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VC

The
VC
factor

INVEST EUROPE #BelieveInSmall

Data-driven insights about
VC-backed start-ups in Europe

Foreword

Invest Europe

Éric de Montgolfier
CEO, Invest Europe

Julien Krantz
**Research Director,
Invest Europe**

Venture capital is a crucial and growing part of Europe's investment ecosystem, contributing to innovation, jobs and growth across the continent. For Invest Europe, the voice of the private equity and venture capital industry, it has been a privilege to cooperate with the European Investment Fund (EIF) on the production of The VC Factor report.

Providing authoritative data is a core function of Invest Europe. Our research helps demonstrate the reach and influence of venture capital in Europe, educating and informing policymakers, press, entrepreneurs and the public at large. As the source of the most comprehensive activity data on European VC, we are delighted to have collaborated with the EIF, the largest investor in European VC funds. The VC Factor is the result of an ambitious research initiative by the EIF – it increases the body of knowledge and provides new data-driven insights into VC's impact on start-ups.

The report's findings do recognise that not all start-ups survive, nor are those that survive as successful as their founders might have hoped. However, it also shows that high-achieving start-ups can grow further and faster with VC support, boosting jobs, innovation, assets and sales growth. Furthermore, it provides evidence that VC backing helps more companies to succeed while limiting the failure of others. In short, VC investment and expertise is an essential part of the recipe for start-up success.

Today, the industry is going through a golden age, helping create world-leading companies in Europe like music streaming service Spotify and Dutch payments processor Adyen. These successes are attracting increased investor interest, which in turn helped VC raise and invest record levels of capital in 2018. The EIF has played a central role in supporting European VC funds over the last 25 years. The VC Factor underpins that track record of support by offering a clear picture of VC's positive impact on some of the continent's most dynamic companies.

European Investment Fund

Pier Luigi Gilibert
Chief Executive,
EIF

Helmut Kraemer-Eis
Head of EIF's Research
& Market Analysis,
Chief Economist, EIF

The core mission of the European Investment Fund (EIF) is to reduce barriers for small and medium-sized enterprises (SMEs) that wish to access financing. By developing and offering targeted products to a number of different financial intermediaries, the EIF enhances SMEs' access to finance in all four corners of Europe. To achieve this, the EIF partners with entities such as banks, guarantee and leasing companies, micro-credit providers, diversified debt funds, crowdfunding platforms, venture capital and private equity funds.

Through its pan-European venture capital (VC) activity, the EIF supports the formation of a resilient VC ecosystem and the emergence of new European VC hubs. Taking cornerstone investments in VC funds – as the EIF has been doing over the last 25 years – translates into vital support to small businesses with a high innovative and growth potential, which further enhances the attractiveness of European venture capital as an alternative asset class.

However, the EIF's prominent role in the European VC ecosystem is not only the result of its significant investment volumes. It is also due to the measureable economic effects of its public policy mission. Through its publications and rigorous research, the EIF strives to support an informed policy debate about the merits of public intervention in the European VC market.

Fortunately, the EIF is not alone in its efforts to shed light on a historically opaque industry. This study, a cooperation between Invest Europe and the EIF, is an example of the two institutions' unity of purpose when it comes to analysing the impact of VC investments on economic growth. Invest Europe's authoritative data and market overview paired with the EIF's expertise in the field of SME performance analysis and economic impact assessment offers an almost unique opportunity. In this setting, numerous and long-standing wisdoms about venture capital in Europe can now be proofed against data-driven insights.

The assessment of the economic effects of its policy instruments will continue to be a key long-term commitment for the EIF. Through data-driven analyses and transparent communication, the EIF will pursue its ambition to assess thoroughly the impact of its activities, thus supporting a flourishing financing market for SMEs in Europe. Not only in this context, we look forward to continuing our fruitful cooperation with Invest Europe.

The VC factor
in a nutshell

European venture capital (VC) investments are reaching a new all-time high. In the last decade alone, around EUR 51bn was directed to innovative start-ups in Europe, while VC fundraising has overcome pre-crisis levels. The European Union (EU) venture capital industry is thriving, but what has happened to investees? What, exactly, is VC's role in the growth of the companies it has financed?

This report is the first large-scale study of EU-based start-ups backed by VC. The novelty is twofold: first, we link invested businesses with their specific financial outcomes and second, we cover the entire EU market. We look at almost 9,000 European firms invested in 2007-15 and analyse their characteristics as well as subsequent performance. In order to study firms' financial growth we need to allow for some time after the investment, which is why our analysis stops after 2015.

Where did investments go? The European VC market is mostly concentrated, with the six largest hubs receiving one third of all investment activity. However, new emerging hubs are shaking up the status-quo. Interestingly, 40% of the financed start-ups are located in cities with more than a million inhabitants while, at the other extreme, 25% operate in smaller cities, with a population of less than 100,000.

By zooming further into VC-financed start-ups, we try to identify other commonalities. Is there a typical European start-up and what does it look like? We find that companies operating in the Nordics region are the most innovative with respect to both their patenting activity and intangible assets. We also discover that early-stage companies are more innovative than their later-stage peers and what is more, they grow faster in terms of revenue and total assets. Our efforts to identify the stereotypical European start-up prove rather futile – there is simply too much variation in the growth patterns.

This is why we need to bring in the heavy statistical artillery. We employ cluster analysis to evaluate and group VC-backed firms according to their four-year growth rates in five financial indicators - revenue, staff numbers, assets, intangibles and costs. Our results show that the 93% of start-ups, which did not default by their fourth year, can be sorted in five distinct profiles – laggards (3%), commoners (56%), all-rounders (19%), visionaries (7%) and superstars (8%). What characteristics define these profiles?

Laggard companies are the slackers, so to say, but luckily they are few and far between. In four years, their financial performance drops to levels lower than those they initially started with. Then come the commoners – nothing too

exciting about them (as the name may suggest), though they grow, especially in revenue (20%) and costs (11%). The all-rounders are definitely worth your attention, with great performance across the board and growth rates ranging from 39% for intangibles to 141% for revenue. However, visionaries and superstars are the headliners in this show. Visionaries progress soundly in all indicators but intangibles where their growth simply skyrockets with an impressive 534%. Superstars not only grow remarkably in turnover (358%), but also record the highest growth rates across all the rest of the indicators, with the exception of intangibles, where visionaries remain on the top.

After identifying the companies which will give you the most bang for your buck, we take it a step further. To determine the true impact of VC on start-ups' growth, we construct a comparable group of firms (the so-called counterfactual group), which could have received VC financing, but did not. To start off, this analysis reveals that VC-backed start-ups grew faster in total assets during the six years after investment and consistently recorded a higher share of intangible assets than their non-VC-backed counterparts, highlighting VC's role in spurring innovation.

By applying our clustering model to non-VC-invested start-ups, we notice that the same five profiles emerge. However, in the absence of VC, there would be more than four times the number of laggards. This already provides some evidence for the merits of VC financing in uplifting some start-ups to more promising growth trajectories.

"VC-backed profiles, apart from laggards, grew considerably more than their non-VC counterparts, in every financial measure."

We also look at the differences between VC and non-VC-backed start-ups in terms of their financial growth rates. VC-backed profiles, apart from laggards, grew considerably more than their non-VC counterparts, in every financial measure. For one, all-rounders recorded 118 percentage points (pp) higher turnover and 36 pp higher costs. In the visionary and superstar clusters, VC-backed start-ups beat their counterparts in intangibles growth by an impressive 331 pp and 190 pp respectively. This proves that VC's role in the development of start-ups is substantial.

"Almost half of high growth start-ups would have fallen into a much less successful profile or defaulted without VC."

Finally, we use the group of comparable non-VC-backed firms to construct a "what if" scenario, revealing where VC-backed start-ups would have ended up had they not received the investment. Almost half of high-growth start-ups (the all-rounders, visionaries and superstars) would have fallen into a much less successful profile or defaulted without VC. In a nutshell: when an entrepreneurial idea has a high potential for success, the "VC factor" expands opportunities for growth and allows excelling start-ups to unleash their full potential.

Table of contents

Chapter 1

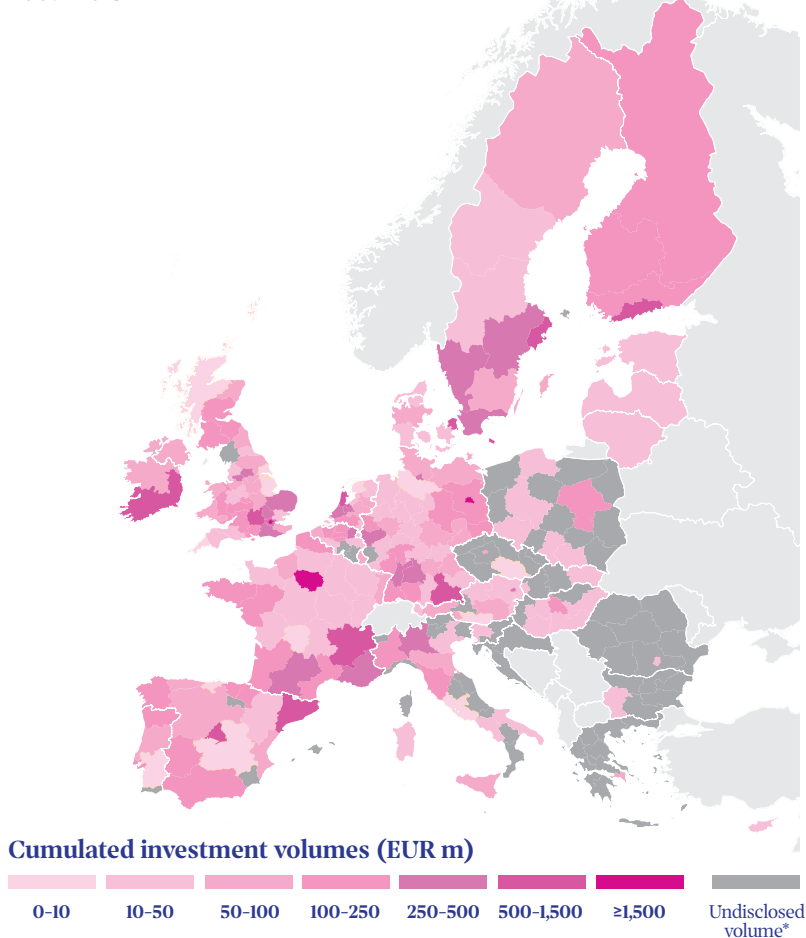# The European VC ecosystem at a glance

What does the last decade of VC investing in Europe reveal?

We are used to the European venture capital (VC) industry making headlines. Investments in innovative start-ups are rampant, on course to reach a new all-time high.[1] From 2007 to 2015, investors poured about EUR 35bn into early and later-stage start-ups located in the 28 EU countries.[2,3]

Where did all this money go? Mostly into a handful of places: out of the 272 sub-national regions in Europe targeted by VC investors, the largest six made up one third of all investment activity (in comparison, two thirds of the total activity took place in 31 regions instead). ▶

The start-up ecosystem in Europe remains heavily concentrated. However, seven new regions have replaced others in the top 20 ranking by investment volumes since 2007. All in all, emerging hubs have started to shake up the status quo.

Regional distribution of venture capital activity
2007–2015

Cumulated investment volumes (EUR m)

| 0–10 | 10–50 | 50–100 | 100–250 | 250–500 | 500–1,500 | ≥1,500 | Undisclosed volume* |

*Regions with less than five recorded investments in the years 2007-2015 not shown.

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[1] See, for instance, Kraemer-Eis et al. (2019).
[2] We group EU28 countries as follows: British Isles (United Kingdom, Ireland); Central and Eastern Europe, CEE (Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia); DACH (Austria, Germany); France and Benelux (Belgium, France, Luxembourg, The Netherlands); Mediterranean countries (Greece, Italy, Malta, Portugal, Spain); Nordics (Denmark, Finland, Sweden).
[3] The cumulated investment volumes in the years 2007-2018 were downward of EUR 51 bn.

Top NUTS[a] regions by received VC volumes
2007-2015

Rank	1	2	3	4	5	6
Country	France	UK	Germany	Sweden	Germany	UK
Region	Île-de-France	Inner London	Berlin	Stockholm	Upper Bavaria	Berkshire, Buckinghamshire and Oxfordshire
Reference Hub/s[b]	Paris	London	Berlin	Stockholm	Munich	Reading, Abingdon and Oxford
Total received investments (EUR m)	3,127	2,801	1,683	1,388	1,358	912

[a]Nomenclature of Territorial Units for Statistics. [b]Most frequent location of start-ups invested in the region.

> " Emerging hubs have started to shake up the status quo. "

Fastest growing NUTS regions
2007-2015

Rank	1	2	3	4	5
Country	Germany	Spain	UK	Austria	Belgium
Reference Hub/s	Berlin	Barcelona	Leeds	Vienna	Louvain-la-Neuve
Share of total received investments in 2015 (vs. share in 2007-2008)	8.0% vs. 2.4%	3.2% vs. 0.7%	2.8% vs. 0.6%	1.8% vs. 0.7%	1.1% vs. 0.1%

What does this mean for the typical start-up? The average amount received in an initial VC round was EUR 1.45m, but due to the high variation, this number doesn't apply to most start-ups. Availability of capital and investment preferences in the region play an important role: ventures in the France and Benelux region secured on average 40% more funding than those in the Nordics and Germany and Austria (DACH) regions. Meanwhile, start-ups in the British Isles received a 25% higher average investment than France and Benelux.

Interestingly, start-ups in the Central and Eastern European (CEE) and Mediterranean countries received the highest average investment volume. This result is likely driven by the smaller size of the VC industry in these regions, which reduces the opportunities to create well-diversified portfolios.

Number of VC-backed start-ups by stage
2007-2015

Later
stage

Start-up

Seed

2007	2008	2009	2010	2011	2012	2013	2014	2015
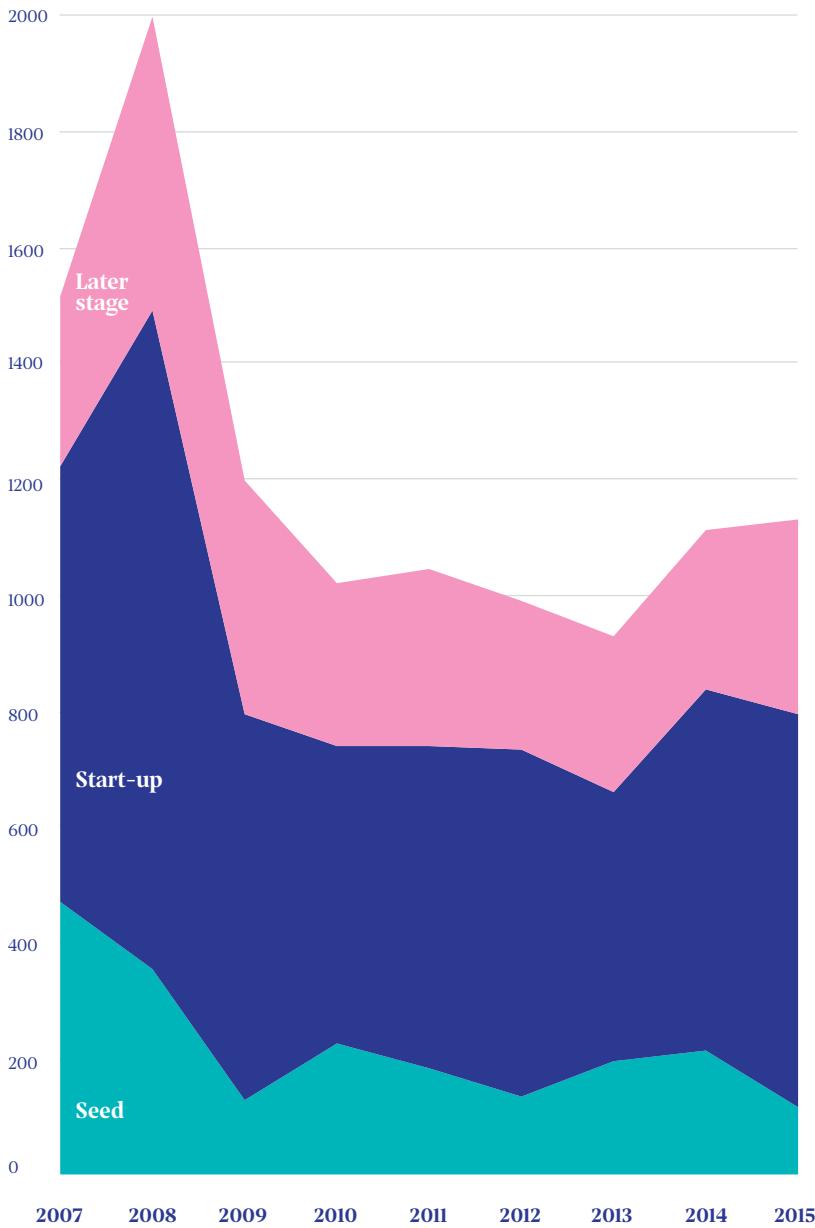
Aside from geography, the amount of money a start-up will receive is also shaped by its stage and industry. It is no surprise that later-stage ventures tend to receive significantly more money than seed and start-up firms. Similarly, the life sciences industry's strong needs for capital translate into larger investment rounds than information and communications technology (ICT), which in turn gets about as much money as manufacturing or green technologies on average. Meanwhile, the services industry[4] records the smallest average amounts.

The European start-up scene might very well be at its most vibrant, but the road to prosperity hasn't exactly been smooth. After rising from the ashes brought by the dot-com crash, the European VC industry suffered another crunch following the 2007 financial crisis. The crisis severely affected the VC market with both the number of invested start-ups as well as total activity volumes decreasing. The data shows that VC investments peaked in 2008 before a decline, which reversed only in 2014.
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The EU start-up scene might be at its most vibrant, but the road to prosperity hasn't been smooth. "

[4] This is a collection of service-oriented industries such as consumer and business services, financial services and transportation.

The downturn affected all VC financing stages, although later-stage investments suffered somewhat more, decreasing by 46% from 2008 to 2014. Investments in the start-up stage (a type of early-stage investment) represented more than half of total investment between 2007 and 2015.

> ❝
> # In the aftermath of the crisis, the average VC round fell by almost 50% in volume. ❞

In the aftermath of the crisis, the average VC round fell by almost 50% in volume compared to the pre-crisis levels in 2007. As a result, the median VC-backed company has shrunk in size. This could be a reflection of VC firms reverting to earlier stage investment opportunities, due to a lack of follow-on opportunities induced by the financial crisis itself.

As the effects of the financial crisis started to subside, there has been a reversed upward trend in VC financing. The average VC investment round since 2013 has been in line with pre-crisis figures. Overall, the industry picked up pace again, with total number of invested companies continuing to increase.

The Data

We analysed a sample of 8,960 EU start-ups, which received for the first time an early/later stage VC investment during 2007-15. Our dataset is the result of a partnership between EIF and Invest Europe. For financial and industry activity data, we used Bureau Van Dijk's Orbis database.

We aggregated countries and sectors into macro-regions and macro-sectors.[5] We weighed the sample according to the total population[6] of invested firms for better result representation. See Appendix A for the details of our methodology. Furthermore, to ensure comparability over time, all monetary amounts in the report are expressed in 2010 Euro.

8,960

European start-ups analysed

VC investment stages and scope[7]

1   **Seed**

Before mass production/ distribution has started with the aim to complete research, product definition or design, also including market tests and creating prototypes.

2   **Start-up**

Once the product or service is fully developed, to start mass production/distribution and to cover initial marketing. Companies may be in the process of being set up or may have been in business for a shorter time, but have not sold their product commercially yet.

Seed and start-up stages can also be combined under the collective term early-stage investment.

3   **Later stage**

Targeting operating companies, which may or may not be profitable and which are likely to have already been VC-backed.

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[5] A table of correspondence from sectors and countries to macro-sector and macro-region respectively can be found in Appendix A.
[6] Population figures are taken from Invest Europe's internal database.
[7] Detailed investment stage definitions can be found in Appendix A.

Is there a "typical" European VC-backed start-up?

Two thirds of European VC-backed start-ups operated in the ICT and services sectors from 2007 to 2015. This was the case in most geographic regions, with the British Isles exhibiting the highest share of ICT start-ups (50%). The Nordics region boasted the highest share of life sciences firms, representing 28% of total investment, distinctly higher than the European average of 17%. ▶

> ## ICT is the sector with most VC-backed firms.

Later-stage investments focused more on the manufacturing and services sectors,[8] where companies are usually more likely to look for funds to expand their business rather than set it up. In all other industries, the general trend was maintained, with early-stage investments taking the lion's share of overall activity. ▼

Share of VC-backed start-ups by sector
2007–2015
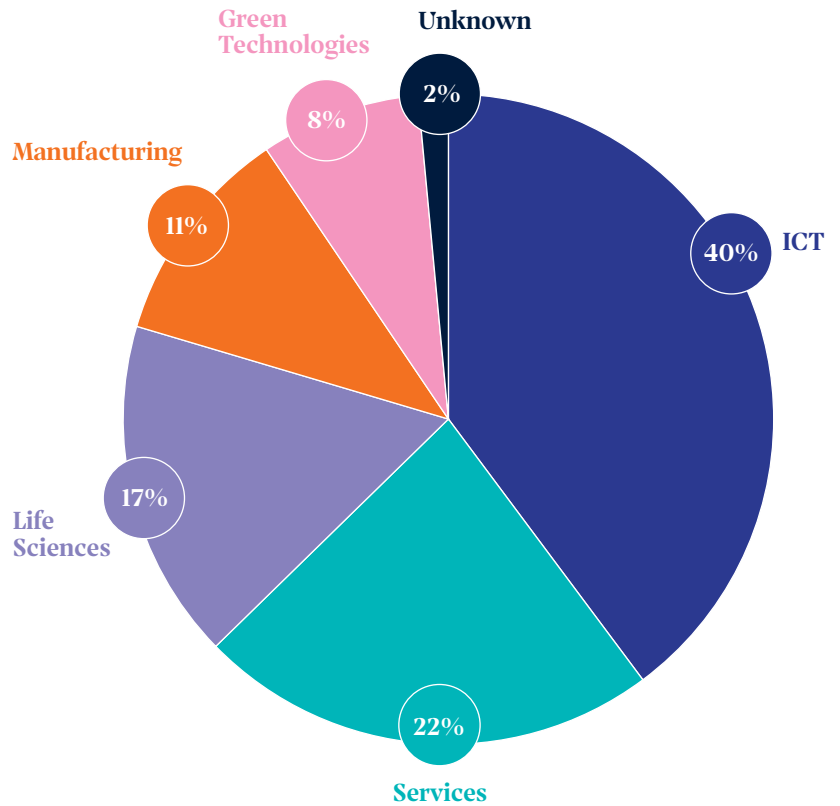
Share of VC-backed start-ups by stage and sector
2007–2015
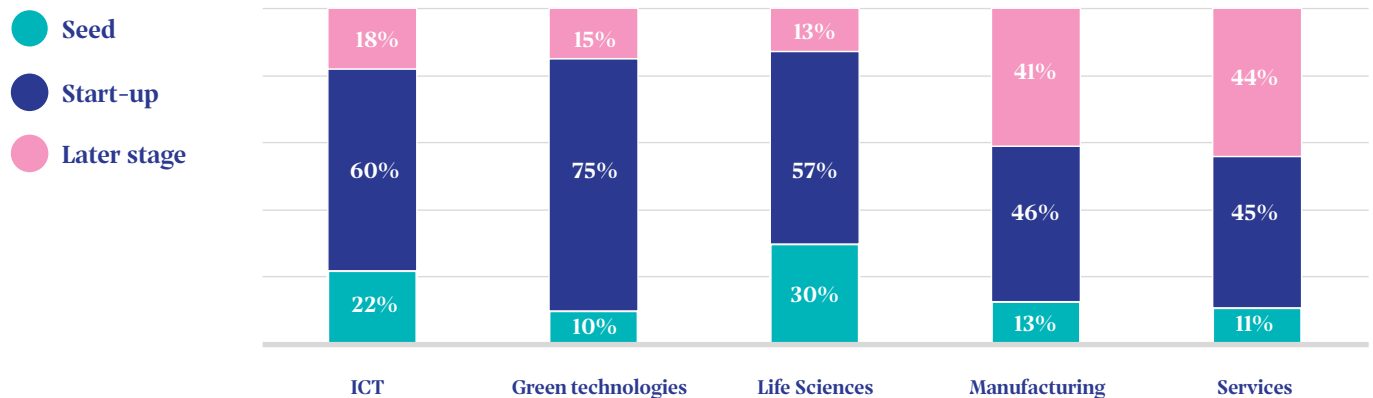
[8] This is also the case for companies without sector affiliation, categorised as "Unknown", however the size of this class is negligible.

The highest concentration of investees was recorded in the DACH and France and Benelux regions, 33% and 22% of total companies invested during the observed period, respectively. Throughout this time, the CEE and France and Benelux regions increased their share of overall new investments, while the relative importance of DACH and the Nordics decreased.

Looking at investment amounts, however, paints a slightly different picture. In this case, France and Benelux together with British Isles top the list, hosting around a quarter of total invested volumes each while DACH arrives third with 21.9%. The geographic disparity between investment totals and invested firms is likely a result of Invest Europe's better coverage of VC-backed companies in the DACH region.[9] ▶

European VC activity does not only take place in VC hubs. VC-backed start-ups are, in fact, spread all over Europe. Around 40% of start-ups are located in cities with more than one million inhabitants, whereas one quarter operate in small urban areas with a population of less than 100,000. ▶

Since 2011, a higher number of VC-financed firms has set up business in large urban areas, mostly at the expense of start-ups established in smaller cities. This development is driven by the two leading sectors, ICT and services, where companies are more likely to benefit from economies of agglomeration (e.g. larger consumer and workforce base).

Share of VC investment amount by region
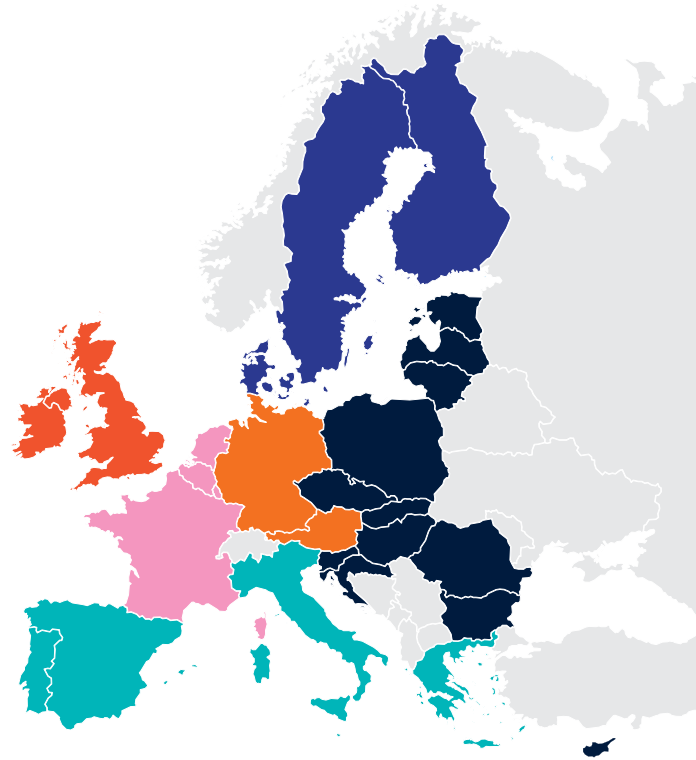2007–2015

25.5%
France & Benelux

25.3%
British Isles
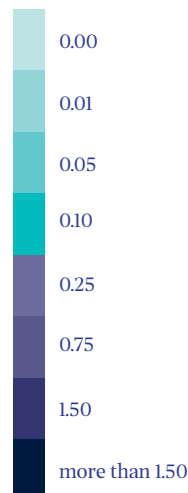
21.9%
DACH

13.2%
Nordics

11.4%
Mediterranean

2.7%
CEE

Concentration of VC-backed start-ups across Europe
2007–2015

No. of start-ups per km²

	0.00
	0.01
	0.05
	0.10
	0.25
	0.75
	1.50
	more than 1.50

[9] This might also be a reason for the relatively smaller average investment amount observed in the DACH region.

How do we track innovation?

We used two measures. First, the share of intangible fixed assets, which is a broad measure including R&D expenses, patents and trademarks. Second, the number of patents submitted to the relevant patenting authority, which is a narrower, but formally more suitable, indication of innovation.

Anatomy of a start-up at the time of investment[10]

In the end, there might be no 'typical' European start-up, but our research has uncovered a few interesting patterns. Companies in the British Isles, for example, record the highest number of employees at investment date, even at a very young stage - 48 employees against an average of 22 for the rest of the regions.

Nordic companies have the highest number of patents and the highest share of intangible assets, both indicators of high levels of innovation. On average, Nordic companies have one patent each, and boast the highest share of intangible assets (29% against an overall average of 15%). Yet, they rank among the worst in terms of operating revenue at the time of investment. This feature is also shared by Mediterranean start-ups, although these companies rank much worse in average number of patents.

On the other hand, France and Benelux and DACH companies record higher levels of operating revenue and, together with Mediterranean start-ups, marginally higher levels of total assets. ▶

" Nordic companies prove to be among the most innovative in Europe. "

Median operating revenue at time of investment by region

in thousands EUR

431 — **British Isles**
min. 148 / max. 715

757 — **France & Benelux**
min. 377 / max. 1136

85 — **CEE**
min. 33 / max. 137

812 — **DACH**
min. 614 / max. 1010

123 — **Nordics**
min. 92 / max. 153

98 — **Mediterranean**
min. 64 / max. 132

[10]Results reported are at year of investment. Firms with missing data at year of investment are omitted from the analysis. Sample is reweighed for each variable due to different missing patterns.

Seed and start-up stage businesses recorded the highest number of patents[11] and share of intangible assets – both indicators of high levels of innovation - issuing on average 90% more patents than later-stage businesses. Although this suggests that the early, rather than later, stage of a business's life cycle is particularly innovative, later-stage firms have other means to signal their potential to venture capitalists (e.g. financial growth) thus they might be less incentivised to engage in high levels of patenting.
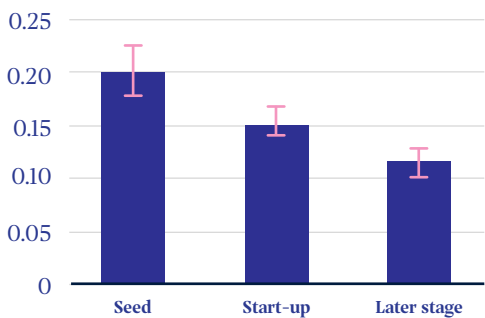
▼

Patenting rate at time of investment by stage
2007-2015
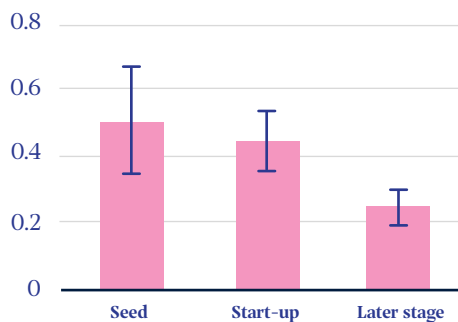
Share of intangible assets as a proportion of total assets at time of investment by stage
2007-2015

⊥ **95% confidence interval**

Start-up story
Octo telematics

Octo Telematics is an Italian company providing usage-based services, stolen vehicle recovery and crash management diagnostics to car insurance companies. It also offers road charging services and real-time traffic monitoring for fleet management and car rental companies as well as public bodies.

The support of venture capital allowed Octo to become independent following its spin-off from the Italian Meta System Group. The investors helped with strategic hires necessary for Octo's development as well as with the optimisation of its supply-chain: for example, the company diversified its supply sources for the manufacture of on-board box units. VC also accelerated Octo's international expansion across Italy, UK, Spain and the US and helped with enlarging its product range through acquisition targets. The company's sales grew by 27% annually while profits increased by 235% over four years following the VC financing. With a European market share of over 80% and an expanded service range, Octo was acquired by Renova in April 2014.

Later vs Early

Later-stage start-ups are on average seven years older than early-stage companies.

Later-stage firms have on average 66 more employees than their younger counterparts.

Later-stages are also larger in terms of turnover (7 times larger with respect to early stage) and total assets (3 times larger).

7
years older

66
more employees

3x
more assets

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[11]Only 25% of the sample's companies have at least one patent at investment date, resulting in an overall average number of patents per company below one.

When it comes to start-up performance across industries, there are only a handful of noteworthy differences. Manufacturing and services firms boasted the highest revenue and staff levels at the time of investment, partly due to their higher rate of later-stage ventures. Start-ups in the ICT sector required relatively modest levels of assets to kick-start their business.

Life sciences companies were the champions in patented innovations, followed by firms in the manufacturing sector. This is driven by the vastly different incentives to patenting across industries, as testified by the much more nuanced picture drawn by the share of intangibles at the date of investment. Here, no sector clearly overshadowed the others, while ICT start-ups are on par with life sciences businesses, slightly topping the rest.

▼

Start-up story
Beddit

Beddit is a Finnish start-up offering a sleep tracker with a cutting-edge technology to monitor sleep quality, heart rate and breathing without any disturbing wearable sensors. It is an ultra-thin sensor placed under the bed sheet instead, which transmits a detailed sleep analysis wirelessly to a smartphone. Beddit's data accuracy and patented sleep tracking methodology have been clinically validated and published in peer-reviewed scientific articles. After less than 3 years on the market, Beddit significantly surpassed its sales expectations towards the end of 2015.

An early-stage venture capital fund invested in Beddit after appreciating its cutting edge in technology and innovation as well as its applicability in the everyday life of the average person. Also thanks to that initial VC investment, Beddit currently employs a team of more than 19 enthusiastic developers, scientists, marketers and designers in two offices, located in Helsinki (Finland) and the Silicon Valley (United States).

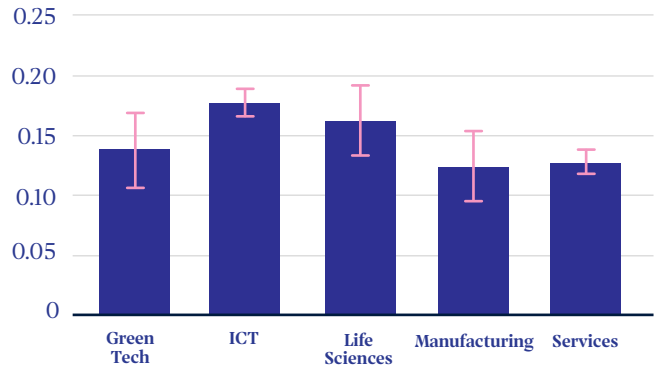## Patenting rate at time of investment by sector
2007-2015
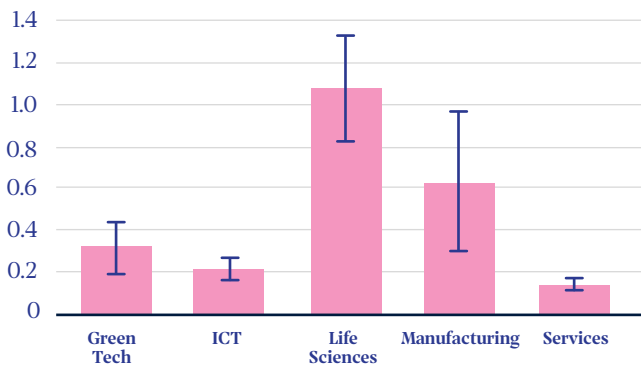
I 95% confidence interval

Share of intangible assets as a proportion of total assets at time of investment by sector
2007-2015

Mind the... missing data

Since we followed companies across time, we restricted our sample to a subset of firms with available data for multiple years. We allowed a company in our sample if at least one data point was available at baseline and in the follow-up period. The baseline is defined as the period one year prior to investment date to one year after, i.e. three years in total. The follow-up is composed of any year after the investment date.

Mind the ... survival bias

We were only able to analyse companies that remained in business at any given moment in time. The further away we move from investment date, a higher number of firms default and only better ones "survive". Average results further away from investment year are, therefore, higher since they exclude firms that went out of business.

What happens a few years after the VC investment?

Most key financial indicators increased over time, with some small differences across sectors. Turnover increased the most in ICT start-ups, while growth in total assets and capital was comparable across industries. Patent activity did not follow an increasing trend but is stable over time, with an average of 0.4 patents generated per year. The share of intangible assets increased following the VC investment but started to decline after a couple of years. Therefore, total assets increased proportionally more than the intangibles.

Early-stage companies grew faster than their later-stage counterparts in all indicators but the share of intangible assets. In general, smaller firms exhibited a higher growth rate since they mainly focused on scaling up their business.

After three years, early-stage firms' sales and staff had grown by 227% and 100% respectively. In comparison, these measures grew by 32% and 30% for later-stage firms.

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High variation in performance trends makes it difficult to identify a "typical" European start-up.

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High variation in performance trends makes it difficult to identify a 'typical' European start-up. We need more powerful analytical tools if we want to dig deeper into the nature of VC-backed start-ups.

Median levels of total assets after investment
2007-2015
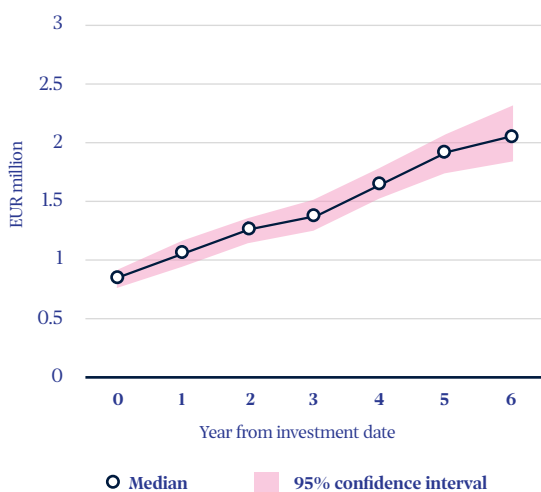
Median levels of operating revenue after investment
2007-2015

○ Median   ▨ 95% confidence interval

Infarm: urban farming (r)evolution

Our food has a long journey to make before it reaches our plate. "Approximately 1500km through 28 pairs of hands," says Martin Weber, CFO of Infarm, a Berlin-based vertical farming company. Fortunately, vertical farming means that it is possible to grow food closer to home, cutting out unnecessary energy waste for transportation and refrigeration, while reducing the need for pesticides and fertilisers.

The impact? The CO_2 footprint of an Infarm-grown lettuce in Berlin is 0.35kg, compared to up to 3.7kg for lettuce imported from abroad.

Chapter 2

Start-up profiles: The Big Five

The cluster analysis suggests that there are five different kinds of European start-ups, some more prevalent than others. Named after their growth pattern, we find laggards, commoners, all-rounders, visionaries and superstars. Can you guess which one will get you the most bang for your buck? To find out, let's have a look at each profile and their characteristics in the rest of the chapter.

Defaulted	Laggards	Commoners	All-rounders	Visionaries	Superstars
7%	3%	56%	19%	7%	8%
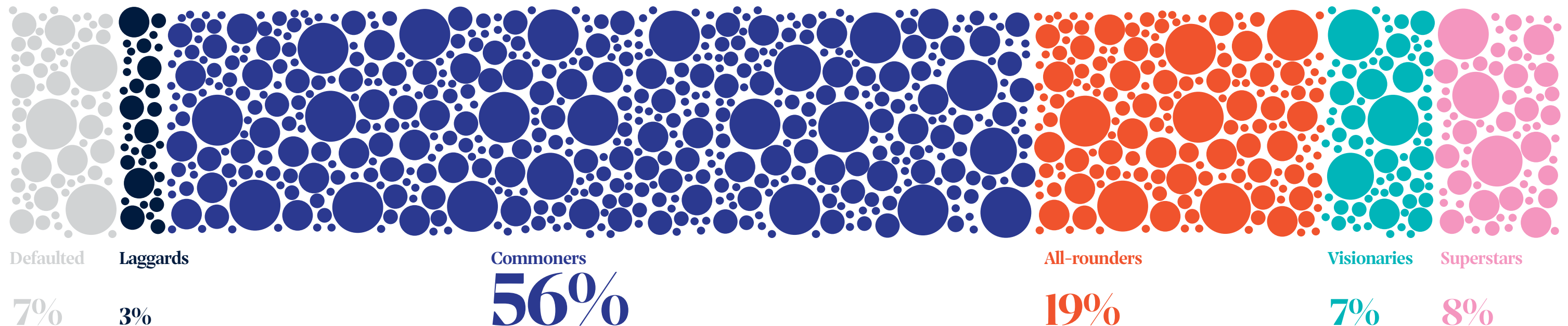
Is there another way to look at start-up growth?

VC-backed start-ups operate in a number of diverse sectors, across various geographic locations, and of course, they were a target of VC investments at different stages of their business development. All of this makes the analysis of VC-influenced growth a daunting task. Therefore, we need to step up our game and introduce a more sophisticated statistical approach.

Multidimensional cluster analysis is a convenient analytical tool that groups start-ups according to common performance characteristics. For example, according to number of employees, turnover, total assets, intangible assets and operating costs. One way to define start-up performance based on these measures is the four-year compound annual growth rate (CAGR), starting from investment year. We could classify 93% of firms, that is, those still active in the fourth year after the VC investment. The rest, 7% of all start-ups, had defaulted by this point.

" Five different start-up profiles: laggards, commoners, all-rounders, visionaries and superstars. "

The Data

We analysed 2,283 start-ups invested between 2007 and 2014. We could not observe four-year growth rates for firms financed in 2015, so we omitted them from this particular analysis. For this exercise, we looked at companies still in business four years after the investment, while keeping track of defaulting companies during this time. For surviving firms, we needed two data points – at the time of investment and four years later. To maximise our data coverage, we pooled growth rates by biennia, using earlier period data should the information in the exact year of interest not be available. For instance, with no available data at investment year, we would use either data from one year before or one year following the investment date. Similarly, if data for the post-investment fourth year were missing, we would use information from the third post-investment year instead. We finally weighed our sample to make it representative with respect to the underlying population of EU start-ups.
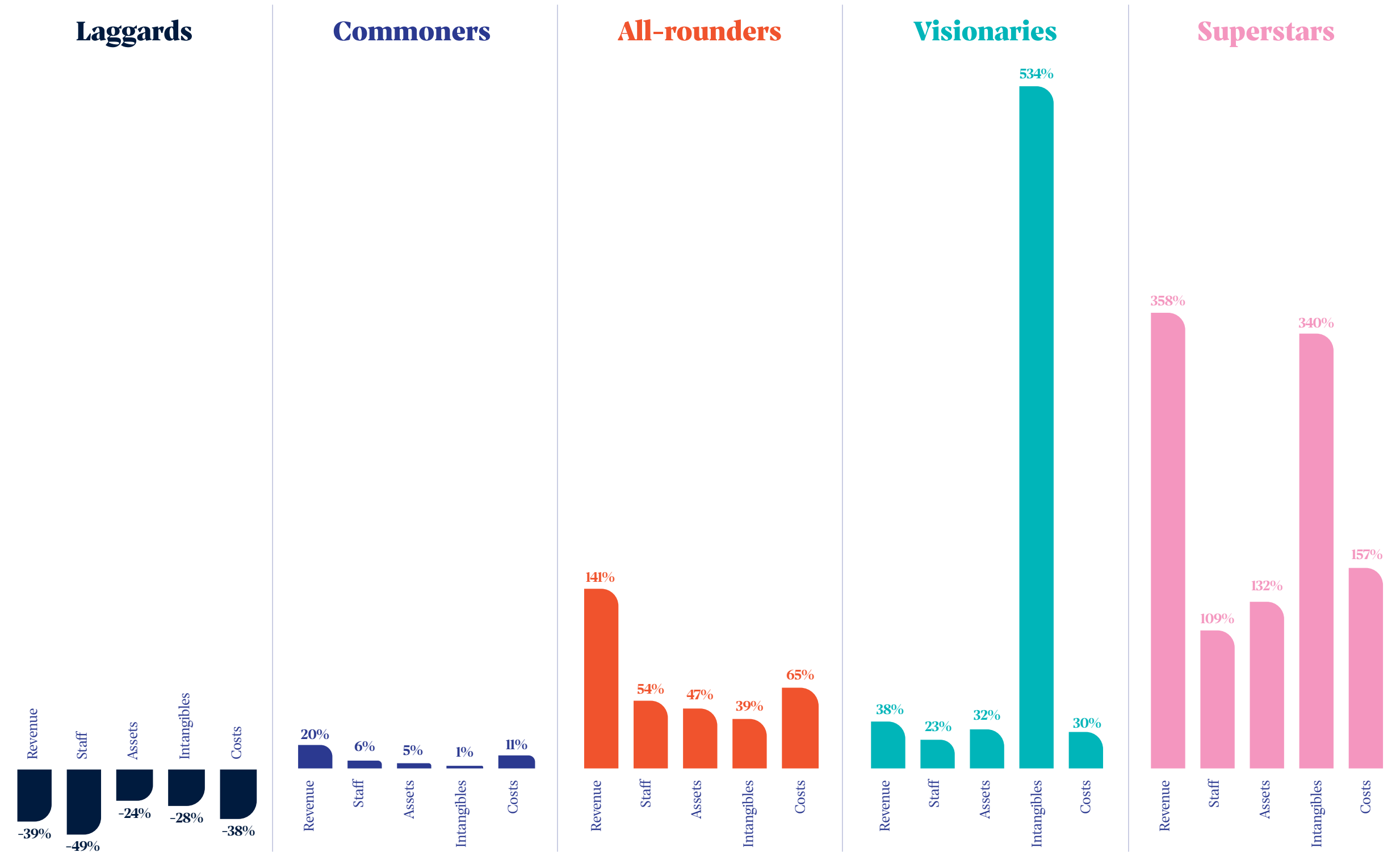
Before we delve into the nitty-gritty of each profile, let's line them up and compare their progress four years after the VC investment. Each profile is characterised by a different pattern of growth across our five key financial metrics. We find that, for example, laggards didn't really advance much, in fact their business contracted. By contrast, the rest of the profiles' growth rates are scattered throughout the positive domain, though with large variations. Just by comparing commoners and superstars, we clearly see why the latter have earned their name. ▶

How do we classify start-ups by growth pattern?

Start-up growth is a complex, multi-faceted process. To study it thoroughly, we must evaluate it across multiple dimensions (turnover growth, staff growth, etc.). The goal of cluster analysis is to combine start-ups in such a way that between groups, companies would differ substantially in terms of growth trends and, at the same time, they would behave rather similarly within a given group. We use a model-based cluster analysis approach, which assumes that our growth rates data is sampled from a finite mixture distribution, i.e. a collection of (hidden) "sub-populations", each characterised by their own multivariate normal distribution. This approach is also called latent class analysis. By the way, how should we measure growth? Our choice to use the CAGR incorporates the view that start-up growth, like many other natural phenomena, should be evaluated on an exponential scale (rather than on the basis of a linear scale). See Appendix B for additional details on our approach.

The five start-up profiles and their average growth rates

Laggards — Revenue -39%, Staff -49%, Assets -24%, Intangibles -28%, Costs -38%

Commoners — Revenue 20%, Staff 6%, Assets 5%, Intangibles 1%, Costs 11%

All-rounders — Revenue 141%, Staff 54%, Assets 47%, Intangibles 39%, Costs 65%

Visionaries — Revenue 38%, Staff 23%, Assets 32%, Intangibles 534%, Costs 30%

Superstars — Revenue 358%, Staff 109%, Assets 132%, Intangibles 340%, Costs 157%
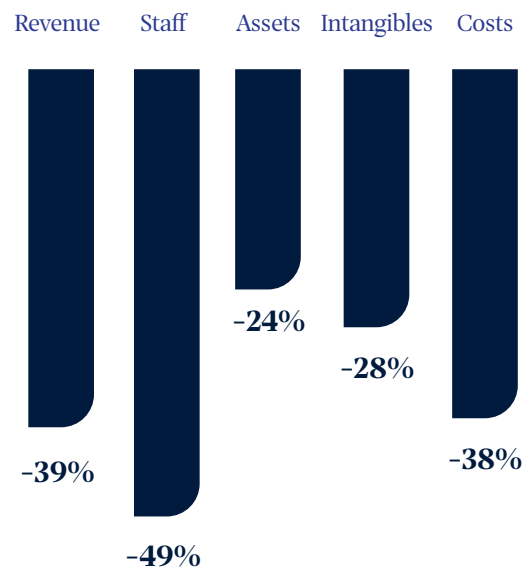
Laggards

"Honey, I shrunk the start-up"

Laggards are the underperforming firms, but fortunately only 3% of start-ups fall into this category, making it the smallest one. Four years after the VC investment, laggards are characterised by negative growth in all financial indicators. They lost half of their staff and about 40% of their turnover. Their intangible assets as well as costs contracted by around a third. Total assets decreased slightly less than the intangibles – by 24%.

Start-ups in the manufacturing sector had a relatively higher probability of underperforming, whereas firms in services stood a lower chance. The laggards group also reveals large regional divergence – DACH firms were less likely to go under, as opposed to those in the British Isles, Benelux, Sweden and Portugal. There were also more underperforming start-ups in the five-to-ten-years-old age group relative to younger or older groups. Proportionally, more laggard firms were invested in 2007 compared to the following years: businesses kick-started immediately before the financial downturn suddenly had to navigate through very rough waters, which may have contributed to their untimely downfall.

Four-year average growth rates

Revenue	Staff	Assets	Intangibles	Costs

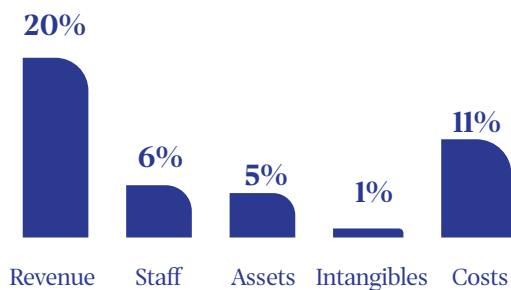-39% -49% -24% -28% -38%

More and less likely to be found in...*

▽ Less than the overall share
▲ More than the overall share
⬜ No strong evidence

*Locations of higher/lower concentration of laggards compared to their overall share.
In places with "No strong evidence", the concentration does not significantly deviate from the overall share in the EU VC ecosystem.

Commoners

Four-year average growth rates

20%

6%

5%

1%

11%

Revenue   Staff   Assets   Intangibles   Costs

More and less likely to be found in...*

▽ Less than the overall share

▲ More than the overall share

▢ No strong evidence

"The good, the bad and the...ordinary"

The commoners group is the most numerous, representing 56% of start-ups, whose growth is best characterised as "mild". Commoner start-ups record positive but sluggish growth rates across all financial indicators. Their workforce increased by 6% while total assets slightly less, by 5%. Turnover recorded the highest growth rate (20%) across all indicators, followed by costs (11%). Commoners are not particularly innovative as evidenced by the intangible assets growth - only 1% on average.

ICT start-ups were the least likely to grow mildly as opposed to firms operating in the services industry, which had the highest probability of following a mild growth trend. Later-stage ventures stood a higher chance of becoming commoners in comparison to seed and start-up firms. Region-wise, firms operating in Germany were relatively more likely to enter this group compared to the rest of Europe. Overall, most commoner start-ups were distributed evenly in the rest of the regions. Young start-ups (two years old or younger at investment date) were the least likely to fall in this profile, while the opposite was true for firms older than five years. Start-ups also had an equal chance of growing mildly across different investment years.
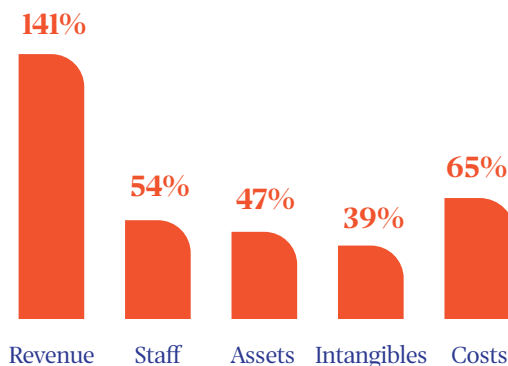
*Locations of higher/lower concentration of commoners compared to their overall share.
In places with "No strong evidence", the concentration does not significantly deviate from the overall share in the EU VC ecosystem.
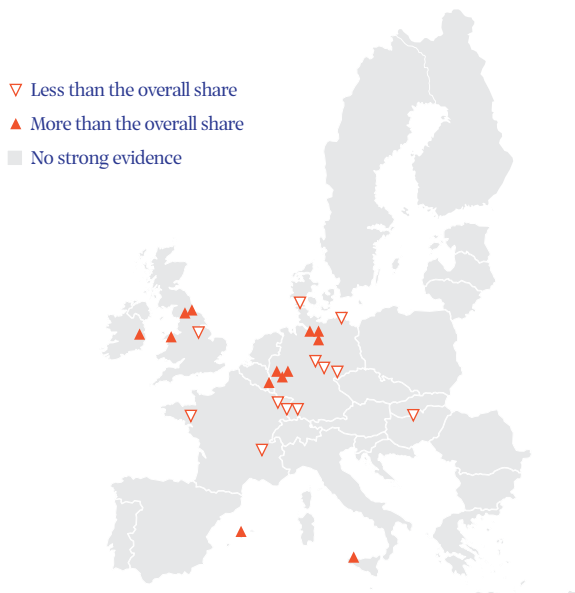
All-rounders

"Eat, pray, grow"

All-rounder start-ups represent 19% of all companies – the second-largest group after the commoners. All-rounders were certainly more innovative than commoners (intangible assets increased by 39%) and what is more, their turnover soared by 141% against an increase in costs by 65%. In the same time, staff as well as total assets grew by around 50%. Therefore, the most fitting way to describe this profile's growth would be "balanced".

Start-ups from different sectors had a comparable probability of ending up in the all-rounders group, with ICT a bit more and services and manufacturing a bit less represented. Later-stage ventures were less likely to fall in this profile in comparison to early-stage ventures. Across regions, start-ups in the British Isles as well as in some areas of Germany, particularly in the northern and western part of the country, had a higher chance of following a balanced growth path. In contrast, firms in other parts of Germany as well as Hungary were less likely to experience balanced growth. With respect to age, there was a greater number of young firms in this profile than older firms, and the probability of investing in all-rounder start-ups increased after 2010.
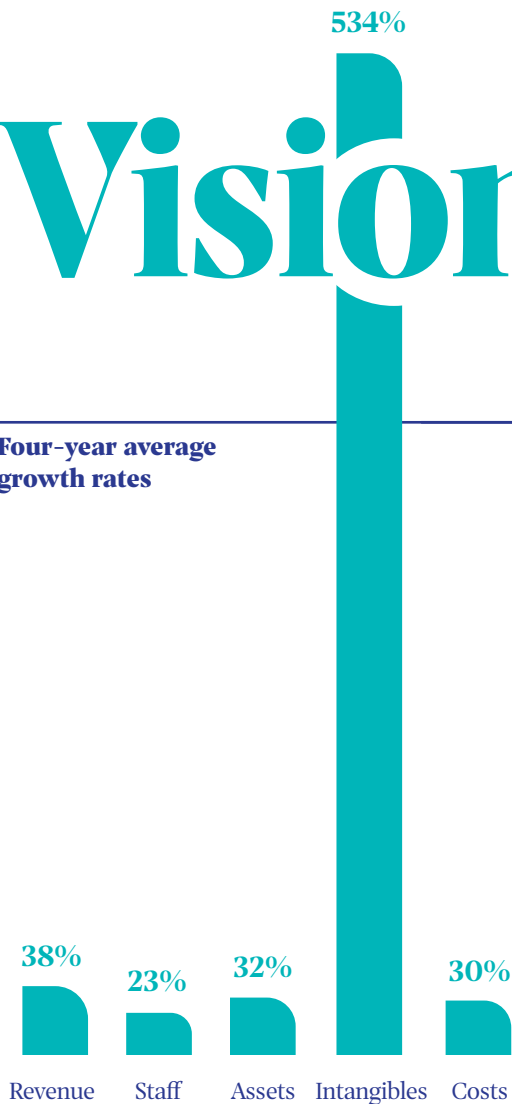
Four-year average growth rates

Revenue	Staff	Assets	Intangibles	Costs
141%	54%	47%	39%	65%

More and less likely to be found in...*

▽ Less than the overall share
▲ More than the overall share
▢ No strong evidence

*Locations of higher/lower concentration of all-rounders compared to their overall share.
In places with "No strong evidence", the concentration does not significantly deviate from the overall share in the EU VC ecosystem.

Visionaries

534%

Four-year average growth rates

38% Revenue
23% Staff
32% Assets
534% Intangibles
30% Costs

More and less likely to be found in...*

▽ Less than the overall share
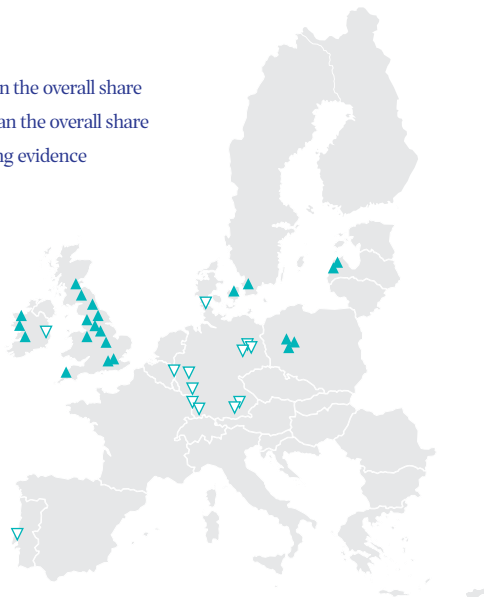▲ More than the overall share
⬜ No strong evidence

"The bold and the innovative"

Visionaries are by far the most innovative firms in the bunch and include 7% of all start-ups. They boast the highest growth rate in intangible assets – an astounding 534% over four years. Visionaries also performed relatively well in other indicators, ranking as the third best profile in most of them. Their turnover grew by almost 40% on average, while costs by 30%. Total assets and staff also increased by respectively 32% and 23%.

Interestingly, there were more visionary start-ups in the manufacturing sector than in any other. There were also fewer seed-stage firms in this group than from the rest of the stages. Poland, Latvia and Denmark hosted relatively higher share of innovative companies. The British Isles, however, recorded the highest number as opposed to DACH, which had the fewest. This result could be linked to the previous finding that there were relatively more laggards in the British Isles than DACH: if British Isles companies take on relatively more risk on average, they are expected to be more innovative but also to fail more often. Firms aged two to five years were the most likely to end up among the visionaries while the youngest start-ups (two years old or younger at investment date), the least.

*Locations of higher/lower concentration of visionaries compared to their overall share.
In places with "No strong evidence", the concentration does not significantly deviate from the overall share in the EU VC ecosystem.
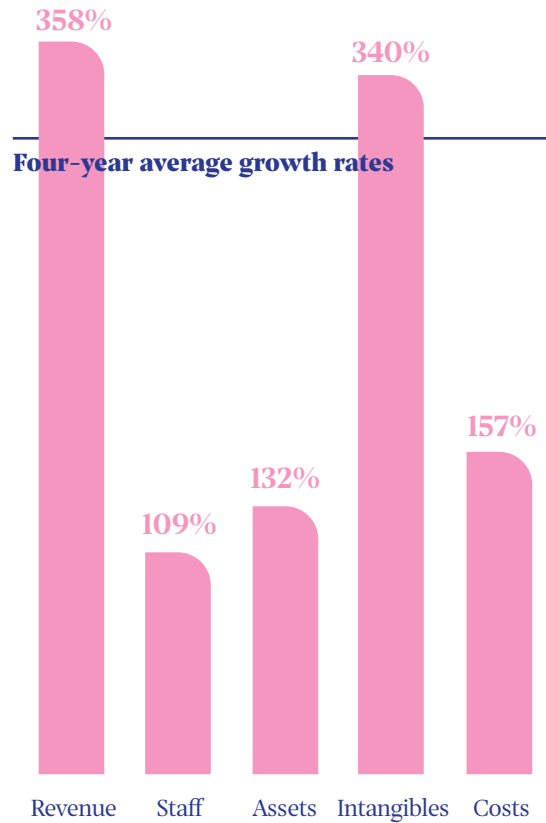
Superstars

"Who wants to be a millionaire?"

What happens when everything goes according to (business) plan? Superstars include 8% of all firms and their most remarkable feature are their sales results. They recorded an impressive growth of 358% in operating revenue compared to a 157% growth in costs. At the same time, superstar(t-up)s more than doubled their staff and total assets. This profile achieved the highest growth rates after four years in almost all indicators but intangible assets, which still grew at a considerable 340%.
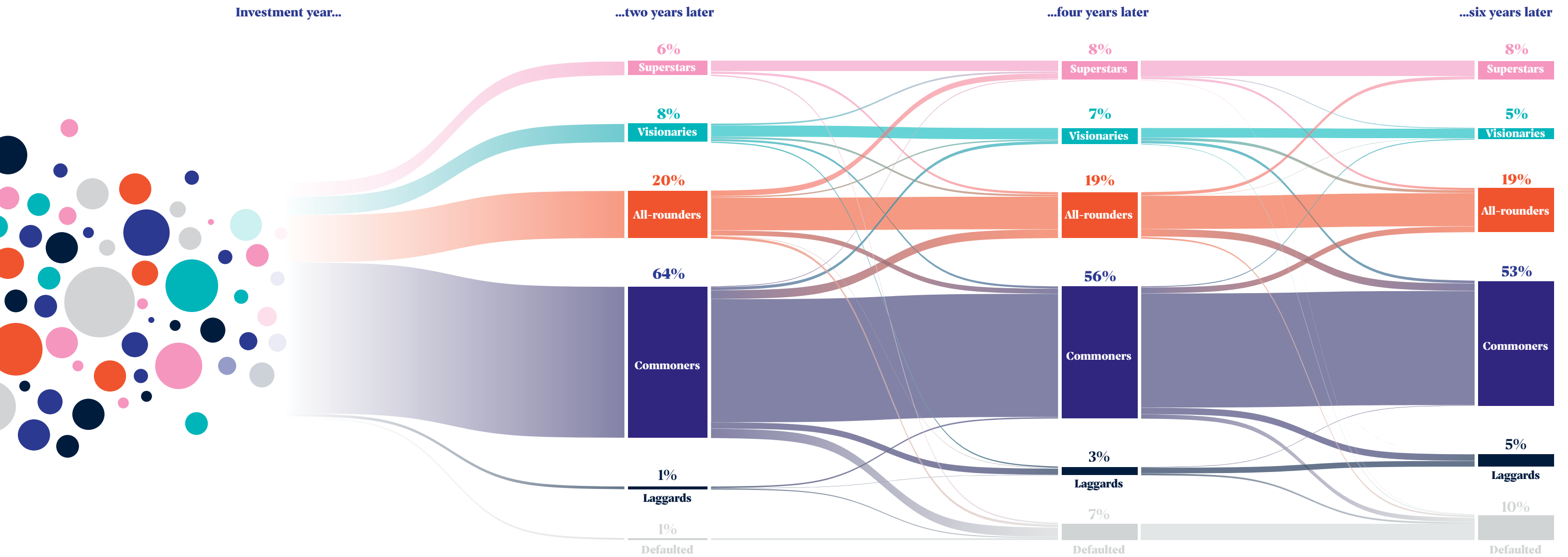
Two-year-old start-ups or younger at investment date are over-represented in this profile while all other age groups were less likely to become superstars. With respect to the investment year, there were relatively more superstars backed in 2011 to 2013. ICT firms had on average 17% higher chance of explosive sales growth than the rest of the sectors. Later-stage ventures were less likely to become superstars than their seed and start-up counterparts. There are some regional differences as well, with relatively more firms operating in Austria, Poland and Denmark and fewer in the British Isles and Benelux.

Four-year average growth rates

Revenue	Staff	Assets	Intangibles	Costs
358%	109%	132%	340%	157%

More and less likely to be found in...*

▽ Less than the overall share
▲ More than the overall share
▪ No strong evidence

*Locations of higher/lower concentration of superstars compared to their overall share.
In places with "No strong evidence", the concentration does not significantly deviate from the overall share in the EU VC ecosystem.

Investment year...   **...two years later**   **...four years later**   **...six years later**

Two years later:
- 6% Superstars
- 8% Visionaries
- 20% All-rounders
- 64% Commoners
- 1% Laggards
- 1% Defaulted

Four years later:
- 8% Superstars
- 7% Visionaries
- 19% All-rounders
- 56% Commoners
- 3% Laggards
- 7% Defaulted

Six years later:
- 8% Superstars
- 5% Visionaries
- 19% All-rounders
- 53% Commoners
- 5% Laggards
- 10% Defaulted

## What happens to start-ups after two years of growth?

Looking at start-up growth two years instead of four years after the VC investment does not result in major differences across start-up profiles. Most companies stick to the same group anyway. The commoners is the most stable profile, with almost 82% of firms remaining after four years as well. They are also the group most start-ups gravitate towards, particularly from the laggards profile – 53%. Laggards are also the companies with the highest probability of defaulting - 39%. However, relatively few start-ups (from any given profile) default before their fourth post-investment year.

...or after six years of growth?

We see more defaults between four and six years of growth than between two and four years. Why? Well, it's a question of fund life. In line with other studies, we find that most VC investors stick to their invested companies for at least four years – resulting in only 7% of defaulted start-ups at year four. After that, under-performing investments tend to be written off, resulting in 10% default rate by year six. Naturally, laggard companies are still the most likely to default, with more than 20% of firms sharing this fate. Conversely, superstars are the least likely to go bust.

The commoners emerge as the most stable profile after six years as well, with 87% of companies maintaining their status. If there were only two groups, under-achievers (laggards and commoners) and high-achievers (all-rounders, visionaries and superstars), it would be more likely for an achieving start-up to switch to a non-achieving profile than vice-versa. At the same time, "big jumps" are very rare, i.e. almost no under-achieving start-up moves to a very successful profile or the opposite. Superstar firms turn out to be the most resilient, as they are the most likely to remain within a high-achieving group.

A recap of the five start-up profiles and their average growth rates

● **Laggards**   ● **Commoners**   ● **All-rounders**   ● **Visionaries**   ● **Superstars**
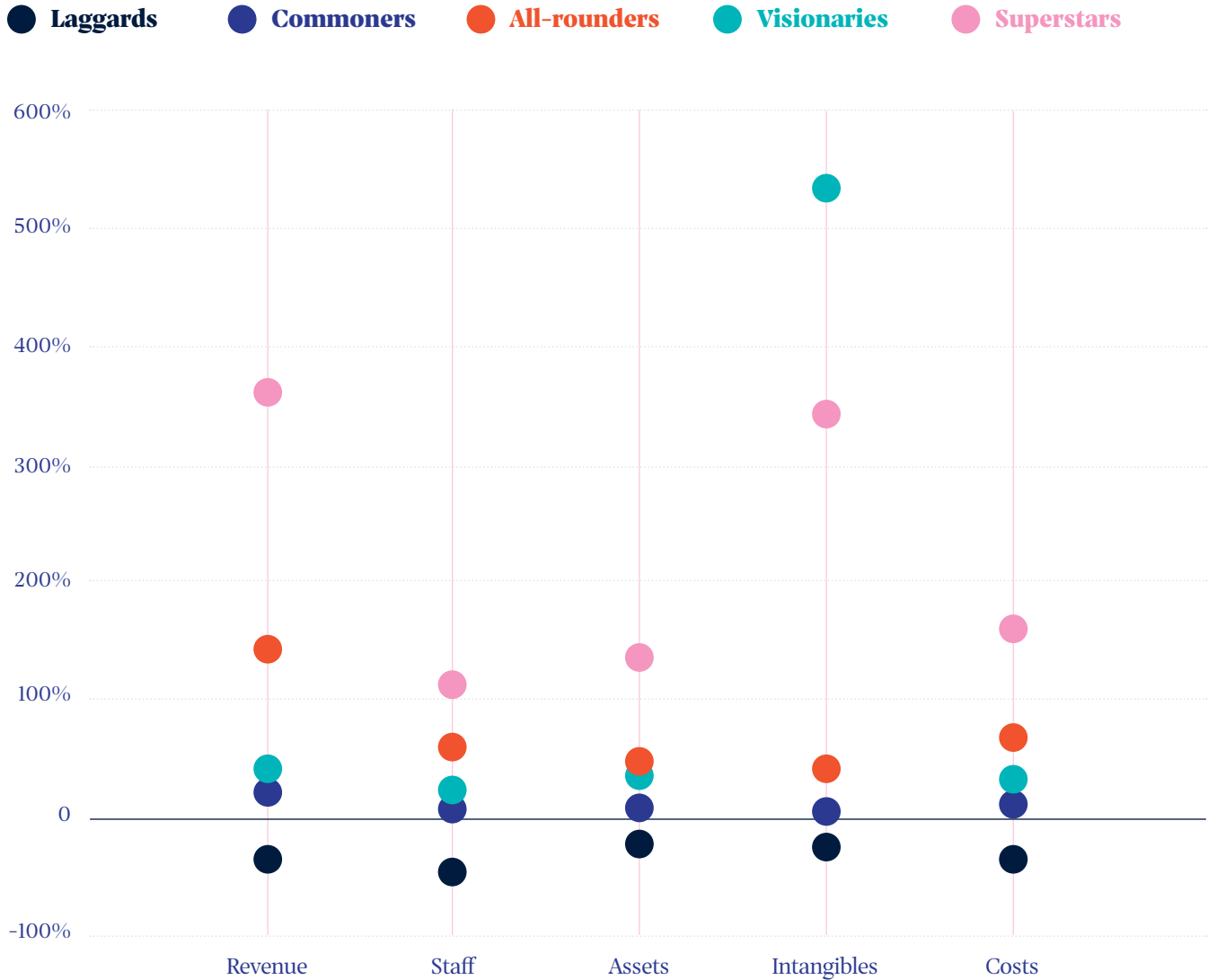
But what really was the role of VC?

The five profiles do a fine job at summarising the different types of VC-backed start-ups in the European ecosystem, as measured by the growth they experience after investment. But where is the "VC factor"? In other words, would start-ups not backed by VC firms (VCs) experience similar trajectories of growth? And if so, are there differences in the actual growth rates? To answer these questions and uncover the true "VC factor", it's time to bring into our analysis a new class of start-ups: those not backed by VC.

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Ever wanted to write? Berlin-based innovative publisher Inkitt wants to hear from you. "Every author should have an equal chance to succeed, from a teenager writing her first novel, to established authors like J.K. Rowling. We want to be the fairest and most objective publisher in the world" says Ali Albazaz, CEO of Inkitt. The world's first reader-powered book publisher offers a platform where authors can post their work, readers can read them for free, and an algorithm predicts future bestsellers. The best performers are offered a publishing deal. With 70,000 authors on the platform and more than 1 million readers every month, it's clearly worked. "Inkitt is where data meets creativity," Ali adds.

Chapter 3

# The added value of VC

Does VC help start-ups grow more?

What happens to a start-up's performance if we remove the VC backing? To find out, we should compare start-ups which received a VC investment and ones that could have, but didn't. How can we do this? Similar to a clinical trial, here the drug is the VC investment, and a group of control firms needs to be identified. Once the tricky task of constructing a comparable group is overcome, measuring the difference in financial growth between VC- and non-VC-backed start-ups will reveal the added value of venture capital.

So, what are the results of our impromptu trial? We found that both VC- and non-VC-backed start-ups grew financially over time on average. However, some differences emerge when the growth trajectories between the two groups are compared against each other over the six years following the VC investment. VC-backed start-ups grew faster in terms of assets throughout the whole period under consideration. ▶

They also consistently recorded a higher share of intangible assets, highlighting VC-backed firms' larger efforts in innovation. As reported previously, this measure for innovation does
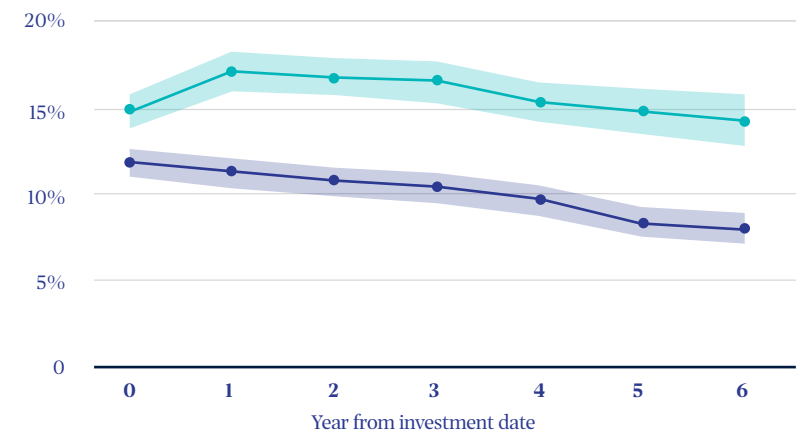
Growth of assets
Median, EUR thousands
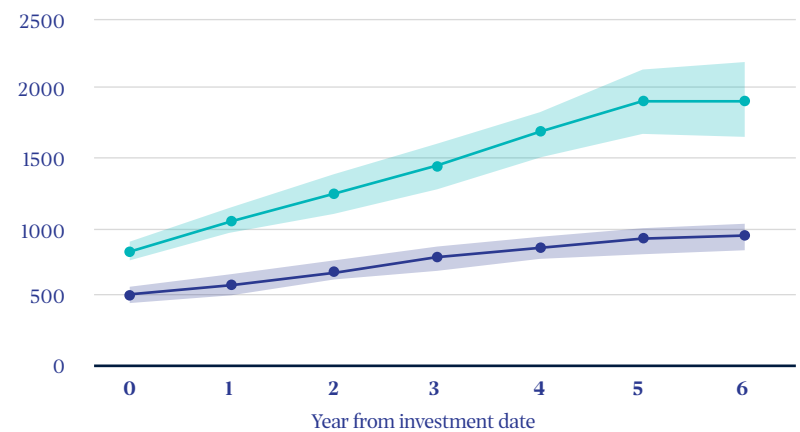
Growth of intangibles (share of total assets)
Average percentage

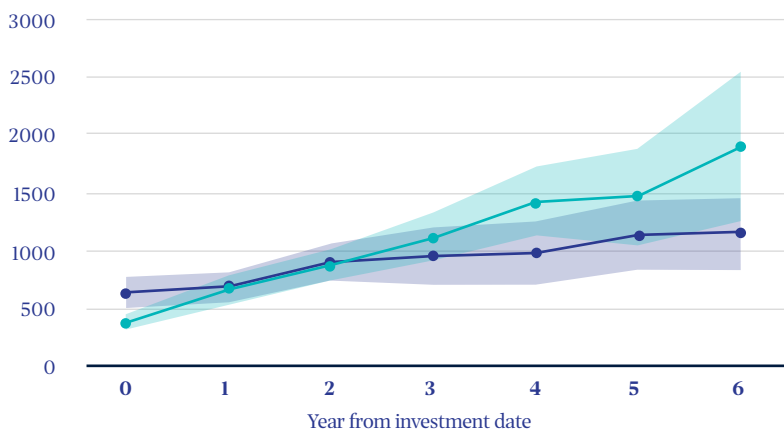● VC-backed   ● Non-VC-backed   95% confidence interval

not increase with time as opposed to the rest of the financial indicators. This is the case for both groups, however, which means the result is not related to the VC investment.

When it comes to revenue and staff growth, the differences between the two groups are more subtle. VC-backed firms start off with lower levels of operating revenue at investment date, but quickly catch up with their non-VC-backed counterparts after just one year. In the following periods, there are no statistically significant differences, mostly due to the high variation across firm performance. This is valid in the case of staff as well – there is no hard evidence of any divergence between VC- and non-VC-backed start-ups. However, growth trajectories do not tell the whole story.
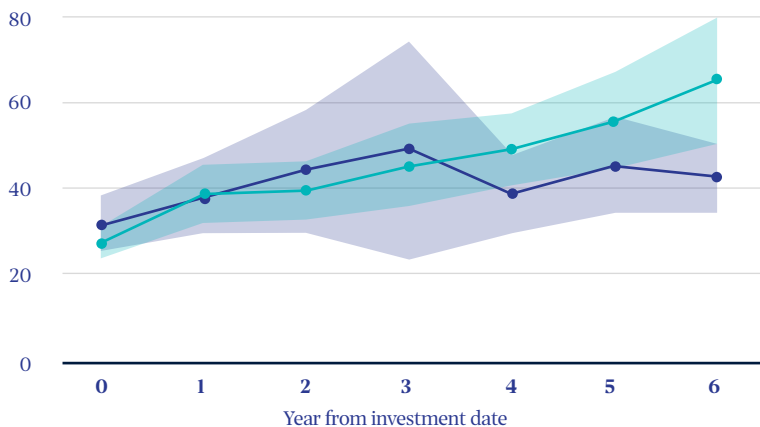
▼

Growth of revenue
Median, EUR thousands

Year from investment date

Growth of staff
Average

Year from investment date

● VC-backed ● Non-VC-backed ▨ 95% confidence interval

The Data

Our comparative analysis is based on 831 start-ups backed by VC in 2007-14, and their associated controls. Due to data restrictions, there were significantly fewer firms we could use for this exercise. First, like in the cluster analysis, we needed companies with performance data for at least four years. Second, to compare pairs of treated and control firms we required data for both groups in the same time span. We should note that growth rates in this chapter may differ from the ones previously reported, due to the smaller number of analysed firms. However, these remain qualitatively similar. Finally, to get as close as possible to the true population results, we once again applied weights to our sample.

831

VC-backed start-ups with full counterfactual data analysed

How to create a control group for VC-backed start-ups?

Following Pavlova and Signore (2019), our control group is made of "investable" start-ups, i.e. firms, which did not receive a VC investment but would have qualified for one. In other words, control firms are the same as VC-backed firms minus the investment. To identify these, we used a number of statistical and econometric techniques. We started with an exact matching on six dimensions – country, sector, age, patent ownership and the degree of innovation. We then built a propensity score model using the former dimensions, plus several other characteristics related to the firm's geographic location. Next, we carried out a ridge matching based on the propensity score, so that non-VC-backed firms would receive different weights, indicating how "relevant" they are for our comparison. In the end, this is how we created a "synthetic" control company for each VC-backed start-up, representing the weighted average of all relevant non-VC-backed firms. See Appendix C for additional technical details.
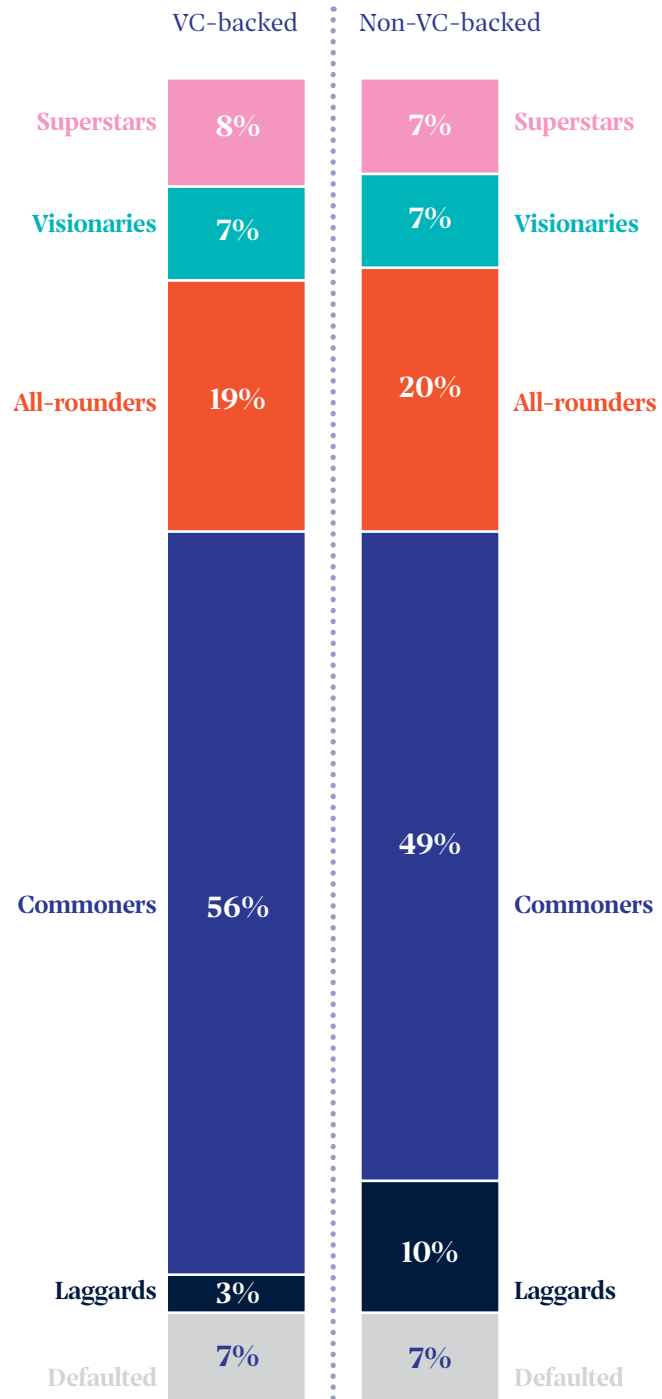
What about start-up growth profiles in the absence of VC investment?

When a comparable growth period for a set of non-VC-backed start-ups is analysed, we find that the same five profiles emerge. However, there are more than three times more laggards in the absence of VC: 10% of non-VC-backed start-ups against 3% of VC-backed companies belong to the worst performing profile. This result already provides some evidence towards the benefits of VC financing, that is, uplifting some start-ups to more promising growth trajectories.

> " **There are three times more laggard start-ups in the absence of VC.** "

In general, firms are distributed very similarly. Irrespective of the VC investment, the majority are commoners, followed by all-rounders with roughly the same share of defaults (7%). Few companies over- or under-perform, as previously found. Be aware, however, that firms are sorted in different profiles according to their relative performance within each group – VC and non-VC. What does that mean? VC- and non-VC-backed start-ups belonging to the same profile did not necessarily record similar results. This becomes more apparent when we look at growth rates' differences within each profile.

VC vs non-VC-backed start-ups' growth profiles

	VC-backed	Non-VC-backed	
Superstars	8%	7%	Superstars
Visionaries	7%	7%	Visionaries
All-rounders	19%	20%	All-rounders
Commoners	56%	49%	Commoners
Laggards	3%	10%	Laggards
Defaulted	7%	7%	Defaulted

## Are growth rates within profiles also similar without VC financing?

We find that VC-backed start-ups grew more than their non-VC-backed counterparts in every financial measure across all profiles, save for VC-backed laggards. In some cases the difference is striking. For example, in the all-rounders cluster, VC-backed firms recorded 118 percentage points (pp) higher turnover and 36 pp higher costs growth. In the visionaries and superstar profiles, VC-backed firms outran their counterparts in innovation by an impressive 331pp and 190 pp respectively. All in all, the VC impact for 90% of companies is substantial - receiving an investment allowed start-ups to improve further and faster than their non-VC-backed peers.

> " **The VC impact for 90% of companies is substantial – receiving a VC investment allowed them to improve further and faster than their peers.** "
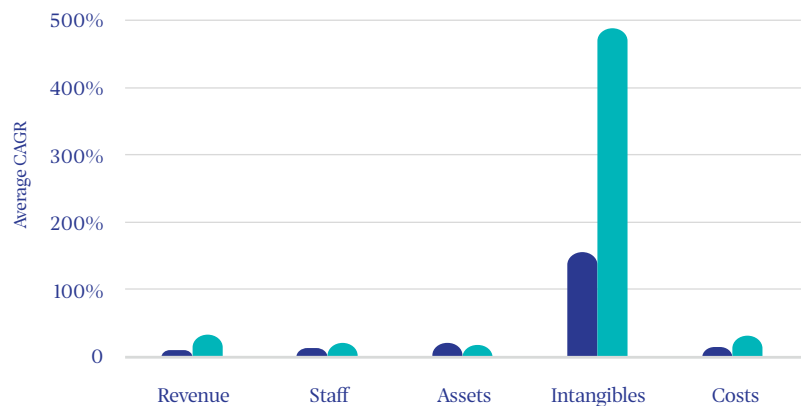
VC vs non-VC-backed start-ups' growth rates across profiles*
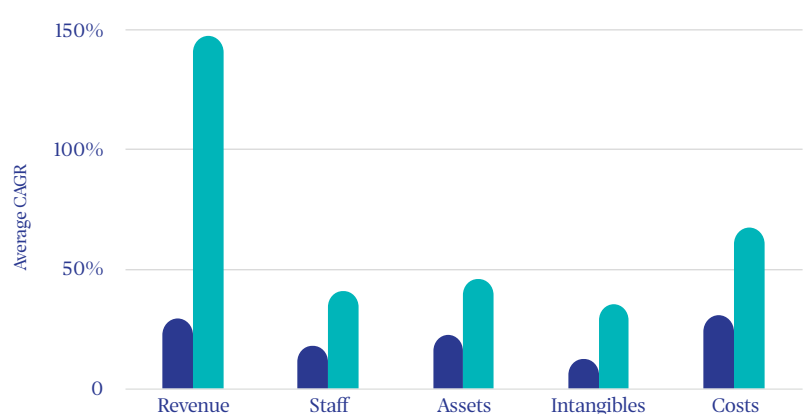
● VC-backed   ● Non-VC-backed
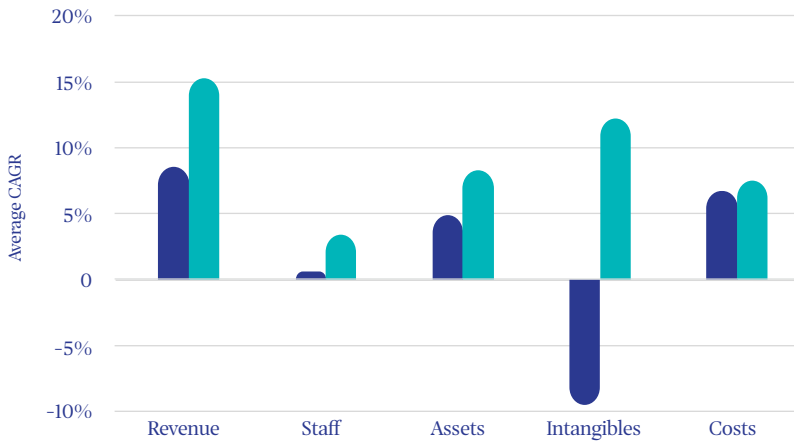
Superstars
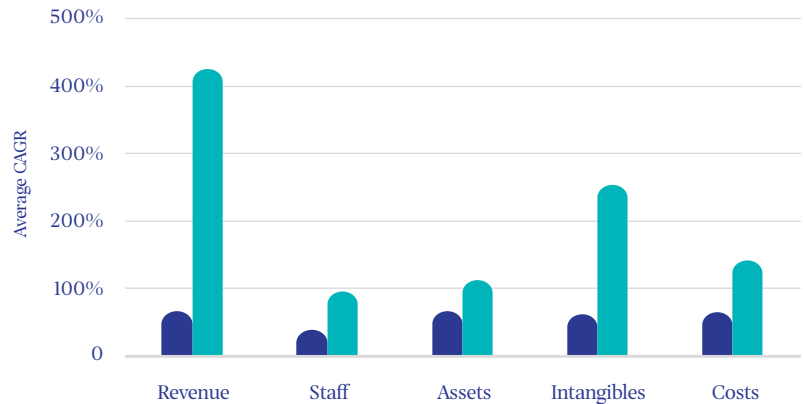
Visionaries

All-rounders

*Growth rates for VC-backed firms may differ from the ones reported in Chapter 2 due to the smaller sample size in this analysis.

VC vs non-VC-backed start-ups' growth rates across profiles*

● **VC-backed**   ● **Non-VC-backed**
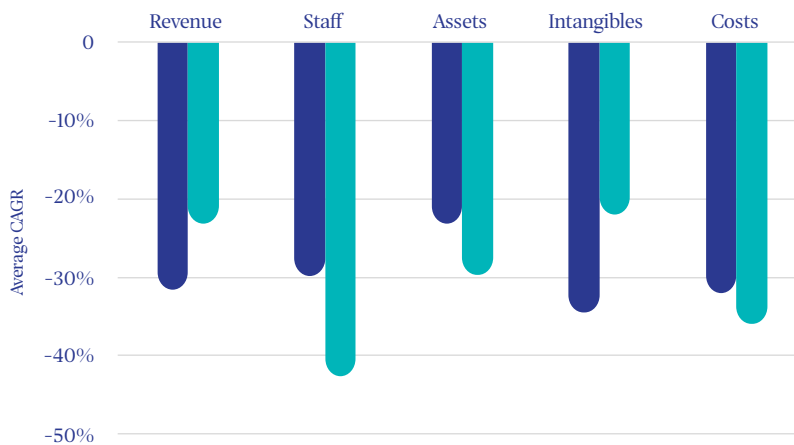
Commoners

As stated above, the sole exception to the rule concerns the laggards, where we see hardly any difference between the VC- and non-VC-backed start-ups. Non-VC-backed companies shrink less than their counterparts in some measures, but fall behind in others. Be that as it may, VC-backed firms still excel against non-VC backed firms in the area of intangible fixed assets – regardless of the growth profile. This highlights VCs' preference for, but also ability to, foster innovation.

Laggards

> ❝
> **VC-backed firms excel against non-VC-backed firms in terms of intangibles – regardless of the growth profile.** ❞

*Growth rates for VC-backed firms may differ from the ones reported in Chapter 2 due to the smaller sample size in this analysis.

## Where would VC-backed start-ups be without the investment?

The VC investment also affects start-ups' overall growth profile. This means that without the additional support of VC, a successful start-up might have ended up in a different cluster, typically exhibiting lower growth. How do we know this? As explained in the beginning of the chapter, for each start-up we compared two states of the world – with and without VC. It's as if we could go back in time, take away the start-up's financing, and look at its future under this "what if" scenario.

Start-ups exhibiting high growth would have actually fallen in much less successful profiles if they hadn't received the VC investment. This is especially the case for superstars since around a quarter of them would have choked somewhere on the steep road to success, turning into laggards or defaulting altogether. Visionaries exhibit a similar trend – over a third would have found themselves among the commoners while only 20% would have still developed their innovative power. Our data shows that, when an entrepreneurial idea has a high potential for success, venture capital will expand opportunities for growth and allow excelling start-ups to unleash their full potential.

However, the effect of VC may not be that obvious for the less successful profiles - commoner start-ups would mostly have remained such while the (few) laggards and defaulters would have largely ended up as commoners without VC. While this result may seem counterintuitive at first, it may be offering evidence that venture capital can do wonders, but it cannot prevent companies from reaching their inevitable fate. In fact, occasionally, poorly growing VC-backed companies would have survived longer without VC – perhaps to meet their dire destiny down the line anyway. In the end, not every frog kissed turns into a prince.

How can we compare two different states of the world?

The creation of the control group enabled us to find a "mirror" start-up for each of our VC-backed companies. We applied the cluster analysis to these peer firms, which then allowed us to identify their profile, similar to what we did earlier with the VC-invested lot. Since the start-ups in the control and treated groups are essentially equivalent prior to the VC investment, we were able to track a start-up in both states of the world – with and without VC.

Mind the… regression to the mean

Regression to the mean takes place whenever repeated measurements of the same phenomenon (e.g. firm growth) tend to converge to the average, rather than remain "extreme". Since our control firms are constructed as the weighted average of a larger set of appropriate start-ups, it is likely that purely because of this construction, their financial growth will be more moderate rather than drifting to either end of the distribution. This type of bias can partially explain the higher or lower results for VC-backed companies, even though our propensity score model ensures that the most similar firm is associated with each treated start-up.

> " **Without VC, around a quarter of superstars would have choked somewhere on the steep road to success, turning into laggards or defaulting altogether.** "

Drilldown into the different growth categories

↱ Worse off without VC*   ↰ Better off without VC*

◌ Size of profile without VC

Most superstar(t-up)s would have been unable to achieve their latent performance growth without a VC investment. Only around 20% would have remained part of the same profile, 28% would have joined the visionaries and 13% - the all-rounders. An even worse fate would have befallen the remaining ones, which would have ended up either as laggards (17%), commoners (18%) or gone out of business by their fourth year (5%).

Only 20% of visionary start-ups would have remained truly innovative, although the majority would have still stayed in a high growth cluster. Around 40% would have switched to the all-rounders profile and the rest would have ended up as commoners (37%) or would have defaulted altogether (5%). This is another solid piece of evidence that venture capital helps companies develop their innovative potential.

More than a third of all-rounders would have remained in the same profile, while the majority would have switched to a different profile in the absence of a VC investment. Only 10% would have been better off – winding up as visionaries or superstars (2% and 8% respectively). More than half of them would have performed considerably worse, becoming part of the laggards', commoners' or defaulters' clubs.

Superstars

Visionaries

All-rounders

Commoners

Laggards

Defaulted
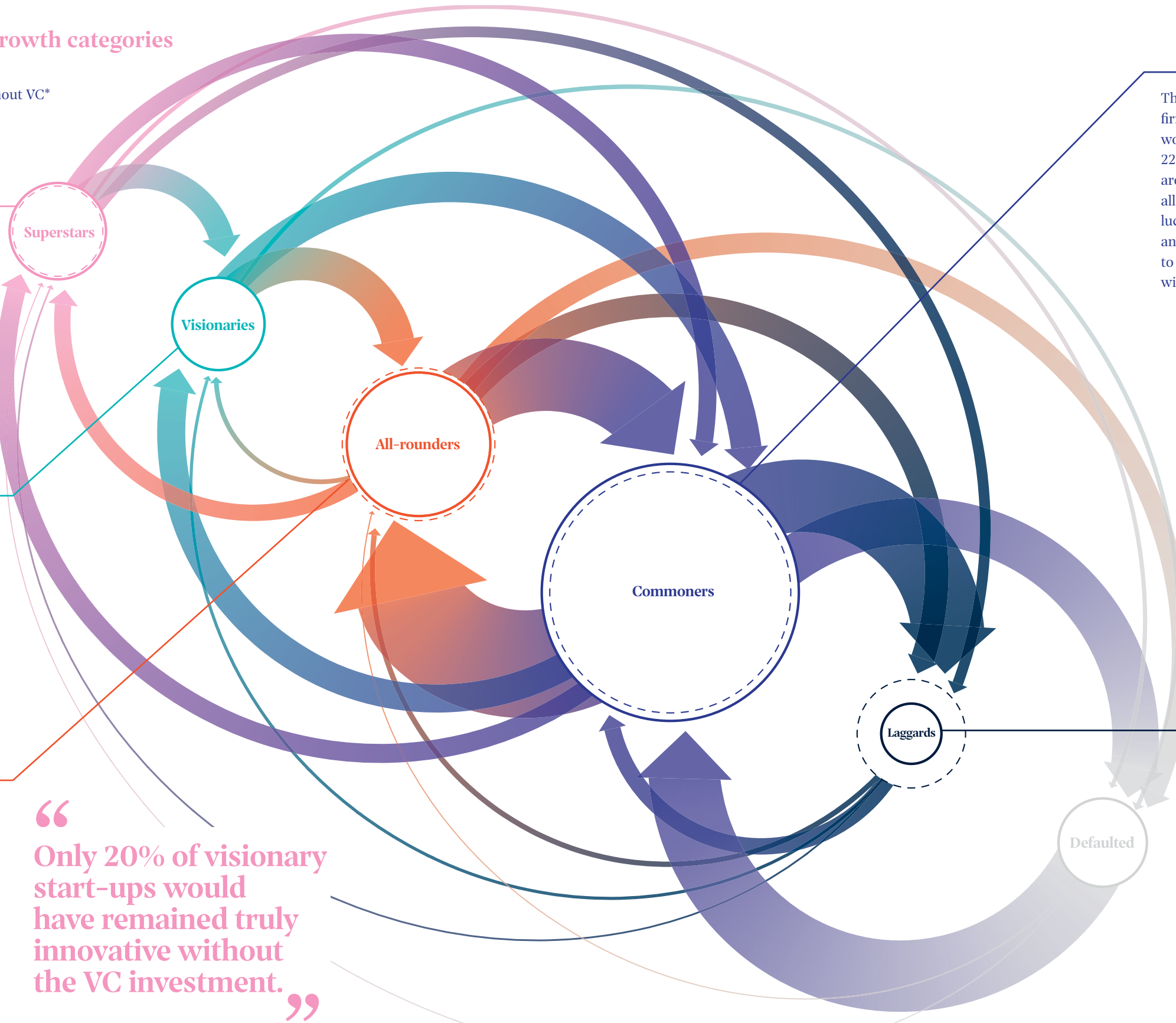
❝ **Only 20% of visionary start-ups would have remained truly innovative without the VC investment.** ❞

The impact of VC investments on commoner firms was mild at best. The majority (58%) would have grown this way in any case. In fact, 22% would have been better off without VC - around 16% would have ended up among the all-rounders, 4% among the visionaries and a lucky 3% would have become superstars. Still, an unlucky 12% would have been downgraded to laggards and 7% would have defaulted without the VC investment.

Mind the... selection bias

In the control group, we can only study "successful" start-ups, i.e. firms, which had a winning business idea and managed to stay afloat. In the same time, some VC-backed companies would have actually failed soon after their incorporation if it were not for the VC support. It is difficult to find equivalents for this type of start-ups in the "non-VC world" since without the significant help of a VC investment, they would have disappeared much sooner. Therefore, in some cases control firms may perform better than VC-backed firms, which would have quickly failed without the investment.

VC investments don't always work out for the best. For the few of laggard start-ups, receiving a VC investment appears to have been an unwelcomed circumstance. Without VC, half of them would have moved to the commoners and only 17% would have remained laggards or have defaulted. The rest would have actually joined the more successful profiles, although in absolute numbers this share is hardly significant.

What are the main takeaways from this hypothetical world without VC?

For one, venture capital may not be that impactful for low growth companies. Most commoners remain such and most of the laggards would not have performed much better. This finding may not be so intuitive, but it essentially means that VC doesn't work like a magic spell, turning every start-up into a unicorn. Some ventures were simply not destined for greatness.

In the same time, however, VC can make all the difference for some bold and innovative ideas. If we remove venture capital backing from the picture, a half of high growth start-ups (superstars, visionaries and all-rounders) move to a less successful profile. In the particular case of superstars, 40% lose their status and become laggards, commoners or even go bust. The same prominent effect strikes visionaries as well – around 40% move down the ladder in a "no-VC" world. This supports the theory that venture capital has an outsize positive effect on innovative businesses. Moreover, performance within profiles is much stronger for VC-backed companies since the latter grew more than their non-VC-backed counterparts in every financial measure. In the end, VC cannot change the business reality where some firms make it while others break it, but it can be the deciding factor in a start-up's road to success.

Solynta: the ultimate potato

Netherlands-based Solynta promises to revolutionise potatoes for the developing world, with 25 grams of potato seed needed to plant a hectare, instead of 2500kg of bulky and perishable potato tubers. "We were doing some tests in Uganda and the Congo, and one of the farmers actually started crying when he saw the potential of these new hybrid seeds," said Solynta CEO Hein Kruyt. "It was – in his own words – the first time he could see a future for his family. It still gives me goose-bumps." Hein has created 10-12 new jobs, boosting the number of employees to 37. "The availability of highly nutritious potatoes, will be better for the planet, the wallet and for health," adds Hein.

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Appendices

Appendix A

Building a representative sample of EU28 VC-backed start-ups

This appendix details the creation of the representative sample of European start-ups used in this report. Our reference population contains all venture-backed start-ups in Europe, whose initial received investment took place in the period 2007-2015.[1] We further narrow our focus to the 28 Member States of the European Union.[2] This leads to a reference population, approximated through Invest Europe's data, which includes 12,277 early and later stage start-ups (see Table 1 for a definition of VC investment stages).[3]

We collected firm financial accounts, industry activity and patent data from Bureau Van Dijk's Orbis database.[4] Using the identities of invested start-ups and their headquarter locations to match the two data sources, we constructed a sample of start-ups with available performance data. In addition, we incorporated the results from a similar identification exercise carried on the sub-sample of EIF investees to enhance our sample coverage ability. Table 2 illustrates the key financial and innovation indicators used throughout the report, together with a brief description.

Table 1: Venture capital investment stages and their definitions

Seed	Funding provided before the investee company has started mass production/distribution with the aim to complete research, product definition or product design, also including market tests and creating prototypes. This funding will not be used to start mass production/distribution.
Start-up	Funding provided to companies, once the product or service is fully developed, to start mass production/distribution and to cover initial marketing. Companies may be in the process of being set up or may have been in business for a shorter time, but have not sold their product commercially yet. The destination of the capital would be mostly to cover capital expenditures and initial working capital.
	This stage contains also the investments reported as "Other early stage" which represents funding provided to companies that have initiated commercial manufacturing but require further funds to cover additional capital expenditures and working capital before they reach the break-even point. They will not be generating a profit yet.
Later-stage	Financing provided for an operating company, which may or may not be profitable. Late stage venture tends to be financing into companies already backed by VCs. Typically in C or D rounds.

Source: Invest Europe

[1] Start-ups with follow-on investments in this period, but with initial investment prior to 2007, are excluded from our population, hence our sample.
[2] Belgium, Bulgaria, Czechia, Denmark, Germany, Estonia, Ireland, Greece, Spain, France, Croatia, Italy, Cyprus, Latvia, Lithuania, Luxembourg, Hungary, Malta, Netherlands, Austria, Poland, Portugal, Romania, Slovenia, Slovakia, Finland, Sweden, United Kingdom.
[3] It is important to note that Invest Europe's population data may not itself be a thorough representation of the underlying EU28 VC ecosystem. For instance, DACH investees tend to be disproportionately better represented in the Invest Europe's dataset. Nevertheless, to our knowledge Invest Europe's population remains the most reliable and accurate representation of the VC ecosystem in Europe.
[4] Orbis is an aggregator of firm-level data gathered from over 75 national and international information providers. Data is sourced from national banks, credit bureaus, business registers, statistical offices and company annual reports.

Table 2: Financial and innovation indicators collected from the Orbis database

Financial/Innovation indicator	Description
Total Assets	Total value of assets.
Number Employees	Total number of employees included in the company's payroll.
(Operating) revenue	Total operating revenues (turnover).
Intangible fixed assets	All intangible assets such as formation expenses, research expenses, goodwill, development expenses and all other expenses with a long term effect.
Cost	All costs directly and not directly related to production of the goods sold (commercial, administrative expenses etc.).
Number of Patents	Number of patent families, that is "a collection of related patent applications covering same or similar technical content".[5]

Source: authors, based on Bureau Van Dijk's Orbis database.

To render financial accounts comparable over time, we deflated all monetary values using harmonised country- and NACE Rev. 2 sector-level producer price indices (collected from Eurostat) with base year 2010. The correspondence between Invest Europe and NACE Rev. 2 classes is illustrated in Table 3.

Table 3: Sectoral classification and concordance with NACE Rev. 2 system

Macro-sector	Sector (full-name)	Nace Rev. 2 classes
ICT	Business related software	6201
	Communications	1810; 1811; 1812; 1813; 1820; 2630; 4652; 4742; 5800; 5810; 5811; 5813; 5814; 5819; 5820; 5821; 5829; 5910; 5911; 5912; 5913; 5914; 5920; 6000; 6010; 6020; 6110; 6120; 6190; 6391; 6399; 7310; 7311; 7312; 9512
	Computer & data services	4651; 4741; 6202; 6203; 6209; 6310; 9511
	Computer and consumer electronics	2610; 2611; 2612; 2620; 2640; 2680; 4743
	Internet technologies	6310; 6311; 6312

[5] This is the definition for patent family as described by the European Patent Office (EPO).

Macro-sector	Sector (full-name)	Nace Rev. 2 classes
Life sciences	**Biotechnology**	7210; 7211; 7219
	Healthcare	2100; 2110; 2120; 2660; 3250; 3313; 4774; 8610; 8621; 8622; 8623; 8690; 8710; 8720; 8730; 8810; 8891; 8899
Services	**Business & industrial services**	3311; 3312; 3314; 3315; 3316; 3317; 3319; 3320; 4661; 4662; 4664; 4666; 4669; 4674; 4690; 5210; 5221; 5222; 5223; 5224; 5229; 5320; 6900; 6910; 6920; 7010; 7020; 7021; 7022; 7110; 7111; 7112; 7120; 7320; 7410; 7420; 7430; 7490; 7710; 7711; 7712; 7721; 7722; 7729; 7730; 7732; 7733; 7739; 7740; 7810; 7820; 7830; 8010; 8020; 8110; 8121; 8122; 8130; 8200; 8210; 8211; 8219; 8220; 8230; 8290; 8291; 8292; 8299; 9412
	Consumer goods & retail	1011; 1013; 1020; 1032; 1039; 1041; 1051; 1052; 1061; 1070; 1071; 1073; 1082; 1083; 1084; 1085; 1086; 1089; 1092; 1101; 1102; 1105; 1107; 1300; 1310; 1320; 1330; 1390; 1391; 1392; 1395; 1396; 1399; 1410; 1413; 1419; 1431; 1439; 1511; 1512; 1520; 2219; 2341; 2342; 2349; 2369; 2751; 3102; 3109; 3212; 3213; 3220; 3230; 3240; 3299; 4631; 4632; 4633; 4634; 4636; 4637; 4638; 4639; 4640; 4641; 4642; 4643; 4644; 4645; 4646; 4647; 4648; 4649; 4711; 4719; 4721; 4722; 4723; 4724; 4725; 4729; 4751; 4753; 4754; 4759; 4761; 4764; 4765; 4771; 4772; 4775; 4776; 4777; 4778; 4779; 4781; 4782; 4791; 4799; 9522; 9529; 9600; 9601; 9603
	Consumer services: other	5510; 5520; 5530; 5590; 5610; 5621; 5629; 5630; 7220; 7900; 7910; 7911; 7912; 7990; 8412; 8510; 8520; 8531; 8532; 8542; 8552; 8553; 8559; 8560; 9001; 9002; 9003; 9004; 9200; 9311; 9312; 9313; 9319; 9321; 9329; 9499; 9600; 9602; 9604; 9609
	Financial institutions and services	4610; 4612; 4613; 4614; 4615; 4616; 4617; 4618; 4619; 6400; 6419; 6420; 6430; 6490; 6491; 6492; 6499; 6512; 6610; 6611; 6612; 6619; 6622; 6629; 6630
	Real estate	6800; 6810; 6820; 6831; 6832
	Transport	2910; 2920; 2932; 3011; 3012; 3030; 3090; 3091; 3092; 3099; 4510; 4511; 4519; 4520; 4530; 4531; 4532; 4540; 4910; 4931; 4939; 4940; 4941; 4942; 4950; 5020; 5040; 5100; 5110

The table continues on the next page.

Macro-sector	Sector (full-name)	Nace Rev. 2 classes
Manufacturing	**Business & industrial products**	1610; 1621; 1623; 1624; 1629; 1712; 1721; 1723; 1729; 2211; 2222; 2229; 2319; 2343; 2410; 2420; 2441; 2442; 2451; 2452; 2453; 2454; 2521; 2529; 2530; 2540; 2550; 2561; 2562; 2572; 2573; 2591; 2593; 2594; 2599; 2650; 2651; 2652; 2670; 2710; 2711; 2712; 2720; 2730; 2731; 2732; 2733; 2740; 2790; 2800; 2810; 2811; 2812; 2813; 2814; 2815; 2821; 2822; 2825; 2829; 2830; 2841; 2849; 2890; 2891; 2892; 2893; 2895; 2896; 2899; 3101
	Chemicals & materials	0893; 2000; 2010; 2012; 2013; 2014; 2015; 2016; 2017; 2020; 2030; 2041; 2042; 2051; 2052; 2053; 2059; 2221; 2312; 2314; 4675; 4676; 4773
	Construction	0812; 2223; 2320; 2331; 2332; 2344; 2350; 2361; 2362; 2363; 2364; 2370; 2399; 2511; 2512; 4100; 4110; 4120; 4200; 4211; 4212; 4213; 4221; 4222; 4299; 4313; 4321; 4322; 4329; 4332; 4333; 4334; 4391; 4399; 4663; 4673; 4750; 4752
Green Technologies	**Agriculture & animal production**	0111; 0113; 0126; 0130; 0147; 0149; 0160; 0161; 0162; 0163; 0164; 0210; 0321; 0322; 4622; 4623; 7500
	Energy & environment	0610; 0620; 0729; 0910; 1920; 3500; 3511; 3512; 3513; 3514; 3521; 3522; 3530; 3600; 3700; 3811; 3820; 3821; 3831; 3832; 3900; 4671; 4672; 4677; 4730

Source: Invest Europe (2016).

Identification (and exclusion) of outliers

Our initial sample covers 83% of the initial population. However, preliminary descriptive statistics show that the sample is highly heterogeneous in terms of start-up size and characteristics, beyond what is explained by the differences in investment stages. We deduce that the population (and the sample) must contain a number of outliers that, if not controlled for, are likely to distort the results of our analysis. To identify a restricted sample of companies that qualify for "true" venture capital investments, we treat the formal definitions of Table 1 as a theoretical compass. As a first step, we translate these into data-driven assumptions about the underlying companies. The following assumptions were made for early stage start-ups (at the date of the first VC investment):

E1) less than 10 years of activity,

E2) no positive turnover in the three years preceding the investment date,

E3) less than 250 employees.

The following assumptions were made for later stage ventures (at the date of the first VC investment):

    L1) recorded turnover in any of the two years preceding the investment,

    L2) active for at least three years and no more than 30 years.

In the absence of relevant financial data, we follow the "benefit-of-the-doubt" approach and keep the existing classification for start-ups in our sample. All firms found non-compliant with the above were discarded from our analytical sample.

According to Table 1, later stage financing tends to back "companies already backed by VCs". As a second step to our strategy to identify later stage outliers, we focus on industries where we do not observe early stage investees, hence we would not expect to find later stage start-ups. The idea is to verify that start-ups classified in the later stage bracket belong to an industry that holds a high (historical) incidence of early stage investments.[6]

In practical terms, we set up the following probit model:

$$y_i = SECTOR\alpha_i + X\beta_i + \epsilon_i$$

where y_i is a dummy variable for the company stage, SECTOR is a categorical variable for the sector, and $X\beta_i$ is a set of controls - firm's age, firm's age squared and country.

We used the model above to estimate the probability of having been an early stage venture investee conditional on the sector and firm's characteristics. We then calculated the average likelihood of each sector[7] to include early stage ventures (p_j), i.e. the average conditional probability of firms in a given sector j.

To identify outliers and at the same time reduce the risk of false positives (i.e. true VC investees identified as outliers), we adopt conservative criteria. For sectors with an average probability $p_j < 25\%$, we discarded companies with probability $Pr(y_{ij}) < 20\%$. These outliers had, on average,

higher levels of turnover and number of employees at investment date. We are thus reassured that this approach discriminates well between VC- and private equity-backed companies, as the latter are usually larger.

The portion of our initial sample stemming from the EIF investment portfolio also included firms in the so-called "expansion stage", a combination of both later stage and "growth stage" firms.[8] Growth firms are typically more mature and hence are not of interest for our analysis of young and innovative start-ups. In order to detect growth stage firms, we first identified and excluded companies with recorded levels of turnover and employment higher than those of any other observed later stage companies.[9]

Furthermore, we constructed a new probit model including only later stage in the non-EIF sub-sample. This time our dependent variable y_i is 1 if the start-up is a later stage venture. The average conditional probability stemming from this model for each sector (p_j) was much higher than in the previous specification. Therefore, we set a higher threshold $p_j < 60\%$ to identify outlying sectors. Among these sectors, firms with a probability of being later-stage $Pr(y_i)$ lower than 60% were considered growth stage. Once again, this approach discriminates well between later stage and growth firms, which, on average, had higher number of employees, and turnover at investment date.

Overall, we identified and discarded 1,199 firms considered non-compliant with the definitions of early and/or later stage VC investees. As a result, our final sample size for the analysis consists of 8,960 companies.

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[6] For this exercise, we employ an extended set of VC investments and relates investees, spanning through the years 1999-2015.
[7] Two-digit NACE code level.
[8] Growth stage investments are a type of private equity investment (often a minority investment) in relatively mature companies that are looking for primary capital to expand and improve operations or enter new markets to accelerate the growth of the business.
[9] Identified as per the procedure described above.

Weighting Procedure

Our data-intensive analyses typically force us to restrict our focus on smaller sub-sets of our sample that hold observable data. This selection process is often non-random, as we encounter large discrepancies in the degree of data usability by e.g., geography, industry, and age.

This implies that, without appropriate adjustment techniques, our results might be influenced by the biased nature of our sub-samples. To address sample representativeness issues, all our analyses employ weights to make each sample more representative of the underlying reference population. This also ensures that our results are more comparable across the report.

To generate our weights, we adopted the so-called Raking approach (Deming and Stephan, 1940). This methodology requires a number of characteristics that can highly predict the existence/absence of data, i.e. the so-called response propensity. Our implementation of the raking algorithm leverages on four key re-weighting dimensions: year of investment, country, sector and stage.

The raking algorithm starts from the unweighted sample and calculates the share of companies in each stratum (analysing one reweighting dimension at a time). It then calibrates the weights so that each sample stratum matches the respective population stratum for the given reweighting dimension, then proceeds to the next reweighting variable in the list (Battaglia et al., 2009). The algorithm iterates until further adjustments do not cause a tangible shift in the weights (Kolenikov, 2014).

Occasionally, we resorted to alternative aggregations of our key re-weighting dimensions. For example, when calculating the weights for the cluster analysis exercise, due to the very small number of observations for a few countries, we aggregated start-ups by macro-regions. This allowed us to improve the data availability in the sample's joint distribution and thus construct more robust weights.

Appendix B

Cluster analysis methods

The objective of "clustering" is to group firms in such a way that between groups, companies would differ substantially in terms of growth trends and, at the same time, they would behave rather similarly within a given group (Everitt et al., 2011). A visual inspection of the distribution of the target variable (i.e. firm growth) would typically be enough to undertake this type of task. However, firm growth is a complex phenomenon that can only be evaluated in a multi-dimensional setting (e.g. turnover growth, staff growth). Against this backdrop, cluster analysis is a convenient approach to classify observations across multiple dimensions.

We evaluate the growth of start-ups along five key dimensions of economic size: total assets (i.e., a measure of economic capital), turnover (measure of output), staff count (measure of labour), intangible assets (a proxy for innovation/productivity) and operating costs (a measure of financial expenditure and a proxy for investments). Growth is measured through the Compound Annual Growth Rate ($CAGR_n$, where n represents the time span, namely 2, 4 or 6 years). For instance, $CAGR_4$ for number of employees is the four-year growth rate of staff starting from the year of investment. We formally calculate $CAGR_n$ using the following formula:

$$CAGR_n = \left(\frac{V_{t_n}}{V_{t_0}}\right)^{\frac{1}{t_n - t_0}} - 1$$

where V_{t_0} is the initial value of the variable under study, V_{t_n} the final value and $t_n - t_0$ is the time horizon in number of years. Our reference time span is four years, and we use the 2- and 6-year time span to compare growth trends over time. As a result, we discard from our cluster analysis all start-ups first invested in the year 2015, as these companies would typically not have enough information to compute four-year growth rates.

To maximise our data coverage, we pool CAGRs by biennia, using earlier period data should the information in the exact period of interest not be available. This approach, based on a relatively mild assumption (e.g., that the three-year growth rate well approximates the four-year growth rate), significantly increases the volume of information at our disposal and reduces our over-reliance on weights to ensure sample representativeness. The exact data rules are as follows:

- If V_{t_0} was missing, we used $V_{t_{-1}}$ instead. In case $V_{t_{-1}}$ was also missing, we took V_{t_1}.
- If V_{t_n} was missing, we used $V_{t_{n-1}}$.

To aggregate companies in profiles, we used a latent class analysis model, also called finite mixture model (Skrondal and Rabe-Hesketh, 2004). This approach proposes a formal statistical model for the sampled data. Specifically, the model assumes that the underlying population is a "collection" of different sub-populations (or clusters), each characterised by its own multivariate normal distribution (i.e., the population has a finite mixture distribution). A drawback of this method, shared with other maximum likelihood strategies, is the considerable number of observations required to obtain robust parameter estimates.

On the one hand, a crucial advantage of formal statistical models is that they allow to hold constant the classification strategy, rendering it "impartial" across samples. This way, we are guaranteed that the same classification approach will hold whether we compare data for 2-, 4- or 6-year growth, or whether we compare VC-backed against non-VC-backed companies. Since data-driven clustering methods (i.e. hierarchical and optimisation clustering) do not allow to hold constant the classification model across samples, this was an important aspect in favour of latent class analysis models.

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[10] In the case of $CAGR_2$ when the first year after investment was used as an initial value, it could not also be used as a final value, therefore such firms were discarded from the analysis.

On the other hand, appropriate data transformation was key to the successful application of this model. This is because the high skewness of the distributions of CAGRs and the sometimes-different ranges of variation make it impossible to observe normality in the data. As a result, without adjustments a few variables and observations would disproportionately influence the clustering process, leading to results of poor practical use. Following Signore (2016), we apply a series of data transformation and smoothing techniques to the CAGRs of our five economic size variables.

The clustering approach allows fitting the data under different assumptions about the number of latent classes. Selecting the optimal number of clusters entails the identification of the most "informative" model, i.e. the model that the data fits best. Our final choice for the number of clusters is both data-driven as well as the result of practical considerations. The Bayesian Information Criterion (BIC) indicates that the informational advantage of assuming one additional latent cluster tapers after the fifth cluster. Moreover, the additional growth profiles observed after the fifth cluster pertain to micro-clusters of modest informative power. This drives our final choice of five clusters in the data.

After fitting our final model with five latent classes, we calculated the posterior probability of cluster membership for each cluster and each firm. The posterior probabilities show a highly polarised distribution (i.e. either very high or very low). Against this backdrop, we assigned each firm to the cluster in which its growth profile was most likely to be found. Overall, we were able to classify the growth pattern of 2,160 VC-backed start-ups, invested in the period 2007-2014. Using the weighting approach discussed in Appendix A, we ensure that the aggregate results are representative of the original population under analysis.

Appendix C

Building a counterfactual sample of non-VC-backed start-ups

The counterfactual analysis of early and later stage venture investments tackles the following query: how would VC-backed start-ups perform in the absence of VC? To address this policy question, we exploit the assumptions of Rubin's Causal Model (RCM, Rubin, 1974) to generate a counterfactual group of non-VC-backed firms. If appropriately selected, these control start-ups simulate the (unobserved and unobservable) performance of VC-backed start-ups had they not received the VC investment.

Our identification strategy is largely based on the work of Pavlova and Signore (2019). We provide here a brief overview of their approach: for additional details, the reader is referred to their work. We first make two key assumptions about the data: a) that the Orbis database (our main source to identify counterfactual start-ups) contains a representative sample of EU28 firms, and that b) the sample described in Appendix A is a near-complete representation of the population of VC-backed firms in Europe.[II] These two assumptions allow separating the "treated" (VC-backed) from the "control" population (non-VC-backed).

Based on a thorough analysis of the literature, Pavlova and Signore (2019) construct a treatment assignment model that entails two sets of start-up attributes. The authors call the first set "discriminants" of VC financing, i.e. necessary (but not sufficient) conditions for a VC investment to take place. The second set, called "predictors" of VC financing, includes features that VC investors evaluate in their investment appraisal process. Attributes in this second set can be "traded-off", i.e. one or more characteristics may prevail on others during the VC financing negotiation process.

The theoretical framework above motivates an empirical approach based on a two-step matching process. Pavlova and Signore (2019) first identify appropriate control start-ups by exactly matching on the discriminants of VC financing – country, industry, investment stage, patent

ownership, age at investment and degree of innovation. As a second step, the authors construct a propensity score model (Rosenbaum and Rubin, 1983) containing both discriminants and predictors of VC financing. The model's results are further used to select the appropriate counterfactual for each VC-backed start-up.

A significant challenge is brought by the Orbis database, the main source of data for this analysis, which does not cater for the specific information needs of the VC industry. Therefore, we are constrained in the choice of drivers of VC financing that we can actually observe. To offset these limitations, Pavlova and Signore (2019) bring their model to the data by introducing various measures, some original to the VC literature. To predict the degree of innovation of start-ups, the authors use a machine learning algorithm trained to recognise highly innovative business models from short trade descriptions. To measure the "accessibility" of start-ups vis-à-vis active VC firms, the authors use network theory, modelling the European VC ecosystem as a network of VC "hubs" connected by flight routes. Finally, to predict the start-up's access to financing other than VC, the authors construct a proxy for the value of home equity based on satellite imagery analysis. For additional details, the reader is referred to the related work.

Three key distinctions set apart the analysis in this report from the methodology of Pavlova and Signore (2019). The main motivation behind these is the desire to maximise our data coverage and enhance our sample representativeness power.

First, our sample also includes later stage companies, which are outside of the remit and thus excluded from the analysis in Pavlova and Signore (2019). According to the literature, there are some differences in the investment decision process between early and later stage companies. In the case of later stage start-ups, a few (initial) financial metrics

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can be observed, which can shape drastically the views of potential investors. For this reason, we estimate a separate matching model for later stage start-ups, which includes pre-investment financials. We find the existing level of capital and the level of current liabilities to be an important predictor of VC financing.

The second key distinction of this report is that our matching model (both for early and later stage firms) does not include human capital factors – leaving a propensity score model composed of the discriminants of VC financing as well as our "accessibility" index and our proxy for the propensity of the start-up to demand for VC. This choice, significantly advantageous in terms of data coverage, likely introduces some bias in our estimates. The reader is referred to Pavlova and Signore (2019), and in particular appendices G and H, for an analysis of the consequences of such empirical decision in terms of the magnitude of the effects. Our robustness checks indicate that the main findings are maintained (albeit with somewhat smaller average treatment effects) once we further control for the human capital characteristics of start-ups.

The third and final distinction lies in the matching strategy. Once again motivated by the goal to maximise data coverage, we implement the ridge matching estimator of Frölich (2004) to estimate the effects of VC. The ridge matching estimator generates an estimate for the counterfactual mean (i.e. the expected outcome for the treated company had it not received the treatment) that has desirable consistency and efficiency properties in finite samples. The ridge matching estimate for the counterfactual mean can be thought as a "weighted" average of control outcomes. The weight is a function of the distance between the propensity score of the control company and the reference treated propensity score, taking into account the features of the propensity score distribution.

Table 4 provides the list of variables included in our matching model (main effects only, not accounting for interactions and/or higher order effect) complemented by a series of descriptive statistics and the balancing power of our matching method. The second and third column of Table 4 display the matched sample averages of the two evaluated groups. The fourth column displays the P-value of the means

test between the groups. Column five displays the percentage bias, i.e. the two samples mean difference as a percentage of the average standard deviation in the treated and non-treated groups.[12] Lastly, column six displays the variance ratio of treated over non-treated. This ratio should equal to one if there is perfect balance. Variables whose post-matching variance ratio exceeds the 2.5th and 97.5th percentiles of the F-distribution are marked with an asterisk in Table 4.

It is worth noting that, similarly to Pavlova and Signore (2019), the ridge matching estimator is constructed separately for each outcome variable. This approach allows flexibility vis-à-vis potential differences in missing patterns across outcome variables, once again benefitting data coverage and representativeness. We evaluate a total of 76,837 candidate control companies in our matching model (both early and later stage). After the matching process, we retain 42,756 control candidates, which are then used to create counterfactual means for 4,039 treated firms.[13]

To carry out our causal analysis of VC on growth patterns, we used the counterfactual means to compute growth rates (and related growth clusters), i.e. comparing counterfactual means across different post-investment periods. Since we are constructing growth rates based on pooled (weighted) counterfactual outcomes, regression to the mean could be an indirect source of bias for this particular exercise. Against this backdrop, more "extreme" results for VC-backed start-ups, i.e. significant under- or out-performance, might be driven to some extent by this phenomenon.

Due to the stringent data requirements (i.e. all financial indicators used for our cluster analysis should be available and the treated companies should be matched), the final sample for this analysis consists of 831 VC-backed start-up and associated counterfactual means. Using the weighting approach discussed in Appendix A, we ensure that the aggregate results are representative of the original population under analysis.[14]

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[12] According to the literature, the matching method is considered effective in balancing the distribution of the covariate if it achieves an absolute bias of 5% or below.

[13] This figure pertains to the sample size with available assets data. For other financial figures, sample sizes are typically half this size or lower.

[14] However, because of the significantly reduced sample size vis-à-vis the cluster analysis discussed in Appendix B, it was not possible to obtains perfectly overlapping medians and averages for the matched treated sample.

Table 4: Descriptive statistics of PSM model and balancing checks

Variables	Average		P-value	Percentage bias	V(T(/V(C(
	Treated	Control			
Innovativeness score °	0.48	0.47	0.17	2.8	0.99
Company accessibility score	0.48	0.47	0.74	0.7	0.97
Company age at inv. Year °	2.06	2.03	0.73	0.7	1
Distance from FUA's centroid*	6.68	8.52	0.00	-8.5	0.48
Undevelopable land	0.10	0.10	0.61	-1.1	0.95
Distance from FUA's airport centroid*	36.51	36.97	0.51	-1.3	1.06
Patent at investment year:					
No patent at inv. year °	0.74	0.76	0.03	-5.2	n.a.
Has a patent at inv. year °	0.26	0.24	0.03	5.2	n.a.
Investment Year:					
2007 °	0.18	0.18	0.62	1.1	n.a.
2008 °	0.18	0.18	0.85	-0.4	n.a.
2009 °	0.11	0.12	0.46	-1.6	n.a.
2010 °	0.10	0.10	0.74	-0.7	n.a.
2011 °	0.10	0.10	0.93	0.2	n.a.
2012 °	0.10	0.10	0.72	-0.8	n.a.
2013 °	0.10	0.11	0.61	-1.1	n.a.
2014 °	0.13	0.12	0.16	2.8	n.a.
Macro-sector:					
ICT °	0.29	0.3	0.75	-0.7	n.a.
Life Sciences °	0.18	0.18	0.85	0.4	n.a.
Manufacturing °	0.15	0.15	0.67	0.9	n.a.
Services °	0.32	0.33	0.89	-0.3	n.a.
Green Technologies °	0.02	0.02	0.98	-0.1	n.a.
Other °	0.03	0.03	0.95	-0.1	n.a.
Investment stage:					
Seed °	0.71	0.71	0.93	0.2	n.a.
Start-up °	0.29	0.29	0.93	-0.2	n.a.
Later stage °	0.21	0.22	0.8	-0.5	n.a.
Macro-region:					
DACH °	0.29	0.3	0.75	-0.7	n.a.
FR&Benelux °	0.18	0.18	0.84	0.4	n.a.
Nordics °	0.15	0.15	0.67	0.9	n.a.
Mediterranean °	0.32	0.33	0.89	-0.3	n.a.
UK&Ireland °	0.02	0.02	0.98	-0.1	n.a.
CEE °	0.03	0.03	0.95	-0.1	n.a.

Note: our final matched samples are specific for each outcome variable, with results above pertaining to total assets.

Results for other outcomes are qualitatively equivalent. ° Exactly matched.

As pointed out in Appendix B, a series of data transformations is rendered necessary in the cluster analysis to ensure normality of the data. One of these transformations is standardisation, i.e. rescaling the data so that their mean is null and their standard deviation is one. To this end, we separately standardise the treatment and control group data. The sub-sample of treated start-ups in the counterfactual analysis is standardised according to the entire cluster analysis distribution, i.e. the 2,160 companies analysed in the second chapter. This ensures that the exact same categorisation of growth rates is maintained for treated firms.

The control group is standardised according to its own distribution. In practical terms, the outcome of using two different distribution on which to rescale the data means that companies will be clustered according to their relative performance in their reference group. This implies that a treatment and a control firm with the same underlying growth rates might fit in two different clusters, due to their different performance relative to the rest of treated and control firms respectively. Start-ups in a given cluster will nevertheless show the same characteristic behaviour, i.e. an overall positive growth with disproportionate intangibles growth for visionaries in both groups. We considered this approach superior to the alternative of standardising both groups according to a common distribution, which would have led to an overwhelming majority of control start-ups being captured by the commoners' group, simply due to the lower intensity of their growth.

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Andrea Crisanti

Andrea is the lead analyst of this project and works in EIF's Research & Market Analysis division. He holds an MSc in Economics from Bocconi University.

andrea.crisanti@eif.org

Since the start of this exercise, he has drunk 483 cups of coffee.

Julien Krantz

Julien is the head of Invest Europe's research department. He holds an MA in International Economics & Finance from Brandeis International Business School and MSc in Management from Institut Mines-Télécom Business School.

julien.krantz@investeurope.eu

Over the course of this collaboration, he spent 31 hours and two lunch breaks inside conference rooms.

Elitsa Pavlova

Elitsa is part of EIF's Research & Market Analysis division. She holds an MSc in Economics and Public Policy from the Paris School of Economics.

e.pavlova@eif.org

During this project, her computer crashed 17 times.