startups within the same industry subsector. This finding is in line with the claims of Sapienza et al. (2006), who argue that early internationalisation increases the scalability of growth, but at the same time might decrease firms' probabilities of survival. The empirical evidence that STs in this research exhibit lower profitability and higher debt levels and at the same time higher failure rate is consistent with recent findings by De Haas et al. (2022), who showed that STs with excessive leverage face the lowest survival probabilities over a 12-year horizon, as well with Fuertes-Callén et al.

(2022) who found an extremely elevated bankruptcy risk for unprofitable one-year-old STs.

Together, these studies reinforce the result of this study that weak profitability and high indebtedness constitute a particularly fragile financial profile for startups. Model fit was evaluated using Akaike Information Criterion (AIC) and McFadden's pseudo-R-squared. Model diagnostics indicate moderate explanatory power (McFadden R-squared is 0.01-0.02) and acceptable multicollinearity levels (all VIFs are less than 2).

3.2.2. Endogenous Growth Determinants

To account for unobserved macroeconomic shocks and other factors that vary across time but are common to all firms, the model was estimated with both individual and time-fixed effects and using heteroskedasticity-consistent robust standard errors (type HC1) to account for potential heteroskedasticity and serial correlation in the residuals. The presence of significant time effects was formally tested using a Breusch–Pagan Lagrange Multiplier test for time effects on the one-way fixed-effects specification. The test produced a χ squared statistic of 25.26 ($p < 0.001$), rejecting the null hypothesis of no time effects. This indicates that common shocks across years materially affect the firm's turnover growth. Four models were estimated: two for firms operating within the NACE 62 sector (ST and HT combined) and two for the only ST sample, each under fixed effects (FE) and two-way fixed effects (TW) specifications.

Table 3.6 provides a simplified summary of the regression results, reporting only statistically significant coefficients and significant smooth terms to highlight the core relationships in an interpretable form. The complete estimation output – including all coefficients (including non-significant estimates), smooth-term diagnostics (edf and F-statistics), model fit measures, and specification tests – is reported in Annex D, Table D.2. Across all specifications, profitability (ROA) and employment growth (EMPL GR) emerge as the strongest and most consistent determinants of firm growth. In the combined ST and HT sample, the coefficient of ROA is large and highly significant (3.15, $p < 0.001$), indicating that profitability is a key determinant of firm expansion in the technology sector. However, the interaction term of ROA for ST is negative and significant (–1.39, $p < 0.05$), suggesting that the growth effect of profitability is substantially weaker for ST. This finding is consistent with the growth and profitability analysis in the chapters above, which showed that during the early, high-turnover growth phases, ST typically experience lower profitability margins despite rapid revenue expansion.

Table 3.6. Internal turnover growth determinants, panel regression results for only startups (ST) and STs with non-startup (HT) NACE 62 firms. Source: calculated by the author

Variable	ST & HT 62, FE	ST & HT 62, TW	All STs, FE	All STs, TW
ROA	3.15***	3.19***	1.42***	1.40***
DTA	2.36***	2.37***	0.80***	0.79***
EBIT margin	—	—	0.92***	0.90***
EMPL GR	0.39***	0.38***	0.38***	0.36***
Age	—	—	–0.27***	—
GDP GR	0.12***	0.55***	0.07***	–0.11*
ROA:TypeST	–1.39*	–1.38*	—	—
DTA:TypeST	–1.84*	–1.85*	—	—
Age:TypeST	–0.24*	–0.30**	—	—

Notes: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; $p < 0.10$. "—" indicates the coefficient is not statistically significant in the original table and is, therefore, omitted here.

The weaker ROA effect, therefore, reflects the structural characteristics of STs, where earnings are frequently reinvested into scaling, product development, and market acquisition rather than generating immediate financial returns. In such phases, growth tends to be driven more by reinvestment and external funding than by internally generated profits.

Similarly, capital structure, measured by the debt-to-assets (DTA) ratio, shows a positive and significant relationship with growth for all firms (2.36, $p < 0.001$), but the interaction term is negative and significant (–1.84, $p < 0.05$) for STs. This implies that while leverage contributes positively to growth among established firms, STs may not benefit equally from higher asset-based financing, possibly due to higher financial risk and weaker debt absorption capacity in the early stages.

The employment growth variable (EMPL GR) is highly significant and stable across all specifications (0.36–0.39, $p < 0.001$), reflecting the labour-driven nature of firm expansion in the high technology sectors without the type difference. However, the Age variable shows divergent effects: it is not significant in the combined sample but becomes strongly negative and significant for STs (–0.27, $p < 0.001$), consistent with typical startup lifecycle dynamics. The interaction Age:TypeST is also negative and significant (–0.24 to –0.30), reinforcing the notion that the firm's age reduces growth more strongly among STs than among HT firms.

In the models estimated only for STs, the coefficient on EBIT margin is positive and highly significant (around 0.9), indicating that, conditional on other factors, a 1-percentage-point increase in EBIT margin is associated with a sizeable increase in turnover growth. This implies that higher operating profitability is strongly associated with faster growth of STs.

The control variable for macroeconomic environment (GDP GR) is generally significant, showing that broader economic expansion positively influences firm growth. However, the coefficient declines or turns slightly negative for STs under the TW model, suggesting that the ST segment may be less sensitive, or even countercyclical to short-term GDP fluctuations, possibly due to their dependence on innovation and niche market opportunities rather than aggregate demand.

Technology sector firm expansion depends mainly on profitability and workforce growth, but capital structure and the firm's age also influence these processes. The growth patterns of STs differ from non-startup firms because their expansion depends more on the operational efficiency rather than on profitability and leverage and declines faster with age due to their unstable financial situation and this finding contradict the statement by De La Fuente (2011) and Añón Higón et al. (2022) who claimed that age is a positive factor for growth, because it enables skill development and accumulation of experience. The two-way fixed effects analysis shows that these findings stem from permanent differences between firms and their lifecycle stages rather than time-dependent events.

3.2.3. Endogenous Productivity Determinants

The econometric analysis of intra-firm factors influencing ST TFP provides further insights into the drivers of ST firm growth and competitiveness. Fixed effects were applied at the firm and year levels, ensuring that the observed effects of the explanatory variables are independent of unobserved firm traits and time-specific shocks. Since the firm's age and size change over time, dummy variables representing age and size categories are retained in the fixed effects model, as they are not perfectly collinear with the firm-specific effects.

The findings indicate that operational profit (EBIT MRG) and turnover growth (TRN GR) are highly significant positive determinants of TFP (coefficients 0.26 and 0.23, respectively, p is less than 0.001) (Table). This could imply that achieving higher profitability and faster growth is also more productive, reinforcing their competitive position. This is intuitive, as more efficient firms (higher TFP) are likely to be more profitable, in line with the claim by Sung et al. (2022). Causality could run both ways: higher TFP leads to better financial performance, and better financial health can enable investments that boost TFP.

Table 3.7. Firm's level TFP determinants (panel OLS with fixed effects result). Source: calculated by the author

Variables	**All ST, TW**
ROA	0.03 (0.03)
DTE	0.01 (0.01)
EBIT MRG	0.26 (0.02) ***

End of Table 3.7

Variables	**All ST, TW**
TRN GR	0.23 (0.02) ***
Age group up to 5	0.14 (0.06) *
Age group up to 7	0.27 (0.11) *
Age group up to 10	0.27 (0.11) *
Age group up to 15	0.22 (0.15)
Age group more than 15	0.13 (0.22)
Size, micro (1–10)	0.84 (0.25) ***
Size, small (11–50)	0.66 (0.24) **
Size, big (51–250 empl.)	0.68 (0.23) **
R-squared	0.26
n	672
N	2235
T	1-9
F statistic (p-value)	26.94 (< 2.22e-16)
Wooldridge test, p-value	0.86

Notes: Robust standard errors are in parentheses. Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$.

The coefficient for leverage (DTE) was insignificant, which contradicts the findings of Nakatani (2023) that TFP levels improve when companies use leverage. The firm's age also plays a role, with peaking positive effect at the age of 7 to 10 years, that was seen as comparing TFP by age group for ST and HT as well (Fig. 3.9). And this result is in line with the findings of De Haas, Sterk, and Van Horen (2022) who showed that large STs that continue to grow throughout time achieve higher productivity levels.

The firm's size matters as well: compared to the extra big size group (more than 250 employees), all other included size categories show positive and statistically significant coefficients, with micro firms (1–10 employees) having the largest effect (0.84, p is less than 0.001), which is in line with the findings by Somya and Saripalle (2023), who found that the larger firms grow at a decreasing rate compared to small firms. This finding suggests that smaller ST exhibit higher TFP, due to greater flexibility, leaner operations, higher innovation intensity per employee, or a selection effect where only highly productive micro-ST survive and grow. Variance Inflation Factor (VIF) diagnostics indicated no multicollinearity issues; the Wooldridge test p-value was 0.86, suggesting no evidence of serial correlation in the error terms, supporting the robustness of the estimates.

3.2.4. Exogenous Growth Determinants

Both panel OLS and GAM showed that selected IE characteristics can be related to ST growth, thereby confirming the findings by Filho et al. (2024). The OLS model explained moderate growth variation (adjusted R-squared is 0.22), but diagnostic tests revealed non-linearities and heteroskedasticity, addressed with GAM smooth terms and robust errors. VIF values: AM (3.034), VC (1.59), KS (1.9), GDP GR (1.25), FS (2.84), HC1 (4.67), and AGE (2.7). The GAM improved model fit (adjusted R-squared is 0.24), confirming most linear relationships while uncovering non-linear patterns. Table 3.8 provides a simplified summary of the regression results, reporting only statistically significant coefficients and significant smooth terms to highlight the core relationships in an interpretable form. The complete estimation output, including all coefficients (including non-significant estimates), standard errors (clustered at the country–year level to account for correlation of residuals across firms exposed to the same macroeconomic conditions), smooth-term diagnostics (edf and F-statistics), model fit measures, and specification tests, is reported in Annex D, Table D.3.

Table 3.8. Exogenous growth determinant base OLS and PLM regression results for all startups (all ST) and only NACE 62 ST (ST 62). Simplified summary. Source: calculated by the author

Variable	**OLS (All ST)**	**GAM (All ST)**	**GAM (ST 62)**
Access to Markets (AM)	0.20***	—	0.16***
Venture Capital (VC)	−0.01*	0.03**	—
Knowledge Spillovers (KS)	−0.05***	−0.03***	−0.07***
Growth profile 3	−0.76*	—	—
Growth profile 5	6.33***	5.17***	—
Smooth terms: GDP GR	—	s(GDP GR): *	s(GDP GR): .
Smooth terms: HC1	—	s(HC1): *	s(HC1): *
Smooth terms: AGE	—	s(AGE): *	s(AGE): *

Notes: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$. "—" indicates the coefficient is not statistically significant in the original table and is, therefore, omitted here.

Subsequently, the PLM modelling was applied for the separate ST Growth profiles (except Growth profile 4, due to the small number of observations) (Annex D, Table D.4).

Access to market (AM): OLS show a strong positive association between better access to market and ST growth. In GAM, the effect is significant for NACE 62 STs and for small to moderate-sized, high and moderate growth STs (Growth profiles 1 and 3).

Human capital (HC1): There is a consistent and significant positive relationship between HC1 and ST growth in both OLS and GAM, implying that in the IE, where there is more relevant HC1, STs that use digital technologies intensively achieve higher growth. These results are in line with findings by Ramírez et al. (2020), who also identified human capital as a fundamental driver of ST expansion and productivity growth through the adoption and effective use of new technologies. GAM reveals a non-linear relationship (Fig. 3.21), suggesting that the impact of HC1 is the strongest at moderate levels and diminishes at very high levels. HC1 was significant as well for all ST profiles, except for very small and the youngest (Growth profile 5), and the highest coefficient value was for big, mature, and low growth (Growth profile 2).

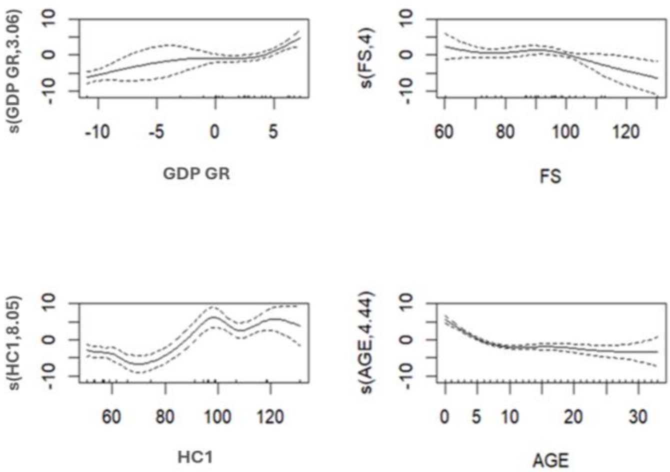

Fig. 3.21. GAM smooth plots. Source: calculated by the author

Venture capital availability (VC): OLS and GAM showed differing results. The OLS found a small negative coefficient for VC that was marginally significant. However, once non-linear patterns and heterogeneity were accounted for in the GAM, the VC effect turned positive and significant for the overall sample and positive and weakly significant for the large, mature type of ST. This discrepancy indicates that the OLS result may have been masking a more complex relationship. For example, very high levels of VC may go to a few firms or later-stage companies, or there may be diminishing returns. In countries with less mature startup ecosystems and weaker, more unstable VC activity, the phenomenon suggested by t Khanna and Mathews (2022) may occur where STs are more likely to compete for and partner with less established VC investors. This is also consistent with X. Li et al. (2023), who demonstrate that the structure of VC firms shapes how the broader innovation ecosystem evolves.

Knowledge spillovers (KS): the models find a negative linear relationship with the knowledge spillovers (KS). The proxy for KS used has negative and significant coefficients in OLS and remained negative in the GAM for all profiles of STs, including NACE 62 ST. It was significant and negative for the small and moderate-sized STs (Growth profiles 1 and 3).

Access to finance and public support (FS): the OLS did not find a statistically significant direct effect. The coefficient was positive but small and not significant, and the GAM likewise did not show a strong effect.

Age. For STs, age has a negative effect on growth. This was significant in both OLS and GAM (and GAM allowed the Age effect to be non-linear (Fig. 3.21) but was insignificant for the big mature (Growth profile 2) and very young and small STs (Growth profile 5). Similarly, for these STs (Growth profile 5), GDP GR was insignificant as well.

The identification of distinct ST growth profiles based on firm maturity and growth dynamics is consistent with previous findings in the literature, e.g., Marcon and Ribeiro (2021) showed that STs function differently within the IE depending on their stage of development.

3.2.5. Exogenous Productivity Determinants

In addition to firm-level (endogenous) factors, ST TFP can also be influenced by broader macroeconomic and ecosystem conditions that are largely exogenous from the perspective of individual firms. To capture these effects, an OLS regression was estimated with the natural logarithm of TFP of STs as the dependent variable and country-level indicators as explanatory variables. The final model includes age-group dummies to control for age, GDP growth (GDP GR), VC investment per capita (VC), the relative size of the ICT sector in gross value added (ICT GV) and job mobility (JOB M) as a proxy for knowledge spillovers. The results are reported in Table .

Among the considered macro-level determinants, only VC stands out as the only statistically significant predictor of TFP for STs, reinforcing its importance as a driver of innovation and technology adoption. Other hypothesised determinants, such as knowledge spillover proxied by job mobility (JOB M), innovation activity (INO ACT) or ICT sector size (ICT GV) and GDP growth, did not show meaningful effects, and in the final model, innovation activity (INO ACT) was removed.

The coefficient on VC is positive and significant at the 1% level, indicating that higher availability of VC is associated with higher TFP of STs. This finding is consistent with the view that VC facilitates innovation and technology adoption by providing not only funding for important ST intangible assets and scaling resources, but also managerial expertise, monitoring and access to networks. In other words, more mature VC markets appear to create an ecosystem in which productive STs can realise their growth and innovation potential more efficiently.

Table 3.9. Exogenous TFP determinants, OLS regression result. Source: calculated by the author

Dependent variable: ln TFP	**Estimates**
Intercept	4.92 (1.85)
Age group up to 3	–0.30 (0.24)
Age group up to 5	0.16 (0.30)
Age group up to 7	0.07 (0.31)
Age group up to 10	0.32 (0.24)
Age group up to 15	–0.19 (0.33)
GDP growth (GDP GR)	–0.08 (0.07)
VC per capita (VC)	0.01 (0.00) ***
ICT sector size (ICT GV)	–0.23 (0.26)
Job mobility (JOB M)	–0.09 (0.09)
R-squared	0.08
N	1318

Notes: Heteroskedasticity- and cluster-robust standard errors (clustered at the country–year level to account for correlation of residuals across firms exposed to the same macroeconomic conditions) are reported in parentheses. Significance level: *** $p < 0.001$

By contrast, the other hypothesised exogenous determinants – GDP growth, the size of the ICT sector and job mobility – do not exhibit statistically significant effects on ST TFP in this specification. The small and statistically insignificant coefficient on GDP growth suggests that short-term macroeconomic fluctuations are less important for productivity than structural ecosystem conditions. Similarly, the ICT sector share and job mobility, although often highlighted in the literature as potential channels of knowledge spillovers, may operate with longer lags or primarily affect entry and scaling rather than the marginal differences in productivity captured here. An additional explanation is that these indicators display limited variation across the three Baltic countries and over the available time window, which reduces their explanatory power relative to firm-level heterogeneity.

The overall explanatory power of the model (R-squared is only 0.08) is modest, but it could be typical for firm-level productivity regressions, where much of the variation reflects idiosyncratic factors that are not observed in administrative data. The results should, therefore, be interpreted as evidence that VC maturity stands out as the most relevant exogenous productivity-enhancing factor among the tested indicators, while the role of other macro-level variables remains inconclusive given the country-level aggregation and potential measurement limitations.

3.3. Assessment of the Startup Ecosystem Impact on the Economy

This section evaluates whether startup ecosystem maturity translates into broader economic outcomes by constructing a composite V index as a proxy for ecosystem maturity based on venture capital activity. Using a multi-country European panel (23 countries, with Lithuania, Latvia, and Estonia aggregated as a Baltic region), the analysis first validates the index structure via PCA and examines cross-country differentiation through clustering and time trends.

Prior to econometric modelling, pairwise correlations and Dumitrescu–Hurlin Granger causality tests are employed to assess co-movement and temporal precedence between the V index and macroeconomic indicators. The section then estimates panel and pooled specifications for four macroeconomic outcomes: labour and capital productivity, trade, and innovation, explicitly testing whether Baltic effects differ from the European baseline through interaction terms.

3.3.1. V Index

The PCA results demonstrate that the V index successfully captures the essential dimensions of economic development potential through its four-component structure. The scree plot analysis confirmed that the first principal component (PC1) dominates the variance explanation (55%). By the Kaiser criterion (components with eigenvalue more than 1), only PC1 was retained (Table 3.10), as it accounts for the largest share of common variance across the four VC indicators and, therefore, provides a good representation of the underlying construct.

Table 3.10. Eigenvalues and proportion of variance explained by each principal component, V index. Source: calculated by the author

PC	Eigenvalue	Variance explained, %	Cumulative variance, %
PC1	2.19	54.81	54.81
PC2	0.83	20.69	75.5
PC3	0.61	15.22	90.72
PC4	0.37	9.28	100

Accordingly, the V index is defined using the PC1 scores, which are a weighted linear combination of the standardised input variables. The weights (loadings) reflect the relative contribution of each component-VC investment and divestment amounts, as well as investment and divestment round to the V index (Table 3.11).

Table 3.11. Variable contributions (loadings) to the V index (PC1) from PCA. Source: calculated by the author

Contribution	VC INV	VC DIV	VC INV COM	VC DIV COM
V index (PC1)	17.16	29.12	25.05	28.66

This choice ensures that the V index captures the shared variance structure of the components rather than treating them with equal weight. To evaluate internal consistency, Cronbach's α coefficients are computed for the item groups identified by PCA. The two items loading on PC1 show acceptable reliability (α is 0.75). By contrast, the components associated with PC2 and PC3 demonstrated weak or insufficient reliability. PCA is used to build an index that reflects the shared information among several variables (not treating them equally). Cronbach's alpha confirms that only the first principal component (PC1) forms a consistent and reliable construct. Therefore, the final V index is effectively one-dimensional and represented by PC1.

3.3.2. V Index Trend

The cluster analysis result (Fig. 3.22) reveals distinct groupings of countries based on their V index characteristics, suggesting that the V index effectively differentiates between countries with varying levels of economic development potential. This clustering provided validation for the index's discriminatory power and its ability to capture meaningful economic differences across countries.

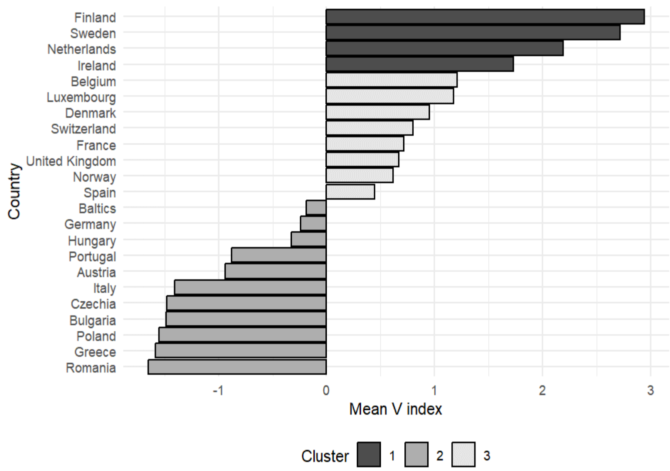

Fig. 3.22. Clusters of countries by V index. Source: calculated by the author

The average V index's temporal trend across European countries shows a low and slightly negative level until 2017, followed by a steady increase from 2018 onwards, peaking sharply in 2021 (up to 0.6). This surge likely reflects a wave of VC activity and ST exits in the post-COVID recovery period, when financing conditions were exceptionally favourable. After 2021, the index declines, turning negative again by 2023, before recovering slightly in 2024, and this could be influenced by the uncertainties related to Russia's war in Ukraine (Fig. 3.23).

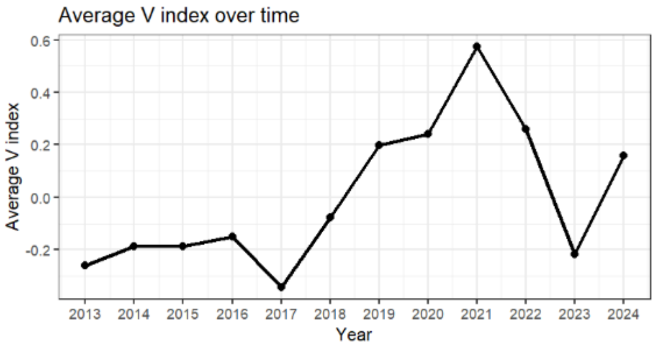

Fig. 3.23. V index over time, European countries (2013–2024).
Source: calculated by the author

The Baltic region (EE, LV, and LT) was separated from the rest of the sample, and a clear divergence emerges. While the Baltic region's V index also rises after 2018 and reaches its peak in 2021, it remains below the rest of Europe's, suggesting that regional VC ecosystems are less developed and more volatile.

In contrast, the other countries' average V index stays near or above zero, with a smoother upward trend and higher levels throughout the period. The gap is particularly wide in the early years (2013–2017) and again after 2022, highlighting specific Baltic region ST ecosystems' vulnerability to geopolitical risks (Fig. 3.24).

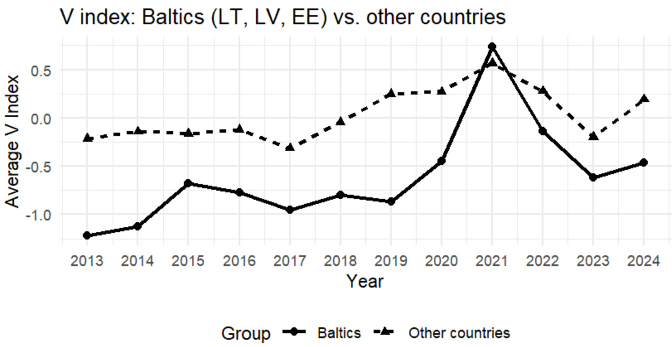

Fig. 3.24. V index over time, Baltic region vs other countries.
Source: calculated by the author

3.3.3. V Index Correlation

The correlation analysis reveals several important patterns in the relationships between the V index and economic development indicators:

Strong positive correlations: The V index demonstrates robust positive correlations with employment in knowledge-intensive sectors (EMPL, r is 0.71), public consumption (PUB CON, r is 0.62), business R&D expenditure (BERD, r is 0.58), and human capital (HC, r is 0.56). These strong correlations suggest that countries with higher V index values tend to have more developed knowledge economies, greater public sector involvement, higher innovation investments, and human capital endowments (Table 3.12).

Moderate positive correlations: high-technology exports (ICT EXP) show a moderate positive correlation with the V index (r is 0.22), indicating that while there is a positive relationship, it is not as strong as the relationships with knowledge-intensive employment and innovation indicators.

Table 3.12. Correlation matrix (Pearson). Source: calculated by the author

	HT EXP	**PRO C**	**PRO L**	**BERD**	**HK**	**EMPL**	**ICT EXP**	**PUB CON**	**GDP GR**
PRO C	–0.11								
PRO L	0.25	0.38							
BERD	0.1	–0.21	0.07						
HC	0.2	–0.29	–0.1	0.44					
EMPL	0.25	–0.27	–0.07	0.61	0.7				
ICT EXP	0.52	–0.14	0.2	0.41	0.17	0.24			
PUB CON	0.14	–0.27	–0.1	0.48	0.58	0.85	0.17		
GDP GR	0.18	0.26	0.3	–0.05	–0.22	–0.21	0.1	–0.25	
V index	0.22	–0.12	0.07	0.58	0.56	0.71	0.51	0.62	–0.11

Notes: the entries report Pearson correlation coefficients r between variables, r ranges from -1 to 1, where values close to 1 indicate a strong positive linear relationship, values close to -1 indicate a strong negative linear relationship, and values near 0 indicate little or no linear association.

Inter-variable relationships: the correlation matrix also reveals important relationships among the economic indicators themselves. Notably, employment in knowledge-intensive sectors (EMPL) shows strong positive correlations with business R&D (BERD, r is 0.61), human capital (HC, r is 0.70), and public consumption (PUB CON, r is 0.85), indicating the interconnected nature of these development dimensions.

3.3.4. Granger Causality

To address questions of temporal precedence and causal direction, Granger causality tests (Dumitrescu–Hurlin) were implemented to examine whether past values of the V index can predict future values of economic development indicators, and vice versa. These tests were performed using 23 countries' observations, providing sufficient degrees of freedom for reliable statistical inference while maintaining adequate power to detect meaningful causal relationships. The bidirectional Granger causality tests were conducted for the following variable pairs (Table 3.13).

The Granger causality analysis yields consistent results across all tested variable pairs, with no evidence of causal relationships in either direction between the V index and the examined economic indicators.

Table 3.13. Granger causality test results. Source: calculated by the author

Direction	If significant	Number of countries
PRO C → V index	No	23
V index → PRO C	No	23
PRO L → V index	No	23
V index → PRO L	No	23
BERD → V index	No	23
V index → BERD	No	23
HT EXP → V index	No	23
V index → HT EXP	No	23

These results suggest that while correlations exist between the V index and various economic indicators, there is no evidence of short-term predictive relationships within the sample period.

3.3.5. Macroeconomic Outcomes

The dataset comprises observations from European countries over varying time periods, with sample sizes ranging from 105 to 219 observations, depending on the specific model and data availability. The temporal dimension spans from 3 to 10 years across 19 to 23 cross-sectional units, providing sufficient variation for analysis.

Labour productivity. The analysis of labour productivity reveals consistent positive effects of the contemporary V index across most specifications, with coefficients ranging from 0.96 to 1.15. Table 3.14 provides a simplified summary of the regression results, reporting only statistically significant coefficients and significant smooth terms to highlight the core relationships in an interpretable form.

The complete estimation output, including all coefficients (including non-significant estimates), smooth-term diagnostics (edf and F-statistics), model fit measures, and specification tests, is reported in Annex E, Table E.1.

The contemporary V index demonstrates a statistically significant positive effect on labour productivity across the FE (1.07, $p < 0.05$) and pooled OLS (0.96, $p < 0.05$) specifications. The random effects model (RE) shows a marginally significant effect (0.96, $p < 0.10$). The lagged values of the V index (V l1 and V l2) show minimal and statistically insignificant effects across all model specifications. The first lag (V l1) coefficients are statistically insignificant (Table). This pattern suggests that the impact of the V index on labour productivity is primarily contemporaneous rather than persistent over time. The Hausman test (p is 0.09) suggests that both FE and RE models are appropriate, though the marginal p-value indicates some preference for the FE specification.

The inclusion of the Baltic region interactions reveals differential effects that fundamentally alter the interpretation of V index impacts for this region. The Baltics show large negative coefficients across both interaction models: –4.64 ($p < 0.001$) in the FE model and –5.51 ($p < 0.001$) in the TW model. These highly significant negative interactions suggest that the positive effect of V index on labour productivity observed for the general sample is substantially diminished or even reversed for the Baltic region. The first lag interaction (V l1: Baltics) shows a positive coefficient of 0.59 ($p < 0.05$) in the FE model, though this becomes non-significant after accounting for time effects (TW). The second lag interaction (V l2: Baltics) remains statistically insignificant across both models.

Table 3.14. Econometric models of the V index on labour productivity. Simplified summary. Source: calculated by the author

Dependent variable: Labour productivity (PRO L)	**Without interactions (FE)**	**Without interactions (RE)**	**Without interactions (OLS)**	**With Baltic interactions (FE)**	**With Baltic interactions (RE, TW)**
V index	1.07*	0.96.	0.96*	1.15*	—
GDP GR	0.31***	0.41***	0.43***	0.33***	—
V index × Baltic	—	—	—	–4.64***	–5.51***
V l1 × Baltic	—	—	—	0.59*	—
GDP GR × Baltic	—	—	—	–0.37***	–0.35*

Notes: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$. "—" indicates the coefficient is not statistically significant in the original table and is, therefore, omitted here.

Capital productivity. The capital productivity analysis presented a more complex pattern of results, with considerable variation across model specifications and generally stronger statistical significance compared to labour productivity. Table 3.15 provides a simplified summary of the regression results, reporting only statistically significant coefficients and significant smooth terms to highlight the core relationships in an interpretable form. The complete estimation output, including all coefficients (including non-significant estimates), smooth-term diagnostics (edf and F-statistics), model fit measures, and specification tests, is reported in Annex E, Table E.2.

V index contemporaneous effects are insignificant; the 2-year lag becomes positive under the TW model (2.39, $p < 0.05$), hinting that improvements in the ecosystem may translate into capital-productivity gains with a 2-year delay. Baltic interactions for all V index variables are not statistically significant, implying no systematic Baltic deviation from the European countries' pattern once country and time effects are controlled.

Table 3.15. Econometric models of the V index on capital productivity. Simplified summary. Source: calculated by the author

Dependent variable: Capital productivity (PRO C)	**Without interactions (FE)**	**Without interactions (RE)**	**Without interactions (OLS)**	**With Baltic interactions (FE)**	**With Baltic interactions (TW)**
V l1	—	—	—	1.79.	1.93.
V l2	1.50.	—	—	—	2.39*
EMPL	2.19*	0.204**	–0.29*	2.35***	3.22**
BERD	–39.09.	–0.24***	—	0.63***	0.87***
GDP GR	0.62**	—	0.42**	–40.32**	–46.97***
Intercept	—	13.76***	15.16**	—	—

Notes: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$. "—" indicates the coefficient is not statistically significant in the original table and is, therefore, omitted here.

The Hausman test (p is 0.71) strongly favours the random effects specification, indicating that unobserved heterogeneity is not correlated with the regressors. The inclusion of interactions improved model fit, with R-squared increasing to 0.34 in the one-way model and 0.30 in the two-way model. However, the statistical significance of the overall models remains strong ($p < 0.01$), suggesting that despite the imprecision of individual interaction coefficients, the interactions collectively contributed explanatory power.

High-tech export. The high-tech exports analysis revealed a distinctive pattern where lagged effects dominate contemporary effects, and the Baltic region shows significant differential responses. The contemporary V index shows small positive coefficients in the FE and RE models, but these effects are statistically insignificant. Table 3.16 provides a simplified summary of the regression results, reporting only statistically significant coefficients and significant smooth terms to highlight the core relationships in an interpretable form. The complete estimation output, including all coefficients (including non-significant estimates), smooth-term diagnostics (edf and F-statistics), model fit measures, and specification tests, is reported in Annex E, Table E.3.

The second lag (V l2) has a consistent and statistically significant positive effect across FE (0.24, $p < 0.01$) and RE (0.22, $p < 0.01$) models. The pooled OLS model shows a larger but only marginally significant effect (β is 0.98, $p < 0.10$). This pattern indicates that the impact of V index on high-tech exports materialises with a two-period delay, suggesting that the mechanisms linking the V index to export performance require time to develop.

Table 3.16. Econometric models of the V index on high-tech export. Simplified summary. Source: calculated by the author

Dependent variable: High-tech exports (HT EXP)	Without interactions (FE)	Without interactions (RE)	Without interactions (OLS)	With Baltic interactions (FE)	With Baltic interactions (TW)
V l2	0.24**	0.22**	0.98.	—	—
ICT EX	—	—	0.17*	—	—
BERD	10.4.	—	—	—	—
Intercept	—	9.32***	5.95*	—	—
V index × Baltic	—	—	—	0.74*	—
V l2 × Baltic	—	—	—	–1.57***	—
BERD × Baltic	—	—	—	–32.52***	–26.73**

Notes: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$. "—" indicates the coefficient is not statistically significant in the original table and is, therefore, omitted here

The Baltic interactions for high-tech exports present a complex pattern with both positive and negative differential effects depending on the time horizon. The contemporary interaction (V index: Baltic) shows a positive and statistically significant effect in the one-way fixed effects model (0.74, $p < 0.05$), though this becomes non-significant when year effects are accounted for. This suggests that the Baltic region may experience additional positive contemporary effects of the V index on high-tech exports, though the robustness of this finding is questionable. The second lag interaction (V l2: Baltic) reveals a large negative coefficient that is highly significant in the one-way model (–1.57, $p < 0.001$) but becomes non-significant in the two-way specification (–1.21). This negative interaction suggests that while the general sample experiences positive effects of the V index on high-tech exports with a 2-year lag, the Baltic region experiences a substantial offsetting negative effect. Combining the main effect with the interaction for the second lag in the one-way model yields –1.38, indicating that the Baltic region experiences a net negative effect of the V index on high-tech exports with a 2-year lag, contrasting sharply with the positive effect observed for other countries. The interaction models show improved fit, with R-squared increasing to 0.28 in the FE specification, though declining to 0.14 in the TW model. The reduction in explanatory power in the TW model, combined with the loss of statistical significance for key interactions, suggests that time fixed effects may absorb some of the variation that drives the Baltic-specific patterns.

Innovation (business R&D). The innovation econometric models show consistent and robust effects of the V index across model specifications, with both contemporary and lagged effects showing statistical significance. Table 3.17 provides a simplified summary of the regression results, reporting only statistically significant coefficients and significant smooth terms to highlight the core relationships in an interpretable form. The complete estimation output, including all coefficients (including non-significant estimates), smooth-term diagnostics (edf and F-statistics), model fit measures, and specification tests, is reported in Annex E, Table E.4.

The contemporary V index shows consistent positive and statistically significant effects across FE (0.03, $p < 0.05$) and RE (0.03, $p < 0.05$) models. The pooled OLS model yields a smaller, but marginally significant coefficient (0.02, $p < 0.10$). The result indicates that increases in the V index are associated with immediate increases in innovation expenditure, suggesting a direct and contemporaneous relationship.

The second lag (V l2) demonstrated highly significant positive effects in both FE (0.02, $p < 0.001$) and RE (0.02, $p < 0.01$) models. The first lag (V l1) shows weaker effects, with no statistical significance in most specifications. This pattern suggested that the V index influences innovation expenditure both immediately and with a 2-year delay, possibly reflecting both direct policy responses and longer-term structural adjustments in innovation investment.

The innovation models demonstrate good explanatory power compared to other dependent variables, with R-squared values ranging from 0.29 to 0.44. The Baltic interactions for innovation expenditure reveal complex temporal patterns with both positive and negative differential effects across different time horizons.

The contemporary interaction shows mixed results: a small positive but non-significant coefficient in the one-way model and a larger, statistically significant positive coefficient in the two-way model (0.03, $p < 0.05$). This suggests that the Baltic countries may experience additional positive contemporary effects of the V index on innovation expenditure, particularly when time-invariant factors are controlled for.

Table 3.17. Econometric models of V index on business R&D. Simplified summary. Source: calculated by the author

Dependent variable: Innovation (BERD)	**Without interactions (FE)**	**Without interactions (RE)**	**Without interactions (OLS)**	**With Baltic interactions (FE)**	**With Baltic interactions (TW)**
V index	0.03*	0.03*	0.02.	0.03.	—
V l1	—	—	—	0.02**	—
V l2	0.02***	0.02**	—	—	—
HC	—	—	0.00.	—	—
PUB CON	0*	—	—	0*	—
Intercept	—	0.17*	0.12*	—	—
V index × Baltic	—	—	—	—	0.03*
V l1 × Baltic	—	—	—	0.04***	0.08***
V l2 × Baltic	—	—	—	–0.11***	–0.19**
HC × Baltic	—	—	—	–0.02***	–0.03***
PUB CON × Baltic	—	—	—	0.00***	—

Notes: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$. "—" indicates the coefficient is not statistically significant in the original table and is therefore omitted here.

The first lag interaction (V l1: Baltics) demonstrates highly significant positive effects in both models: (0.04, p is less than 0.001) in the one-way model and (0.08, p is less than 0.001) in the two-way model. These large positive interactions indicate that the Baltic region experiences substantially amplified effects of V index on innovation expenditure with a one-year lag. Conversely, the second lag interaction (V l2: Baltics) shows large negative coefficients: (–0.11, p is less than 0.001) in the one-way model and (–0.19, p is less than 0.01) in the two-way model. This negative interaction suggests that the positive second-lag effect observed in the general sample is substantially reduced or eliminated for Baltic countries. The complex interaction pattern creates a distinctive temporal profile for Baltic countries:

- contemporary effect: 0.04 (FE) or 0.05 (TW)
- first lag effect: 0.06 (FE) or 0.09 (TW)
- second lag effect: -0.10 (FE) or –0.18 (TW)

This pattern suggests that the Baltic region experiences stronger immediate and short-term responses to V index changes but negative longer-term effects on innovation expenditure. The interaction models maintain strong explanatory power, with R-squared values of 0.29 in the one-way model, though declining to 0.12 in the two-way specification. Despite this reduction, the statistical significance of key interactions remains robust.

Across the 4 dependent variables, systematic differences between pooled OLS and panel estimates suggest the presence of omitted variable bias. For labour productivity, pooled OLS and panel estimates are relatively similar, indicating limited bias from unobserved heterogeneity. However, for capital productivity and high-tech exports, substantial differences emerge. The pooled OLS model for capital productivity shows negative V index coefficients, while panel models yield positive coefficients, suggesting that country-specific factors that correlate with both V index and capital productivity create downward bias in the pooled estimates. The addition of time fixed effects controls for common time-varying factors such as global economic conditions, technological trends, or international policy changes that affect all countries simultaneously. This specification was important to see whether the analysed macroeconomic variables are subject to common shocks or trends. The inclusion of time fixed effects generally reduced the magnitude and statistical significance of V index coefficients across most dependent variables. This pattern suggests that part of the apparent V index effect in one-way models may reflect common time trends rather than genuine causal effects.

3.3.6. Baltic Region-Distinctive Macro Level Effects

Across the macroeconomic outcomes, the fixed-effects (FE) specification with Baltic interaction terms was adopted as the reference framework because it controls for time-invariant cross-country heterogeneity while directly testing the dissertation's core hypothesis of regional effect heterogeneity. In three of the four outcomes (labour productivity, high-tech exports, and innovation), the Baltic interaction terms are statistically significant, meaning that pooled European baseline effects would be misleading for interpreting Baltic ecosystem impacts; therefore, interaction-augmented FE models are preferred even when Hausman tests marginally (or formally) favour RE.

Capital productivity is the only exception, where interaction estimates are too imprecise, and the Hausman test strongly supports RE; however, for comparability and to preserve the focus on Baltic-specific mechanisms, the reported benchmark interpretation emphasises the FE-with-interactions structure where it is empirically justified.

The differential effects vary substantially across dependent variables, indicating that the Baltic region's distinctive responses are not uniform but depend on the specific economic domain being examined (Table 3.18).

Labour productivity shows the most differential effect, with the Baltic countries experiencing strongly negative effects (–3.49) while other countries show positive effects (+1.15). High-tech exports and innovation show the Baltic countries experiencing stronger positive contemporary and first-lag effects, suggesting enhanced responsiveness to V index improvements.

Table 3.18. V Index effects comparison for the Baltic region vs Europe. Source: calculated by the author

Dependent variable	Predictor	Europe baseline	Baltic-specific effect (interaction)	Net Baltic effect (baseline + interaction)
Labour productivity (PRO L)	V index	1.15*	–4.64***	–3.49
	V index lag 1 (V l1)	0.01	0.59*	0.60
Capital productivity (PRO C)	V index lag 2 (V l2)	1.79.	–0.57	1.22
High-tech exports (HT EXP)	V index	0.19	0.74*	0.93
	V index lag 2 (V l2)	0.19	–1.57***	–1.38
Innovation (BERD)	V index	0.03.	0.01	0.04
	V index lag 1 (V l1)	0.02**	0.04***	0.06
	V index lag 2 (V l2)	0.01	–0.11***	–0.10

Note: Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; • $p < 0.10$.

Both high-tech exports and innovation demonstrate a consistent pattern where the Baltic countries show positive short-term effects that reverse to negative effects in the second lag period. For capital productivity (PRO C), the European baseline, the two-year lag of the V index (V l2) is positive but only marginally significant (+1.79). The Baltic interaction for the same lag is negative (−0.57) and not statistically significant, implying no reliable evidence that the Baltic response differs from the non-Baltic pattern. The implied net Baltic effect remains positive (+1.22), but it should be interpreted as a point estimate with substantial uncertainty, and, therefore, weaker and less policy-informative than the clearer Baltic differentials observed for labour productivity, high-tech exports, and innovation.

3.4. Conclusions of the Third Chapter

1. *Structural orientation and heterogeneity.* The comparative and determinant analysis confirms that startups form a distinguishable category of firms relative to non-startup (HT) firms, but the distinction is multi-dimensional and strongly lifecycle dependent. Baltic startups are concentrated in high-technology and knowledge-intensive services industry sectors, indicating a strong ICT specialisation. At the same time, self-reported activity descriptions reveal more granular technological niches, implying that conventional classifications understate technological

diversity within the startup population. Importantly, the ecosystem is highly heterogeneous: a small subset of firms accounts for a disproportionate share of scaling, while most startups follow modest growth paths. Economically, this implies that aggregate startup outcomes are driven by tail dynamics rather than by an "average startup", which is critical for interpreting both performance and policy effectiveness.

2. *Lifecycle and scaling pattern.* Startups are younger than comparable non-startups yet tend to employ more workers and pay higher wages, consistent with stronger demand for skilled labour and higher marginal returns to talent in scaling-oriented firms. The data indicate rapid early scaling, but the growth premium fades as firms mature, with convergence occurring after a decade. This pattern supports the view that startup growth is concentrated in the early expansion window and decays faster with age than in non-startups. Profitability and leverage correlate positively with growth among non-startups, but their marginal growth relevance is weaker for startups, consistent with a financing logic that relies less on retained earnings and conventional balance-sheet strength and more on reinvestment and external funding. Ecosystem conditions matter, but not uniformly: market access and human capital operate as enabling factors with diminishing returns at high levels. By contrast, the negative association between measured knowledge spillovers and startup growth suggests that spillovers in this context may reflect competitive pressure, talent reallocation, or diffusion that benefits the broader ecosystem more than incumbent startups. Once heterogeneity is considered, venture capital availability becomes positively associated with startup growth, indicating that simple linear averages can understate the role of VC in the segments where scaling is most responsive.

3. *Improving productivity with age.* Startups outperform non-startups in later stages, consistent with learning, selection, and efficiency improvements as surviving firms accumulate capabilities. Productivity is positively linked to operational performance – operating margins and turnover growth – and tends to peak around mid-age groups (approximately 5–10 years), suggesting an economically meaningful "capability-building" phase where process improvements and market fit translate into efficiency gains. Higher estimated productivity among smaller startups is consistent with lean operating models, selection effects, and higher innovation intensity per employee. Among external determinants, venture capital availability emerges as the clearest productivity-enhancing factor, supporting the interpretation that VC contributes not only capital but also selection, governance, networks, and capability upgrading.

4. *Financial performance and risk.* Startups exhibit lower and more volatile profitability in early years, converging towards non-startup profitability after roughly 7–10 years. They are structurally more reliant on external financing, with leverage rising sharply during the early expansion window (up to around 5–7 years). Failure risk is distinctly higher and concentrated in the first 3–5 years, consistent with experimentation, market-validation uncertainty, and the fragility of early scaling. The results imply that elevated failure risk is not explained solely by observable firm structure; it is a structural feature of startup business models under uncertainty. Survival is most closely tied to internal resilience and capital structure: higher profitability and age reduce failure odds, while higher leverage increases risk.
5. *Macroeconomic impact assessment framework.* For macroeconomic impact assessment, the empirical setting is expanded to European countries to increase variation in ecosystem maturity and macroeconomic outcomes and to strengthen benchmarking and external validity. Startup ecosystem maturity is proxied by the V index, constructed from venture capital activity metrics using PCA, and countries are subsequently grouped into maturity clusters using k-means clustering to identify relative ecosystem development levels and position the Baltic countries within the European distribution. By constructing the V index and clustering countries according to ecosystem maturity, the model provides a structured benchmarking framework that allows positioning the Baltic startup ecosystems within the European distribution. The relationships among ecosystem maturity and macroeconomic outcomes are examined using correlation analysis and econometric techniques, complemented by time-series causality testing (Granger causality) to assess temporal precedence. This empirical application demonstrates the model's practical relevance by generating interpretable indicators that can inform ecosystem development strategies and innovation policy design.
6. *Systematic associations on the macroeconomic impact level.* The V index differentiates countries into meaningful maturity groups and tracks time trends consistent with varying ecosystem depth across Europe. Lower and more volatile levels in the Baltic region are consistent with small-economy sensitivity to external shocks and thinner capital markets. Econometric results indicate that the maturity–outcome relationship is outcome-specific and time-dependent: effects are more contemporaneous for labour productivity, while lag structures are more relevant for high-tech exports and business R&D. Capital productivity estimates are comparatively less stable, suggesting that the transmission from ecosystem

maturity to capital efficiency may be weaker or mediated by additional factors.

7. *Baltic region heterogeneity.* Relative to Europe, the Baltic region exhibits a weaker (and in net terms negative) association between ecosystem maturity and labour productivity, while for high-tech exports and innovation, the relationship appears positive in the short run but turns negative at longer lags. Economically, this implies that venture-capital depth and ecosystem maturity do not translate into macro gains uniformly; outcomes depend on regional transmission mechanisms, timing, and vulnerability to shocks. This points to the importance of complementary conditions – absorptive capacity, scaling pathways, and linkages between startups and the broader production base, if ecosystem maturity is to yield sustained macroeconomic benefits.
8. *Empirical validation of the proposed assessment model.* The empirical results reported in the Third Chapter confirm that the enabling-environment assessment methodology developed in the Second Chapter and grounded in the core innovation-ecosystem pillars of human capital, market access, finance/venture capital, and knowledge spillovers can be applied in a consistent and analytically informative way. The comparative analysis also empirically validates the dissertation's startup concept: startups constitute a distinct firm category not only by age, but by their scaling-oriented trajectories, characterised by faster early growth and different productivity, financial, and survival patterns relative to comparable non-startups. In addition, the European cross-country assessment demonstrates that the V index is a suitable proxy for startup ecosystem maturity, as it reliably captures the common variance in venture-capital activity and differentiates countries into meaningful maturity groups. Taken together, these results indicate that the proposed model is transferable and can be applied to assess and benchmark startup ecosystems in other countries beyond the Baltic region.
9. *Research limitations.* Although this research provides valuable information, it also has limitations related to the startup definition, data availability, and the nature of the research object:
   9.1. Residual differences in national startup definitions remain a limitation and may affect cross-country comparability. A further limitation is that there may be cross-country differences in how startups are identified, reported and recorded in the national databases. As a result, the coverage and classification of startups may not be fully comparable across the countries in the sample, which could introduce measurement error and attenuate some of the estimated effects.

9.2. Empirical analysis is affected by non-uniform reporting and missing observations in some firm-level financial variables and ecosystem indicators, resulting in an unbalanced panel. In addition, differing time-series lengths across countries may influence the precision of country-specific estimates and should be kept in mind when interpreting the results. Because estimation relies only on observations with complete data for all included covariates, missingness reduces the effective sample size in certain model specifications. A smaller effective sample size typically increases standard errors and widens confidence intervals, lowering statistical power and, in turn, the precision of some estimated effects. To evaluate whether the substantive conclusions are sensitive to these data limitations, key relationships were examined using alternative panel specifications (fixed effects and two-way fixed effects models), and inference relied on robust variance estimators (heteroskedasticity-robust and clustered standard errors.

9.3. As startups are very dynamic types of businesses with a low survival rate, it is difficult to make a temporal analysis. There is a high level of heterogeneity in their financial and operational data. Financial accounting statements, especially across countries and economic activities, often lack uniformity in standards and quality, and the scope of the disclosed data differs. Firms report financial data in different regularities (having different fiscal years).

9.4. The information on how many new startups enter the ecosystem each year was not available. Because the inflow of new firms into the population is unknown, it is not possible to construct a consistent entry–exit panel and, consequently, to estimate startup survival rates or conduct formal survival analysis. As startup identifiers (firm registry codes) were received only in 2023, the analysis defines a 2023 baseline cohort and evaluates the activity status of each firm in 2024. The time window is restricted to 2023–2024 to ensure consistent labelling and comparability with non-startups, and this limits the robustness of the findings.

9.5. The paradoxical negative effects of knowledge spillovers on startups and the negative impact on labour productivity in the Baltic region require further investigation. Future research should aim to unravel the complex interplay of factors that contribute to these phenomena. Understanding the dynamics of innovation ecosystems and the interplay of market factors is crucial for startups to maximise their growth potential and maintain competitiveness in their respective markets. Additionally, the rapid convergence of technologies and the hybrid nature of many startups challenge existing classification industry frameworks. There is a growing need to update or complement these frameworks to better capture the complexity of modern innovation ecosystems.

9.6. Overall, the chosen dataset and regional focus strike a balance between policy relevance, data quality and feasibility. The analysis covers the full observable startup populations in Estonia, Latvia, and Lithuania, but its findings should be interpreted considering the remaining differences in national startup definitions, the unbalanced time dimension and the absence of a broader set of countries.

General Conclusions

1. The research results confirm that startups, based on the case of the Baltic region, constitute an empirically distinguishable category of firms in comparison with non-startups operating in comparable industry contexts. Startups exhibit higher early-stage turnover and employment growth, stronger labour productivity dynamics, and distinctive total factor productivity patterns; however, they are also characterised by significantly higher failure risk in the early stages and lower short-term profitability. These findings demonstrate that the distinction between startups and non-startups is multidimensional and dependent on the firm lifecycle: startup-specific characteristics are most pronounced in the early and middle stages of development and tend to weaken as firms mature and gradually converge towards the performance patterns of non-startups. Accordingly, the research enables the systematisation and theoretical substantiation of the startup concept by integrating empirically validated characteristics into a coherent definitional framework. On this basis, a *startup may be defined as a young, innovation-oriented firm pursuing early-stage scaling intent, typically characterised by distinct growth, productivity, financing, and risk patterns, especially during the first years of development.* This formulation reflects the empirically observed profile of startups in the Baltic region and provides a coherent definition grounded in both theoretical and empirical analysis.

2. The dissertation develops and validates an integrated methodological framework that assesses the startup ecosystem enabling environment, maturity and links it explicitly to macroeconomic implications. The framework demonstrates that ecosystem-level conclusions can be grounded in firm-level evidence and that macroeconomic effects can be assessed through structured indicator systems and outcome-specific models.
3. The research identifies and operationalises a coherent indicator set for assessing both ecosystem-enabling conditions and macroeconomic impact. By integrating these indicators into a methodological framework, the research develops a comprehensive model. A central contribution within this model is the construction of a composite V index from venture-capital activity metrics. This index operationalises the ecosystem maturity assessment called for in Task 2, functioning as a parsimonious proxy that provides meaningful cross-country differentiation, notably identifying higher volatility and generally lower maturity levels in the Baltic region.
4. The empirical application confirms the model's practical applicability and external relevance. At the firm level, the framework's empirical application to the three Baltic countries consistently reproduces established startup behavioural patterns, faster early growth and job creation, coupled with higher early exit risk and weaker short-run profitability relative to non-startups. This consistency across all three Baltic ecosystems demonstrates the framework's reliability and practical validity for startup characterisation. At the macro level, the cross-country assessment shows that startup ecosystem maturity is associated with macroeconomic outcomes in an outcome-specific and time-dependent manner, with lag structures particularly relevant for innovation and exports. The divergence between Baltic and European patterns demonstrates both the framework's discriminative capacity and its critical value for differentiated evidence-based ecosystem development strategies.

Recommendations

To support practical application, it is recommended to interpret the model outputs as a structured diagnostic and benchmarking tool. For policymakers, the model can be used to identify binding constraints and to align intervention timing with expected lag structures; for investors, it provides a cross-country maturity benchmark for pipeline depth and scaling conditions. It is recommended to implement a practical application of a model in steps:

- Diagnose the enabling-environment profile (inputs). Interpret the input indicators (human capital, market access, knowledge spillovers, finance/VC, and related demand/support conditions) as a constraint map. The key practical insight is that the profile imbalance can often occur: weaknesses in one pillar can limit the returns to improvements in other pillars (e.g., deeper VC without sufficient talent supply or market access may yield weaker scaling outcomes).
- Interpret ecosystem maturity (central layer) via the V index. Treat the V index as a proxy for ecosystem maturity, capturing the depth of risk capital, selection quality, and exit-based capital recycling. Practically, it answers "how deep and self-reinforcing is the scaling-and-financing mechanism in this ecosystem?" Changes in the V index are interpreted alongside the enabling-environment profile to distinguish whether maturity

constraints stem from input gaps (e.g., insufficient human capital/market access) or from weaker conversion of inputs into scalable dynamics.

- Translate maturity into expected outcome patterns. Use the model's estimated relationships to interpret which outcomes are more likely to respond contemporaneously versus with lags. In practice, this implies aligning policy evaluation horizons to the outcome type: short-run monitoring for contemporaneous channels, and medium-run monitoring where lags dominate.
- Apply non-linearity and heterogeneity logic. Where the empirical results indicate diminishing returns and heterogeneous effects across the distribution, interpret improvements in inputs or maturity as state-dependent: the same incremental change may have larger effects at low baseline levels and smaller effects at already high levels. Therefore, recommended interventions should be differentiated by the ecosystem's initial position and by the targeted outcome (growth, productivity, exports, and innovation).

The model primarily quantifies systematic associations consistent with the theory-based pathway. It is recommended to use its results for prioritisation, benchmarking, and scenario reasoning, while strict causal claims require additional identification strategies and richer data.

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List of Scientific Publications by the Author on the Topic of the Dissertation

Papers in the Reviewed Scientific Journals

Okunevičiūtė Neverauskienė, L., & Kleponė, D. (2024). Empirical evidence on the startup growth in the Baltic region high-tech landscape. *Transformations in Business & Economics, 23*(3A/63A), 1164–1191.

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Kleponė, D., & Okunevičiūtė Neverauskienė, L. (2025). Financial performance and capital structure dynamics of the high-tech startups in the Baltic region. *Business: Theory and Practice, 26*(1), 153–161. https://doi.org/10.3846/btp.2025.22184

Summary in Lithuanian

Įvadas

Problemos formulavimas

Ekonominį augimą fundamentaliai skatina naujų idėjų (Bloom et al., 2020), kurios taip pat katalizuoja technologinį progresą, leidžiantį pasaulio ekonomikoms spręsti iškylančius iššūkius, ir pasireiškia naujomis verslumo formomis, tokiomis kaip startuoliai, generavimas. Startuoliai – tai jaunos, inovatyvios, rizikos kapitalo finansuojamos įmonės, veikiančios aukštųjų technologijų sektoriuose ir pasižyminčios ankstyva tarptautine plėtra. Nepaisant augančios jų svarbos, nei politikos formuotojų, nei akademinėje bendruomenėse vis dar nėra konsensuso dėl aiškaus, praktiškai pritaikomo startuolio apibrėžimo. Trūkstant empirinių įrodymų, nesutariama ir dėl startuolių ekosistemų ekonominio poveikio – ar, kokiomis sąlygomis ir kokiu mastu jie prisideda prie produktyvumo, inovacijų ir ekonomikos augimo. Kai kurie mokslininkai perspėja, kad į pasaulines „superžvaigždes“ ar monopolistines platformas išaugantys startuoliai gali keisti rinkų struktūras ir net kelti pavojų demokratijai bei konkurencijai, nukreipdami verslumą nuo tradicinių mažų įmonių, kurios yra daugumos ekonomikų pagrindas, į dominuojančius technologijų gigantus (Kuratko & Audretsch, 2022).

Darbo aktualumas

Nepaisant esančių neapibrėžtumų, politikos formuotojai ir investuotojai startuolių ekonominės veiklos formą laiko vienu svarbiausių būsimo ekonominio augimo variklių. Daroma prielaida, kad, palyginti su tradicinėmis smulkiojo ir vidutinio verslo (SVV) įmonėmis, startuoliai yra labiau linkę greitai augti, kurti darbo vietas ir stiprinti konkurencingumą, diegdami naujas technologijas bei verslo modelius. Europos Komisijos (EK) strateginiuose dokumentuose pripažįstama, kad „klestinti startuolių ekosistema atlieka svarbų vaidmenį ekonomikos augime ir rinkų evoliucijoje, skatindama produktyvumą, didindama investicijų paskatas ir kurdama kokybiškas darbo vietas“ (European Commission, 2025). Vis dėlto apie 60 % pasaulinių startuolių įsikūrę JAV, o Europos Sąjungai (ES) tenka tik 8 %. Tarptautinis valiutos fondas įspėja, kad nesugebėjimas inovatyvių startuolių „užauginti“ iki „superžvaigždžių“ įmonių yra viena pagrindinių ES produktyvumo augimo atsilikimo priežasčių (Arnold et al., 2024). Draghi (2024) pastebi, kad Europa praleido skaitmeninę revoliuciją ir jos atneštą produktyvumo augimą, atotrūkį aiškindamas technologijų sektoriaus silpnumu. Tai paskatino politines iniciatyvas kurti į startuolius orientuotas paramos priemones: 2023 m. EK paskelbė į proveržio technologijas orientuotą 1,6 mlrd. Eur vertės paketą, o pati Europos inovacijų taryba, veikianti programoje „Europos horizontas“, valdo daugiau nei 10 mlrd. Eur biudžetą.

Disertacija aktuali tiek akademiniu, tiek praktiniu požiūriu. Akademinėje aplinkoje startuolių tyrimai išlieka fragmentiški – nėra sisteminių, kiekybiškai startuolių ekosistemų vystymąsi bei poveikį tiriančių darbų. Šiuo požiūriu darbas mažina esamą spragą, prisideda prie teorijos plėtros ir empirinių rezultatų palyginamumo. Praktiniu (politikos formavimo) požiūriu ši fragmentacija riboja patikimos įrodymų bazės, reikalingos startuolių paramos priemonėms kurti, taikyti ir vertinti, formavimą. Todėl disertacijoje pateikiamas ir pagrindžiamas konceptualus modelis, integruojantis startuolio apibrėžimo kriterijus, įgalinančios inovacijų ekosistemos aplinkos rodiklius ir makroekonominio poveikio dimensijas į vieną empiriškai patikrinamą sistemą bei pateikiamos praktinio įgyvendinimo rekomendacijos.

Tyrimų objektas

Disertacijos tyrimų objektas yra startuolių ekosistema.

Darbo tikslas

Sukurti ir empiriškai pagrįsti konceptualų modelį, grindžiamą empiriškai patvirtintu startuolio apibrėžimu, kuris leistų operacionalizuoti startuolių ekosistemos brandą ir empiriškai analizuoti jos sąsajas su makroekonominiais rezultatais.

Darbo uždaviniai

Darbo tikslui pasiekti sprendžiami šie uždaviniai:

1. Sisteminti ir teoriškai pagrįsti startuolio sampratą, empiriškai patvirtintas startuolio charakteristikas integruojant į nuoseklią apibrėžimo sistemą.
2. Sukurti integruotą metodiką ir konceptualų modelį, skirtą startuolių ekosistemos brandai ir jos makroekonominiam poveikiui vertinti.
3. Operacionalizuoti startuolių ekosistemos brandą, identifikuojant pagrindines jos raidos dimensijas ir suformuojant rodiklių rinkinį, tinkamą empiriniam testavimui.

4. Patikrinti siūlomo konceptualaus modelio empirinį veikimą ir aktualumą, taikant jį Baltijos regiono (Lietuvos, Latvijos, Estijos) ir Europos šalių startuolių ekosistemų analizei.

Tyrimų metodika

Tyrimas remiasi dviejų etapų tyrimo dizainu: konceptualaus modelio kūrimu ir empiriniu patikrinimu Baltijos bei Europos šalių kontekste. Loginė analizė ir sintezė naudojamos kuriant konceptualų modelio pagrindą, apibrėžiant startuolių identifikavimo kriterijus, jų vystymąsi veikiančias palankios aplinkos dimensijas, bei startuolių ekosistemų ryšį su makroekonominiais rezultatais. Teorinis modelio pagrindas remiasi Stam (2015) integruotu verslumo ekosistemos modeliu, kuris susieja inovacijų ekosistemų įvestis su startuolių vystymosi dinamika ir makro lygmens rezultatais, o įmonių lygmens bendrasis gamybos veiksnių produktyvumas (BGVP) apskaičiuojamas taikant Cobb–Douglas gamybos funkciją.

Empirinėje analizėje naudojami kiekybiniai metodai, įmonių finansinės apskaitos duomenys, ekosistemos ir makro lygmens rodikliai. Taikomi lyginamosios analizės, ekonometrinio modeliavimo ir mašininio mokymosi metodai. Ekosistemų branda aproksimuojama V indeksu – sudėtiniu rodikliu, apimančiu rizikos kapitalo aktyvumo metrikas – kuris vėliau, siekiant įvertinti ekosistemų poveikį, siejamas su makroekonominiais rezultatais. Visi skaičiavimai atlikti „RStudio“ aplinkoje.

Darbo mokslinis naujumas

Šios disertacijos mokslinis naujumas slypi integruoto požiūrio į startuolių ekosistemų vertinimą sukūrime ir empiriniame pagrindime, siejant mikrolygmens įmonių dinamiką su makro lygmens ekonominiais rezultatais, ir pasireiškia šiais aspektais:

1. Pasiūlyta nauja empiriškai pagrįsta startuolio apibrėžtis, taip sprendžiant vieną pagrindinių spragų teorijoje ir praktikoje – nuoseklaus pagrindo atskirti startuolius nuo kitų įmonių nebuvimą.
2. Sukurtas integruotas startuolių ekosistemos vertinimo modelis, apimantis tiek ekosistemos įgalinančios aplinkos, tiek įmonių lygmens raidos veiksnius. Pasiūlyta modelio taikymo metodika ir rodiklių sistema.
3. Operacionalizuota startuolių ekosistemos brandos samprata, sudarant sudėtinį brandos indeksą, pagrįstą rizikos kapitalo aktyvumo rodikliais, ir integruojant jį į makroekonominių rodiklių analizę. Tai sudaro metodinį pagrindą nuosekliai tirti ekosistemos brandos ir ekonominių rezultatų sąsajas.
4. Išplėsta startuolių tyrimų empirinė bazė. Tai leidžia atlikti nuoseklią lyginamąją startuolių ir kitų įmonių analizę bei įvertinti jų veiklos dinamikos skirtumus, papildant dabar dominuojančius kokybinius ir ribotos apimties kiekybinius tyrimus platesniu, sisteminiu empiriniu pagrindu.

Darbo rezultatų praktinė reikšmė

Praktinė šio darbo vertė siejama su galimybe prisidėti prie politikos formavimo ir investicinių sprendimų priėmimo startuolių ekosistemų srityje. Politikos formuotojams tyrimo rezultatai suteikia empirinį pagrindą pereiti nuo tik tiesioginiais finansiniais instrumentais paremtų skatinimo priemonių prie tikslingos, įrodymais grįstos ekosistemos vystymo politikos. Atsižvelgiant į nuolatines diskusijas, ar startuoliai iš tiesų atspindi „tikrąją“ inovaciją (daugelis jų neregistruoja patentų ir nevykdo MTEP veiklos) bei į aukštą rinkos ir produkto neapibrėžtumų nulemtą žuvimo riziką, įrodymais grįstas intervencijų kūrimas yra būtinas. Siūlomas modelis sudaro prielaidas atlikti šalių lyginamąją analizę, nustatyti struktūrines kliūtis ir kryptingai formuoti politikos scenarijus, o praktinio taikymo gairės pateikiamos rekomendacijų skyriuje. Investuotojams šis modelis suteikia galimybę vertinti ekosistemų brandą, planuoti investicijų apimtį ir prognozuoti jų grąžą.

Ginamieji teiginiai

Remiantis šio tyrimo rezultatais, suformuluojami šie oficialūs ginamieji teiginiai (hipotezės):

1. Startuoliai sudaro empiriškai išsiskiriančią įmonių kategoriją toje pačioje pramonės šakoje.
2. Startuolių augimo, produktyvumo, finansinių rezultatų ir išlikimo dėsningumus lemia veiksniai, kurie skiriasi nuo tų, kurie veikia kitą ankstyvosios stadijos SVV.
3. Startuolių vystymąsi skatinančią aplinką galima visapusiškai įvertinti taikant struktūruotą rodiklių sistemą.
4. Startuolių ekosistemos branda gali būti aproksimuojama V indeksu, sudarytu iš rizikos kapitalo aktyvumo rodiklių.
5. Siūlomas konceptualus modelis, operacionalizuotas per integruotą startuolių ekosistemos brandos indeksą, leidžia empiriškai įvertinti startuolių ekosistemos makroekonominį poveikį.

Darbo rezultatų aprobavimas

Disertacijos tyrimo rezultatai paskelbti dviejose publikacijose mokslo žurnaluose, įtrauktuose į *Scopus* duomenų bazę su citavimo rodikliais: Kleponė & Okunevičiūtė Neverauskienė (2025); Okunevičiūtė Neverauskienė & Klepone (2024).

Disertacijoje atliktų tyrimų rezultatai paskelbti 2 mokslinėse konferencijose:

- „Institutions and Survival: Challenges for Sustainability“, 2024 m. kovo 23 d., Balstogėje, Lenkijoje.
- 13-oji tarptautinė taikomosios ekonomikos konferencija „Contemporary Issues in Economy“, 2025 m. birželio 26 d., Olštyne, Lenkijoje.

Disertacijos rezultatai taip pat pristatyti dviejuose akademiniuose seminaruose: Universitat Autònoma de Barcelona (Barselona, Ispanija) ir Universitat Rovira i Virgili (Reusas, Ispanija).

Disertacijos struktūra

Disertaciją sudaro įvadas, 3 skyriai, bendrosios išvados, rekomendacijos, literatūros sąrašas, autorės publikacijų sąrašas, santrauka lietuvių kalba ir 5 priedai. Disertacijos apimtis – 157 puslapiai, tekste pateikti 36 paveikslai, 39 lentelės. Rašant disertaciją panaudoti 239 literatūros šaltiniai.

Padėka

Autorė dėkoja savo mokslinei vadovei prof. dr. Laimai Okunevičiūtei Neverauskienei už vadovavimą ir paramą rengiant šią disertaciją. Taip pat prof. Ricardui Esparzai Masanai, Universitat Autònoma de Barcelona Ekonomikos ir ekonomikos istorijos katedros profesoriui, už sudarytą galimybę apsilankyti UAB, taip pat UAB „Verslo departamentui“ už vertingas įžvalgas, padėjusias tobulinti šią disertaciją. Padėka Lietuvos socialinių mokslų centrui, Ekonomikos ir kaimo vystymo institutui bei jo vadovei dr. Rasai Melnikienei už paramą ir paskatinimą.

1. Startuolio vaidmuo ekonomikoje

Šiame skyriuje nuosekliai pagrindžiama startuolio samprata ir analizuojamas jo vaidmuo ekonominėje raidoje, pereinant nuo startuolio apibrėžties problematikos prie kuriamos vertės mechanizmų bei priklausomybės nuo inovacijų ekosistemos sąlygų. Atskleidžiama, kad akademinėje literatūroje „startuolio“ sąvoka išlieka konceptualiai fragmentuota ir priklausoma nuo tyrimo konteksto. Tekste nagrinėjama pagrindinė metodologinė problema – kaip empiriškai atskirti startuolius nuo kitų įmonių, kai ši sąvoka literatūroje ir viešajame sektoriuje neturi bendro, nuoseklaus apibrėžimo. Parodoma, kad istoriškai terminas kito: iki 1980 m. jis reiškė ankstyvą bet kurios įmonės raidos etapą, o vėliau imtas sieti su specifine, inovacijomis ir tam tikrais regionais (pvz., Silicio slėniu) susijusia veiklos praktika.

Dabar įvairūs autoriai startuolių atskyrimo nuo nestartuolių kriterijams naudoja skirtingas dimensijas: struktūrines, strategines ir operacines. Naudojamų kriterijų – technologijų subsektorius, įmonės amžius ir dydis, vystymosi stadija, inovacijų intensyvumas, tarptautinės plėtros modelis, verslumo kultūra, augimo potencialas, išlikimo dinamika, finansinės rizikos profilis bei finansavimo modeliai – gausa riboja vieningo startuolio apibrėžimo (termino) taikymą. Tolesniam konceptualiam modeliui kurti pasirenkamas pragmatiškas, literatūra pagrįstas apibrėžimas: startuoliai traktuojami kaip jaunos ir santykinai mažos įmonės, dažniausiai veikiančios didelę pridėtinę vertę kuriančiuose sektoriuose, siekiančios inovacijomis grįsto ir lengvai mastelio didinamo augimo, neretai pasižyminčios specifinėmis finansavimo struktūromis ir padidintu rizikos lygiu.

Toliau startuolio samprata įtvirtinama ekonomikos augimo teorijų kontekste, atskleidžiant jų vaidmenį struktūriniuose ūkio pokyčiuose ir produktyvumo didėjime, kuris kyla iš gebėjimo kurti, komercializuoti ir skleisti inovacijas. Klasikinėse ir neoklasikinėse ekonominio augimo interpretacijose technologinė pažanga dažnai laikoma egzogeniniu veiksniu, todėl startuolių vaidmuo yra labiau netiesioginis. Tuo tarpu endogeninio augimo ir šumpeteriškose perspektyvose inovacijos, žinių kaupimas, žmogiškasis kapitalas ir kūrybinė destrukcija laikomi esminiais ilgalaikio augimo varikliais, o startuoliai veikia kaip mechanizmas, kuris naujas idėjas paverčia rinkoje realizuojamais sprendimais, skatina technologijų difuziją ir prisideda prie produktyvumo didėjimo bei rinkos struktūrų transformacijos. Vis dėlto pabrėžiama, kad šie efektai neatsiranda savaime: startuolių inovacinis ir disruptyvus (proveržio) potencialas priklauso nuo palankių aplinkos sąlygų, kurios lemia jų galimybes telkti išteklius, ugdyti organizacinius gebėjimus ir greitai augti plečiantis į tarptautines rinkas.

Dėl šios priežasties skyriuje dėmesys perkeliamas į startuolių ekosistemos kaip inovacijų ekosistemos dalies raidos veiksnius, kurie apibrėžiami endogeninių ir egzogeninių veiksnių rinkiniu. Endogeniniai (vidiniai) veiksniai suskirstyti į dvi kategorijas – struktūrinius ir funkcinius veiksnius bei apima vidinius startuolio išteklius ir gebėjimus: įmonės amžių ir dydį, įkūrėjų bei komandos žmogiškąjį kapitalą, nuosavybės ir kapitalo struktūrą, inovacijų kūrimo pajėgumus, verslo modelio plėtros potencialą ir finansavimo strategiją. Egzogeniniai (išoriniai) veiksniai, kurie taip pat suskirstyti į makroekonominius ir ekosistemos, apima įgalinančias aplinkos sąlygas, kurių startuoliai tiesiogiai nekontroliuoja, tačiau kurios reikšmingai formuoja jų galimybių erdvę: makroekonominę dinamiką, institucijų ir politikos kokybę, viešosios paramos instrumentų prieinamumą ir efektyvumą, ekosistemos lygmens žmogiškąjį kapitalą ir infrastruktūrą, žinių sklaidos mechanizmus, tinklaveikos intensyvumą, taip pat rizikos kapitalo ir kitų finansavimo šaltinių prieinamumą.

Remiantis šia logika, startuolių ekosistema suprantama kaip inovacijų ekosistemos dalis su specifiniais veikėjais, kurioje startuolių raida yra įgalinama arba ribojama tarpusavyje priklausomų institucijų, tinklų ir išteklių. Tai leidžia konceptualiai pagrįsti, kad ekosistemos vystymas nėra redukuotinas į vieną politikos priemonę ar vieną rinkos sąlygą; veikiau tai yra koordinuota, vienas kitą papildančių veiksnių konfigūracija, bendrai formuojanti startuolių kūrimosi, išlikimo ir ekonominio augimo procesus.

Galiausiai skyriuje apibendrinamas startuolių ekosistemų socialinis-ekonominis poveikis, išskiriant kelis tarpusavyje susijusius kanalus, per kuriuos kuriama makroekonominė vertė:

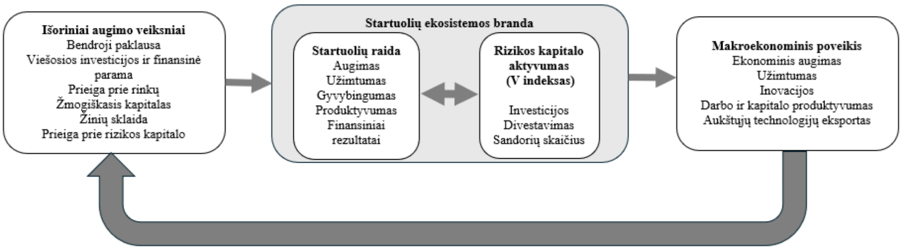
- Startuolių ekosistemos prisideda prie ekonomikos augimo, nes sparčiai kuriantis ir plečiantis naujoms įmonėms ištekliai perskirstomi į produktyvesnes veiklas. Vis dėlto spartus augimas dažniausiai koncentruojasi santykinai nedidelėje įmonių dalyje;
- Startuolių įmonės dažnai sukuria reikšmingą dalį naujų darbo vietų, taip keisdamos darbo rinkos struktūrą ir neproporcingai veikdamos užimtumo dinamiką.
- Inovacijų ekosistemose startuoliai gali paspartinti inovacijų kūrimą ir sklaidą, technologijų įsisavinimą bei produktyvumo didėjimą;
- Didelė veiklos rizika ir nematerialiojo turto dominavimas lemia finansų rinkų transformacijas: atsiranda specializuoti finansavimo instrumentai, rizikos kapitalo tinklai ir investavimo infrastruktūra, pritaikyta didelės rizikos verslams;
- Startuolių ekosistemos kuria ilgalaikį konkurencingumo pagrindą per mokymąsi, stiprindamos žmogiškąjį kapitalą, verslumo kultūrą, mentorystę ir tinklaveiką.
- Startuolių ekosistemos prisideda prie aukštųjų technologijų eksporto augimo;

Skyrius atskleidžia, kad startuolių indėlis į ekonominę raidą yra reikšmingas, tačiau priklauso nuo to, ar susiklosto palanki endogeninių gebėjimų ir įgalinančios aplinkos (egzogeninių) institucinių bei rinkos sąlygų kombinacija, leidžianti startuoliams pereiti nuo idėjos prie tarptautinės plėtros ir sisteminio makroekonominio poveikio.

2. Startuolių ekosistemą įgalinančios aplinkos ir makroekonominio poveikio vertinimo metodika

Šiame skyriuje pristatomas disertacijoje taikomų tyrimų metodinis pagrindas. Disertacijos tyrimas suplanuotas nuoseklia seka. Pirmiausia, remiantis sisteminės literatūros analizės rezultatų sinteze sukonstruojamas konceptualus startuolių vystymąsi ekosistemoje įgalinančios aplinkos bei pačios ekosistemos įtakos ekonomikai modelis. Antra, modelis operacionalizuojamės į struktūruotą rodiklių sistemą, kuri apima (i) įgalinančias inovacijų ekosistemos sąlygas nacionaliniu mastu, (ii) startuolių raidą įmonės mastu, (iii) startuolių ekosistemos brandą, aproksimuojamą iš rizikos kapitalo aktyvumo rodiklių sudarytu sudėtiniu V indeksu, ir (iv) makroekonominius rezultatus. Trečia, siekiant patvirtinti modelio vidinį nuoseklumą ir praktinį pritaikomumą, jis empiriškai analizuojamas mikrolygmeniu (įmonių) ir makrolygmeniu.

Teorinis metodikos pagrindas integruoja Romer (1990) endogeninio augimo teoriją ir Stam (2015) verslumo ekosistemų modelį bei remiasi priežastine logika, kad inovacijų ekosistemos įeigos (įgalinančios sąlygos) veikia kaip išoriniai startuolių raidos veiksniai. Startuolių raida ir rizikos kapitalo aktyvumas didina ekosistemos brandą, kuri veikia makroekonominius rezultatus, o kartu susiformuojantys grįžtamieji ryšiai ilgainiui keičia ir pačią įgalinančią aplinką. Konceptualiame modelyje (S2.1 pav.) susiejami startuolius nuo kitų įmonių skiriantys kriterijai, įgalinantys inovacijų ekosistemos veiksniai ir poveikio grandinė nuo ekosistemos įeigų iki startuolių ekosistemos brandos rezultatų bei makroekonominių išeigų.



S2.1 pav. Konceptualus modelis, siejantis startuolių ekosistemą su ekonomikos plėtra (sudaryta autorės)

Šiame tyrime startuoliams identifikuoti ir atskirti kaip pagrindiniai raidos rodikliai sąmoningai pasirenkami jų apyvartos augimas ir produktyvumas, nes pagrindinės startuolių identifikavimo charakteristikos – ankstyva internacionalizacija ir inovatyvūs verslo modeliai turi poveikį būtent šiems rodikliams. Pasirinktas modelio operacionalizavimo būdas grindžiamas tuo, kad startuolių ekosistemos ekonominis poveikis empiriškai stebimas per palyginamus ir kiekybiškai išmatuojamus rodiklius: apyvartos augimą, produktyvumą, įmonių gyvybingumą. Tai leidžia modelį nuosekliai suderinti su ekonomikos augimo teorijų perdavimo mechanizmais (inovacijomis grįsta plėtra ir produktyvumo augimas), taip pat sudaro prielaidas sukurti vieningą rodiklių sistemą, tinkančią tarptautiniams palyginimams.

Modelyje išskiriami trys analitiniai sluoksniai. Įeigų sluoksnis apima išorinius augimo ir produktyvumo veiksnius (paklausą, viešąsias investicijas ir paramą, prieigą prie rinkų, žmogiškąjį kapitalą, žinių sklaidą, infrastruktūrą ir rizikos kapitalo prieinamumą). Centrinis sluoksnis – tai ekosistemos branda, suprantama kaip gebėjimas aplinkos įgalinančias sąlygas paversti plėtros potencialą didinančia startuolių raida (apyvartos ir darbuotojų skaičiaus augimu, gyvybingumu, produktyvumu ir finansiniais rezultatais) ir aproksimuojama V indeksu. Išeigų sluoksnis – makroekonominis poveikis, matuojamas ekonominio bei užimtumo augimo, inovacijų rezultatų, darbo ir kapitalo produktyvumo bei aukštųjų technologijų eksporto rodikliais. V indekso ir startuolių raidos ekosistemoje ryšys modeliuojamas kaip abipusis ir stiprinantis: geresni startuolių rezultatai didina investuotojų susidomėjimą ir sandorių srautą, o aktyvesnis rizikos kapitalas, savo ruožtu, sudaro sąlygas startuoliams augti, gebėjimams stiprinti ir tarptautinei plėtrai.

Metodikos skyriuje taip pat apibrėžiama rodiklių sistema, kurią sudaro trys blokai: (i) įgalinančios aplinkos rodikliai (išoriniai inovacijų ekosistemos ir vidiniai įmonės lygmens veiksniai), (ii) startuolių mikrolygmens raidos rodikliai lyginamajai ir faktorinei analizėms (augimas, darbo ir bendras daugiaveiksnis produktyvumas, gyvybingumas, finansiniai rezultatai), ir (iii) makroekonominių kintamųjų rinkinys, skirtas vertinti, kaip startuolių ekosistemos branda siejasi su ekonomikos rezultatais.

Empirinėje kiekybinio tyrimo strategijoje integruojamos dvi analitinės pakopos: mikro ir makro lygmens. Mikrolygmeniu, siekiant patikrinti, ar startuoliai empiriniu požiūriu sudaro išskirtinę įmonių kategoriją ir kokie veiksniai lemia jų augimą, produktyvumą bei gyvybingumą, Baltijos šalių (Lietuvos, Latvijos ir Estijos) startuoliai lyginami su tame pačiame pramonės sektoriuje veikiančiomis kitomis įmonėmis, analizuojant veiklos rezultatų palyginimus gyvavimo ciklo metu bei tarp šalių, taip pat augimo, gyvybingumo bei bendro daugiaveiksnio produktyvumo determinantų modelius.

Makrolygmeniu startuolių ekosistemos brandos ir makroekonominių rezultatų sąveikai vertinti, siekiant sustiprinti identifikavimą ir užtikrinti pakankamą tarptautinę rezultatų variaciją, taikomas platesnis Europos šalių kontekstas. Regresinėje analizėje papildomai taikomos Baltijos šalių sąveikos specifikacijos leidžia patikrinti, ar perdavimo mechanizmas nuo ekosistemos brandos iki makroekonominių rezultatų Baltijos regione reikšmingai skiriasi nuo bendrųjų Europos dėsningumų.

Metodų požiūriu skyrius apima tris viena kitą papildančias kiekybinių analizių technikų grupes: (1) lyginamąjį startuoliai vs. kitos įmonės veiklos rodiklių (augimas, produktyvumas, finansiniai rezultatai ir gyvybingumas) gyvavimo ciklo metu vertinimą; (2) ekonometrinį modeliavimą, skirtą įvertinti endogeninių (įmonės lygmens) ir egzogeninių (ekosistemos lygmens) veiksnių poveikį startuolių augimui ir produktyvumui, taip pat makrolygmens ekonometrinę analizę, testuojančią ryšį tarp startuolių ekosistemos brandą reprezentuojančio V indekso ir makroekonominių išeigų; (3) mašininio mokymosi metodus – principinių komponentų analizę (PCA) ir k vidurkių klasterizavimą – taikomą tiek startuolių augimo profilių latentiniams komponentams išgauti ir klasifikuoti Baltijos šalių mikroduomenyse, tiek sudėtiniam V indeksui konstruoti ir Europos valstybėms grupuoti į ekosistemų brandos klasterius makroanalizėje.

Empirinėje tyrimo dalyje naudojami Lietuvos (LT), Latvijos (LV) ir Estijos (EE) įmonių lygmens finansinių ataskaitų duomenys, gauti iš atvirų duomenų šaltinių bei nacionalinių ekosistemų, ir makrolygmens duomenys iš tarptautinių duomenų bazių.

Startuolių įmonės identifikuojamos pagal nacionalinių agentūrų LT, LV ir EE, atsakingų už startuolių plėtrą, pateiktus startuolių registro įmonių identifikacinius kodus. Palyginimui sudaroma kitų įmonių imtis, atrenkant įmones, priskirtas NACE 62 ekonominės veiklos kodui, nes net 63 % startuolių veikia šioje kategorijoje. Startuolių ir kitų įmonių gyvybingumo analizei kontrolinė grupė sudaroma taikant polinkio balų suderinimo (PSM) metodą. Visos statistinės procedūros – duomenų parengimas, aprašomoji ir lyginamoji analizė, ekonometriniai įverčiai, PCA, klasterizavimas ir indeksų konstravimas – atliekamos naudojant R (4.4.1) ir RStudio (2024.12.1.563) aplinkas.

Metodikos skyrius literatūra paremtą konceptualų modelį paverčia empiriškai įgyvendinamu tyrimo dizainu: (i) nustato strategiją, kaip empiriškai patikrinti startuolių išskirtinumą ir jų raidos veiksnius; (ii) apibrėžia daugiasluoksnę vertinimo sistemą, susiejančią įgalinančias sąlygas, startuolių ekosistemų brandą ir makroekonomines išeigas; (iii) sukonstruoja nuoseklų rodiklių rinkinį, įskaitant dvi produktyvumo dimensijas (darbo ir bendrąjį daugiaveiksnį produktyvumą), bei V indeksą kaip ekosistemos brandos aproksimaciją; (iv) patikrina praktinį pritaikomumą, derindamas Baltijos šalių mikrolygmens validaciją su platesniu Europos makrolygmens palyginimu, taip sustiprindamas rezultatų palyginamumą ir išorinį validumą.

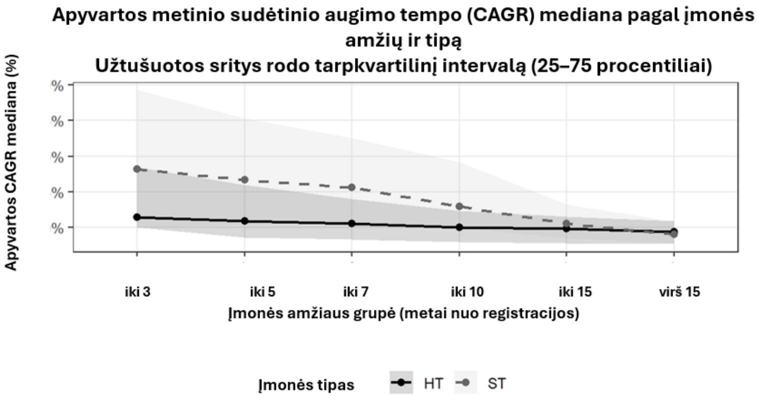
3. Empirinis startuolių ekosistemos modelio pagrindimas: raidos veiksniai ir makroekonominis poveikis

Trečiajame disertacijos skyriuje pateikiami praktiniai antrojo skyriaus metodikos empiriniai įrodymai, patikrinamas siūlomas startuolių ekosistemos modelis. Skyriuje siekiama dviejų tarpusavyje susijusių tikslų: (i) įmonių lygmeniu patvirtinti, kad startuoliai Baltijos šalyse sudaro empiriškai išskirtinę kategoriją, palyginti su kitomis įmonėmis, taip pat nustatyti jų augimą ir produktyvumą lemiančius veiksnius; (ii) ekosistemos ir makroekonominiu lygmeniu įvertinti, kaip startuolių ekosistemos branda, aproksimuojama V indeksu (sudarytu iš rizikos kapitalo aktyvumo rodiklių), siejasi su makroekonominiais rezultatais Europoje, nustatyti Baltijos regionui būdingus dėsningumus.

Lyginamosios analizės rezultatai atskleidžia išskirtines startuolių charakteristikas, nuosekliai juos lyginant su kitomis įmonėmis atitinkamais gyvavimo ciklo etapais Lietuvoje, Latvijoje ir Estijoje. Nustatyta, kad Baltijos šalių startuoliai empiriškai skiriasi nuo kitų įmonių, tačiau tie skirtumai yra daugiamačiai ir priklauso nuo raidos etapo. Pagal ekonominės veiklos sektorius startuoliai koncentruojasi aukštųjų technologijų ir žinioms imlių paslaugų sektoriuose, pasižyminčiuose ryškia specializacija informacinių ir ryšių technologijų (IRT) vertikalėse. Vis dėlto jų veiklos aprašymų analizė atskleidžia technologines nišas, kurių neapima standartiniai ekonominės veiklos klasifikavimo kodai.

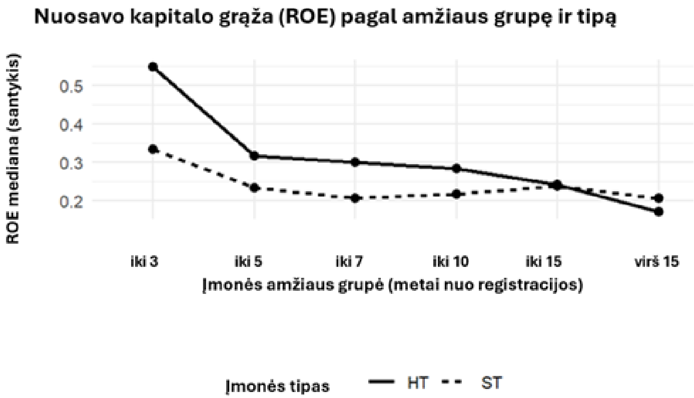
Startuolių ekosistemai būdingas aukštas heterogeniškumas. Taikant PCA ir k vidurkių klasterizavimo metodus, remiantis trimis kintamaisiais – CAGR (sudėtiniu metiniu augimo tempu), amžiumi ir įmonės dydžiu – startuoliai suskirstomi į penkis augimo profilius: nuo brandžių ir didelių, bet lėtai augančių, iki jaunų, labai / itin sparčiai augančių įmonių. Tai pagrindžia interpretaciją, kad jų rezultatai yra stipriai asimetriški, o bendrą ekosistemos augimą lemia palyginti nedidelė aukštos grąžos įmonių dalis, todėl „vidutinio startuolio“ samprata yra ribotai informatyvi.

Startuolių ir kitų įmonių raidos palyginamoji analizė rodo, kad nors startuoliai vidutiniškai jaunesni, jie dažnai turi daugiau darbuotojų ir moka aukštesnius atlyginimus. Spartaus augimo pranašumas ryškus ankstyvaisiais raidos etapais, tačiau maždaug po dešimties metų šie skirtumai mažėja ir priartėja prie kitų įmonių rodiklių, o augimo tempas su amžiumi lėtėja labiau nei palyginamojoje grupėje (S3.1 pav.).



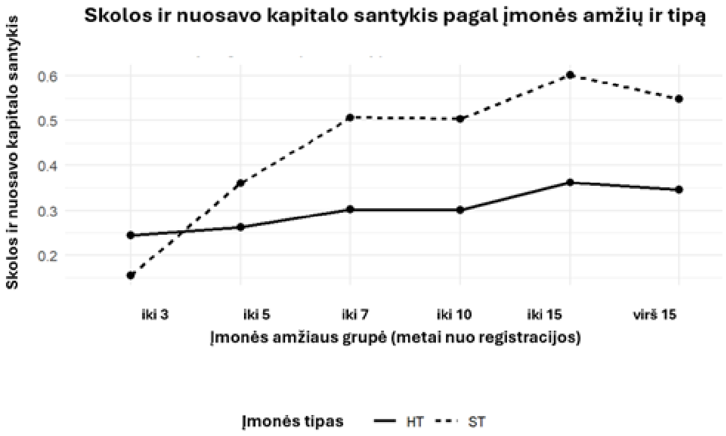
S3.1 pav. Startuolių (ST) ir kitų įmonių (HT) metinio sudėtinio augimo tempo (CAGR) dinamika (sudaryta autorės)

Finansavimo struktūros ir rizikos analizė rodo, kad ankstyvaisiais raidos etapais startuolių nuosavo kapitalo grąža (ROE) yra mažesnė ir labiau svyruoja, o įmonėms pasiekus maždaug 10 metų amžių, ROE rodikliai palaipsniui suartėja su kitų įmonių lygiu (S3.2 pav.).



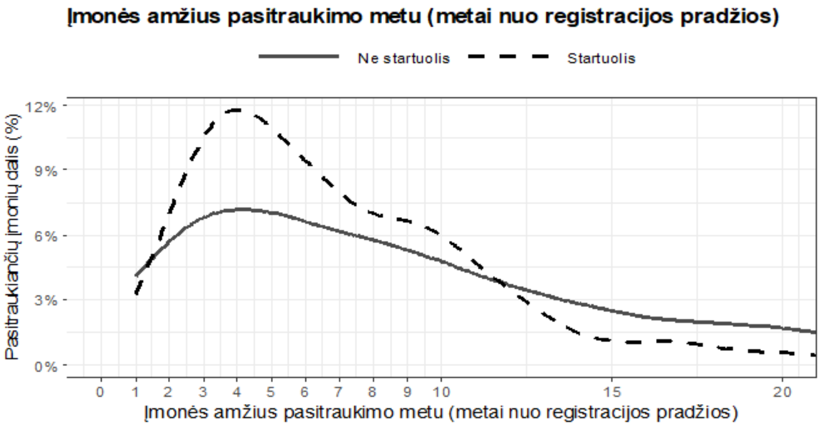
S3.2 pav. Startuolių (ST) ir palyginamosios grupės įmonių (HT) nuosavo kapitalo grąžos (ROE) dinamika (sudaryta autorės)

Tuo pat metu įsiskolinimo rodikliai ankstyvuoju plėtros laikotarpiu (iki 7 metų) auga sparčiai (S3.3 pav.).



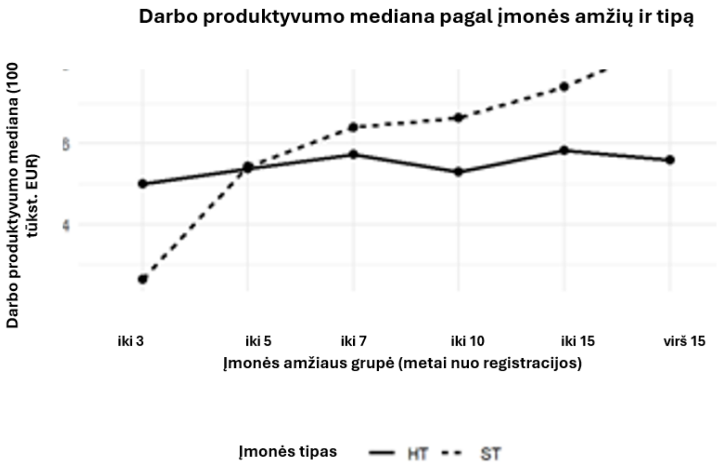
S3.3 pav. Startuolių (ST) ir palyginamosios grupės įmonių (HT) skolos ir nuosavo kapitalo santykio dinamika (sudaryta autorės)

Startuolių mirtingumo rizika yra itin aukšta ir piko tašką pasiekia maždaug 3–5 veiklos metais (S3.4 pav.). PSM metodu suderintoje imtyje, sulyginus lyginamų įmonių charakteristikas, nustatyta, kad priklausymas startuolių grupei siejamas su 26 % mažesne išgyvenamumo tikimybe. Ši rizika nėra paaiškinama vien stebimomis finansinėmis charakteristikomis, tad ji interpretuojama kaip struktūrinė startuolių savybė, susijusi su padidinta rizika vykdant proveržio inovacijas.



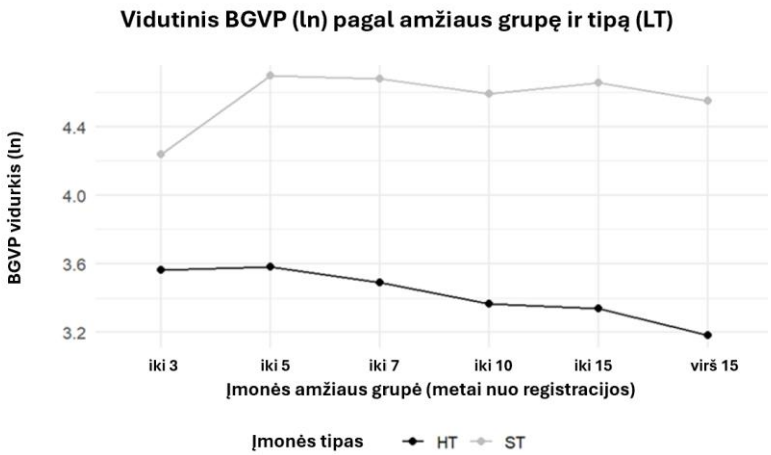
S3.4 pav. Startuolių ir kitų įmonių įmonių pasitraukimo rizikos palyginimas (sudaryta autorės)

Startuolių produktyvumas auga su amžiumi – tai būdinga tiek darbo produktyvumo rodikliui (S3.5 pav.), tiek bendrajam gamybos veiksnių produktyvumui (BGVP) (S3.6 pav.).



S3.5 pav. Startuolių (ST) ir palyginamosios grupės įmonių (HT) darbo produktyvumo dinamika (sudaryta autorės)

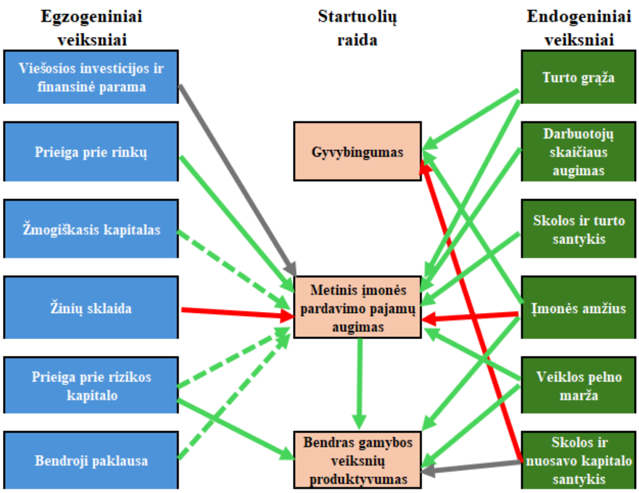
Vėlesniais raidos etapais startuoliai galiausiai pranoksta kitas įmones, o tai rodo su mokymusi ir veiklos efektyvumo didėjimu susijusius procesus, vykstančius augant ir plečiantis.



S3.6 pav. Startuolių (ST) ir palyginamosios grupės įmonių (HT) bendrojo gamybos veiksnių (BGVP) produktyvumo dinamika (sudaryta autorės)

BGVP teigiamai siejasi su veiklos marža ir apyvartos augimu, o didžiausios jo reikšmės dažniausiai pasiekiamos vidutinio amžiaus grupėse (apie 5–10 metų). Be to, šis rodiklis yra didesnis mažesniuose startuoliuose (mažiau darbuotojų), kas dera su „lean“ veiklos logika arba didesniu inovacijų intensyvumu vienam darbuotojui.

Faktorinės analizės rezultatai atskleidžia įgalinančios inovacijų ekosistemos aplinkos sąlygų (egzogeninių veiksnių) ir vidinių startuolių charakteristikų (endogeninių veiksnių) poveikį jų augimui, produktyvumui ir gyvybingumui. Empirinėje tyrimo strategijoje derinami parametriniai ir semiparametriniai metodai: rizika gyvybingumui vertinama taikant apibendrintus tiesinius modelius (GLM), augimo rezultatai siejami su įmonės vidiniais veiksniais taikant regresines specifikacijas, o BGVP determinantams vertinti naudojami modeliai, izoliuojantys firmos specifinį indėlį ir kontroliuojantys laiko bei sektoriaus heterogeniškumą. S3.7 pav. pateikiama konceptualaus startuolių ekosistemos modelio empirinio tikrinimo rezultatų schema, kurioje apibendrinama, kurie ir kaip egzogeniniai bei endogeniniai veiksniai statistiškai siejasi su startuolių raidos rezultatais – gyvybingumu, metiniu pardavimo pajamų augimu ir bendru gamybos veiksnių produktyvumu (BGVP).



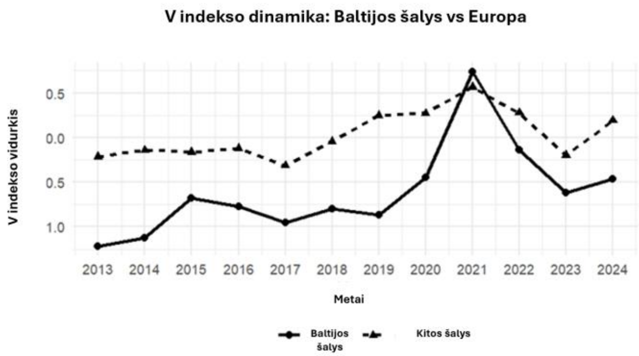
S3.7 pav. Empirinio tyrimo metu gautos egzogeninių ir endogeninių veiksnių sąsajos su startuolių raidos rodikliais. Žalios spalvos rodyklės parodo teigiamas sąsajas, raudonos – neigiams, o pilkos spalvos sąsajos nebuvo statistiškai reikšmingos. Punktyrinės linijos žymi nelinijinį ryšį (sudaryta autorės)

Startuolio gyvybingumą labiausiai formuoja vidiniai struktūriniai ir operatyviniai veiksniai: didesnė turto grąža ir amžius didina išgyvenimo tikimybę, o didesnis finansinis svertas ją mažina. Turto grąža, darbuotojų skaičiaus augimas bei veiklos pelno marža ir skolos bei turto santykis teigiamai veikia ir startuolių augimą. Tačiau pastariesiems dviem būdingas silpnesnis poveikis startuoliams, palyginti su kitomis įmonėmis, o tai atitinka interpretaciją, kad startuoliai plėtrą finansuoja ne iš sukaupto pelno, o labiau remiasi išoriniais finansavimo šaltiniais.

Išorinės ekosistemos sąlygos yra svarbios augimui, tačiau jų poveikis yra nelinijinis ir heterogeniškas. Semiparametrinis modeliavimas patvirtina, kad prieiga prie rinkų ir žmogiškasis kapitalas yra startuolių augimą įgalinančios sąlygos, tačiau ryšys nėra vienodas visame pasiskirstyme: poveikis priklauso nuo startuolio augimo profilio ir pasižymi nelinijiškumu (aukštesniuose lygiuose pasireiškia mažėjančios grąžos efektai). Žinių sklaidos rodiklis daugelyje specifikacijų yra neigiamai susijęs su startuolių augimu, o tai leidžia manyti, kad naudotas žinių sklaidai matuoti naudojamas rodiklis greičiau atspindi didesnį konkurencinį spaudimą, talentų perskirstymą ar žinių difuziją, kuri naudingesnė inovacijų ekosistemai apskritai, bet ne joje veikiantiems startuoliams. Rizikos kapitalo prieinamumas tampa teigiamas tada, kai atsižvelgiama į nelinijiškumą ir heterogeniškumą, rodant, kad linijiniai modeliai gali užmaskuoti tikrąjį ryšio pobūdį.

Startuolių produktyvumas pirmiausia siejasi su operaciniu veiklos efektyvumu ir apyvartos augimu. Iš tirtų egzogeninių produktyvumo determinantų rizikos kapitalo (RK) prieinamumas yra aiškiausias produktyvumą didinantis veiksnys, patvirtinantis jo vaidmenį ne tik finansavimo, bet ir atrankos, valdymo bei gebėjimų stiprinimo procesuose.

Toliau vertinami startuolių ekosistemos ryšiai su makroekonominiais rezultatais, tikrinant, ar ekosistemos branda persiduoda į platesnius ekonomikos rezultatus. Kaip sudėtinis ekosistemos brandos matas sudaromas rizikos kapitalo aktyvumo rodikliais pagrįstas V indeksas. Analizei naudojami Europos šalių paneliniai duomenys (23 šalys, LT, LV, EE šalys agreguojamos į Baltijos regioną). Siekiant įvertinti V indekso diferencijuojančią galią, papildomai taikomas klasterizavimas ir laiko tendencijų analizė. Rezultatai rodo, kad V indeksas yra tinkama startuolių ekosistemos brandos aproksimacija ir prasmingai diferencijuoja Europos šalis pagal rizikos kapitalo aktyvumą, o Baltijos regionui būdingas žemesnis ir nepastovesnis brandos lygis, suderinamas su mažų atvirų ekonomikų jautrumu išoriniams šokams (S3.8 pav.).



S3.8 pav. V indekso dinamika. Baltijos regiono šalių ir Europos skirtumai (sudaryta autorės)

Prieš atliekant ekonometrinį modeliavimą, apskaičiuojamos porinės koreliacijos ir taikomi Dumitrescu–Hurlin Grangerio priežastingumo testai, leidžiantys įvertinti bendrą kintamųjų judėjimą ir laikinę pirmystę. Europoje V indeksas stipriai koreliuoja su žinių ekonomikos ir inovacijų pajėgumo rodikliais (žinioms imliu užimtumu, žmogiškuoju kapitalu, viešosiomis išlaidomis ir verslo MTEP). Ekonometriniai įverčiai pateikiami keturiems makroekonominiams rezultatams – darbo ir kapitalo produktyvumui, prekybos (aukštųjų technologijų eksporto) rodikliams ir inovacijų kintamiesiems. Kartu tikrinama, ar Baltijos regiono poveikis statistiškai skiriasi nuo bendro Europos ryšio (naudojant sąveikos terminus). Ekonometriniai įverčiai patvirtina, kad ryšys tarp ekosistemos brandos ir makroekonominių rezultatų yra nevienalytis ir priklauso nuo nagrinėjamo rezultato bei laiko dimensijos: darbo produktyvumui dažniau būdingas tiesioginis poveikis, tuo tarpu aukštųjų technologijų eksportui ir verslo MTEP ryškesni vėlavimo efektai, o kapitalo produktyvumo įverčiai yra silpniausi bei mažiausiai stabilūs.

Ypatingai svarbus skyriaus indėlis – regioninio heterogeniškumo išvados. Sąveikos modeliai rodo, kad Baltijos regione ryšys tarp V indekso ir darbo produktyvumo yra gerokai silpnesnis ir net neigiamas, palyginti su Europos vidurkiu.

Aukštųjų technologijų eksporto ir inovacijų rodikliuose Baltijos šalims būdingas teigiamas trumpalaikis diferencinis efektas, tačiau dviejų metų vėlavimo laikotarpiu jis tampa neigiamas. Tai leidžia daryti išvadą, jog ekosistemos brandos sąsaja su makroekonominiais rezultatais nėra savaiminė ir priklauso nuo regioninių struktūrinių apribojimų, laiko faktorių bei išorinių šokų poveikio.

Galimos šių skirtumų priežastys siejamos su mažų ekonomikų efektais, ribotomis ekosistemų plėtros galimybėmis, talentų ir rinkų prieigos apribojimais, rizikos kapitalo pasiūlos nepastovumu bei paramos mechanizmų nestabilumu. Apskritai rezultatai rodo, kad 2020–2021 m. palankių sąlygų laikotarpiu Baltijos ekosistemos galėjo reikšmingai sustiprėti (S3.8 pav.), tačiau jų struktūrinė bazė išlieka silpnesnė ir mažiau stabili nei daugumoje Europos šalių. Todėl konvergencijai būtinos tikslingos priemonės, ypač orientuotos į rizikos kapitalo prieinamumo didinimą, institucinių investicijų skatinimą, prieigos prie eksporto rinkų plėtrą ir stabilios, ilgalaikės ekosisteminės politikos įgyvendinimą.

Apibendrinta modelio implikacija, paremta trečiojo skyriaus rezultatais, yra tokia: inovacijų ekosistemos sąlygos formuoja startuolių raidą, o rizikos kapitalo aktyvumas veikia kaip katalizuojantis startuolių plėtros finansavimo kanalas. V indeksu aproksimuojama ekosistemų branda leidžia lyginti jas tarpusavyje ir nustatyti ryšį su makrolygmens rezultatais. Kartu Baltijos regiono rezultatai rodo, kad startuolių ekosistemų poveikis makroekonomikai nėra savaiminis – jis priklauso nuo perdavimo mechanizmų, struktūrinių apribojimų ir išorinių šokų. Todėl paramos priemonių politika turi būti diferencijuojama, atsižvelgiant į ekosistemos tipą ir startuolių augimo profilius.

Bendrosios išvados

1. Tyrimas patvirtina, kad startuoliai (Baltijos šalių pavyzdžiu) sudaro empiriškai išskirtinę verslo kategoriją, palyginti su tomis pačiomis ekonominėmis veiklomis užsiimančiomis kitomis įmonėmis. Startuoliai pasižymi spartesniu apyvartos ir užimtumo augimu ankstyvaisiais raidos etapais, specifine darbo ir bendrojo gamybos veiksnių produktyvumo dinamika, tačiau taip pat ir reikšmingai didesne ankstyvojo laikotarpio mirtingumo rizika bei mažesniu trumpalaikiu pelningumu. Šie rezultatai rodo, kad startuolio išskirtinumas yra daugiamatis ir

priklauso nuo gyvavimo ciklo: ryškiausiai jis atsiskleidžia ankstyvaisiais ir vidutiniais etapais, o įmonėms bręstant palaipsniui silpnėja ir artėja prie kitų įmonių dinamikos. Atsižvelgiant į tai, tyrimas sudaro prielaidas sistemiškai pagrįsti startuolio sampratą, integruojant empiriškai patvirtintas jo charakteristikas į nuoseklią apibrėžties sistemą. *Remiantis gautais rezultatais, startuolis gali būti apibrėžiamas kaip jauna, į inovacijas orientuota įmonė, siekianti sparčios plėtros ankstyvuoju veiklos etapu ir paprastai pasižyminti savitais augimo, produktyvumo, finansavimo ir rizikos raidos modeliais, ypač pirmaisiais veiklos metais.* Ši formuluotė tiesiogiai atitinka Baltijos šalių startuolių profilį ir operacionalizuoja startuolio apibrėžties kriterijus į nuoseklią sistemą.

2. Disertacijoje sukuriama ir empiriškai patvirtinama integruota metodika, leidžianti įvertinti startuolių raidą ekosistemose įgalinančias sąlygas, ekosistemų brandą ir jos sąsajas su makroekonominiais rezultatais. Konceptualaus modelio empirinis pritaikymas rodo, kad ekosistemos lygmens išvados gali būti pagrįstos mikrolygmens įrodymais, o makroekonominis poveikis gali būti vertinamas taikant struktūruotą rodiklių sistemą ir rezultatui specifinius modelius.
3. Darbas identifikuoja ir į konceptualų modelį integruoja rodiklių rinkinį, skirtą vertinti tiek startuoliams palankias sąlygas, tiek pačios ekosistemos makroekonominio poveikio mastą. Esminis šio modelio indėlis yra sudėtinio V indekso, pagrįsto rizikos kapitalo veiklos metrikomis, sukūrimas. Šis indeksas operacionalizuoja ekosistemos brandą ir leidžia prasmingai diferencijuoti šalis (įskaitant didesnio nepastovumo ir apskritai žemesnio brandos lygio identifikavimą Baltijos regione).
4. Empirinis modelio taikymas patvirtina jo praktinį taikomumą ir išorinį aktualumą. Įmonės lygiu modelio taikymas trijose Baltijos šalyse nuosekliai atskleidžia tipines startuolių charakteristikas – greitesnį ankstyvąjį augimą ir darbo vietų kūrimą, kartu su didesne ankstyvojo išėjimo rizika ir mažesniu trumpalaikiu pelningu, palyginti su kitomis įmonėmis. Šis nuoseklumas visose trijose ekosistemose patvirtina modelio patikimumą ir tinkamumą startuoliams charakterizuoti. Makrolygmeniu tarpšalinis vertinimas parodo, kad startuolių ekosistemos branda siejasi su makroekonominiais rezultatais tam tikru, nuo laiko priklausančiu būdu, kuriame vėlavimo struktūros yra ypač reikšmingos inovacijoms ir eksportui. Skirtumas tarp Baltijos ir Europos atskleidžia tiek modelio gebėjimą diferencijuoti, tiek jo vertę formuojant diferencijuotas, įrodymais grįstas ekosistemų plėtros strategijas.

Rekomendacijos

Praktikoje modelį rekomenduojama taikyti struktūruotai diagnostikai ir lyginamajam vertinimui. Politikos formavimo procese modelį rekomenduojama naudoti ribojančių aplinkos veiksnių nustatymui bei planuojant intervencijų laiką; investuotojams jis suteikia galimybę atlikti ekosistemų palyginimus vertinant plėtros potencialą. Praktikoje modelio taikymą rekomenduojama įgyvendinti etapais:

- Diagnozuoti įgalinančios aplinkos profilį (įvestis). Įvesties rodiklius (žmogiškąjį kapitalą, prieigą prie rinkų, žinių sklaidą, finansavimą / rizikos kapitalą ir paklausos bei paramos sąlygas) interpretuoti kaip įgalinančius arba ribojančius veiksnius. Rekomenduojama atsižvelgti į galimą profilio disbalansą: vieno rodiklio efektas gali turėti įtakos kitų rodiklių poveikiui (pvz., didesnė rizikos kapitalo pasiūla, nesant pakankamos talentų pasiūlos ar prieigos prie rinkų, gali lemti silpnesnį poveikį).
- Rekomenduojama ekosistemos brandą (centrinis sluoksnis) matuoti pakaitiniu rodikliu V indeksu, atspindinčiu rizikos kapitalo intensyvumą, atrankos kokybę ir kapitalo įsisavinimą. Praktiniu požiūriu šio rodiklio reikšmė atsako į klausimą: „Koks yra šios ekosistemos plėtros ir finansavimo atsinaujinimo potencialas?“. Rekomenduojama V indekso pokyčius interpretuoti kartu su įgalinančios aplinkos profiliu, siekiant atskirti, ar mažesnę brandą sąlygoja žemesni įvesties rodikliai (pvz., žmogiškojo kapitalo ar prieigų prie rinkos trūkumas), ar nepakankama įvesčių konversija į plėtros rodiklius.
- Paversti brandą laukiama makro rezultatų dinamika. Modelio įverčius naudoti rezultatų dinamikos prognozavimui: kurie rezultatai labiau tikėtina reaguos esamuoju laikotarpiu, o kurie – su vėlavimu. Praktikoje tai reiškia, kad politikos priemonių poveikio vertinimo horizontai turi būti suderinti su rezultatų tipu: trumpalaikė stebėsena iš karto pasireiškiantiems poveikiams, o vidutinio laikotarpio – ten, kur vyrauja vėlavimo efektai.
- Rekomenduojama taikyti netiesiškumo ir heterogeniškumo logiką. Kai empiriniai rezultatai rodo, kad nauda iš papildomų pagerinimų laikui bėgant mažėja ir kad skirtingose ekosistemose poveikis nėra vienodas, tuomet įvesčių ar brandos rodiklių didinimą rekomenduojama planuoti atsižvelgiant į pradinę padėtį: tas pats papildomas pokytis gali turėti didesnį poveikį esant žemam pradiniam lygiui ir mažesnį poveikį jau esant aukštam lygiui. Todėl rekomenduojamos intervencijos turėtų būti diferencijuojamos pagal ekosistemos pradinį brandos lygį bei siekiamą rezultatą (augimą, produktyvumą, eksportą ir inovacijas).

Modelis pirmiausia parodo sisteminius ryšius, kurie dera su teorija grindžiama priežastine seka. Jo rezultatus rekomenduojama naudoti prioritetų nustatymui, lyginamajam vertinimui ir galimų scenarijų analizei. Tačiau griežtiems priežastiniams teiginiams pagrįsti reikalingos papildomos identifikavimo strategijos ir išsamesni duomenys.

Annexes

Annex A. Descriptive summary of a firm, ecosystem-enabling environment, and macroeconomic impact indicators used in empirical validation

Annex B. Descriptive summary of startup and non-startup operational indicators across the Baltic states

Annex C. Econometric estimation results for total factor productivity (TFP) of startups and non-startup firms

Annex D. Econometric estimation results for startup and non-startup failure, growth, and productivity determinants

Annex E. Econometric estimation results for startup ecosystems' macroeconomic impact

Annex A. Descriptive summary of a firm, ecosystem-enabling environment, and macroeconomic impact indicators used in empirical validation

Table A.1 Median (IQR) firm–level indicators: startups (ST) versus comparable high–tech (HT) firms within industries, the Baltic states

Variable	**Abbre-viation**	**ST, EE**	**HT, EE**	**ST, LT**	**HT, LT**	**ST, LV**	**ST 62, EE**	**ST 62, LT**
Age, average at observation	Age	4.0 (5.0)	8 (12)	6.0 (7.0)	8.0 (11.0)	4.0 (4.0)	4.0 (4.0)	6.0 (7.0)
Employees, annual average count	EMPL	5.0 (10.0)	3 (4.0)	8.67 (19.17)	4.0 (7.67)	5.0 (7.0)	5.0 (8.0)	9.83 (26.9)
Turnover, annual, EUR*	TRN	2.95 (9.8)	2.33 (6.38)	3.99 (17.57)	1.5 (5.06)	1.22 (5.56)	2.74 (9.58)	4.18 (17.64)
Earnings before interest and taxes, annual, EUR*	EBIT	0.0 (2.08)	0.19 (0.82)	0.11 (1.56)	0.13 (0.75)	0.01 (0.9)	0.0 (1.99)	0.28 (1.75)
Total assets, annual, EUR*	TA	4.25 (10.19)	1.64 (4.88)	3.08 (13.93)	0.93 (2.82)	1.53 (6.88)	3.4 (7.42)	2.56 (8.86)
Equity, annual, EUR*	EQT	1.65 (5.81)	0,94 (2.85)	0.85 (5.07)	0.43 (1.5)	0.31 (2.77)	1.61 (5.29)	0.81 (3.51)
Total liabilities, annual, EUR*	LBL	1.04 (2.87)	0.31 (1.13)	1.42 (7.03)	0.34 (1.23)	1.07 (3.95)	0.87 (2.33)	1.11 (4.4)
Average monthly salary per employee, EUR	AVG SAL			2375.19 (1785.16)	1977.0 (2068.96)			2617.86 (1868.31)

Note: * Monetary values are denominated in EUR 100,000. EE = Estonia, LT = Lithuania, LV = Latvia. IQR denotes the interquartile range (75th–25th percentile). “62” denotes firms classified under NACE Rev. 2 industry code 62 only.
Data sources: “Lithuanian Registry Centre”, “Lithuanian State Social Insurance Fund (SODRA)”, “Estonian Open Government Data Portal”, and “Latvian Open Data Portal”.

Table A.2. Descriptive summary of indicators for external growth drivers (startup ecosystem enabling environment)

Indicator, explanation, source	**Ab-brevi-ation**	**Mean (SD)**	**Min**	**Max**
Financial support, composite indicator of: R&D expenditures public sector (% of GDP); Direct government funding and government tax support for business R&D (% of GDP); Venture capital expenditures (% of GDP). EIS.	FS	94.6 (14.1)	60.1	130.4
Access to the markets, composite indicator of: Medium and high–tech product exports (% of total); Knowledge–intensive services exports (% of total); Sales of new or improved products (% of turnover). EIS	AM	62.5 (15.1)	38.1	96.8
Human capital, composite indicator of: Enterprises providing training to develop or upgrade ICT skills of their personnel (% of total); Employed ICT specialists (% of total). EIS.	HC1	83.7 (25.6)	50.6	131

End of Table A.2

Indicator, explanation, source	Ab-brevi-ation	Mean (SD)	Min	Max
Knowledge spillover, composite indicator of: Innovative SMEs collaborating with others (% of total); Public–private co–publications per million population; Job–to–job mobility of human resources in science & technology (% of total). EIS	KS	166 (58.6)	60.6	277
Venture capital expenditures (% of GDP). Eurostat.	VC	126.7 (39.2)	65.8	199.8
Average annual GDP growth, %. Eurostat.	GDP GR	2.2 (3.6)	– 10.9	7.2

Note: Period of 2016–2023. SD = standard deviation. EIS=European Innovation Scoreboard.

Table A.3. Descriptive summary of macroeconomic impact indicators and the V index components

Variable, explanation, period, source	Abbre-viation	Mean (SD)	Min	Max
GDP growth, average annual growth, %; 2013–2024, Eurostat.	GDP GR	1.71 (3.38)	–10.9	7.2
High–tech products export, annual share of total exports, %; 2013–2024, Eurostat.	HT EXP	12.00 (7.37)	0.94	43.5
Capital productivity growth in the ICT sector: gross value added per unit of net fixed assets; % change on previous period, 2015–2024, Eurostat.	PRO C	3.67 (7.24)	–30.7	31.7
Labour productivity growth in knowledge–intensive sectors, change from previous period, %; 2015–2024, Eurostat.	PRO L	2.04 (5.57)	–15.5	22.6
Research and development in the ICT sector, % from GDP; 2014–2023, Eurostat.	BERD	0.17 (0.10)	0.02	0.63
Employment in the knowledge–intensive sector, annual, % from total; 2013–2024, Eurostat.	EMPL	41.70 (8.34)	20	60.2
Public consumption, annual, denominated by 10k EUR; 2007–2024, Eurostat, Office of UK national statistics	PUB CON	0.16 (0.10)	0.02	0.47
Job–to–job mobility of human resources in science and technology, individuals who changed their employment, %; 2017–2020, Eurostat.	JOB M	9.04 (2.09)	4.6	11.1
Innovative enterprises in the ICT sector, annual share of total enterprises, %; 2014–2023, Eurostat.	INO ACT	7.00 (6.19)	0.2	15.4
Human capital and research index, 2013–2022, WIPO.GII.2.	HC	50.23 (10.30)	27.7	68.1
Venture capital investment, EUR*, 2007–2024, INVEST EUROPE.	VC INV	21.17 (31.90)	0.07	315.99
Venture capital investment, number of companies**, 2007–2024, INVEST EUROPE.	VC INV COM	11.27 (10.77)	0.05	72.82
Venture capital divestment, EUR*, 2007–2024 INVEST EUROPE.	VC DIV	5.23 (6.46)	0	52.27
Venture capital divestment, number of companies**, 2007–2024, INVEST EUROPE.	VC DIV COM	2.59 (2.49)	0	13.88

Note: *denominated by 100 thousand EUR, **normalised per 1 million of population

Annex B. Descriptive summary of startup and non–startup operational indicators across the Baltic states

Table B. 1. Median (IQR) firm–level estimated variables of startups and the comparative group of firms (HT) across the Baltic states

Variable, formula	**Abbreviation**	**ST, EE**	**HT, EE**	**ST, LT**	**HT, LT**	**ST, LV**	**ST 62, EE**	**ST 62, LT**
Return on assets, EBIT/TA, ratio	ROA	0.0 (0.64)	0.14 (0.37)	0.04 (0.35)	0.13 (0.38)	0.01 (0.69)	–0.01 (0.67)	0.11 (0.38)
Return on equity, EBIT/EQT, ratio	ROE	0.13 (0.97)	0.27 (0.61)	0.26 (0.69)	0.31 (0.7)	0.38 (0.97)	0.16 (1.0)	0.35 (0.75)
EBIT margin, EBIT/TRN, ratio	EBIT MRG	0.0 (0.96)	0.07 (0.24)	0.04 (0.27)	0.07 (0.24)	0.02 (0.76)	0.0 (0.9)	0.05 (0.18)
Debt to equity, LBL/EQT ratio	DTE	0.31 (0.89)	0.25 (0.69)	0.43 (1.62)	0.34 (1.09)	0.28 (2.49)	0.23 (0.81)	0.48 (1.46)
Debt to assets, LBL/TA, ratio	DTA	0.28 (0.44)	0.22 (0.38)	0.54 (0.7)	0.38 (0.59)	0.66 (1.04)	0.26 (0.51)	0.5 (0.64)
Annual labour productivity, TRN/EMPL, EUR*	PRO L	0.55 (0.95)	0.66 (0.77)	0.59 (0.92)	0.44 (0.54)	0.26 (0.57)	0.6 (0.95)	0.56 (0.62)
Annual turnover growth, %	TRN GR	0.73 (80.61)	7.56 (59.8)	20.45 (91.58)	5.94 (70.87)	34.05 (145.47)	18.51 (110.69)	21.86 (83.48)
Annual employee growth, %	EMPL GR	0.0 (37.5)	0.0 (33.33)	0.84 (27.41)	0.0 (21.98)	7.03 (54.8)	0.0 (41.67)	0.0 (22.41)
Turnover CAGR, %	CAGR	0.73 (80.61)	7.56 (59.8)	20.45 (91.58)	5.94 (70.87)	34.05 (145.47)	18.51 (110.69)	21.86 (83.48)

Note: *denominated by EUR 100 thousand

Annex C. Econometric estimation results for total factor productivity (TFP) of startups and non–startup firms

Table C.1. 2SLS regression results for TFP estimation of startup (ST) and non–startup firms (HT), across Lithuania, Estonia, and Latvia

Country, Type	Stage: dependent variable	Intercept (SE)	lag lnTA (SE)	lag lnEMPL (SE)	lnTA (SE)	lnEMPL (SE)	F	R–squared
EE, all ST	1st Stage: lnTA	12.72*** (0.64)	0.12** (0.04)	0.26*** (0.07)			28.24	0.95
	1st Stage: lnEMPL	1.29*** (0.37)	0.10*** (0.02)	0.33*** (0.04)			27.76	0.95
	2nd Stage: lnTRN	11.67 (18.14)			–0.08 (1.52)	1.28 (1.38)		0.93
LT, all ST	1st Stage: lnTA	6.49*** (0.51)	0.43*** (0.02)	0.34*** (0.06)			31.97	0.90
	1st Stage: lnEMPL	0.55*** (0.15)	0.03*** (0.01)	0.78*** (0.02)			128.34	0.97
	2nd Stage: lnTRN	2.87*** (0.69)			0.67 *** (0.05)	0.62*** (0.09)		0.90
LV, all ST	1st Stage: lnTA	8.22*** (0.52)	0.27*** (0.04)	0.36*** (0.07)			37.22	0.93
	1st Stage: lnEMPL	0.42 (0.26)	0.10*** (0.02)	0.51*** (0.04)			39.97	0.94
	2nd Stage: lnTRN	3.30 (2.79)			0.69* (0.30)	0.38 (0.36)		0.90
EE, NACE 62 ST	1st Stage: lnTA	11.97*** (0.88)	0.17** (0.06)	0.25* (0.11)			30.85	0.95
	1st Stage: lnEMPL	0.79+ (0.46)	0.06+ (0.03)	0.35*** (0.06)			36.89	0.96
	2nd Stage: lnTRN	–2.11 (8.23)			1.10+ (0.65)	0.16 (0.75)		0.94
EE, NACE 62 HT	1st Stage: lnTA	11.87*** (0.57)	0.21*** (0.03)	0.05 (0.06)			50.88	0.97
	1st Stage: lnEMPL	2.70*** (0.25)	0.06*** (0.02)	0.30*** (0.03)			119.89	0.99
	2nd Stage: lnTRN	12.47*** (2.18)			–0.06 (0.18)	0.88*** (0.20)		0.93
LT, NACE 62 ST	1st Stage: lnTA	4.15*** (0.53)	0.49*** (0.04)	0.46*** (0.11)			19.60	0.86
	1st Stage: lnEMPL	–0.27+ (0.16)	0.04** (0.01)	0.84*** (0.03)			122	0.97
	2nd Stage: lnTRN	5.15*** (0.70)			0.54*** (0.07)	0.72*** (0.13)		0.92

End of Table C.1

Country, Type	**Stage: dependent variable**	**Intercept (SE)**	**lag lnTA (SE)**	**lag lnEMPL (SE)**	**lnTA (SE)**	**lnEMPL (SE)**	**F**	**R–squared**
LT, NACE 62 HT	1st Stage: logTA	10.03*** (0.41)	0.14*** (0.02)	0.31*** (0.05)			21.48	0.91
	1st Stage: lnEMPL	1.13*** (0.12)	0.03*** (0.01)	0.50*** (0.02)			119.97	0.98
	2nd Stage: lnTRN	3.08+ (1.58)			0.69 *** (0.15)	0.50** (0.16)		0.94

Notes: Robust standard errors are in parentheses. Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.10

Annex D. Econometric estimation results for startup and non–startup failure, growth, and productivity determinants

Table D.1. Results of the Firth models for full and PSM–matched samples

Full sample					**PSM matched sample**			
Variables	**OR**	**Coefficient (SE)**	**Lower_95**	**Upper_95**	**OR**	**Coefficient (SE)**	**Lower_95**	**Upper_95**
Intercept	0.11	–2.18 (0.09) ***	–2.37	–2.00	0.12	–2.15 (0.10) ***	–2.35	–1.95
TRN GR	1.00	0 (0)	0	0	1.00	0 (0)	0	0
TRN	1.00	0 (0)	0	0	1.00	0 (0)	0	0
ROA	0.92	–0.09 (0.03) **	–0.15	–0.02	0.86	–0.15 (0.06) **	–0.26	–0.04
ROE	1.00	0 (0)	0	0	1.00	0 (0).	0	0.01
EBIT margin	1.00	0 (0)	0	0	1.00	–0 (0)	0	0
DTE	1.00	0 (0)	0	0	1.01	0.01 (0) **	0	0.01
DTA	1.00	0 (0.02)	–0.05	0.04	0.89	–0.11 (0.07)	–0.27	0.02
EMPL	1.00	0 (0) *	–0.01	0	1.00	–0 (0).	–0.01	0
Type ST	1.27	0.24 (0.09) **	0.07	0.42	1.26	0.23 (0.10) *	0.04	0.42
Age	0.97	–0.03 (0.01) ***	–0.05	–0.02	0.97	–0.03 (0.01) **	–0.05	–0.01
n		7243				5558		
AIC		4085				3254		
McFadden R–squared		0.02				0.01		

Notes: Odds ratios (OR) are calculated as exp (coefficient). Robust standard errors are in parentheses. Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

Table D.2. Internal turnover growth determinants, panel regression results for only startups (ST) and ST with non–startup (HT) NACE 62 firms

Variable	**ST and HT 62, FE**	**ST and HT 62, TW**	**All ST, FE**	**All ST, TW**
ROA	3.15 (0.37) ***	3.19 (0.36) ***	1.42 (0.24) ***	1.40 (0.18) ***
DTE	0.06 (0.1)	0.05 (0.10)	0.08 (0.06)	0.07 (0.06)
DTA	2.36 (0.51) ***	2.37 (0.51) ***	0.80 (0.28) ***	0.79 (0.22) ***
EBIT margin	0.47 (0.48)	0.47 (0.47)	0.92 (0.23) ***	0.90 (0.10) ***
EMPL GR	0.39 (0.03) ***	0.38 (0.02) ***	0.38 (0.03) ***	0.36 (0.02) ***
Age	0.05 (0.04)		–0.27 (0.04) ***	
GDP GR	0.12 (0.01) ***	0.55 (0.07) ***	0.07 (0.02) ***	–0.11 (0.05) *
ROA:TypeST	–1.39 (0.63) *	–1.38 (0.62) *		
DTE:TypeST	0.06 (0.17)	0.02 (0.17)		
DTA:TypeST	–1.84 (0.82) *	–1.85 (0.80) *		
EBIT margin:TypeST	0.28 (0.66)	0.22 (0.64)		
EMPL GR:TypeST	–0.02 (0.06)	0.00 (0.05)		
Age:TypeST	–0.24 (0.09) *	–0.30 (0.09) **		
GDP GR:TypeST	–0.06 (0.04)	–0.06 (0.04)		
N	6445	6445	3971	3971
T	1–10	1–10	1–10	1–10
n	2271	2271	1164	1164
R–squared	0.17	0.16	0.19	0.15
F stat. p value	0.00	0.00	0.00	0.00

Notes: Robust standard errors are in parentheses. Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table D.3. Exogenous turnover growth determinants OLS and PLM regression results for all startups (all ST) and only NACE 62 ST (ST 62)

Model: OLS		**Model: GAM**				
Estimate (all ST)		**Estimate (all ST)**			**Estimate (ST 62)**	
Intercept	–11.84*** (1.03)	Intercept	–3.68. (2.14)		–1.56 (2.97)	
AM	0.20*** (0.04)	AM	0.04 (0.04)		0.16*** (0.05)	
VC	–0.01* (0.00)	VC	0.03** (0.01)		0.02 (0.02)	
KS	–0.05*** (0.00)	KS	–0.03*** (0.01)		–0.07*** (0.01)	
Growth profile 2	0.18 (0.59)	Growth profile 2	0.41 (0.60)		–1.82. (1.08)	
Growth profile 3	–0.76* (0.33)	Growth profile 3	0.69. (0.36)		–0.37 (0.64)	
Growth profile 4	10.47 (9.56)	Growth profile 4	12.69 (9.47)			
Growth profile 5	6.33*** (1.48)	Growth profile 5	5.17*** (1.47)		3.23 (2.67)	
		Smooth terms	edf	F–value	edf	F–value
GDP GR	0.38*** (0.04)	s(GDP GR)	3.06 ***	8.30	4.91**	4.33
FS	0.01 (0.01)	s(FS)	4.00	1.90	2.31	2.01
HC1	0.09*** (0.01)	s(HC1)	8.05 ***	7.35	3.35***	7.76
AGE	–0.32*** (0.04)	s(AGE)	4.44 ***	27.74	3.12***	7.31
n=5719		n=5719			n=1589	
R–squared 0.23		R–squared adj.	0.24		0.31	
F stat. p value< 2.2e–16		Deviance explained	24.6%		32%	
BP test p value< 2.2e–16		GCV	89.64		76.29	
Reset test p value 0.00		Optimiser	magic		magic	

Notes: Heteroskedasticity– and cluster–robust standard errors (clustered at the country–year level to account for correlation of residuals across firms exposed to the same macroeconomic conditions) are reported in parentheses. Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.10

Table D.4. Turnover growth GAM regression results for startup Growth Profiles

All ST, GAM	**Growth profile 1 (small, young, fast growth)**		**Growth profile 2 (big, mature, low growth)**		**Growth profile 3 (small, mature, moderate growth)**		**Growth profile 5 (small, young, extra fast growth)**	
Parametric coefficients (SE)								
(Intercept)	–2.50 (4.08)		6.48 (5.24)		1.89 (3.67)		3.86 (106.28)	
AM	0.12** (0.04)		–0.02 (0.07)		0.16*** (0.04)		–0.90 (0.66)	
VC	–0.00 (0.01)		0.05. (0.02)		0.02 (0.01)		0.19 (0.23)	
KS	–0.04*** (0.01)		–0.04 (0.02)		–0.05***(0.01)		0.06 (0.19)	
AGE	–0.93*** (0.10)		–0.02 (0.05)		–0.42*** (0.06)		–0.67 (1.31)	
FS	0.05 (0.03)		–0.08 (0.06)		–0.04 (0.03)		0.20 (0.49)	
Smooth terms	edf	F	edf	F	edf	F	edf	F
s(GDP GR)	6.78.	1.65	3.03***	11.71	3.81***	8.35	3.99	1.44
s(HC1)	2.19*	3.72	5.51***	8.65	4.53***	5.17	1.82	0.26
n	1779		1219		2677		43	
R–squared adj.	0.13		0.37		0.22		0.31	
Deviance explained	14%		37.7%		21.8%		48.8%	
GCV	72.91		99.75		96.16		82.02	
Optimiser	magic		magic		magic		magic	

Notes: Heteroskedasticity– and cluster–robust standard errors (clustered at the country–year level to account for correlation of residuals across firms exposed to the same macroeconomic conditions) are reported in parentheses. Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

Annex E. Econometric estimation results for startup ecosystems' macroeconomic impact

Table E.1. Econometric models of V index on labour productivity

Dependent variable	**Without interactions**				**With Baltic region interactions**		
	Independent variables	**Estimate (SE), FE**	**Estimate (SE), RE**	**Estimate (SE), OLS**	**VIF, (OLS)**	**Estimate (SE), FE**	**Estimate (SE), RE, TW**
Labour productivity (PRO L)	V index	1.07 (0.54) *	0.96 (0.49).	0.96 (0.41) *	3.08	1.15 (0.54) *	0.98 (0.66)
	V l1	0.00 (0.27)	–0.12 (0.21)	–0.13 (0.43)	3.22	0.01 (0.29)	–0.027 (0.42)
	V l2	–0.03 (0.33)	–0.26 (0.26)	–0.30 (0.42)	3.20	–0.06 (0.34)	0.002 (0.4)
	EMPL	–0.23 (0.32)	–0.08 (0.07)	–0.07 (0.07)	2.80	–0.22 (0.34)	–0.17 (0.5)
	GDP GR	0.31 (0.09) ***	0.41 (0.09) ***	0.43 (0.10) ***	1.06	0.33 (0.09) ***	0.30 (0.18).
	V index: Baltic					–4.64 (0.54) ***	–5.51 (1.04) ***
	V l1: Baltic					0.59 (0.29) *	0.97 (1.45)
	V l2: Baltic					–0.18 (0.34)	–0.35 (0.88)
	EMPL: Baltic					0.14 (0.34)	0.31 (0.46)
	GDP GR: Baltic					–0.37 (0.09) ***	–0.35 (0.17) *
	Intercept		4.74 (3.20)	4.28 (3.09)			
	R–squared	0.08	0.10	0.11		0.09	0.05
	F stat	3.19	24.81	5.4		1.79	0.92
	p–value	0.01	0.03	0.03		0.06	0.51
	N=219, T=9–10, n=22; Hausman test, p–value=0.09; Wooldridge test, p–value=0.01						

Note: Cluster–robust (HC1) standard errors clustered at the country (panel) level. Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; . $p < 0.10$

Table E.2. Econometric models of V index on capital productivity

Dependent variable	Without interactions				With Baltic region interactions		
	Independent variables	**Estimate (SE), FE**	**Estimate (SE), RE**	**Estimate (SE), OLS**	**VIF**	**Estimate (SE), FE**	**Estimate (SE), TW**
Capital productivity (PRO C)	V index	0.88 (0.94)	13.76 (3.49)	–0.37 (0.98)	5.25	1.23 (1.06)	0.80 (1.13)
	V l1	1.82 (1.77)	–0.45 (0.88)	0.51 (1.02)	5.97	1.79 (0.98).	1.93 (1.00).
	V l2	1.50 (0.7).	0.89 (1.32)	0.28 (0.96)	4.95	1.52 (1.02)	2.39 (1.11) *
	EMPL	2.19 (1.06) *	0.204 (0.54) **	–0.29 (0.13) *	2.83	2.35 (0.60) ***	3.22 (0.96) **
	BERD	–39.09 (20.62).	–0.24 (0.08) ***	–2.17 (7.86)	1.92	0.63 (0.14) ***	0.87 (0.25) ***
	GDP GR	0.62 (0.19) **	–4.89 (8.08)	0.42 (0.14) **	1.03	–40.32 (12.79) **	–46.97 (13.69) ***
	V index: Baltic					2.83 (15.94)	7.93 (16.25)
	V l1: Baltic					–0.57 (7.45)	4.38 (7.68)
	V l2: Baltic					16.89 (26.64)	20.30 (27.23)
	EMPL: Baltic					–9.67 (13.21)	–13.45 (13.48)
	GDP GR: Baltic					–1.59 (2.42)	–1.89 (2.45)
	BERD: Baltic					145.02 (199.51)	146.81 (203.79)
	Intercept		13.76 (3.49) ***	15.16 (4.95) **			
	R–squared	0.32	0.14	0.17		0.34	0.30
	F stat	7.92	18.74	3.96		4.1	3.03
	p–value	0.00	0.00	0.00		0.00	0.00
	N=126, T=4–9, n=19; Hausman test, p–value=0.71; Wooldridge test, p–value=0.51						

Note: Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.10

Table E.3. Econometric models of the V index on high–tech export

Dependent variable	**Without interactions**				**With Baltic region interactions**		
	Independent variables	**Estimate (SE), FE**	**Estimate (SE), RE**	**Estimate (SE), OLS**	**VIF**	**Estimate (SE), FE**	**Estimate (SE), TW**
Hitech export (HT EXP)	V index	0.17 (0.27)	0.17 (0.27)	–0.35 (0.57)	5.15	0.19 (0.30)	0.06 (0.27)
	V l1	0.15 (0.28)	0.11 (0.26)	–0.92 (0.56)	5.80	0.46 (0.47)	0.35 (0.49)
	V l2	0.24 (0.07) **	0.22 (0.08) **	0.98 (0.49).	4.69	0.19 (0.21)	0.19 (0.21)
	BERD	10.4 (6.1).	9.53 (6.07)	–4.45 (7.02)	1.65	10.19 (6.89)	7.55 (8.13)
	ICT EX	–0.01 (0.02)	0.02 (0.03)	0.17 (0.07) *	1.58	0.01 (0.03)	–0.003 (0.026)
	Intercept		9.32 (2.12) ***	5.95 (2.36) *			
	V index: Baltic					0.74 (0.30) *	0.81 (0.57)
	V l1: Baltic					–0.43 (0.47)	–0.25 (0.41)
	V l2: Baltic					–1.57 (0.21) ***	–1.21 (0.99)
	ICT EX: Baltic					0.01 (0.03)	–0.04 (0.04)
	BERD: Baltic					–32.52 (6.89) ***	–26.73(8.38) **
	R–squared	0.20	0.20	0.19		0.28	0.14
	F stat	155.90	151.77	4.63		3.03	1.14
	p–value	0.00	0.00	0.00		0.00	0.34
	N=105, T=3–7, n=19; Hausman test, p–value=0.91; Wooldridge test, p–value=0.00						

Note: Cluster–robust (HC1) standard errors clustered at the country (panel) level. Significance levels: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table E.4. Econometric models of the V index on business R&D

Dependent variable	**Without interactions**				**With the Baltic region interactions**		
	Independent variables	**Estimate (SE), FE**	**Estimate (SE), RE**	**Estimate (SE), OLS**	**VIF**	**Estimate (SE), FE**	**Estimate (SE), FE. TW**
Innovation (BERD	V index	0.03 (0.02) *	0.03 (0.01) *	0.02 (0.01).	5.11	0.03 (0.02).	0.02 (0.01)
	V l1	0.01 (0.02)	0.01 (0.01)	0.00 (0.01)	5.64	0.02 (0.01) **	0.01 (0.01)
	V l2	0.02 (0.01) ***	0.02 (0.01) **	0.01 (0.01)	5.01	0.01 (0.02)	0.01 (0.01)
	HC	0.00 (0.00)	0 (0.00)	0.00 (0.00).	2.29	0.00 (0.00)	–0.00 (0.00)
	PUB_CON	0 (0) *	0 (0)	0 (0)	1.21	0 (0) *	0 (0)
	V index: Baltic					0.01 (0.02)	0.03 (0.01) *
	V l1: Baltic					0.04 (0.01) ***	0.08 (0.02) ***
	V l2: Baltic					–0.11 (0.02) ***	–0.19 (0.06) **
	HC: Baltic					–0.02 (0.00) ***	–0.03 (0.01) ***
	PUB CON: Baltic					0.00 (0) ***	–0.00 (0.00)
	(Intercept)		0.17 (0.08) *	0.12 (0.05) *			
	R2	0.29	0.30	0.44		0.29	0.12
	F stat	8.42	47.5	19.21		4.1	1.275
	p–value	0.00	0.00	0.00		0.00	0.26
	N=129, T=3–7, n=19; Hausman test, p–value=0.09; Wooldridge test, p–value=0.00						

Note: Cluster–robust (HC1) standard errors clustered at the country (panel) level. Significance levels: *** p < 0.001; ** p < 0.01; * p < 0.05; . p < 0.10

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