EUROPEAN
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EIF Research & Market Analysis

Working Paper **2017/41**

The European venture capital landscape: an EIF perspective

Volume III: Liquidity events and returns of EIF-backed VC investments

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Luxembourg, April 2017

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Abstract†

Despite the sometimes intensive media coverage and exuberant storytelling around the industry, venture capital (VC) investors tend to operate in highly opaque markets. On this premise, this work contributes to the literature via a hand-collected dataset of about 3,600 EIF-backed VC investments made in the 1996-2015 period, with the aim to analyse their liquidity events and returns. The paper finds, *inter alia*, that VC returns show sensitivity to the economic cycle. At the same time, it discusses how their heterogeneity leaves room for VC firms to pursue diversification strategies and minimise the correlation with other asset classes. Moreover, this work provides preliminary evidence in support of the often claimed heuristic that VC returns follow a *power-law*. Finally, it employs competing risks models to analyse time-to-outcome data, observing that VC firm experience only relates positively to performance when *outstanding* (*e.g.* 3rd generation fund or above). However, this may also be a reflection of EIF's high-standard screening of first-time VC teams. The paper is structured as follows. Section 1 introduces the key research motivations, while section 2 discusses the features of the analysed dataset. Section 3 provides a descriptive overview of the data, while section 4 discusses the statistical test of power-law behaviour. Section 5 explores exit outcomes against the background of profitable or unprofitable trade sales. Last, section 6 analyses the determinants of exit outcomes. Section 7 concludes.

Keywords: EIF; venture capital; performance; fat tails; divestment; IPO; competing risk analysis

JEL codes: G11, G24, L11, M13

† I thank Simone Signore for his continuous support and the long hours of constructive discussion behind this work. I would also like to acknowledge the invaluable contribution of my EIF Research & Market Analysis colleagues Helmut Kraemer-Eis, Frank Lang, Wouter Torfs and Salome Gvetadze. I am also grateful to Uli Grabenwarter, Laurent Braun, Arnaud Vanbellingen, Stephanie Descoubes, Alicia Bodeau for their useful remarks, as well as Margherita Biffi and Frank Vancamelbecke for their help with the data. Finally, I thank prof. Stephen Jenkins, London School of Economics, prof. Xavier Gabaix, Harvard University and prof. Thomas Hellmann, Oxford University for their insightful comments. All errors are attributable to the author.

Non-technical Summary

This work is the third volume of the series of working papers entitled "The European venture capital landscape: an EIF perspective". The series aims at assessing whether EIF's VC activity positively affected beneficiary start-up companies, contributing to the broader theme of government intervention in the field of venture capital. With the aim to investigate exit returns in Europe, this paper analyses data on about 3,600 EIF-supported seed and start-up VC investments from 1996 to 2015.

Throughout 20 years of EIF-supported venture capital (VC) activities, the exit scenery of venture investments has shown sensitivity to the business cycle. While trade sales steadily increased following the expansion of EIF's VC activity, major recession events such as the *dot-com bubble* (2001–2002) and the European sovereign debt crisis (2009–2010) were linked to peaks in investment write-offs. On the upside, profitable trade sales continue the increasing path started in 2010, following the modest economic recovery, low interest rates and a rekindled confidence in the tech industry.

The data illustrated in section 3.1 provides evidence that start-up valuations are responsive to movements in the NASDAQ Composite index. However, while the European VC ecosystem may be shaped by common macro-factors, we observe high heterogeneity in the exit trends within Europe, particularly across geographies and industries. At fund or fund-of-funds level, the diversity and the granularity of start-up investment opportunities leave room for investors' diversification strategies that can effectively lower the correlation with other asset classes. Moreover, recent years display a clear upward trend in both average and median returns: the weighted average of the multiples on cost (MoCs) at exit for realised VC investments stands at 1.16x for the entire period, the median being 0.12x. The distribution of exit MoCs is extremely right-skewed: 70% of exited investments are either written-off or sold for an amount below cost. Deals in which venture capitalists (VCs) sell at cost account for 8%, whereas the remaining 20% are profitable liquidity events.

Noteworthy, 4% of the exits have returned more than 5 times the investment. This 4% generates almost 50% of the total aggregated proceeds. As a result, the performance of VC firms is mainly driven by the occurrence of *tail events* in a VC fund. In order to better understand the process leading to such distribution, section 4 formally tests the standard assumption that returns in the VC industry are *power-law distributed*. Power-laws rarely surface works in the field of financial economics. However, the presence of this empirical regularity delivers concrete implications for VC investment strategies and risk management. For instance, it might shed light on the changes of portfolio valuations following a *Unicorn* exit and/or to the share price collapse of a quoted investee. In light of this, empirical evidence from our data partially confirms the assumption, in that EIF-backed VC returns comply with the power-law distribution for multiples over 2.35x. Nevertheless, as alternative distributions (and theories) fit the data as effectively, only further research will be able to reach conclusive evidence.

Section 5 focuses on exit outcomes, providing further descriptive insights on M&As and IPOs of EIF-backed start-ups. Among several other findings, we observe that, on average, about 50% of the performing EIF-backed European investees are acquired by non-European corporations, particularly from the US. US-based buyers are typically larger in terms of assets and revenues, more innovative and mostly active in the ICT domain. This raises the issue of whether the missing *scale-up* phenomenon in Europe could be linked to the lack of serial tech buyers, that is, incumbents in highly innovative and competitive sectors (and often former successful start-ups). At the crossroads between *scaling-up* or being acquired, later-stage funding becomes essential. While both acquisitions or foreign buyers are not *per se* negative, their joint existence may be a signal that European start-ups lack the growth capital necessary to expand and strengthen their position. As such they may end up being acquired, unless they have the chance to *go public*: in section 5, we also map 152 IPOs of EIF-backed start-ups observed in 1996–2015 and 20 different stock exchanges around the world.

Finally, section 6 concludes our analysis by focusing on the factors affecting the exit performance of VC investments. The empirical analysis delivers key results that can be summarised as follows:

- *Geography-related take-away*. While fund managers from the NORDICS region display higher propensity to write-off their positions, investments performed by UK&IRELAND investors are strongly associated to a greater incidence of profitable trade sales and an initial public offerings.

  Although causality is never claimed, British and Irish VC funds might play an important role in shaping performance at fund-of-fund level. Moreover, in some specifications of our model, a shorter fund-company geographic distance is associated with a higher chance of a positive trade sales.

- *Industry-related take-away*. Compared to ICT, Life Sciences investments have a significantly higher chance of IPO. On the other hand, investees in the Services industry seem related to a higher probability of profitable trade sales.

- *Startups-related take-away*. Becoming a *Unicorn* is related to a large increase in the probability of being acquired, but not significantly related to the chance of going public. This dynamics might suggest investors' caution for IPO exit strategies when the company private valuation is very high.

- *Investors-related take-away*. More recent vintage years are associated with less likely write-offs and IPOs. Moreover, the first investment amount, *i.e.* the size of the initial investor's bet on a start-up, is negatively associated with the probability of unprofitable trade sales and positively associated with IPO likelihood. Hence, investors appear able to recognize and cherry-pick successful companies at the time of the first check.

  In some specifications, a larger number of investments made by a VC fund is related to a higher probability of experiencing a write-off, but also to a greater chance of IPO. This last result is non-trivial, because it advocates for the idea that enlarging the number of portfolio companies in a fund increases the chance of getting an *outlier* on board for an investor.

  Last, venture capitalist's experience is strongly correlated with a lower probability of write-off and higher probability of profitable sale. However, *first-time VC teams* are no significant predictors of any exit outcome, a finding that defies the expectation of under-performance. This might hint that VC experience is relevant only when it is markedly high. At the same time, it might also suggest the strong selection effect of EIF to choose only *high-potential* first-time VC teams.

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1 Introduction

There are numerous reasons in support of a study on the return perspectives of venture capital (VC) investments in Europe. First, it would increase transparency among market players. The importance of such first point cannot be understated: despite the sometimes intensive media coverage and exuberant storytelling around the industry, VC investors tend to operate in highly opaque markets (Da Rin *et al.*, 2013).[1] Against this backdrop, prospective venture capitalists (VCs) may lack the expertise and in-depth knowledge that is crucial to mitigate information gaps and to deliver good performance (Sorensen, 2007; Sorensen, 2008). The provision of new comprehensive data on European VC returns may thus advance investors' current knowledge of the market and potentially enhance their investment strategy (Chaplinsky and Gupta-Mukherjee, 2016; Masters and Thiel, 2014).

Second, the lower presence of venture funding in Europe has been repeatedly ascribed to the chronic lack of attractive and liquid markets for VC exits (Black and Gilson, 1998; Hege *et al.*, 2009; Tykvová *et al.*, 2012). As such, evidence on exit dynamics throughout Europe becomes of paramount importance for policy-makers in charge of designing public intervention in the European VC ecosystem.[2]

Third and last, there is an inherent need to enlarge the body of economic research on the performance of venture capital investments in Europe. Currently, the evidence produced for European VC is dwarfed by the volume of publications focusing on the US VC market. A key challenge in this area is obtaining data to compute investment returns, which typically restricts the focus — particularly in Europe — to *exit-type* data.

In this paper, we employ a novel micro-level dataset of 3,600 VC investments performed via EIF-backed venture capital funds from 1996 to 2015 to address the topic of VC returns. Data is sourced from EIF internal records, *i.e.* the quarterly reports submitted by private equity funds in which EIF is Limited Partner (LP). Departing from the commonly used data sources, we avoid some of their well-known limitations.[3] On the other hand, as EIF only supports a limited portion of European VC fundraising,[4] an important disclaimer relates to the potential non-representativeness of our sample with respect to the overall population of European VC investments. However, the breadth of EIF's geographic and sectoral focus, coupled with the diversity of EIF-supported VC teams in terms of experience and past performance, guarantee sufficient heterogeneity across the analysed sample.

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[1] The case for severe information asymmetries in venture capital has often been discussed, *e.g.* by Bergemann and Hege (2005), Casamatta (2003), Schmidt (2003), Hellmann and Stiglitz (2000). Lack of information on expected returns and the existence of double moral hazard shape some of the industry's defining features, such as, *inter alia*, investors' activism, usage of convertible securities and equity rationing.

[2] Arguments supporting the need for governments to tackle such "European VC gap" are discussed in Tykvová *et al.* (2012) and Kraemer-Eis *et al.* (2016b). For a critical view of public intervention in the VC market, see Lerner (2009).

[3] Most empirical research on VC exits is grounded on either data from *ad-hoc* surveys or commercial databases, such as VentureXpert and Venture Source (see Kaplan and Lerner 2016 and Da Rin *et al.* 2013 for an overview.). The limitations of such data sources are well-known: reporting bias, bias towards US investments, lack of complete time series on financing rounds, under-representation of the Biotech sector and the difficulty in knowing the status of investments whose outcome is other than IPO or acquisition.

[4] In 2007 (2014), 27% (30%) of VC funds' final closings in Europe have been backed by EIF. For the complete time series, see Kraemer-Eis *et al.* (2016b).

The aim of this paper is threefold. First, it provides a descriptive overview of venture capital returns in Europe: while section 2 describes the main features of our sample, section 3 looks at historical exit trends. In this first part, we discuss investee valuations over time, comparing them to stock market behaviour. In addition, we provide a descriptive analysis of VC investment returns.[5]

The second objective, based on the insights of the opening sections, is to investigate the empirical regularities of VC investment returns. To this end, section 4 dives deep into the statistical properties of the returns distribution with the aim to identify and discuss the *physical process* that underlies European venture capital returns.

Third and last, this paper looks at the outcomes of EIF-backed investments. Section 5 matches realised investment data with Bureau Van Dijk's (BvD) M&A database Zephyr. This enables the retrieval of further insights on acquisitions and IPOs experienced by EIF-backed VC investees. It also allows to tackle our final research question, related to the determinants of VC exit performance: to this end, section 6 follows the approach in Giot and Schwienbacher (2007) to estimate a series of *competing risks models*. These are used to assess which fund- and investee-level factors can significantly predict the probability of experiencing a write-off, liquidation, acquisition or IPO.[6] Section 7 concludes.

2 The Data

This work builds on multiple data sources. The starting point is a dataset of 2,951 start-ups invested by 355 EIF-backed funds between 1996 and 2014.[7] For this analysis, we focus on investment-level data, comprising 3,592 fund-investee records. Each record has been augmented with information on the status of investments throughout their lifespan, producing quarterly-updated panel data.[8] As EIF typically acts as LP in funds it invests into, data on investment statuses is considered unbiased, *i.e.* not suffering from the reporting bias of voluntary self-disclosure. Instead, the information analysed results from the formal reporting requirement fulfilled by general partners (GPs) since the date of final closing up until the fund's liquidation. This guarantees that our data is complete up to a reasonable extent and that it allows following all portfolio companies from vintage to exit, independently of the economic, financial and legal outcome of their investments. Finally, data is *standardized*, *i.e.* EIF-backed VC firms comply with IPEV Reporting Guidelines.[9]

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5 In this paper, the expression *returns* points to the *gross returns* of VC investments. These focus on the performance of the underlying companies, thus meant to quantify the ability of VCs to generate returns. *Net returns* gauge instead the ability of LPs to pick successful VC fund managers (Da Rin *et al.*, 2013).

6 In the listed order: a *write-off* is a divestment where the investor assigns zero to the value of its equity holdings (or a symbolic amount), thereby withstanding a full or partial investment loss; a *liquidation* indicates every non-write-off liquidity event whose proceeds for the VC investor are less than her original investment, *i.e.* an *unprofitable trade sale*; *acquisition* is used as a synonymim for *profitable trade sales*; an *Initial public offerings*, or IPO, marks the first time that shares of a company can be publicly traded.

7 Details of its construction were discussed in Kraemer-Eis *et al.* (2016b) and Signore (2016). Consistent with these studies, this work only focuses on EIF-backed investments in seed and start-up stage companies.

8 The panel is *unbalanced* because of different investment periods and sample attrition, *i.e.* investments dropping out of the sample when exited.

9 In a small number of cases investments are carried out by legal structures other than "standard" VC funds, *e.g.* co-investments with business angels. Nevertheless, their reporting requirements mostly hold the same.

Choosing a well-suited metric for VC returns is far from trivial. Even in the case of granular and unbiased data, standard asset-pricing models (*i.e.*, CAPM) deliver estimated measures of risk-return that can be challenging to interpret. Indeed, the assumptions of liquid and transparent markets underlying the CAPM are far from being satisfied in private equity investments (Ang and Sorensen, 2012).[10] At the same time, alternative metrics such as the Public Market Equivalent (PME) or the Internal Rate of Return (IRR) present some relevant drawbacks when applied to a company-level framework. Despite being a robust relative performance indicator, the PME, introduced by Kaplan and Schoar (2005), has been used in the literature only to evaluate net fund returns for LPs. The IRR introduces computational issues and manipulation risk with the unrealistic assumption that the investment proceeds can be reinvested by the VC fund manager at the IRR rate.

Therefore, as our return measure, we use the Total Value to Paid-In multiple (TVPI), or Multiple on Cost (MoC, henceforth) measured at exit. Despite the MoC being *rougher* than the IRR, in that it does not embed *time value of money* in its calculation, it is the most popular performance measure among investors and entrepreneurs, mostly because of its intuitiveness and computational simplicity. On the other hand, analyses based on the MoC — which assumes a zero-rate reinvestment of cash flows — tend to be more conservative than those based on the IRR (Ang and Sorensen, 2012).

Define $t_0 = 0$ as the vintage quarter and T_i as the exit quarter for investment $i = 1, \ldots, 3592$. In this work, we define the MoC for investment i at quarter $t \in [t_0, \ldots, T]$ as follows:

$$\text{MoC}_{i,t} = \frac{\text{valuation}_{i,t} + \text{cumulated\_proceeds}_{i,t}}{\text{total\_invested\_amount}_{i,t}} \tag{1}$$

where $\text{total\_invested\_amount}_{i,t}$ is the overall cost of the investment and $\text{cumulated\_proceeds}_{i,t}$ is the total amount of cash realised from sale or liquidation at quarter t. The term $\text{valuation}_{i,t}$ is the end-of-quarter valuation of the start-up *shares held by the VC firms*. This valuation is typically equal to cost at t_0 and it reaches zero when the investment is fully exited, *i.e.* at T_i. As funds report their equity stakes on a quarterly basis, we are also able to track the start-up valuation over time.[11] To ensure the comparability of time series, all monetary amounts in Equation 1 are expressed in real terms, by using GDP deflators of the country hosting the main headquarters of each VC firm.

Quarterly reports submitted to EIF also provide data on two main types of exit route: *trade sales* and *write-offs*. By combining this information with the MoC at exit date, we further define "unprofitable sales" as trade sales with $\text{MoC}_{i,T_i} < 1$, and "profitable sales" as trade sales with $\text{MoC}_{i,T_i} \geq 1$. Profitable trade sales indicate that start-up shares were sold, in either private or public markets, for

[10] Building on Cochrane (2005), Korteweg and Sorensen (2010) use US company-level data to estimate CAPM alphas and betas for VC investments in start-ups. By using a dynamic selection model to correct for endogenous selection of the observed returns, they find an average beta of 2.8 and negative alphas after 2000. However, due to specificities of their continuous-time model, interpreting the economic magnitude of the excess return is not clear-cut.

[11] Comparing valuations of VC-backed start-ups on the basis of this approach entails a number of stronger assumptions. Most critically, we must assume that VC firms' equity stakes are always reported based on the outstanding *fully diluted shares*. If instead the reported equity stake refers to the basic outstanding shares, we expect a potential downward bias in the computed valuations, due to the lack of consideration for equity-related instruments such as employee stock options, warrants and convertible notes.

an amount no less than the investment cost. Instead, unprofitable trade sales mark an exit event also referred to as *liquidation*, *i.e.* the investor's attempt to minimise the loss of a low-performing investment. Table 1 shows the sample split by exit outcome and provides some descriptive statistics.

Table 1: EIF-backed VC investments by exit status[12]

Exit Status	N	Perc.	Start-up Age	Investment Age	Tot. Invested (EUR m)
Company in portfolio	1527	42.5%	n.a.	n.a.	3.0
Write-Off	709	19.7%	7.2	4.9	2.6
Unprofitable Sale	829	23.1%	8.5	6.0	3.0
Profitable Sale	527	14.7%	7.9	5.1	3.3

Note: based on a sample of 3,592 investments in 1996–2015. Columns 4 and 5 contain the exit age for companies and investments respectively. Column 6 provides the average of total (*i.e.* first and follow-on) investments from vintage to exit.

Besides some well-expected data features, *e.g.* more profitable investments receiving additional financing along the way, a robust finding immediately emerges by looking at the percentages. That is, in venture capital, gains come from the *outliers*. Moreover, investments resulting in a write-off are, on average, the quickest to be terminated, whereas liquidations take the longest to materialise.

An obvious limitation with investment performance figures is that, despite the insights on *whether* returns were realised, not much is known about *where* such realisations stem from. We therefore complete our dataset on exits with data on equity deals sourced from BvD's Zephyr.[13] While write-offs and non-exited investments are typically not traceable in the Zephyr database, the exercise still allows to retrieve deal information on 591 exits, out of 1,356 profitable and unprofitable trade sales. Not surprisingly, Table 2 shows that most exit types not matched in Zephyr tend to be the ones generating the lowest returns for VC firms.[14] A case-by-case inspection of quarterly reports reveals that untraced exits mostly correspond to liquidation-related share buybacks or management buy-outs (MBOs).

Table 2: Exit MoCs for VC exits by deal type

Deal Type	Avg MoC	Median MoC	Min MoC	Max MoC	N
Acquisition	2.1x	1.0x	0.0x	105.4x	447
IPO	4.3x	1.5x	0.0x	139.0x	111
Other	2.1x	1.2x	0.0x	12.5x	33
No Zephyr Deal Data	1.0x	0.3x	0.0x	28.5x	765
Total	**1.7x**	**0.6x**	**0.0x**	**139.0x**	**1356**

Note: based on 1,356 EIF-backed trade sales. Write-offs and non-exited investments are excluded. Deal type "Other" includes IBOs, MBOs, MBIs, joint ventures and buybacks. Source: BvD Zephyr (2016).

Equity deals data will be extensively used in section 5.1 and section 5.2 to provide descriptive evidence on acquisitions and IPOs experience by EIF-backed investees, with the specific aim to pinpoint start-up buyers and the stock exchanges used to go public. Moreover, the deal-level information allows a finer identification of the different exit outcomes used in the competing risks models of section 6.

[12] Unless otherwise stated, all figures in this research are an elaboration of the author, based on EIF data.

[13] BvD Zephyr is an information solution containing merger and acquisition (M&A), IPO, private equity and venture capital deals. As of April 2017, Zephyr has information on over 1.5 million deals and deal rumours.

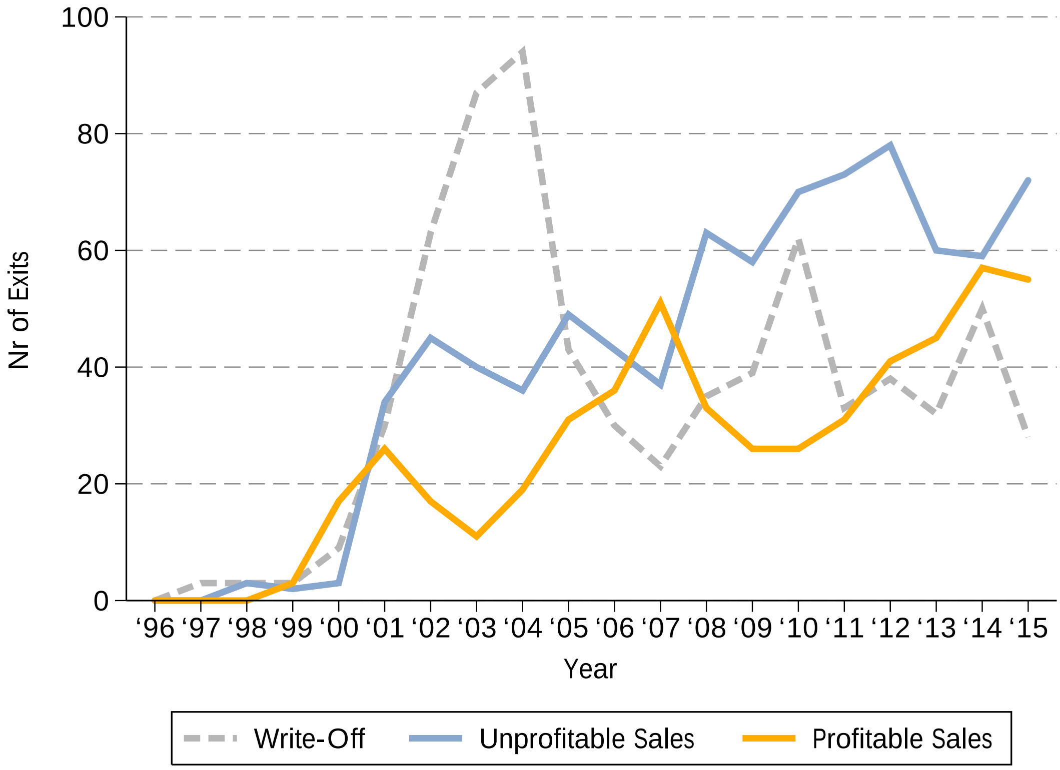
[14] Note that the number of IPOs reported in Table 2 does not show all the EIF-backed IPOs, but only the divestments through IPO. Indeed, it might well be that an IPO happens after the VC has sold its shares.

3 Trends and Returns

3.1 The European exit environment

Throughout 20 years of EIF-supported VC activities, the exit scenery of venture investments has shown sensitivity to the business cycle. While both profitable and unprofitable trade sales steadily increased following the expansion of EIF's VC activity, major recession events such as the dot-com bubble (2001–2002) and the European sovereign debt crisis (2009–2010) were linked to peaks in write-offs. On the upside, successful trade sales have been firmly increasing since 2010, alongside an economic recovery, low interest rates and a rekindled confidence in the tech industry, evidenced by the upturns of NASDAQ and venture capital valuations.[15] Figure 1 shows the trends for EIF-backed VC exits.

Figure 1: Exit trends of EIF-backed VC investments by exit type



Note: based on 2,065 EIF-backed early-stage VC investments exited between 1996 and 2015.

The EIF-backed subset of the European VC ecosystem appears to be shaped by common macroeconomic and institutional factors.[16] However, there is also significant heterogeneity in the exit trends, particularly across geographies and industries.[17] Following the dot-com crash, for instance, the

[15] Nevertheless, some caution is necessary when looking at the last years of the sample period, as most of the recent investments are likely to be still held by funds' portfolios.

[16] Remarkably, the observed trends are in line with European-level statistics based on data regarding the entire European VC market. See Kraemer-Eis *et al.* (2016a) for details.

[17] Eight geographical regions were defined as follows: **DACH**: AT, CH, DE; **NORDICS**: DK, FI, NO, SE; **FR&BENELUX**: BE, FR, LU, NL; **SOUTH**: GR, ES, IT, MT, PT; **UK&IRELAND**: IE, UK; **CESEE**: BG, CZ, EE, LT, LV, PL, RO, SK, TR, CY; **US**; **ROW (Rest Of the World)**: AR, AU, CA, CN, CR, HK, IL, IN, MX, PH, RU, SG, UY. See Signore (2016) for a breakdown of the EIF activity by regions. The industrial nomenclature follows Invest Europe's classification. For details, see Signore (2016).

SOUTH macro-region endured the highest relative incidence of write-offs,[18] while at the same time showing greater resilience to the sovereign debt crisis — despite the economy of the region being impacted the most — which only caused a short-lived reduction in trade sales. Conversely, the region UK&IRELAND seems to have been highly sensitive to the worsening of the macroeconomic conditions. During both crises, investments in UK accounted for 30% of the overall write-offs. As expected, investments in Life Science companies were almost unaffected by the dot-com crash, contrary to ICT.

The sensitivity of aggregate divestments to the economic cycle may be due to multiple circumstances. Write-off waves might follow VC firms' negative growth expectations of portfolio companies in the aftermath of a recession, while M&A activity might be affected by tech-buyers' appetite to invest and expand their business. This appetite, in turn, is impacted by expectations, uncertainty and volatility. Notwithstanding, the main driver of these patterns seems to be the stock market, as documented by a well established literature. According to Gompers *et al.* (2008), fluctuations in VC activity are related to changes in the stock market, so that public market shifts can provide useful insights to investors. Black and Gilson (1998) stress how the stock market affects VC exit strategies, while Michelacci and Suarez (2004) develop a model in which stock markets trigger start-up creation. Pastor and Veronesi (2005) provide evidence that IPO figures vary in response to changes in public market conditions.

Further responsiveness to macroeconomic conditions emerges when looking at start-up valuations. The outstanding volatility of start-up valuations is certainly a well-known fact (Gompers *et al.*, 2008). Phenomena like *winner-takes-all* competition may give raise to natural outliers that heavily affect the average start-up valuation. Figure 2 shows the evolution of average and median valuations over time. Median valuations tend to be more stable than averages, although both of them follow the cyclical pattern suggested by Figure 1. Interestingly, there is a clear upward trend in both series over recent years, with the median start-up valuation reaching its historical peak.

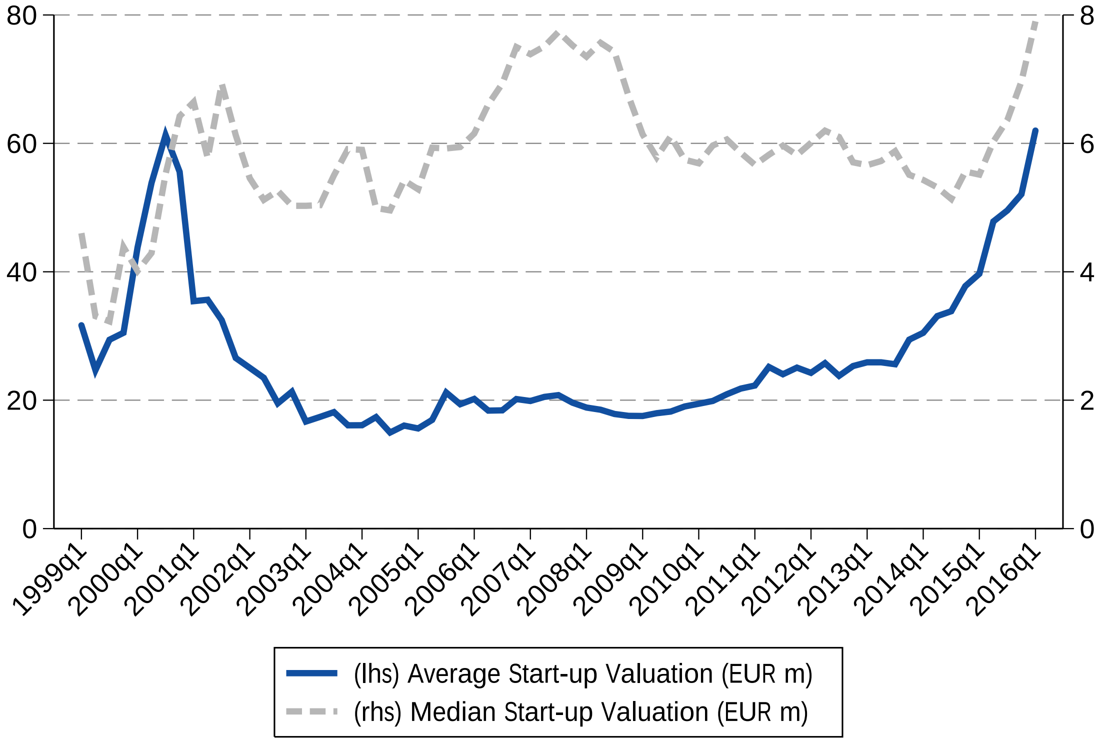
To understand whether these trends are in line with the public markets behaviour, in Figure 3 we plot the median VC investee valuation against the real value of the NASDAQ Composite Index, an index of all common stocks and similar securities listed on the NASDAQ stock market. The use of this index is motivated by its significant bias towards information technology and biotech companies and, in turn, by its suitability to represent VC-backed start-ups that go public.[19] Apart from the 2009–2012 period, where the flat pattern of European valuations might have been a reflection of the sovereign debt crisis, the valuation trend seems to be anticipated by the NASDAQ shifts. We formally test the assumption that NASDAQ movements help predicting median start-up valuations by means of a Granger-Causality test (Granger, 1969).[20] The Granger-Causality test is a statistical test to determine whether one time series is useful in forecasting another. Results suggest that variations in the NASDAQ Composite Index contain useful information on future short-term fluctuations of the median valuation of start-ups. Further details on this finding are discussed in Appendix A.

[18] For instance, Italy accounted for 15% of all the write-offs between 2000 and 2002.

[19] For a discussion on the role of stock exchanges in providing exit routes to European venture capitalists, see Da Rin *et al.* (2006) and Bottazzi and Da Rin (2003).

[20] We choose median valuations by quarter over average, as the latter can be significantly influenced by VC investments in start-ups that undergo a public listing.

Figure 2: VC investees quarterly real valuation over time



Note: valuation statistics prior to 1999Q1 not considered due to negligible sample size. Amounts refer to *company valuations* (see section 2), as opposed to *investment valuations*, used instead to compute the MoC. Average and median values only consider start-ups whose shares are held by at least one EIF-backed fund at each respective quarter. Monetary values expressed in constant EUR prices, with 2005 as the base year.

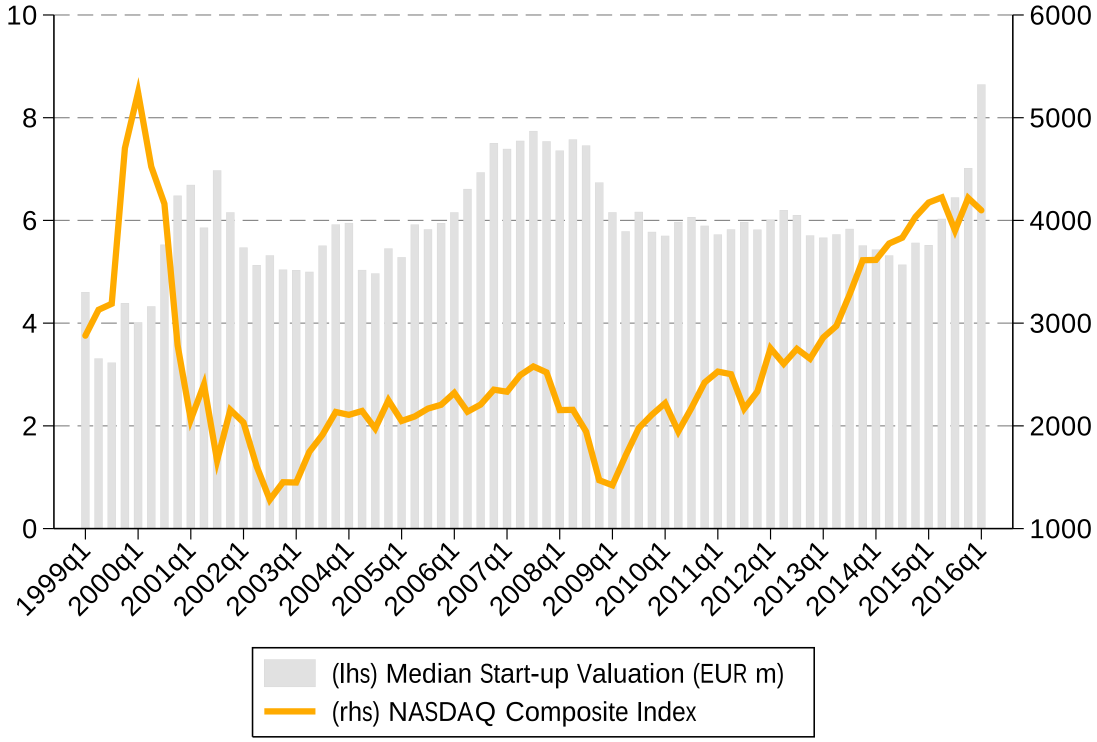
In principle, venture capitalists aim at maximising their profit by realising their investments when valuations are at their highest. The challenge of choosing the right time to exit a VC investment is not trivial, and it may have a significant impact on the return on investment of VC firms.[21] As time-to-exit is a key parameter shaping the general exit environment, we might be interested in looking at how the average holding period evolves for our sample of investments. However, the time series we analyse are not long enough to establish a significant trend, as many of the investments are still held in the VCs' portfolios. Also, short holding periods in the first years of the sample are intrinsic to the first EIF-backed investments being carried out no earlier than those years. Longer time series are needed in order to establish a clearer holding period pattern.

Overall, data so far shows that the exit environment for EIF-backed VC investments is not only linked to technological cycles,[22] but also to economic cycles. Accordingly, venture capital is likely to show

[21] The VC investment in Tiscali, an Italian telco company founded in 1998, is a textbook example: the company, one of the pioneers of flat-rate solutions for consumer Internet services, sailed on the enthusiasm of the dot-com boom and faced an IPO in October 1999. The share price at IPO was EUR 3.75 and peaked at EUR 61.59 in March 2000, +1540% in less than 6 months. In June 2002, share price went below 3.15 and steadily declined ever since, where the current price fluctuates around EUR 0.04 (Source: Thomson Reuters Eikon). While the investment generated more than 100x MoC for an early seller, a different investor obtained around 2.5x by exiting the investment a mere 18 months later.

[22] By *technological cycle*, we mean the rise and fall in the adoption of new technologies and its effects on the economy. For instance, several different industries nowadays face new business opportunities due to the advent of technologies such as AR/VR, blockchain, driverless cars, *etc.*

Figure 3: Median VC investee valuation and NASDAQ Composite Index



Note: the NASDAQ Composite Index is a market capitalization weighted index with more than 3,000 common equities listed on the NASDAQ Stock Market. The index includes all NASDAQ listed stocks that are not derivatives, preferred shares, funds, exchange-traded funds (ETFs) or debentures. Series expressed in real terms (2005 = 100). Source: FRED, Federal Reserve Bank of St. Louis.

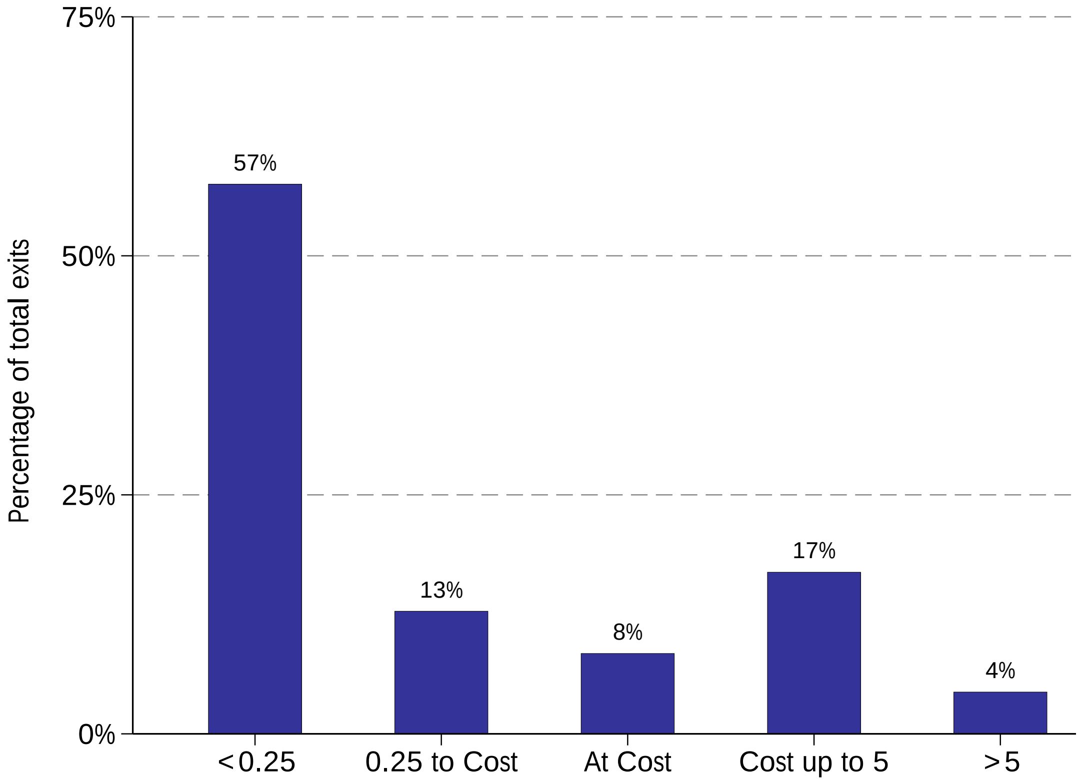
correlation with other asset classes. However, the geographic and sectoral heterogeneity of venture capital investments leaves room for VC firms to pursue diversification strategies. From a portfolio management perspective, *finding the tail events* remains a key condition to generate excess return. On the other hand, exploiting the granularity of the start-up ecosystem via diversified investment strategies may allow VC firms to hedge against the business cycle and the stock market.

3.2 VC investment returns

With the aim of providing a descriptive analysis of the EIF-backed VC exits, we start by inspecting exit returns for 2,065 realised investments (58% of the overall 3,592 EIF-backed investments in the sample, see Table 1). To ease the visualisation of highly skewed data, Figure 4 breaks down the distribution of exit multiples in five discrete classes. About 70% of the exited investments have been either written-off or sold for an amount below cost. Deals where the VC sells at cost account for 8%, whereas the remaining 20% of the liquidity events are profitable. Only 4% of exits have returned more than 5 times the investment.

The reader acquainted with VC dynamics will not find Figure 4 much surprising. Venture capital is mostly a losing game, with investments falling on the right-hand tail of the distribution destined to return the amounts necessary for the fund to break-even and make profits. To this purpose, Table 3 reports, for each exit class, the average share of the investor's fund returned by the exit.

Figure 4: Distribution of the exit return class, unweighted MoCs



Note: based on 2,065 early-stage VC investments, exited, made between 1996 and 2015 by EIF-backed VC funds. The figures include all the exit types, *i.e.* write-off, liquidations and successful sales. Exit MoCs are not weighted. The "At Cost" bucket includes all the MoC values such that $0.8 \leq \text{MoC} < 1.2$.

The percentages in Table 3 can be interpreted as follows: suppose a VC investor realises an investment with an exit multiple between 1 and 5. Then, as per our findings, (s)he should expect that exit to return, on average, 10% of the fund.

Table 3: Average share of VC fund returned by an exit, by exit class

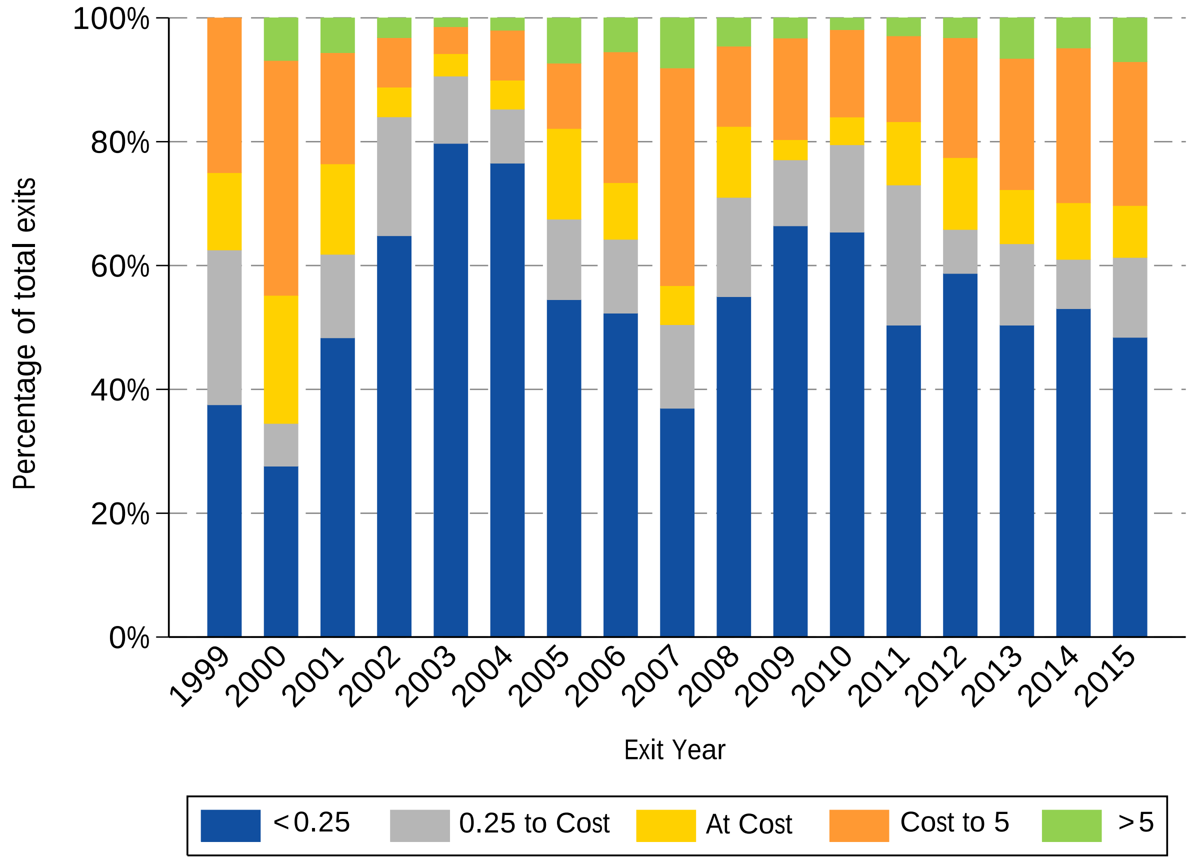
Exit Class	Share of the fund returned (Mean)	Share of the fund returned (Median)
<0.25	0.1%	0.0%
0.25 to Cost	1.7%	1.0%
At Cost	3.7%	2.5%
Cost up to 5	10.0%	7.3%
>5	43.9%	25.3%

Note: based on 2,057 EIF-backed exited investments, including write-offs. Exit classes defined as per the MoC at exit.

Although the right-skewdness of venture returns is intrinsic to the venture capital business model, some heterogeneity in the distribution can be observed across time, space and domain (see Figures B1 — B3 in Appendix B). Investments in Life Sciences and Services display less under-performers (and more out-performers) than investments in the broader ICT space. At the geographical level, start-ups in the FR&BENELUX and US macro-regions have returned more than the average. The vintage year plays an important role in shaping the returns distribution. While the share of profitable exits was 16% of all the investments made between 1996 and 2001, the proportion of successful investments made between 2007 and 2015 was higher than 30%.

The question of whether this phenomenon is *cyclical* rather than *structural* is certainly relevant. In order to shed more light on the time dimension of the investments performance, Figure 5 depicts how the distribution of unweighted exit returns fluctuated in recent years.

Figure 5: Distribution of the exit return class over time, unweighted MoCs



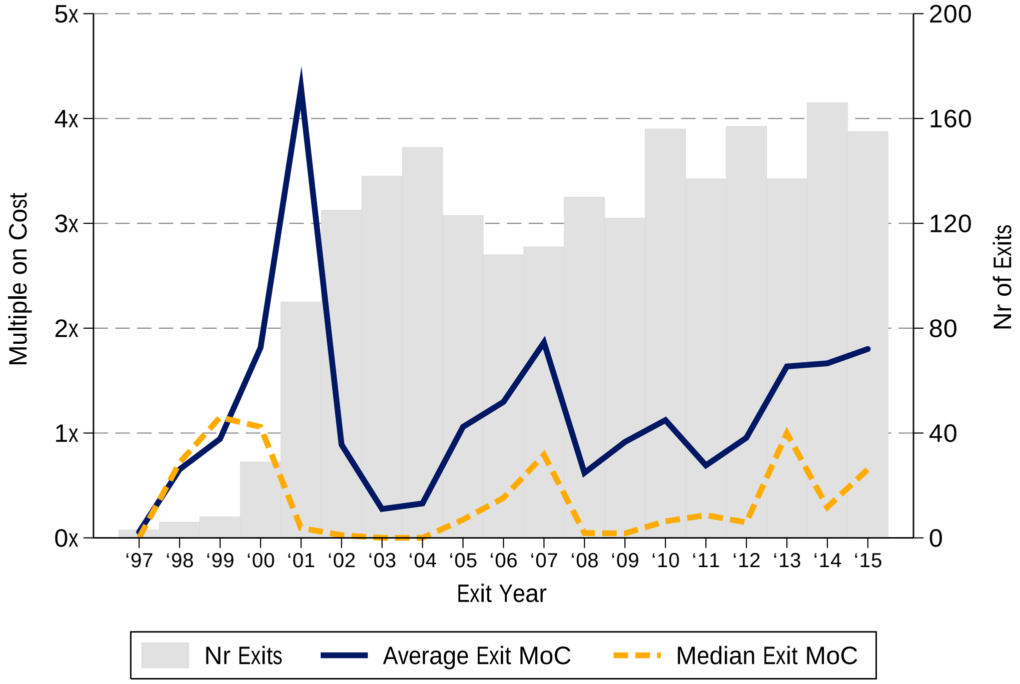
Note: based on early-stage VC investments exited between 1999 and 2015 by EIF-backed VC funds. The figure includes all the exit types, *i.e.* write-off, liquidations and successful sales. Exit MoCs are not weighted. The "At Cost" bucket includes all the MoC values such that $0.8 \leq$ MoC < 1.2.

There seems to be cyclicality in the returns distribution, with the proportion of non-performing exits increasing during recessions and shrinking over growth periods, in line with section 3.1 as regards to the number of exit deals. Remarkably, 2010 can be marked as the starting year for an expansionary trend of profitable EIF-backed investments. The extent to which this points to an improvement in VCs' ability, or it simply reflects the positive momentum in tech company valuations, is not as easy to say.

On the one hand, the representation of the unweighted exit multiples gives information about the "biological" properties of start-ups, *i.e.* how much they return given their business performance and growth. On the other hand, from an investor perspective, there is value in considering these figures taking into account how much has been invested in each of these companies. That is, studying returns *weighted* by total investment cost (the denominator of the fraction in Equation 1).

Against this backdrop, given two VC investments with different exit returns, the exit MoC of the start-up receiving more financing will outweigh the exit MoC of the lesser financed start-up in the calculation of average returns. Figure 6 shows weighted average and weighted median exit returns over time.

Figure 6: Exit Returns of EIF-backed VC investments over time, weighted MoCs



Note: based on early-stage VC investments exited between 1997 and 2015 by EIF-backed VC funds. The figure includes all the exit types, *i.e.* write-off, liquidations and successful sales. Exit MoCs are weighted. Grey bars report the number of exits in each year (right-hand axis).

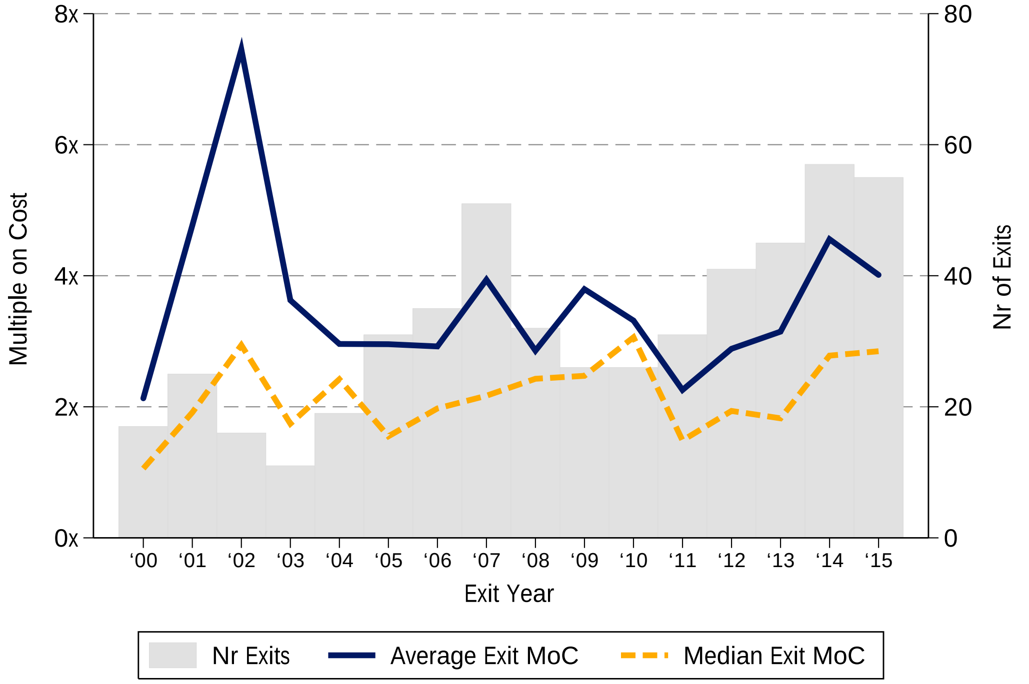
The weighted average of the MoC at exit for realised VC investments over the entire sample period is 1.16x, whereas the median is 0.12x. As shown by the grey bars, the statistics computed for the first years of the sample period are based on a small number of exits, therefore they should be interpreted with caution. Returns show sensitivity to the cycle. When the average return peaks during pre-crises periods,[23] the median return follows, but almost never exceeds the 1x threshold. Recent years display a clear upward trend in both average and median VC investment returns.

Given the asymmetric returns pattern of VC, some insights can be also derived from the evolution of MoCs linked to purely profitable investments. To this end, Figure 7 computes the weighted average and median returns for investments with exit MoC ≥ 1. Against the undoubtedly lower number of exits covered in Figure 7, the data offers a snapshot of the upper-tail of the returns distribution. And it may actually prove as representative as Figure 6, *e.g.* in the case venture capitalists were to employ *liquidation preferences* provisions to protect themselves against hypothetical losses.

Figure 8 shows instead the returns by vintage year. The vintage of investments is an important element in the analysis of the cyclicality of returns. Indeed, vintages from downturn years should have lower entry prices that, *ceteris paribus*, lead to a higher expected exit MoC. Conversely, in "boom" periods, when valuations may become inflated, higher entry prices could affect exit returns. This pattern is not so clear-cut when looking at Figure 8, with vintages 2000 and 2001 under-performing and vintage year 2007 scoring rather positively. Figure 8 discards vintage years with less than 10% of total investments realised (2012 being the last observed vintage year). However, both Figure 6 and Figure 8 bring evidence of generally increasing returns for EIF-backed start-up investments.

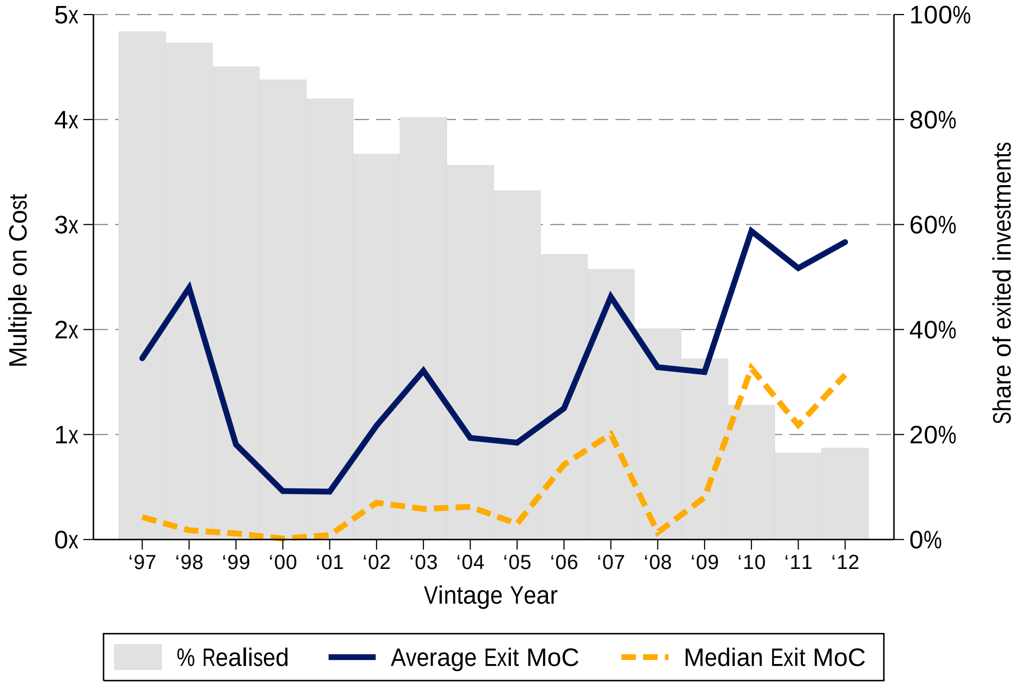
[23] The peaks in Figure 6 are driven by two *outlying* exits in 2001 (Tiscali) and 2007 (Skype). Their omission leads to an average return of 1.15x and 1.37x for 2001 and 2007 respectively.

Figure 7: Exit Returns of EIF-backed VC investments exited with MoC ≥ 1, weighted MoCs



Note: based on 520 early-stage VC investments, exited with MoC ≥ 1, made between 2000 and 2015 by EIF-backed VC funds. Exit MoCs are weighted. Grey bars report the number of exits with MoC ≥ 1 in each year (right-hand axis).

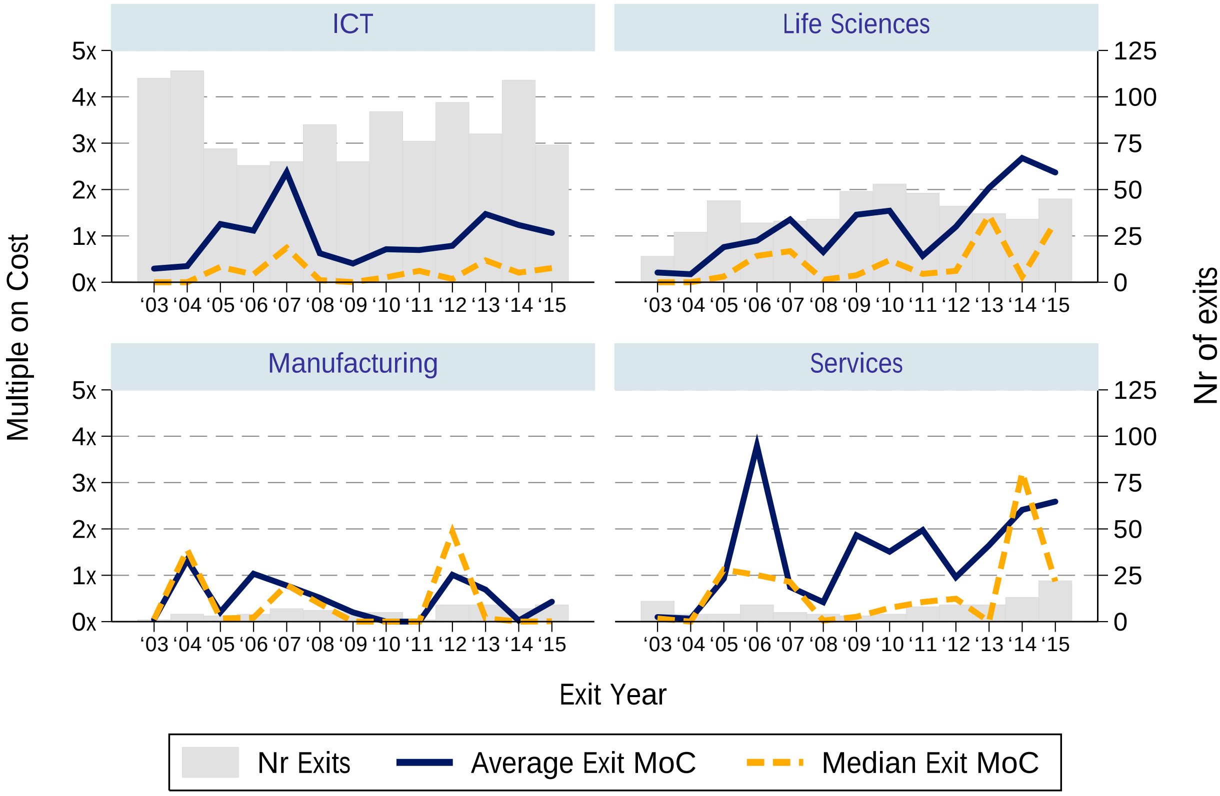
Figure 8: Exit Returns of EIF-backed VC investments by vintage year, weighted MoCs



Note: based on early-stage VC investments taking place between 1997 and 2012 by EIF-backed VC funds. The figure includes write-offs, liquidations and profitable trade sales. Exit MoCs are weighted. Grey bars report the portion of each vintage year that has been realised to date (right-hand axis).

In order to investigate the return profile for specific subsets of VC investees, we create "synthetic" portfolios by grouping different groups of start-ups (*e.g.* Biotechnology for sectors DACH for regions). Results are displayed in Figure 9 and Figure 10.

Figure 9: Exit Returns of EIF-backed VC investments over time, by macro-sector, weighted MoCs

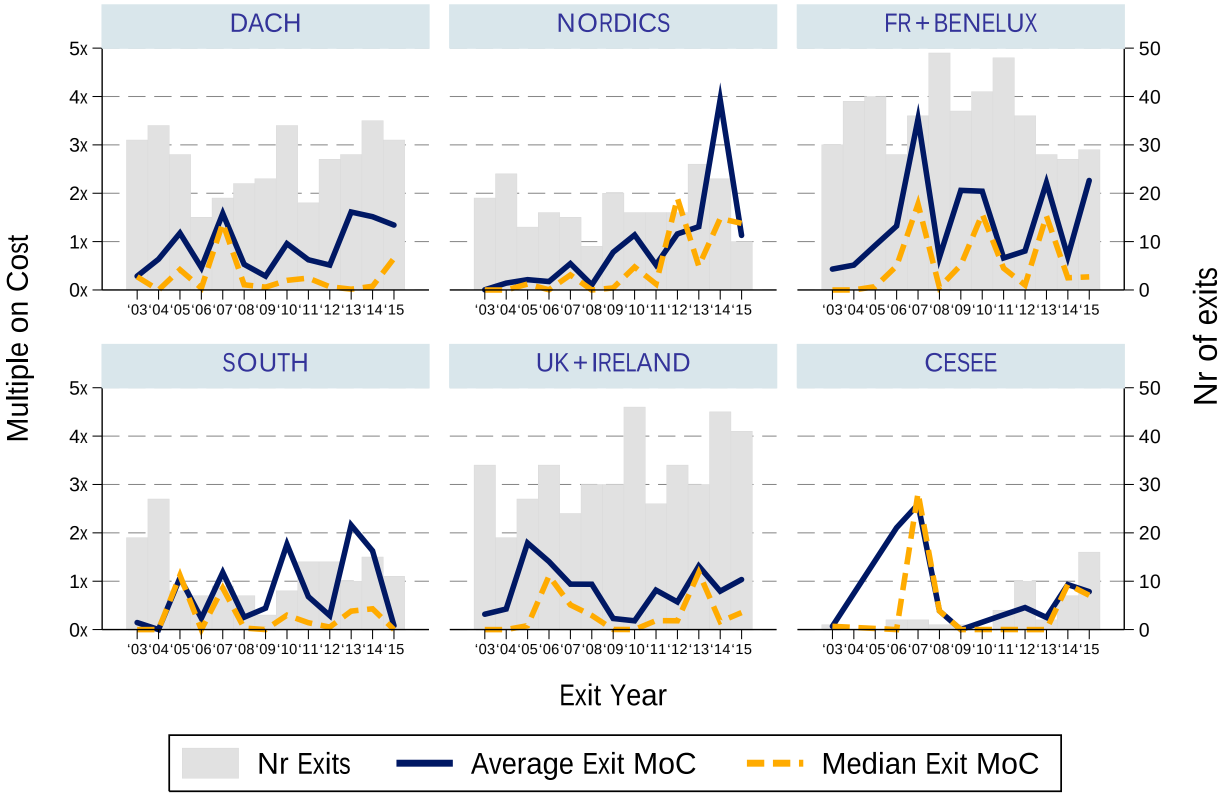


Note: based on early-stage VC investments exited between 2003 and 2015 by EIF-backed VC funds. The figure includes write-offs, liquidations and profitable trade sales. Exit MoCs are weighted. Grey bars report the number of exits in each year (right hand axis).

Among ICT investments, those in Computer Related and Electronics/Automation have performed better than investments in Communications (see Figure B4 in Appendix B). Life Sciences investment returns have significantly soared in the recent years, with average exit MoCs floating over 2x between 2013 and 2015. Despite the relatively low number of exits achieved so far, start-ups in the Services domain (mainly Consumer Related and Financial Services) have shown above-average returns over the last years. Noteworthy, despite low performance in the past, exit multiples in the NORDICS region have thrived from 2011 onward.

Interestingly, there seems to be no significant difference between returns from start-ups invested by first-time VC teams and VC firms with one or more past raised funds (See Figure B5 in Appendix B). However, investments carried out by first-time teams perform worse during market downturns (see 2008-2010 period in Figure B5), where experience turns out to be key in shaping the investment outcome.

Figure 10: Exit Returns of EIF-backed VC investments over time, by macro-region, weighted MoCs



Note: based on early-stage VC investments exited between 2003 and 2015 by EIF-backed VC funds. The figure includes write-offs, liquidations and profitable trade sales. Exit MoCs are weighted. Grey bars report the number of exits in each region-year (right-hand axis). To avoid over-inflating trends for CESEE, the exit return of LiveRail (Romanian start-up acquired by Facebook in 2014) was omitted from the calculation.

4 On the empirical features of venture capital returns

This section shows evidence on an empirical regularity that is often postulated in the economics of venture capital. That is, *returns follow a power-law*.[24] Before diving into the topic, we may first question its relevance. In other words, how useful can it be to know how VC returns are distributed?

4.1 Rationale: from data to theory

As Clauset *et al.* (2009) argue, for many purposes it may be enough to know that a quantity follows a heavy-tailed distribution. In our case, observing Figure 4 would be sufficient for investors to derive basic implications of VC economics. However, if the aim is to infer plausible mechanisms that might lie behind the formation and evolution of exceptionally successful start-ups (or an entire ecosystem

[24] Practitioners and investors are acquainted with the topic, although it has hardly been subject to rigorous research, at least with regards to venture capital. For instance, according to Marc Andreessen from Andreessen Horowitz (a Silicon Valley-based VC firm) *"The key characteristic of venture capital is that returns are a power-law distribution"*. The VC firm itself published data showing the skewness of the returns distribution (see https://a16z.com/tag/power-law/). Sandeep Bhadra, Principal at Menlo Ventures, discusses this in a lecture at UC Berkeley called *"Power-Law Returns in Venture Capital: Strategies for Building and Working with Great Companies"*. VC investor and entrepreneur Peter Thiel builds further on power laws in VC and their implications for investors in Masters and Thiel (2014). For a comprehensive investor-perspective review on power laws in VC, see Neumann (2015).

of these), then it is of utmost importance to comprehend the mechanism — the *physical process* — that is the cause of such empirical regularities. Why are 70% of start-up investments unprofitable while a few of these reach companies like Skyscanner and are sold for amounts greater than the VC fund itself?[25] Assessing whether VC returns follow a power law — or *Paretian* — distribution is thus the *first step* towards an understanding of the broader economic phenomenon.

Quoting Scherer (2000), "the potential variability of economic outcomes with Paretian distributions is so great that large portfolio draws from year to year can have consequences for the macroeconomy". Indeed, if the size of companies[26] in a certain industry (*e.g.*, ICT sectors that are typically affected by network externalities and *winner-takes-all* effects) is power law distributed, then a random shock to the largest companies, or to the narrowly defined sector, can generate aggregate fluctuations in the entire economy (Gabaix, 2011).[27] This finding yields concrete implications to be factored in when designing, for instance, policies in support of "scale-ups" (Hellmann *et al.*, 2016).

Perhaps more fascinating, the topic of power-law distributed returns entails concrete suggestions for portfolio management in venture capital. First, on the risk management side, the exact characterisation of the distribution would allow to better predict shocks from "extreme returns" in a VC portfolio, in particular with respect to listed portfolio companies — more exposed to market risk — and in general to sudden shifts in valuations due to unexpected factors. Second, as discussed in Sornette (2002),[28] the power-law *scale parameter* α dictates whether VC financing is characterised by economies of scale (specifically, if $\alpha < 2$). That is, whether the expected return of a VC fund increases with its portfolio size, *i.e.* the number of investments carried out. Although subject to the existence of some additional conditions, the power of such result lies in the implication that, *ceteris paribus*, a higher number of small bets at very early stage is a better strategy than a smaller number of larger bets.

As venture capital is about building companies and relationships, money is only one part of the story. Starting from the assumption of power law-distributed returns, Masters and Thiel (2014) argue that the VC should focus time and resources only on those companies that have the potential to be in the "upper-tail" of the returns distribution. The heuristic the authors derive by combining years of literature on VC power-laws reads as follows: in the first round, invest small amounts in as many promising companies as you can. Then, once the few fast-growing portfolio investments start emerging (*e.g.* via *positive feedback* mechanisms), mostly revert your focus to these few *winners*.

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[25] In the VC jargon, these companies are called *Dragons*. A Dragon is a VC investee that returns no less than the entire VC fund when exited. This means that, for a VC fund, the proceeds from selling the equity stake of that company (in a trade sale or IPO) are bigger than or equal to the fund size measured at closing date of fund-raising. Although nowadays Unicorns are by far the focal core of the tech community talks, a Dragon is the first item in each venture capitalist's wish-list.

[26] Hence returns: as generally assumed, VC returns from a start-up investment follow both past and prospective growth of the underlying firm. Further details based on EIF data were discussed in Signore (2016).

[27] The tumble in the Nokia-led Finnish economy's outlook following the telco company's decline (partly due to the rise of Apple) is an example (see http://www.economist.com/node/21560867). Also, Pomeroy (2016) claims that the rise of VC-backed "giants" (such as Amazon, Uber, Spotify) might have exerted an important downward pressure on global prices and inflation.

[28] Sornette (2002) discusses the case of returns from a portfolio of R&D projects. Without loss of generality, the framework can be extended to returns from a portfolio of start-up investments.

4.2 Testing the power-law distribution of VC investment returns

Several phenomena observed and measured in the real world tend to have a size or "scale", *i.e.* a typical value around which individual measurements cluster (Newman, 2005). Among several classic examples, the height and weight of human beings, the speed of cars on a motorway, the temperature in Luxembourg at noon on vernal equinox.[29] However, there are also natural processes that do not show a *central tendency*, due to few "extreme" observations or events affecting the shape of the entire distribution and of course the central tendency itself. For instance, in our data 4% of investments realised with MoC greater or equal than 5x account for about 50% of the total aggregated exit proceeds. When certain mathematical conditions are satisfied, these processes driven by "extreme events" are called Paretian, or *power laws*.[30]

The study of natural power laws is an increasingly fertile research field. One reason being that they occur in many different areas: the population of cities, earthquakes size, the frequency of use of words in any human language, the sales of books, music records and other branded commodities, people's income, stock market returns and many others.[31] To our purpose, a nonnegative random variable X follows a *power law* distribution if:

$$\Pr(X = x) = Cx^{-\alpha} \tag{2}$$

for all the x s.t. $x \geq x_{min} > 0$,[32] where $C > 0$ is a normalization constant and $\alpha > 0$ is the *scale* parameter. In a power law, the tails fall according to the scale parameter α. The lower the α, the higher the amount of probability gathered in the tails. Roughly speaking, a power law distribution foresees a much higher probability of "extreme events" than the one admitted by other common distributions used in financial economics. Remarkably, when $2 \leq \alpha < 3$, the mean exists but the variance and higher-order moments of the underlying population diverge as the number of observations tends to infinity. When $\alpha < 2$ the situation becomes even more extreme, as the population mean becomes undefined, *i.e.* infinite, and the sample average is dominated by extreme events. Accordingly, as the sample size or time series enlarges, "standard" summary statistics are dominated by "black swan" phenomena (Taleb, 2007), or *"meaningful outliers"* (Sornette, 2009).[33]

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29 This regularity is widespread — "normal" — because of the Central Limit Theorem: when independent random variables are added, their sum tends toward a normal distribution, even if the underlying variables are not themselves normally distributed.

30 The formal treatment of power laws goes well beyond the scope of this section. Newman (2005) and Clauset *et al.* (2009) provide an in-depth review of both theory and empirics of power laws. For a thorough discussion of power laws in economics and finance, see Gabaix (2009). Seminal works in the power law literature are also Zipf (1949) and Mandelbrot (1997).

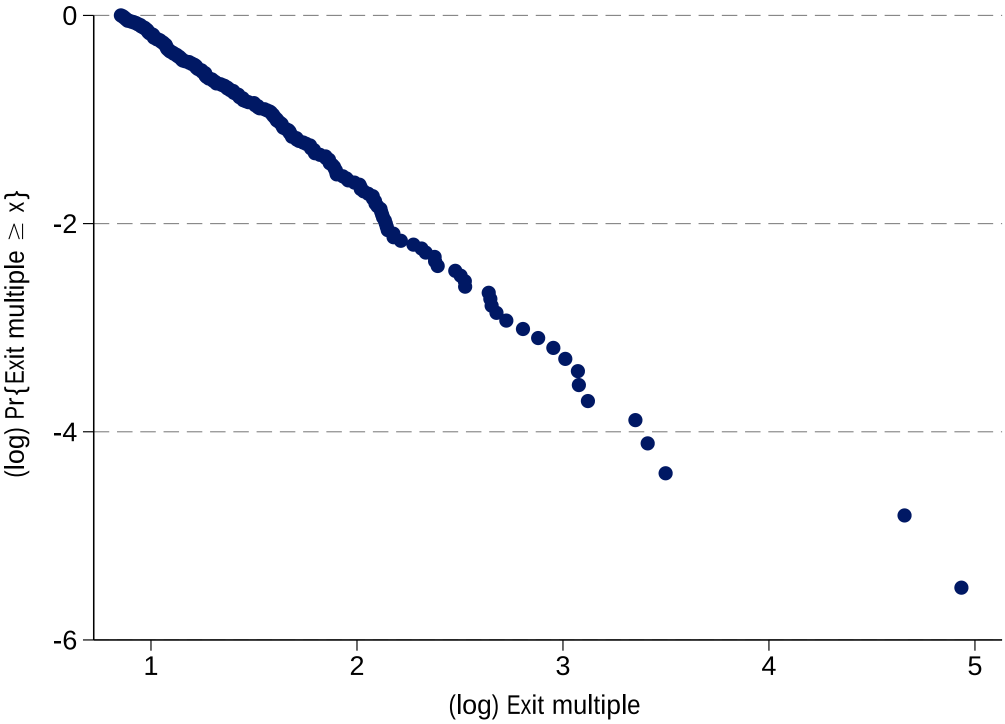
31 See Newman (2005), Clauset *et al.* (2009) and Gabaix (2016) for a comprehensive list.

32 As Equation 2 shows, this probability diverges as $x \to 0$. Therefore, there must be a lower bound x_{min} such that the power law holds from that point onward.

33 An on-going research debate is concerned with extreme events originating from power law distributions in stock markets. On the one hand, Taleb (2007) argues that extreme events are *intrinsically* unpredictable, due to scale-invariance and self-similarity in power laws. That is, a stock market crash starts as a small ordinary drop (that keeps building up), thus not distinguishable *ex ante* from other standard small-scale fluctuations. On the other hand, according to Sornette (2009), positive feedback phenomena that give rise to power laws implies a phase transition that can be identified, *e.g.* a market bubble before its burst.

To investigate the presence of a power law we first revert to visualisation, *e.g.* by looking at the empirical distribution of exit multiples. However, the extreme right-skewness and kurtosis of the VC returns data make standard histograms hardly readable. For this reason, Figure 11 displays the *complementary cumulative distribution function* (CCDF). That is, $\Pr(X \geq x)$, the probability that the exit multiple is greater than a certain value x. For data to follow a power law, we expect that the higher the x, the lower $\Pr(X \geq x)$, *i.e.* the chance of being observed. The use of log-values in Figure 11 is not accidental: the log-transform of Equation 2 implies that a necessary (but not sufficient) condition for power-law behaviour is that such *log-log* plot approximates a straight line, with slope $-\alpha$.

Figure 11: CCDF log-log plot of VC investment exit returns



Note: based on the MoC data for 2,065 early-stage VC investments, exited, made between 1996 and 2015 by EIF-backed VC funds. The chart plots the logarithm of the empirical complementary CDF against the logarithm of the exit MoCs for the upper-tail of the distribution.

Despite Figure 11 showing an approximately straight line in the tail of the distribution, this cannot be taken as conclusive evidence that VC exit multiples follow a power-law, as documented by Clauset *et al.* (2009) and Cirillo (2013). In this respect, a more rigorous procedure is necessary. We thus follow the quantitative approach formalised in Clauset *et al.* (2009) in order to test whether the tail of the distribution is consistent with a power law.[34] Table C1 in Appendix C presents the key estimated quantities obtained by implementing the Clauset *et al.* (2009) procedure for continuous data.

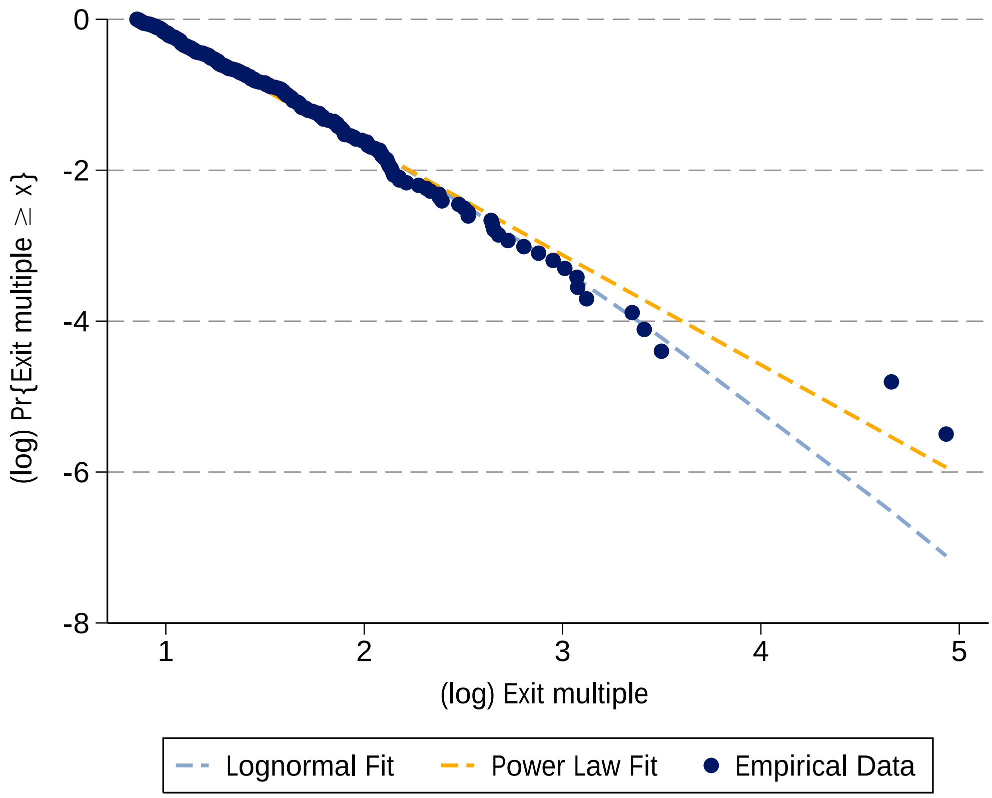
[34] The procedure involves a Monte Carlo goodness-of-fit test based on measurements of the "distance" between the distribution of the empirical data and the hypothesized model. The distance measurement, based on the Kolmogorov-Smirnov statistic, is derived by comparing data and theoretical model. The quantity is further confronted with distance measurements for comparable synthetic datasets drawn from the original hypothesized model. The p-value is defined as the fraction of the synthetic distances that are larger than the empirical distance. If p is small, *i.e.* less than 0.1, the model is not a plausible fit to the data. For further details, see Clauset *et al.* (2009).

The method delivers an estimated scaling parameter $\alpha = 2.45$ (± 0.09). The statistical test also yields a p-value of 0.915, implying that the *null hypothesis* of the data being consistent with a power law distribution cannot be rejected at most typical confidence levels.

Overall, the empirical evidence does not contradict the claim that VC returns are approximately Paretian. However, not much is said about whether the power law fits the data *better than any other distribution*. Indeed, there are several distributions that behave similarly to power laws. For instance, despite its finite moments, the *log-normal distribution* is very similar in shape to the Paretian distribution (Mitzenmacher, 2003). The point of which distribution fits the data better is important in order to understand the underlying economic mechanism that generates the distribution, as different models yield significantly diverse predictions and implications.

We test the goodness of fit of the power-law against other plausible distributions, following Clauset *et al.* (2009) and adopting the methodology of Vuong (1989). Figure 12 provides a graphical representation of fitting a power law and a log-normal distribution against our data, while Appendix C discusses the implementation details. Findings point to the sample size being too small to unequivocally assert the supremacy of power law in fitting VC exit returns. Virkar and Clauset (2014) mention a "rule of thumb" threshold for n_{tail} — the minimum size of the tail-end sample to identify a best fit — *i.e.* $n_{tail} > 300$, which is not matched by the number of observations currently at hand (details in Appendix C). Thus, further research with larger datasets may lead to future conclusive evidence.

Figure 12: CCDF log-log plot for empirical data, power law and log-normal fit



Note: the plot represents the upper tail of the distribution only, as in Figure 11. The distribution fits are obtained with the Maximum Likelihood method of Clauset *et al.* (2009). Software implementation follows Ginsburg (2012) and Alstott *et al.* (2014).

Against this background, some insights can be derived from a theoretical discussion of these two well-fitting distributions. Power laws and log-normal distributions are intrinsically connected, for similar generative models can lead to either distribution on the basis of seemingly trivial variations (Mitzenmacher, 2003). A log-normal distribution arises from a *multiplicative process*. To see why, suppose X_0 to be the MoC at investment date: if in every subsequent quarter the MoC grows by a random *i.i.d.*[35] factor, then the MoC at exit can be shown to be log-normally distributed.[36] Instead, Reed and Hughes (2002) show that a process whose *finite-time* expected growth is exponential (as is the case for most start-ups) follows a double Pareto distribution, *i.e.* a distribution with a log-normal *body* and a Pareto *tail*.[37] An additional mechanism leading to power laws in venture returns is *preferential attachment*, or *positive feedback*: in markets characterised by strong network effects, growth can generate additional growth. That is, initially successful start-ups can raise more capital, attract more talents and extend their user-base, leading to a virtuous cycle of sustained growth.

In conclusion, this section brings evidence that EIF-backed VC investment returns are consistent with a power law behaviour in the upper-tail of their distribution. This has first-hand implications for the analytical tools used by risk and portfolio managers in VC. When the investment returns are power law distributed, standard tools used in asset allocation that rely on the variance, such as *Sharpe ratios*, become unreliable. It may be argued that this only affects direct VC investments, in that the distribution becomes more "normal" when collecting returns at fund or at fund-of-funds level (Weidig *et al.*, 2005). However, the mathematical properties of power laws imply that a *combination* of power-law distributed investments (*e.g.* a VC fund or fund-of-funds) also follows a power-law (Gabaix, 2009). As a result, alternative statistical approaches (*e.g.*, based on extreme value theory) could be considered more appropriate in the context of VC returns. All in all, additional work may shed further light on this certainly promising field of research.

5 Exit Outcomes

5.1 Acquisitions: who are the active buyers?

In this section, we focus on the acquisitions experienced by EIF-backed VC investees, with the goal to identify profiles of start-up buyers in Europe. We thus focus on 447 VC investments exited through acquisition (regardless of exit MoCs). These are defined as equity deals in which *at least* the majority stake of the VC investee[38] is purchased by an external company — either industrial or financial — and contextually a major liquidity event is reported by the VC firm. As introduced in section 2, the analysis leverages on the retrieval of data from the BvD Zephyr database, allowing for detailed information not only on investee companies, but also on buyers.

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35 Independently and identically distributed.

36 A standard reference for this type of processes in financial economics is Hull (2006), that builds on Black and Scholes (1973) to model the value of a security that moves in discrete time steps.

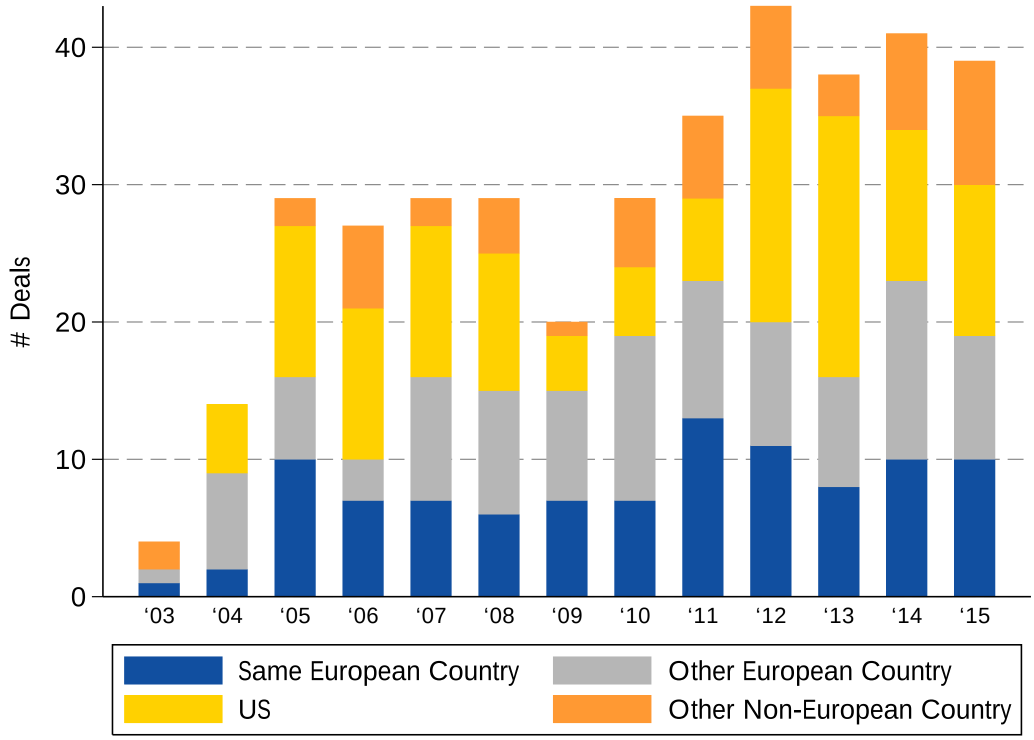
37 There are several theories of why power laws arise in natural and men-made phenomena. For a review, see Newman (2005) and Gabaix (2009).

38 It should be noted that more than 90% of these deals report a 100% stake purchase, *i.e.* full acquisition.

In light of the above, we first split acquisitions according to the geographic location of the buyer. We restrict the analysis to exits with Europe-based VC investees as the deal target.[39] We further distinguish between:

- *Same European Country*: the buyer shares the same European country[40] with the acquired start-up;
- *Other European Country*: the buyer is from an European country but from a different country than the start-up headquarters;
- *US*: the buyer is from the US;
- *Other Non-European Country*: the buyer is from any non-European country but the US.

Figure 13: Private acquisitions of European EIF-backed VC investees, by buyer geography



Note: based on private acquisitions of EIF-backed early-stage VC investees occurred between 2003 and 2015. Source: BvD Zephyr (2016).

Figure 13 shows the distribution of the buyer's geographic origin over time. From 2003 to 2015, an average of 44% of exited EIF-backed VC investees was acquired by non-European buyers, particularly from the US. Deals in which a US buyer acquires a European start-up represent 1/3 of all acquisitions

[39] We thus discard 58 observations for which either we do not have geographic data or the start-up location is outside Europe. Moreover, we observe that some companies report multiple headquarters located in different countries. In such cases, we rely on the country of the company's Global Ultimate Owner (GUO) as reported by Bureau Van Dijk.

[40] All EU28 countries plus Norway, Switzerland and Turkey.

(For additional details, see Figure D1 in Appendix D). [41] As Table 4 shows, US buyers targeting EIF-backed investees are typically the largest in terms of assets and turnover, are more innovative (*i.e.* more patents registered). They also are more technology-focused[42] (see Figure D2 in Appendix D) and mostly active in the ICT space (see Figure D3 in Appendix D), while European buyers seem generally more specialised in Life Sciences.

Figure 14 shows the extent to which these start-up acquisitions represent more vertical- or horizontal-type integrations. Moreover, we distinguish between *financial* and *industrial* acquisitions. Financial acquisitions are defined as deals in which the buyer is an independent private equity firm (*e.g.* private equity or hedge funds). Remarkably, most US buyers acquire start-ups from the same industry in which they operate (vertical integration), while European buyers largely populate more traditional sectors. However, the latter are more willing to integrate and/or expand *horizontally* towards innovative technologies. Furthermore, financial buyers are often from the same European country of the acquired start-up, suggesting that geographic proximity — perhaps signalling knowledge of local markets and regulations — plays a relevant role in these transactions. The most frequent corporate buyers of EIF-backed start-ups in our sample are GlaxoSmithKline, Broadcom Corp., Alcatel, eBay, Microsoft and Apple (see Table D1 in Appendix D for further details).

Table 4: Economic and financial profile of EIF-backed start-ups buyers, by buyer geography

Buyer Geography	Total Assets* (EUR m)	Turnover* (EUR m)	Nr of Patents*	Size of the Corporate Group*	Nr of Buyers
Same European Country	168	126	0	24.5	105
Other European Country	763	231	5	166	106
US	1182	618	132	86	125
Other Non-European Country	1459	626	38	65	53

Note: *expressed in median terms. Based on 389 private acquisitions of early-stage VC investees, invested between 1996 and 2015 by EIF-backed VC funds. The "Size of the Corporate Group" reports the number of all ultimately owned subsidiaries by the Global Ultimate Owner of the subject company. Source: BvD Orbis (2016), BvD Zephyr (2016).

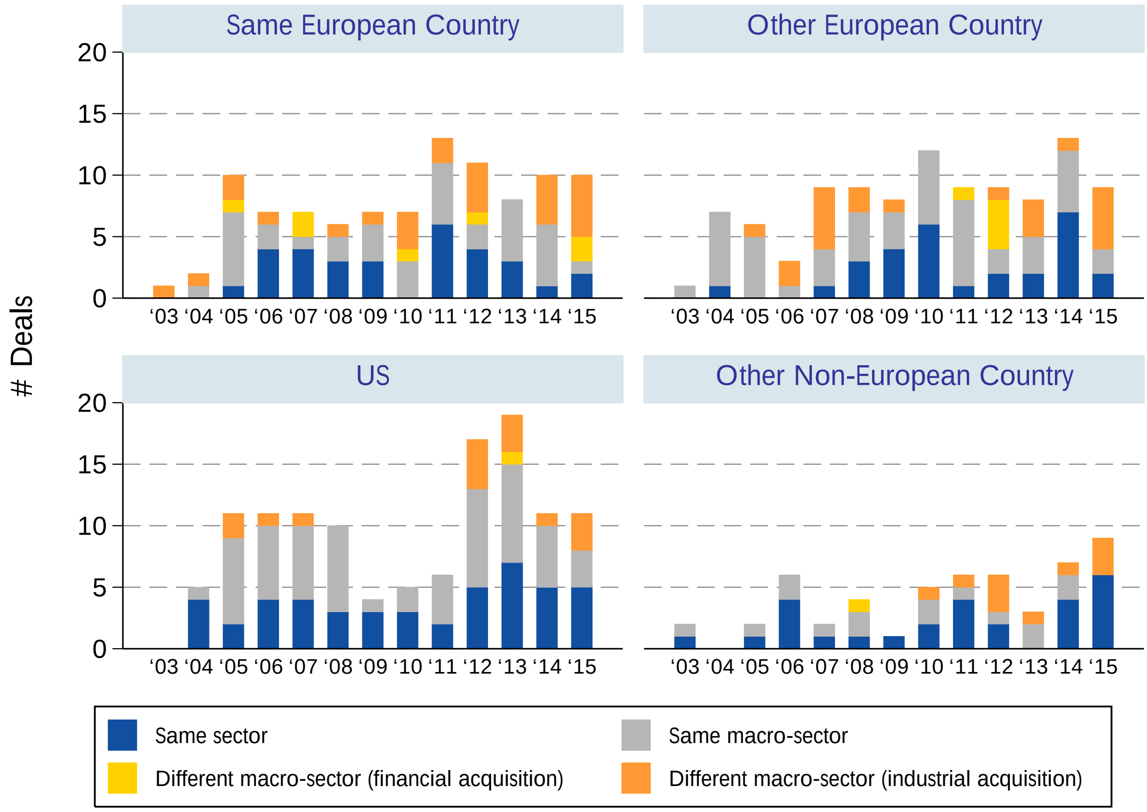
Overall, these figures provide preliminary evidence in support of the missing "scale-up" opportunity for start-ups in Europe, which is often claimed by many experts as one of the primary reasons behind the US vs EU venture capital gap (Mind the Bridge and CrunchBase, 2016; Hellmann *et al.*, 2016; Duruflé *et al.*, 2017). Duruflé *et al.* (2017) discuss a conceptual framework for the "scale-up" crossroads. During the lifetime of a successful start-up, there comes a moment when the company faces three options: going public, staying private or being acquired. While the first route is often jeopardised by the lack of European stock exchanges suited to host scale-ups (Duruflé *et al.*, 2017), the

41 As a reference, Mind the Bridge and CrunchBase (2016) exhibit M&A data regarding 1,271 European start-ups acquired from 2012 onward by US and European companies. They find 44% of start-up acquisitions to be performed by US companies. However, their data does not track acquisitions performed by non-European, non-US buyers. Thus, while our data may perhaps be less representative, the time span of our figures is larger and we account for non-US (*e.g.* Asian) buyers as well.

42 Shown by the higher proportion of US buyers listed on tech-focused stock markets, specifically the NASDAQ stock exchange. It could be reasonably argued that US companies benefit from an over-representation in the NASDAQ — an American stock exchange — but Pagano *et al.* (2002) show how also European high-tech firms have a strong tendency to cross-list on US stock exchanges.

second option requires an important pre-condition. That is, additional capital to make the necessary investments to foster growth (*e.g.* acquire competitors, expand internationally). The lack of *follow-on* growth funding might thus force companies to their last option, *i.e.* being acquired. It should be noted that the existence of acquisitions from foreign buyers is *not* negative *per se*. In fact, this may be perfectly in line with market supply and demand dynamics. Moreover, this phenomenon may reflect the often discussed *higher risk-aversion* of European entrepreneurs and investors, compared to US. However, we should not rule out the presence of a deeper structural problem, *i.e.* a lack of growth capital driving the scale-up gap. We leave it to further research to shed more light on this key issue.

Figure 14: Sector type of acquisitions of European EIF-backed VC investees, by buyer's geography



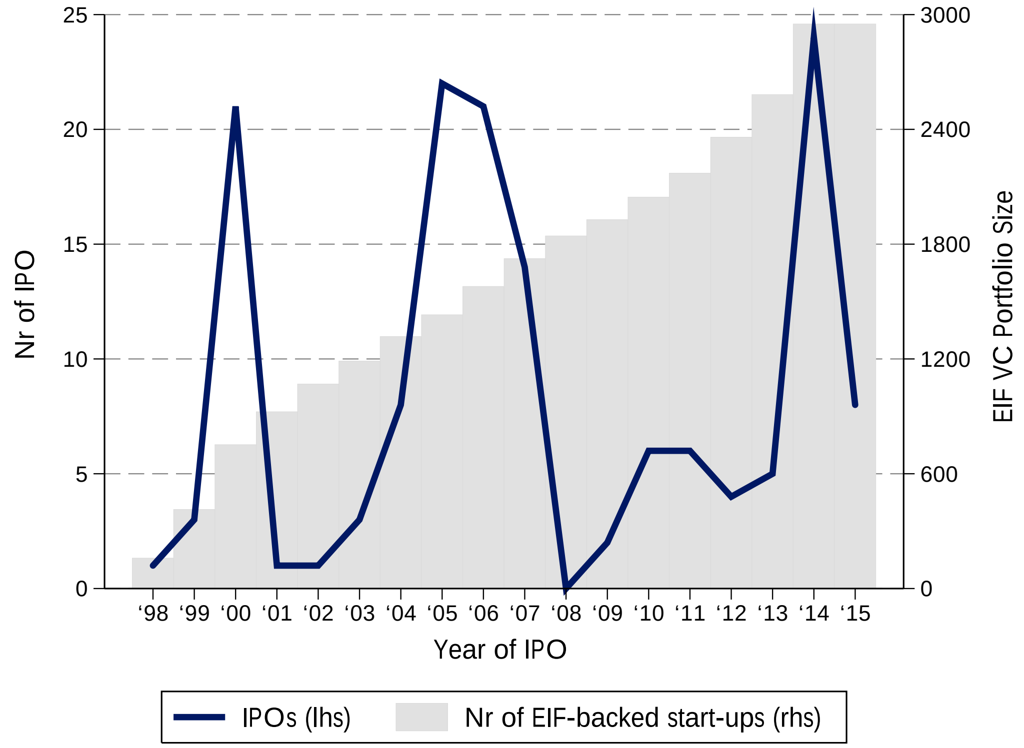
Note: based on private acquisitions of EIF-backed early-stage VC investees occurred between 2003 and 2015. Source: BvD Zephyr (2016).

5.2 IPOs: going public after VC in Europe

Back in section 2, Table 2 showed how the Initial Public Offering is the type of VC exit that generates the highest average and median return for the venture capitalist. The finding is in line with a well-established literature that documents the positive correlation between IPOs and investor returns as well as the IPOs' out-performance and their relative rarity with respect to other forms of exit (*e.g.* acquisitions, management buyouts and buybacks, see Phalippou and Gottschalg, 2008; Amit *et al.*, 1998). A total of 111 EIF-backed VC investments exited through IPO. That exclusively accounts for liquidity events in which the VC firm sold its shares following the company's IPO. Moreover, the average IPO return is more than 100% higher than the average VC return from acquisitions.

However, not all IPOs of EIF-backed start-ups are quickly followed by a divestment of the VC firm. In fact, there are several cases where the stocks of newly listed companies continue being held by the investor. By adding these to the former, we reach an all-time 152 EIF-backed start-ups to have gone public in 20 different stock exchanges worldwide. Figure 15 shows the trend of EIF-backed IPOs over time, alongside the total number of start-ups supported by EIF. Although 2014 sees the highest number of IPOs to date, there is a decrease in the IPO rate over time, considering the rise in EIF VC activity in the period. In general, IPOs show extreme sensitivity not only to stock market conditions but also to changes in technology-related sentiment and uncertainty about the future profitability of innovative firms.[43]

Figure 15: EIF-supported tech IPOs over time

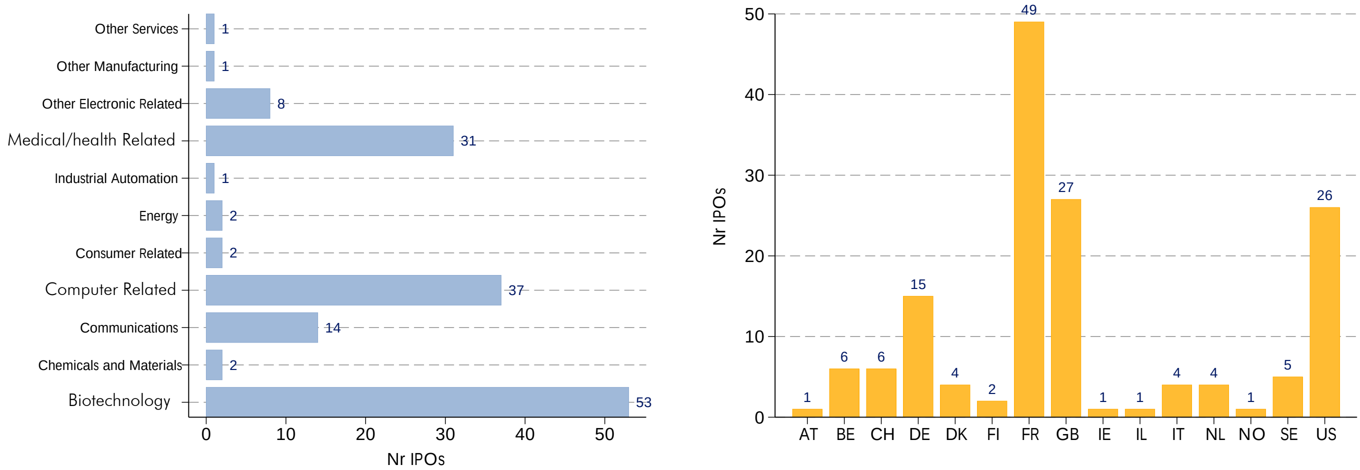


Note: based on IPOs of EIF-backed start-ups occurring between 1998 and 2015. Grey bars indicate the historical cumulative number of EIF VC-supported companies. Source: BvD Zephyr (2016), Thomson Reuters Eikon (2016).

Figure 16 provides some descriptive evidence of the sector and the original location of the listed VC investees. French start-ups have been the most prolific in terms of IPOs (49), followed by UK (27) and US (26). Interestingly, more than 50% of all IPOs have been originated by companies in the Life Sciences sector. Furthermore, Figure 17 exhibits the geographic distribution of the stock exchanges hosting EIF-backed tech IPOs, showing *where* start-ups went public most frequently. The stock exchange harbouring the highest number of EIF-backed IPOs is the Euronext Paris (50), followed by the NASDAQ (29), the London Stock Exchange (23) and the Boerse Frankfurt (14). Moreover, there are some peculiarities in the geographic-sector choice of listing. For instance, Euronext Paris and LSE have featured more Computer Related listings, whereas NASDAQ and Boerse Frankfurt were preferred by companies in the Biotech space (see Table D2 in Appendix D.).

43 See Berk *et al.* 2004; Pastor and Veronesi 2005, 2006, 2009 for a thorough discussion.

Figure 16: Country and sector distribution of EIF-backed tech IPOs



(a) IPOs by industry

(b) IPOs by start-up location

Note: based on IPOs of start-ups invested between 1996 and 2015 by EIF-backed VC funds. The industrial nomenclature follows Invest Europe's classification. For details, see Signore (2016). "Country" indicates the newly listed company location. Source: BvD Zephyr (2016), Thomson Reuters Eikon (2016).

6 Understanding exit outcomes: a competing risks analysis

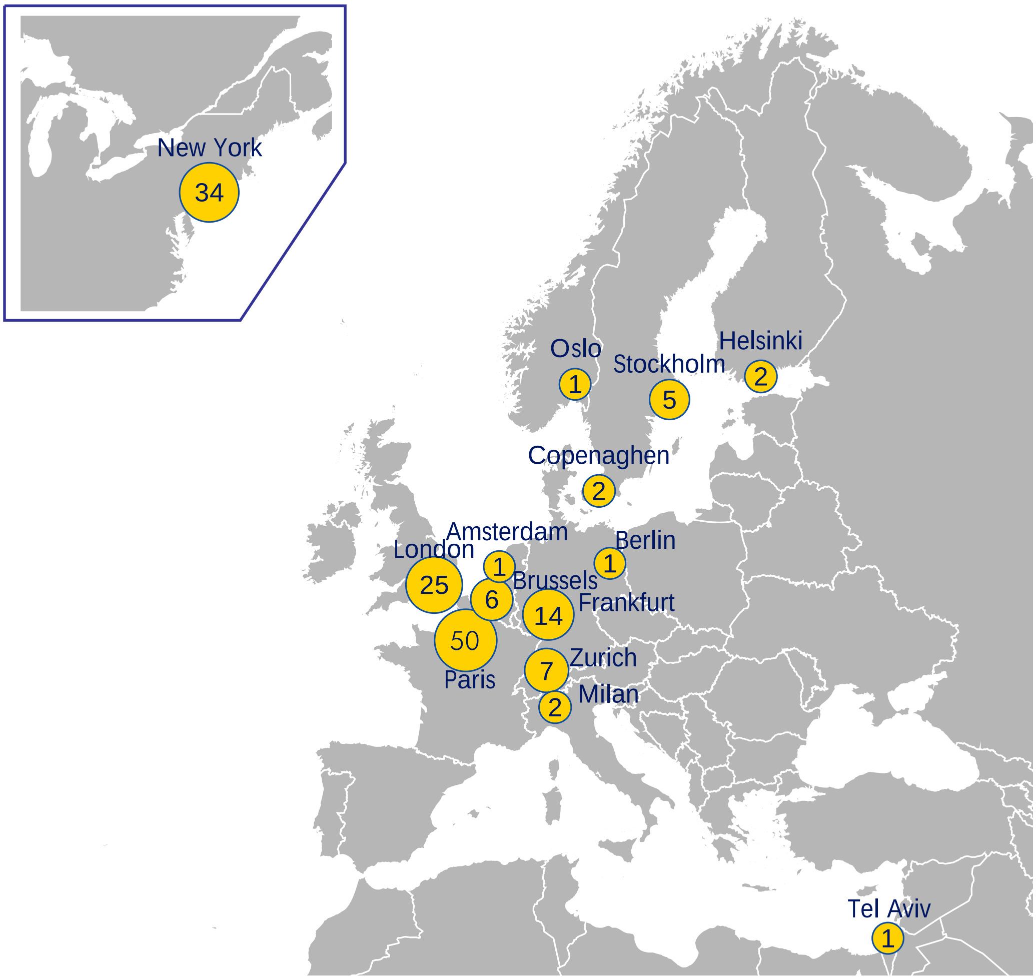
In this section we build on the descriptive findings on exit outcomes of EIF-backed VC investments to discuss their underlying *process*. In addition to the pre-divestment valuation, a realised exit multiple can certainly be influenced by the *exit route* as well as the *exit timing* chosen by venture capitalists. In turn, these could be linked to a multitude of endogenous factors, both at micro- and macro-level.

Against this background, the goal of this section is to analyse the correlation between exit outcomes' dynamics against a series of company-, fund- and cycle-related factors. While no causal relation can be claimed throughout the exercise, there is arguably value in assessing how the likelihood of a certain exit event varies according to, *e.g.*, time, geography, VC teams characteristics, and so forth.

A number of works shed light on how European VC performs in terms of exit events. With a comparative focus, Axelson and Martinovic (2013) study the determinants of successful exits in Europe and US. They find no systematic difference in the success rate of European and US VC investments in relation to IPOs, but lower probability of exit through trade sale for European start-ups. Regardless of geographical location, the experience of venture capitalists and founders is shown to be positively related to higher rates of trade sales. The authors argue that the shortage of serial entrepreneurship in Europe may be the driving factor behind the VC performance gap between Europe and the US. Closer to the approach in this work, Bottazzi *et al.* (2008) use a survey-driven and hand-collected dataset of European VC investments, augmented with data from other commercially available databases. The authors observe a strong positive correlation between VC investor's activism — proxied by investor's business experience — and exit performance, measured through IPO and trade sale exit rates.

On the technical side, most studies analyse VC exit dynamics by focusing on binary outcomes modelled via a Logit, Probit or linear probability approach (see *e.g.*, Sorensen, 2007; Bottazzi *et al.*, 2008; Gompers *et al.*, 2008; Brander *et al.*, 2015). However, these models fail to account for the

Figure 17: Geographic distribution of the EIF-supported tech IPOs



Note: based on 152 IPOs of start-ups invested between 1996 and 2015 by EIF-backed VC funds. Source: BvD Zephyr (2016), Thomson Reuters Eikon (2016).

time-to-exit dimension of VC investing. Moreover, this strategy only allows to model the occurrence of broadly defined exit events,[44] disregarding the *competing* nature of different kinds of exit events, a feature intrinsic to the venture investment life-cycle. That is, not only start-ups can face a multitude exit outcomes, but these events are also fundamentally different from one another: the factors and circumstances behind a sensational IPO are typically very different from those leading to a management buy-out. On this premise, Axelson and Martinovic (2013) revert to survival analysis techniques, specifically a *competing risks model* to account for the time dimension in their data and to disentangle IPOs from trade sales exits. Priorly, Giot and Schwienbacher (2007) estimated a competing risks model accounting for three main exit routes for US VC investments: *IPO*, *trade sales* and *liquidations*.

[44] The approach typically builds on binary "exit statuses", indicating investee companies that went public or were acquired. It does not distinguish between unrealised investments and *unprofitable* exits (write-offs, liquidations), mainly for the challenges in obtaining accurate VC returns data (see Da Rin *et al.*, 2013).

This work aims at contributing to this literature by further enriching the body of competing risks analyses. Based on exit deal type and return performance, we classify exited investments into four main categories.[45] These are based on all exit outcomes discussed in section 2 and read as follows:

- *Write-off*: the VC firm divests by declaring its stake in the company fully unreturned (*i.e.* assigning zero or a symbolic amount to its value).;
- *Liquidation*: the VC firm sells its stake realising less than the investment cost (MoC < 1);
- *Acquisition*: the VC firm profitably realises its investment through a trade sale (MoC ≥ 1);
- *IPO*: the VC firm trades its company shares following the company's listing.

6.1 Model set-up

The venture capital business model provides a suitable framework for the use of survival analysis. Survival analysis, mostly used in medical research, deals with the (expected) time-to-event, where an "event" can be *e.g.* the death of a biological organisms or the disappearance of a particular disease for patients under medical treatment.[46] Against this background, a VC-backed start-up can be viewed as the *patient* and a risk capital investment as the *treatment*. Hence, the *observed lifetime* is nothing but the *random* time it takes for such investment to reach a liquidity event.[47] The virtue of survival analysis is that it allows modelling data that is inherently *right-censored*, *e.g.* for investments, perhaps too recent, whose realisation has yet to materialise. This is a crucial advantage *vis-á-vis* Least Squares estimation, as it allows to factor in evidence from exits that have yet to happen.

However, real-world patients may not be exposed to one exclusive outcome — say the occurrence of a specific disease — but can experience alternative events, such as disease disappearance, occurrence of other diseases or death. In the same way, VC investments may face different, *mutually exclusive* outcomes. To address these aspects, scholars extended the standard survival analysis framework through *competing risks* theory. Competing risks models appropriately account for multiple and mutually exclusive exit events. The advantage of this methodology is that it allows each exit option to feature its own dynamics, together with the variables that can affect such outcome.

In line with Giot and Schwienbacher (2007), we estimate a competing risks model for 3,592 VC investments backed by EIF. More specifically, the goal is to study how a set of covariates affect the probability of a specific exit outcome, taking into account that alternative exit types can occur. In this context, as discussed by Gooley *et al.* (1999), the standard Kaplan and Meier (1958) approach fails to deliver correct estimates of the exit probabilities, because it treats competing events as if they were

[45] It should be remarked how a wider range of contractual arrangements exists for VC exits (*e.g.*, MBOs, MBIs, shares buy-backs, replacement, options and warranties, etc.). However, given the main goal to disentagle the key economic paths of different exit routes, we apply here some reasonable simplifications.

[46] See Jenkins (2004) for one of the most comprehensive reviews of survival analysis methods.

[47] The reader might note that this random lifetime mechanism is, together with expected exponential growth, one of the ingredients for the potential rise of power laws in venture capital (see section 4).

censored.[48] Another approach involves modelling an outcome-specific — or *destination-specific* — hazard function for each exit type under the assumption of proportional hazards (Prentice *et al.*, 1978).[49] However, as pointed out in Fine and Gray (1999) and Jenkins (2004), the interpretation of regression coefficients is not straightforward with this method. As such, the key metric for our analysis is instead the *probability that an exit of type* k *has occurred by time* t, accounting for the fact that other exit types can occur in the meantime. This is known as the *cumulative incidence function* (CIF):

$$C_k(t; \mathbf{X}) = \Pr(\text{exit time } \mathbf{T} \leq t, \text{exit type} = k \mid \mathbf{X}) = \int_0^t S(u) h_k(u \mid \mathbf{X}) du \tag{3}$$

where $S(\cdot)$ is the overall survival function, $h_k(\cdot)$ is the *destination-specific* hazard and $\mathbf{X}$ is a vector of explanatory variables.

To give an example that fits our context, the CIF for an *acquisition* at *5 years* is the probability that a VC portfolio company is profitably acquired in the first 5 post-investment years, accounting for the likelihood of other exit events (*e.g.*, the start-up goes bankrupt and is written-off, the founders buy back their shares following an argument with the investors) and a set of company/investment features. Fine and Gray (1999) specify a semi-parametric transformation for the *CIF*, also called subdistribution hazard — or *subhazard* — that is rather similar to Cox regression (Cox, 1972), commonly used in survival models. We use this as our main approach, as the complexity of this model is offset by the easiness of its estimation and its ability to provide a more direct interpretation between the covariates and the probabilities of interest.[50]

The Fine and Gray (1999) method yields estimated coefficients known as *subhazard ratios*, expressed in exponential form. Their interpretation is as follows: a ratio *above one* implies that an increase in the covariate x_1 *raises* the incidence of exit type k. Conversely, a ratio *below one* means that an increase in the covariate x_1 *lowers* the incidence of exit type k.[51] The interpretation of subhazard ratios bears resemblance to that of *odds ratios* in the context of standard survival analysis.

Table 5 provides some descriptive evidence on the time-to-exit for the four types of exit classes. These statistics suggest an *average* pecking order for exit strategies in Europe: most hopeless bets are divested the earliest through write-off, while profitable trade sales start being monetised shortly after that. Liquidations further take place with tumbling growth expectations. Finally, the highest-growers are brought to public markets to capitalise their post-IPO shares.

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[48] For instance, suppose we were interested in modelling the probability of a profitable *vs* an unprofitable exit, say, a write-off. Now assume that a certain number of investments are indeed written-off at time t. When modelling profitable exits in $t + 1$, the approach in Kaplan and Meier (1958) treats write-off occurrences as if they were still unrealised, altering the *risk set* and producing a bias in the estimated exit probabilities.

[49] Any *hazard function* denotes the likelihood of exiting at time *t* having survived thus far. The *destination-specific* hazard, $h_k(t)$, is instead the risk of exiting at time t specifically through exit type k, given that the exit has not occurred thus far (see Prentice *et al.*, 1978).

[50] See Cleves *et al.* (2010) for the Stata routine used in this work.

[51] The Fine and Gray method assumes proportionality of the subhazards and independent risks. The latter is a strong assumption, implying that the probability of a certain exit type k is unrelated to the probability of other exit types. Releasing this assumption adds considerable computational complexity and yields likelihoods which are hardly tractable. While theoretical works have shed light on this issue, there are still few empirical applications of competing risks models that assume correlated risks (Jenkins, 2004).

Table 5: Years from vintage to exit for EIF-backed VC investments, by exit outcome

Exit Outcome	Average Time to Exit	Median Time to Exit	St.Dev.	N
In Portfolio	5.7	4.0	4.2	1523
Write-off	4.9	4.2	3.1	705
Liquidation	5.8	5.5	3.3	779
Acquisition	4.9	4.3	3.3	448
IPO	7.1	7.0	3.3	109
Total	5.5	4.5	3.7	3564

Note: 28 investments made by non-European EIF-backed VC funds were dropped. The data was computed by counting the number of days between first investment and exit date and further converting back to years.

6.2 Results

Appendix E describes all variables used in the model, constituting a set of investment-, company- and investor-level features that often appear in numerous leading studies in the literature. Table 6 shows the estimation results of the competing risks model using the Fine and Gray method. Categorical variables are presented in bold and are to be interpreted with respect to the omitted class, set to the mode of the distribution. For instance, the coefficients for "Fund macro-region" dummies are relative effects with respect to the omitted class of DACH-based VC firms.[52]

The empirical evidence concerning the four different exit routes can be summarised as follows. For *write-offs*, the predicted incidence is lower for more recent vintage years. This may be both driven by the high rate of write-offs during the dot-com crash as well as the longer-term decline in write-off rates observed in Figure 1. However, note that the shorter holding period of very recent vintages may bias later write-off rates. A lower probability of write-off is also linked to a higher VC firm experience (proxied by the number of funds raised previously), to investees active in the Life Sciences industry, and to the fund's investment strategy being expansion-focused.[53] Last, investments from VC firms based in the NORDICS region are linked to a higher incidence of write-offs.

Lower probabilities of *liquidations* are linked to higher first investment amounts. As in the case of write-offs, more recent vintage year and Life Sciences investments are also associated to lower liquidation rates. Interestingly, an increase in the size of the VC fund is linked to a higher probability for the investee to be unprofitably sold. This seemingly counter-intuitive fact suggests that a large portion of the money gathered at fund-raising stage is not necessarily correlated with investee companies' growth. One might argue that, *ceteris paribus*, a greater fund size would lead to a larger number of investments, thus a higher incidence of unprofitable sales due to the limited stock of time and resources that can be allocated across portfolio companies (Masters and Thiel, 2014). However, we do not find confirmatory evidence of this reasoning since the size of the portfolio is not significantly

[52] The set of *"Geographic macro-region"* and *"Fund investment focus"* dummies are included in the estimated model. Note that, out of 3,592 VC investments initially in the sample, 2,823 enter the model, mainly due to a high number of missing values for very few covariates, such as *"Fund Distance"*, the distance between VC firm and investee, that requires the companies to be matched and geolocalised in the BvD Orbis database. See Kraemer-Eis *et al.* (2016b) for details.

[53] This finding is omitted from Table 6 for the sake of conciseness. It may be linked to a higher propensity — perhaps experience-driven — of *venture capital-specialised* funds to quickly write-off their positions.

Table 6: Fine & Gray Competing Risks Model Estimates

	Write-off	Liquidation	Acquisition	IPO
Age at investment	1.004	0.988	1.014	0.959
	(0.23)	(-0.70)	(0.61)	(-0.88)
First Investment	0.953	0.840***	1.069	1.387**
	(-1.14)	(-4.87)	(1.13)	(2.38)
Fund Distance	1.011	0.977	0.977	1.032
	(0.68)	(-1.49)	(-1.20)	(0.67)
Vintage Year	0.919***	0.945***	1.006	0.824***
	(-6.05)	(-4.49)	(0.47)	(-4.32)
Unicorn status	0.347	1.160	2.698***	0.824
	(-1.57)	(0.42)	(2.80)	(-0.19)
First-time VC teams	1.033	1.018	1.000	1.233
	(0.28)	(0.15)	(0.00)	(0.59)
Fund Size	0.994	1.205***	0.994	0.999
	(-0.09)	(2.89)	(-0.07)	(-0.00)
Portfolio Size	1.011	0.963	0.896	1.483
	(0.14)	(-0.47)	(-1.29)	(1.55)
Funds raised by VC firm	0.809***	1.037	1.109**	0.947
	(-4.36)	(1.01)	(2.53)	(-0.64)
Investee macro-sector (omitted: ICT)				
Life Sciences	0.617***	0.707***	0.853	4.087***
	(-4.60)	(-3.43)	(-1.24)	(6.42)
Manufacturing	1.260	0.933	1.097	0.000***
	(1.04)	(-0.30)	(0.34)	(-85.89)
Services	0.768	1.082	1.512**	0.000***
	(-1.26)	(0.46)	(2.28)	(-83.16)
Green Technologies	0.846	0.301**	1.304	0.000***
	(-0.40)	(-2.00)	(0.70)	(-59.65)
Fund macro-region (omitted: DACH)				
NORDICS	2.264**	1.630	0.888	0.473
	(2.29)	(1.54)	(-0.38)	(-0.71)
FR&BENELUX	1.078	0.909	1.506*	1.203
	(0.37)	(-0.56)	(1.87)	(0.47)
SOUTH	1.039	0.956	1.156	0.159*
	(0.13)	(-0.15)	(0.36)	(-1.88)
UK&IRELAND	0.933	0.778	1.979***	2.463**
	(-0.30)	(-1.14)	(3.32)	(2.33)
CESEE	0.598	1.468	1.061	0.000***
	(-0.67)	(0.64)	(0.09)	(-10.46)
Observations	2823	2823	2823	2823
Log-Likelihood	-4059.96	-4512.15	-2839.67	-617.40
LR Chi-Sq.	929.63	1065.82	811.44	39738.44
Chi-Square(p-value)	0.000	0.000	0.000	0.000
Geographic macro-region	Yes	Yes	Yes	Yes
Fund investment focus	Yes	Yes	Yes	Yes
Nr Subjects	2823	2823	2823	2823
Nr Exits	555	618	380	94

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Exponentiated coefficients; t statistics in parentheses

Note: based on 2,823 EIF-backed VC investments. Estimated coefficients reported are exponentiated coefficients, *i.e.* subhazard ratios. A subhazard ratio above (below) one means that the effect of increasing the covariate is to increase (decrease) the probability of the exit outcome modelled. Fine and Gray (1999) estimation implemented through the Stata program in (Cleves *et al.*, 2010).

related to a rise in the incidence of liquidation.[54] We leave to future research on the topic the task to shed further light on the potential spurious nature of this finding.

Higher rates of *acquisitions* are linked to the number of funds previously raised by the VC firm, to investees operating in the Services industry, and to the VC firm being located in UK&IRELAND. Interestingly, becoming a *unicorn*[55] strongly increases the chance of being privately acquired, while it does not significantly affect the incidence of IPOs. This dynamics might suggest investors' caution for IPO exit strategies when the company valuation is very high.

Last, the chances of an *IPO* decreased in recent vintage years. Of course, a similar disclaimer to the one described above on write-offs applies: this could be driven by IPOs requiring more time to materialise, as shown in Table 5. Therefore, recent vintages may naturally experience such lower probabilities. A Life Sciences portfolio company has a significantly higher probability of going public compared to other industries. The result is perfectly in line with the previous findings in Signore (2016). Moreover, first investment amount is linked to a higher IPO rates. As this feature can be interpreted as the size of the first "bet" in the company, this finding bears an important implication, suggesting that VC firms were able to *cherry-pick* successful companies already at the time of their first check. This finding is also in line with the evidence brought by Sorensen (2007) on *sorting* being twice as important as direct VC *influence* to explain IPO incidence rates. Finally, being invested by a UK&IRELAND firm is significantly correlated to a higher likelihood of going public. This key result conveys some indications of where the VC asset class tends to be more profitable across Europe. Although causality is never evoked, Irish and British VC firms are observed to play an important role in shaping the performance of returns at fund-of-fund level.

A further advantage of the Fine and Gray (1999) approach lies in the ability to model how the *cumulative incidence function* — the exit probability for a given outcome having survived thus far — evolves throughout the years following an EIF-backed investment. In other words, the model can provide, for a change in a given variable, the change in the day-by-day predicted exit outcome probability. For instance, Figure 18 shows how the probability of an *acquisition* evolves given different values of, respectively, the first investment amount and the number of funds raised by a VC firm.

Differences in the cumulative incidence curve provide useful insights on the relationship between investment features and the chances of reaching an acquisition. In the case of Figure 18b, the probability of being acquired within 10 years after the VC investment is observed to be 5% higher when the VC firm has already raised 4 funds, compared to first time VC teams. Similarly, in Figure 18a the cumulative incidence of acquisition by the 10^{th} year is 5% larger when the first investment is around EUR 3m, compared to an initial investment of EUR 50,000.

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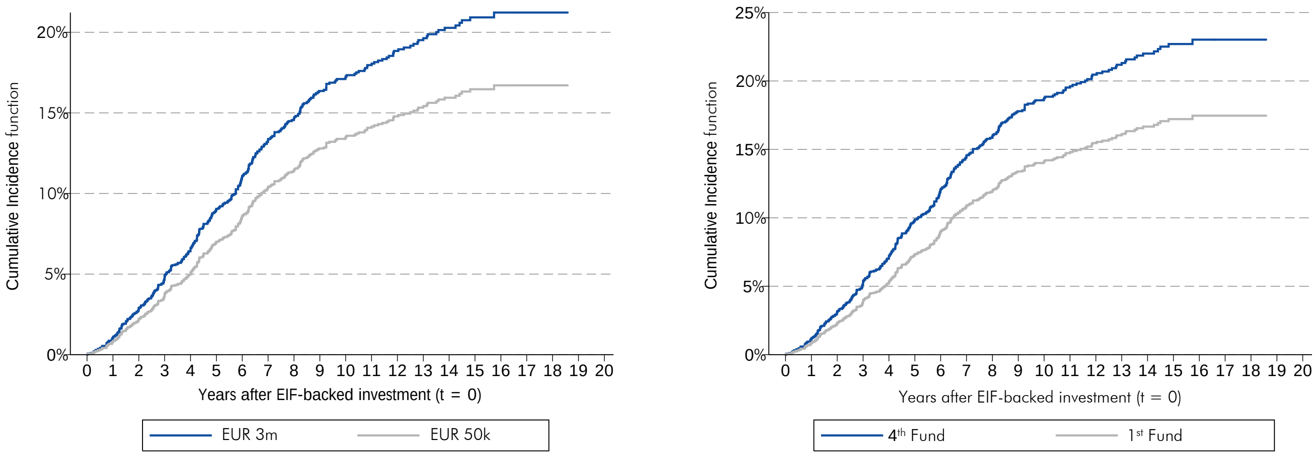
[54] As an heuristic on the fact that fund size is not necessarily related to underlying portfolio companies' performance, one can think of Lowercase Capital as example. The US VC firm launched its first Lowercase Ventures I in 2010, raising *only* USD 8m. The fund is claimed to be *the best-ever performing VC fund*, generating massive returns from the sale of Twitter and Instagram (Uber and Docker still in portfolio) and investing almost only in seed rounds. Despite the outstanding returns, the firm has kept their fund sizes consistently under USD 50m to maintain their strategy and focus on early investments in very small companies with very high growth potential (Source: CBInsights).

[55] In VC jargon, a Unicorn is a privately-held VC-backed start-up whose valuation is greater or equal than USD 1 bn (Aileen, 2013). See Appendix G for a list of EIF-backed unicorns to date.

Figure 18: Changes in the cumulative incidence function for acquisition



(a) First investment amount

(b) Number of funds raised by the VC firm

Note: based on 2,823 EIF-backed VC investments. Fine and Gray (1999) estimation implemented through the software in (Cleves *et al.*, 2010).

Finally, we find evidence of the investors' experience playing a crucial role. Interestingly, our "First time-team" dummy is never significant and the findings from section 3.2 also hint at no significant returns differences. This finding points to the *convexity* of the effect, for the experience of VC firms matters only when *outstanding*. However, an alternative, perhaps leaner explanation for this effect may be the *selection effect* of EIF, *e.g.* during the due-diligence process. In other words, the fact that EIF may select only high-potential first-time teams may be a source of bias for this particular result.

To ensure the robustness of our results, we compare the estimates of the methodology in Fine and Gray (1999) with results from the *destination-specific* hazard. Specifically, we seek to test whether our results are sensitive to the *continuous-time* assumption of Fine and Gray (1999). To do so, we revert to a *discrete-time* setting, following the approach outlined in Jenkins (2004). In particular, we estimate a *multinomial logit model*, [56] assuming independent risks and proportional hazards. Table F1 in appendix F shows the estimation output. Overall, results hold qualitatively similar.

7 Conclusions

This work represents a further step towards an increased understanding of venture capital in Europe and its financial performance. It uses a sample of about 3,600 EIF-backed venture capital investments made in the 1996-2015 period to analyse their liquidity events and returns. The key contribution of this work lies in the analysis of historical VC exits and start-up valuations. The paper provides evidence that VC returns are related to the economic cycle. At the same time, it emphasises the heterogeneity that arises from different industries and geographies, which leaves room for VC firms to pursue diversification strategies and minimise the correlation with other asset classes.

A second key contribution pertains to the analysis of return distribution. The paper discusses the statistical features of VC returns in Europe, providing preliminary evidence of their *power-law* be-

[56] The approach is justified by the theoretical results discussed in Allison (1982).

haviour. While further research will be needed to reach conclusive evidence on whether power-law is the *best*-fitting distribution for VC returns, the insights yield practical implications for practitioners and policy-makers. Namely, it calls for a cautious rethinking of investment strategies and portfolio management approaches that do not account for the possibility of extreme outcomes. Secondly, it suggests that policies to address the "scale-up" gap in Europe need to carefully assess the implications of start-ups' exponential growth in their respective markets, as well as their potential impact on the broader economy.

Third, the paper looks at exit outcomes and finds that the largest share of VC returns is generated by two different exit types: private trade sales and IPOs. A careful investigation of these two exit events provides an overview of start-ups buyers, their domain and their geographic location. Moreover, a total of 152 IPOs experienced by EIF-supported companies are discussed in detail.

Closing the circle, a final contribution of this work relates to the analysis of the determinants of successful exit outcomes, and is sought to put into perspective the numerous findings discussed thus far. The correlation analysis finds, *inter alia*, that the experience of VC firm is positively linked to lower rates of write-offs and higher rates of profitable trade sales. However, first time teams backed by EIF are shown to perform not significantly different than more experienced teams, hinting that the contribution of experience is relevant only when *outstanding*. Alternatively, an equally plausible explanation could be the selection bias brought by EIF's own high-standard screening of first time VC teams. In turn, this implies that this particular result may not hold for the entire VC ecosystem.

While the focus of this work is purely on *gross returns* of investments into start-ups, some lessons can certainly be transferred to the field of fund or fund-of-funds performance. In the spirit of the broader series of working papers, forthcoming issues will continue to tackle start-up-level dynamics with the perspective of enriching the body of research on the effects of EIF-supported venture capital investments. Against this background, forthcoming issues will have a specific look at the innovative ability of European start-ups.

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Appendices

A Granger-Causality Test

This section outlines the details of the Granger-Causality test (Granger, 1969) implemented in section 3 to evaluate whether a *stock market technology index* (the NASDAQ Composite Index) predicts movements in the *median start-up valuation*. These are two quarterly time series spanning the period 1999Q1 - 2016Q1.

The intuition behind the method is that, given two time series x_t and y_t, we use the test to determine whether one of the two series is useful in forecasting the other. The variable x is said to *Granger-cause* variable y if predictions of the future value of y based on past lags of both y and x are better than predictions of y based on its own past values only.

The test is implemented by estimating a vector autoregressive model (VAR) for the two time series of interest x and y. The two time series are required to be *stationary*. Hence, in case of non-stationary data, one must "difference" the time series until having them stationary, ensuring that there is no unit root in the model. Then, a F-test on the joint significance of the other variable's past lags is performed on each system equation (Chi-square, LR or Wald tests are used as well).

In our context, we can think of the *median start-up valuation* as y and the *stock market technology index* as x. Before estimating the VAR model, we check for the stationarity of the quarterly time series by means of an augmented Dickey-Fuller (ADF) test[57]. When unit root is not rejected, we first-difference the series. Noticeably, the *median start-up valuation* series is differenced twice in order to get it stationary. Then, we estimate a 4-lags quarterly VAR model, where the number of lags is selected jointly by lowest AIC, HQIC, SBIC.

Once estimated the VAR model, a Wald test on the joint significance of the coefficients of past lags of NASDAQ (Median Valuation) in the Median Valuation (NASDAQ) equation is performed. In particular, for each VAR equation, the null hypothesis is that past lags of the "excluded" variable are not significant in predicting values of the dependent variable. As Table A1 shows, the null hypothesis can be rejected only for the Median Valuation equation with respect to the NASDAQ. Therefore, there is evidence that a stock market technology index *Granger-causes* valuations, *i.e.* it brings informational content useful to predict movements in the median start-up valuation.

Table A1: Granger-Causality test of NASDAQ Composite Index and median start-up valuation

Equation	Excluded	F statistic	df	df-r	p-value
NASDAQ	Median Valuation	.923	4	54	.4575
Median Valuation	NASDAQ	2.886	4	54	.0308

Note: the null hypothesis of the first test (first block) is that the median valuation does not Granger-cause the NASDAQ Composite index. The null hypothesis of the second test (second block) is that the NASDAQ does not Granger-cause the median valuation.

[57] For the technical details of the test procedure, see Dickey and Fuller (1979) and Hamilton (1994).

B Additional evidence on the distribution of exit returns

Figure B1: Distribution of the exit return class, unweighted MoCs, by sector

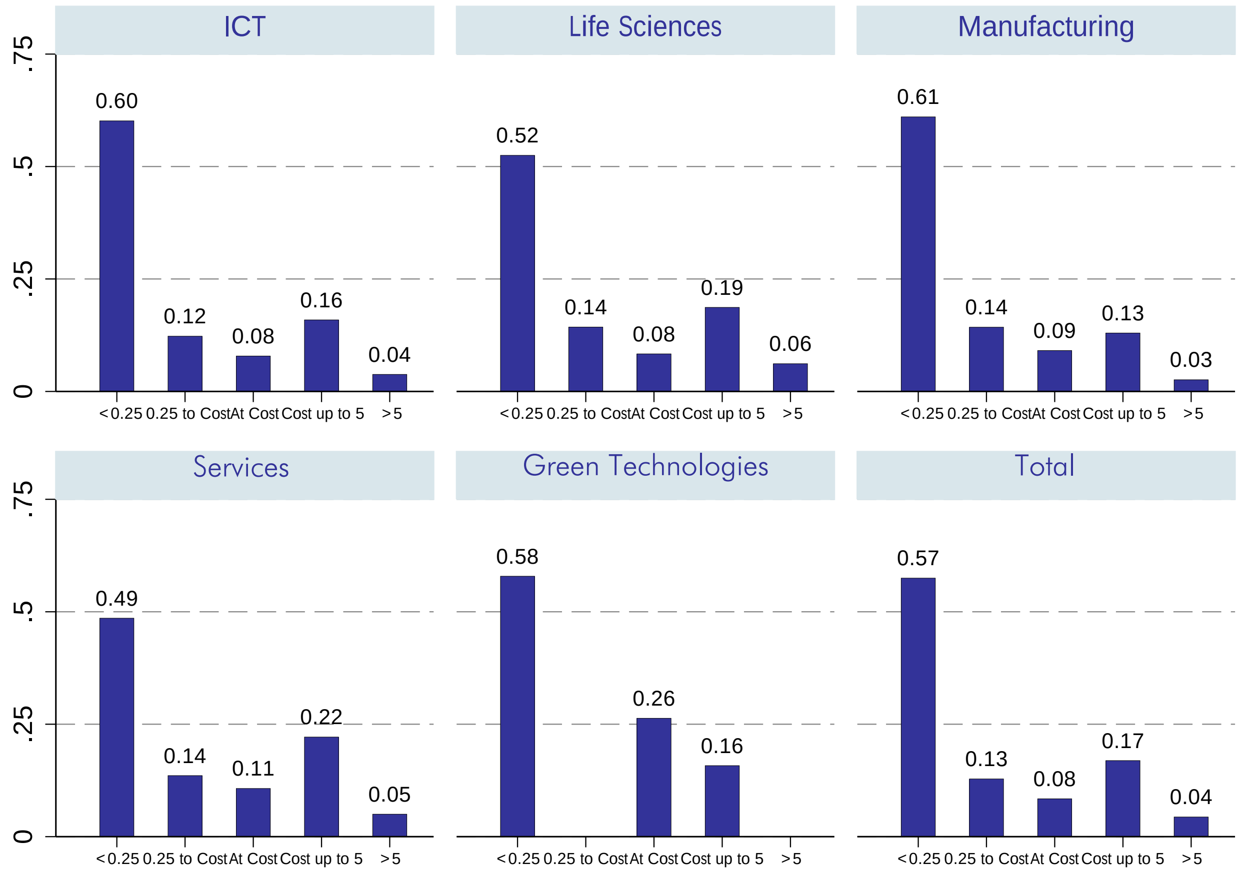


Figure B2: Distribution of the exit return class, unweighted MoCs, by vintage year

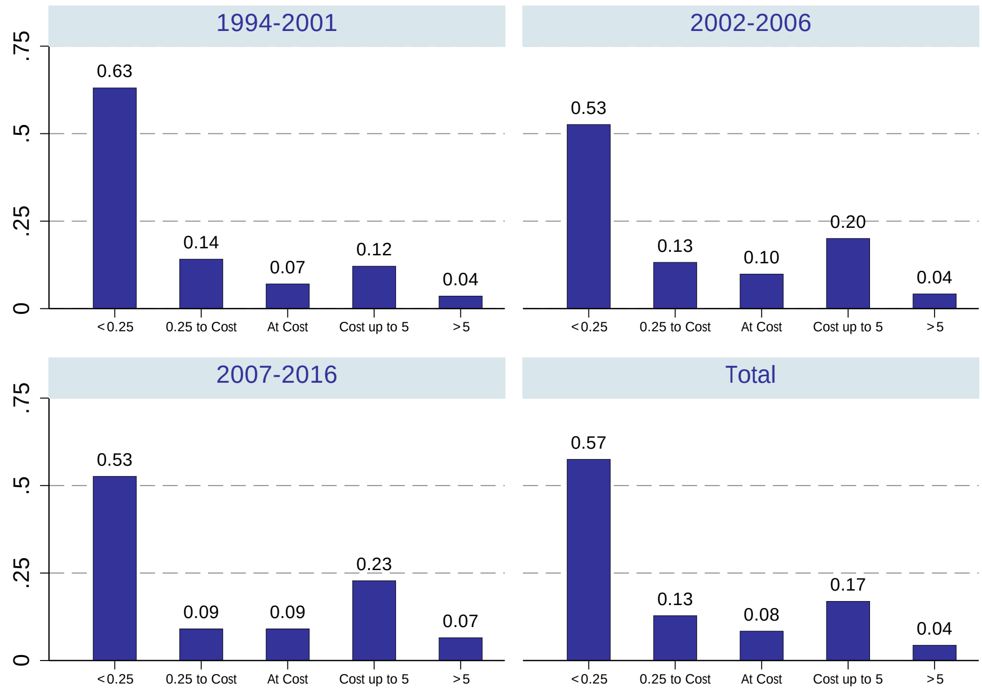
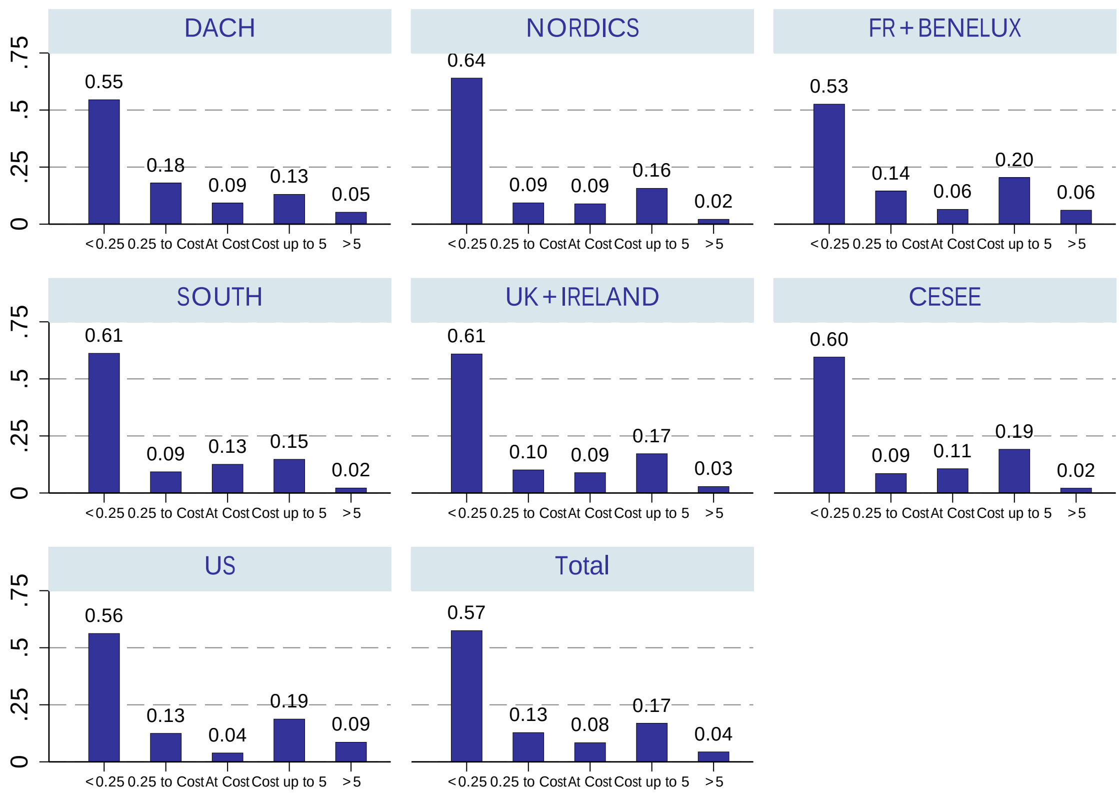


Figure B3: Distribution of the exit return class, unweighted MoCs, by region



Note: based on 2,065 early-stage VC investments, exited, made between 1996 and 2015 by EIF-backed VC funds. The figures include all the exit types, *i.e.* write-off, liquidations and successful sales. Exit MoCs are not weighted. The "At Cost" bucket includes all the MoC values such that $0.8 \leq$ MoC < 1.2. "Total" category reflects Figure 4. "ROW" excluded for its negligibility of number of observations.

Figure B4: Weighted exit MoCs of EIF-backed VC investments, by sectors

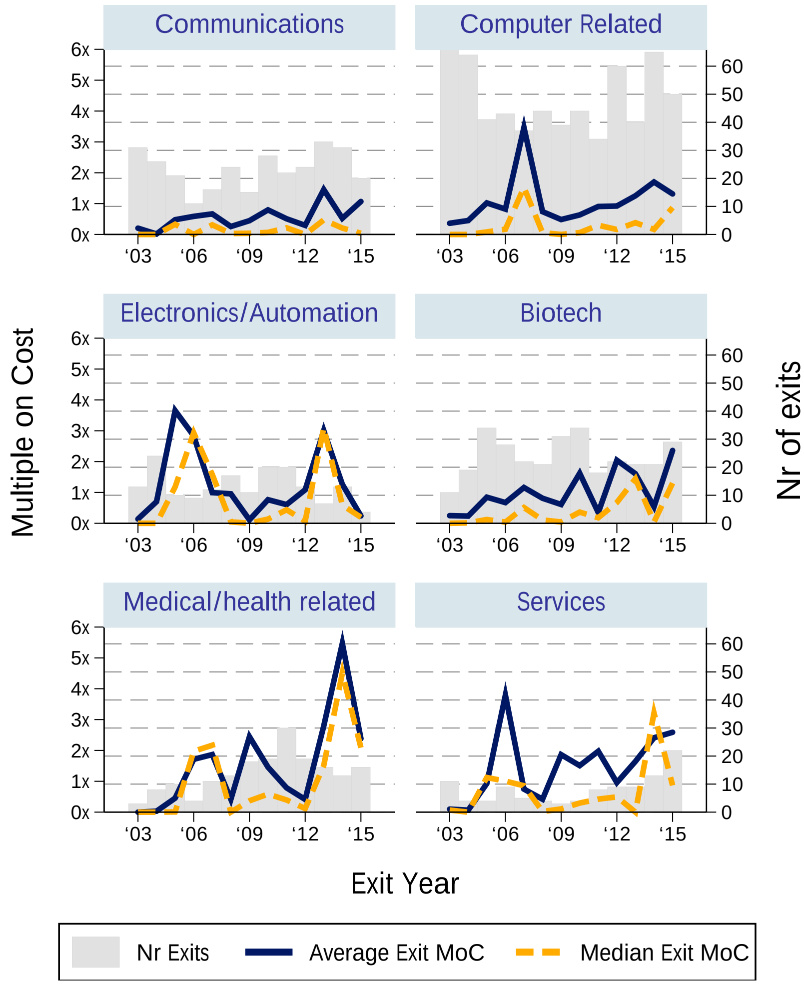
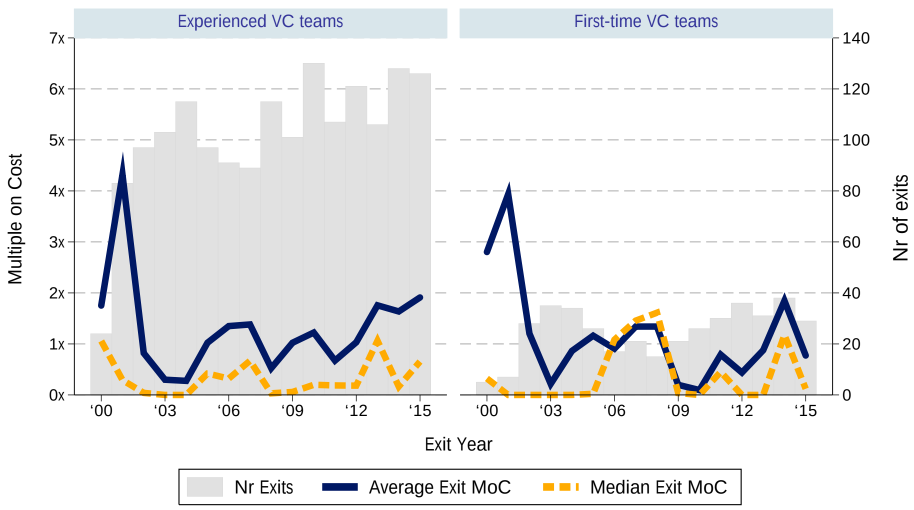


Figure B5: Weighted exit MoCs of EIF-backed VC investments, experienced *vs* first-time VC teams



Note: based on 2,065 early-stage VC investments, exited, made between 1996 and 2015 by EIF-backed VC funds. The figures include all exit types, *i.e.* write-off, liquidations and successful sales. Exit MoCs are weighted. Grey bars report the number of exits per year in the sample (right hand axis).

C Additional evidence on the power-law assumption in VC returns

This section outlines the key procedure and estimates obtained by implementing the Clauset *et al.* (2009) procedure for the validation of power law distributions with continuous data.

Table C1: Clauset *et al.* (2009) goodness-of-fit test for power law distributions

Obs	Mean	Max	Std	n (Tail)	alpha	sigma	xmin	MC p-value
1414	1.59x	138.98x	5.34	244	2.45	0.09	2.35x	0.915

Note: based on 1,414 non-zero exit returns observations. The power law parameters are obtained with the ML estimators proposed in Clauset *et al.* (2009). Given an estimated lower bound of $\hat{x}_{min} = 2.35$, $n_{tail} = 244$ observation have been used in order to implement the Monte Carlo goodness-of-fit test. The number of MC draws is $k = 1,000$. The test p-value is based on the null hypothesis that the data is consistent with power law behavior. Software implementation based on Ginsburg (2012) and Alstott *et al.* (2014).

The method delivers an estimated scaling parameter of 2.45 ($\pm$ 0.09). More importantly, the p-value of the test equals 0.915, therefore the hypothesis that the data is consistent with a power law distribution cannot be rejected. The empirical evidence does not contradict the claim that VC returns are approximately Paretian. However, this does not tell us whether a power law fits the data *better than any other distribution*. Indeed, there are several models that appear to behave like power laws for some extent. For instance, despite its finite moments, the lognormal distribution is extremely similar in shape to Paretian distributions (Mitzenmacher, 2003). The point of which distribution fits the data better is important in order to understand the underlying economic mechanism that generates the distribution, as different models yield very different predictions and implications.

Hence, following Clauset *et al.* (2009), we adopt the method of Vuong (1989) and we build a battery of Likelihood Ratio (LR) tests to compare the power law fit with a series of competing distributions. When the ratio is positive, the power law is favored against the competing model and *vice versa*. Against this backdrop, a p-value < 0.1 indicates that the sign of the LR is statistically significant. One of the main advantages of this approach is that it does not only state which of the two hypothesized models is favored, but also when the data is not sufficient to discriminate between the distributions (Clauset *et al.*, 2009). Table C2 shows the tests' outcome. The result of the tests indicates that we can clearly favor the power law against the exponential distribution. At the same time, we cannot claim that the power law has a better fit than the other competing models, *inter alia* the lognormal model (see Figure 12). Indeed, as outlined in Virkar and Clauset (2014), a rule of thumb threshold for the number of tail observations necessary to discern between Paretian and lognormal is $n_{tail} > 300$. Thus, larger samples are needed to produce further evidence on this.

Table C2: Log-Likelihood Ratio tests of power law behavior

Distribution	Log-likelihood Ratio	p-value	Support for Power Law
Lognormal	-0.815	0.541	Cannot say
Exponential	**62.577**	**0.037**	**Yes**
Truncated power law	-0.320	0.424	Cannot say
Stretched Exponential	-0.661	0.699	Cannot say
Positive Lognormal	1.774	0.674	Cannot say

Note: (Vuong, 1989) test based on 244 upper-tail observations. The first column shows the distribution to which the power law is compared. Positive values of the LR test statistic indicate that the power law model is favored over the alternative. Statistically significant p-values are indicated in **bold**. A large p signals that there is insufficient amount of data to discern among the two alternatives.

D Additional evidence on exit outcomes

Figure D1: Geographic trends in the acquisitions of European EIF-backed VC investees

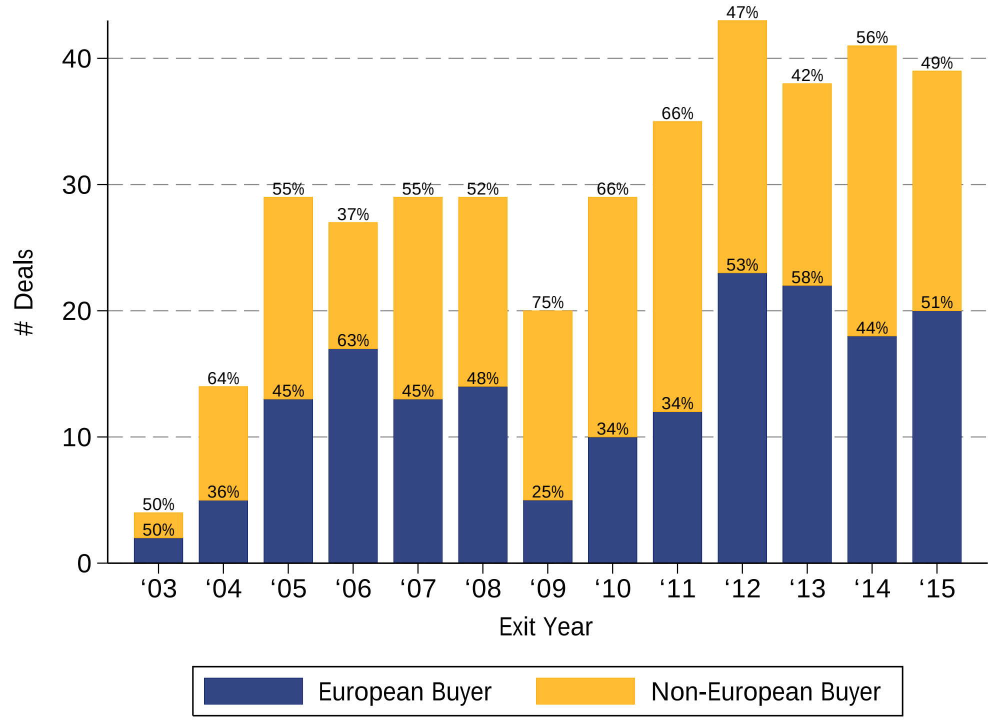
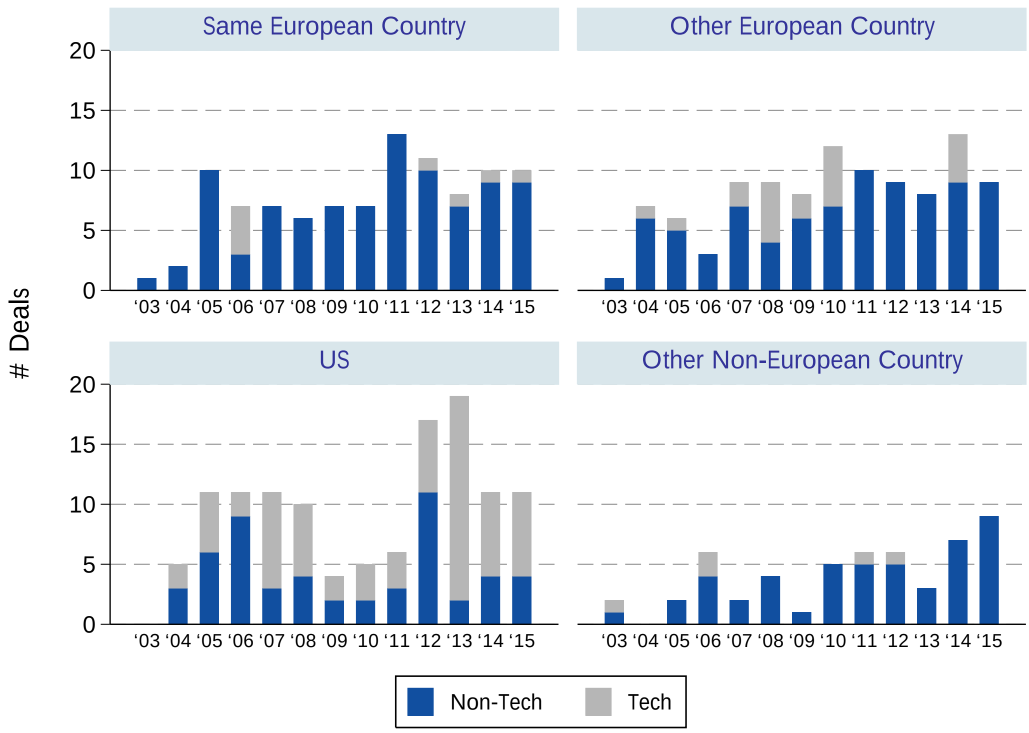
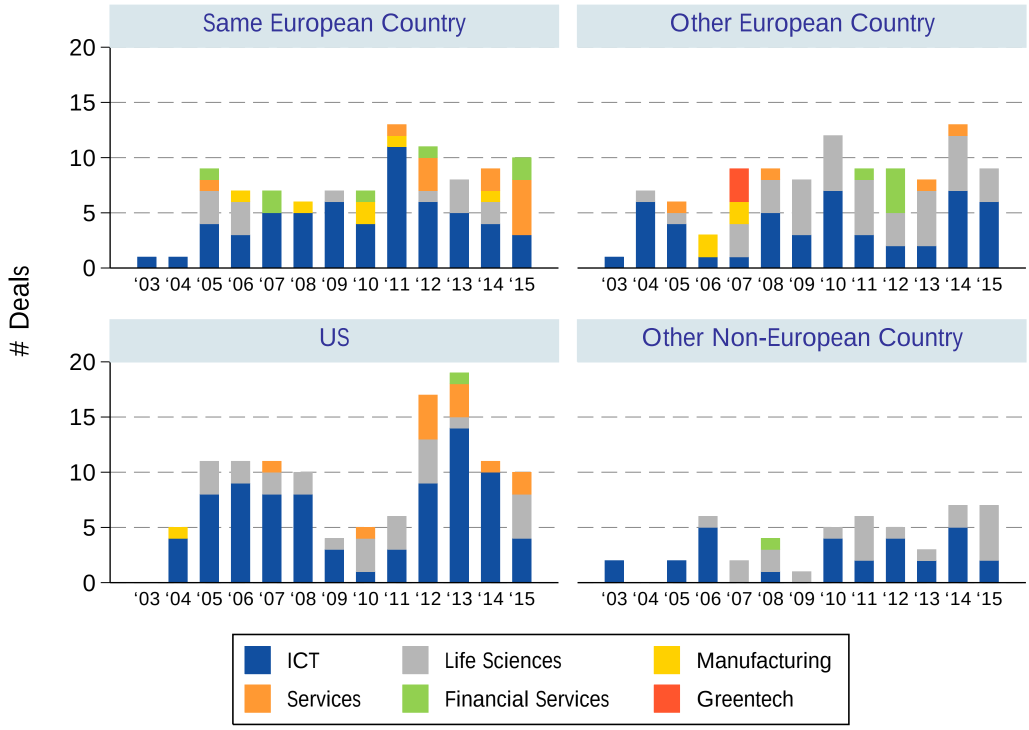


Figure D2: Buyer Technological Focus, by macro-area



Note: based on 389 private acquisitions of early-stage VC investees, invested between 1996 and 2015 by EIF-backed VC funds. “Tech” if listed on NASDAQ, “Non-Tech” otherwise. Source: BvD Zephyr (2016).

Figure D3: Buyer Sector Focus, by macro-area



Note: based on 389 private acquisitions of early-stage VC investees, invested between 1996 and 2015 by EIF-backed VC funds. Source: BvD Zephyr (2016).

Table D1: Most frequent buyers of EIF-backed VC investees

Buyer	Buyer Country	Buyer Sector	Nr Acq. EIF Investees	Acquired EIF Investees
GLAXOSMITHKLINE PLC	GB	Medical/Health Related	4	Domantis Ltd.; Okairos; Glycovaxyn; Cellzome AG
BROADCOM LTD.	US	Computer Related	4	Dune Networks; Element 14 Inc.; Alphamosaic Ltd; Siliquent Technologies Inc.
ALCATEL SA	FR	Communications	3	Right Vision; Open Plug; Native Networks
EBAY INC.	US	Consumer Related	3	Brands4Friends; Shutl; Skype Technologies
MICROSOFT CORPORATION	US	Computer Related	3	Sunrise Atelier Inc; Screen Tonic; 6Wunderkinder
APPLE INC.	US	Computer Related	3	Semetric Ltd.; Polar Rose; Acunu Ltd.

Note: Source: BvD Orbis (2016), BvD Zephyr (2016).

Table D2: IPO Stock Exchanges of EIF-backed VC investees

IPO Market	Total Listings	Foreign Listings	MktCap At IPO (EUR m)*	Revenues At IPO (EUR m)*	Time To IPO*	Most Frequent Sector
Euronext Paris	50	2	85.1	11.7	8.0	Computer Related
NASDAQ	29	7	280.5	4.0	7.6	Biotechnology
London Stock Exchange (LSE)	23	1	172.1	15.4	5.1	Computer Related
Boerse Frankfurt	14	0	155.2	24.2	6.7	Biotechnology
Swiss Exchange (SWX)	7	1	1337.3	88.7	7.5	Biotechnology
Euronext Brussels	5	1	125.0	1.9	5.5	Biotechnology
NASDAQ OMX - Stockholm	4	0	126.0	22.1	6.3	Communications
OTC Bulletin Board	3	1	107.5	23.1	9.7	Medical Related
AIM (LSE)	2	0	24.1	8.2	12.3	Computer Related
NASDAQ OMX - Helsinki	2	0	n/a	2.8	2.9	Computer Related
New York Stock Exchange (NYSE)	2	1	190.9	25.6	7.8	Computer Related
NASDAQ OMX - Copenhagen	2	0	112.0	0.4	3.6	Biotechnology
Borsa Italiana (MTA)	2	0	653.5	51.4	5.9	Communications
NASDAQ OMX - Oslo	1	0	n/a	0.0	10.2	Medical Related
Boerse Berlin	1	0	n/a	1.3	4.3	Biotechnology
Tel Aviv Stock Exchange	1	0	n/a	0.4	7.2	Medical Related
AktieTorget	1	0	7.6	n/a	7.5	Medical Related
Australian Securities Exchange	1	1	33.1	1.0	6.0	Computer Related
EASDAQ (Brussels)	1	0	n/a	n/a	2.2	Electronics
Euronext Amsterdam	1	1	n/a	7.8	8.3	Biotechnology

Note: *average values. Based on 152 EIF-backed start-up IPOs. Source: BvD Zephyr (2016), Thomson Reuters Eikon (2016).

E List of covariates in the competing risks model

Name	Label	Type	Transformation	Description
eif_macroreg	Geographic macro-region	Categorical	none	Set of dummies for each geographic macro-region. The dummy switches on when the investee's headquarter is located in that region.
eif_macrosec	Macro-sector focus	Categorical	none	Set of dummies for each macro-sector. The dummy switches on when the investee's activity is classified in that macro-sector.
vintage	Vintage Year	Continuous	none	Year of first investment by the VC fund for the portfolio company.
fund_newteam	New Team	Indicator (dummy)	none	Dummy equal to 1 if the VC fund is the first one raised by the VC firm.
nr_raisedfunds	Funds raised by VC firm	Continuous	none	Number of funds raised by the VC firm. It is a proxy for the VC firm's experience.
fund_macroreg	Fund macro-region	Categorical	none	Set of dummies for each geographic macro-region. The dummy switches on when the VC firm's operative headquarter is located in that region.
fund_macrofocus	Fund investment focus	Categorical	none	Set of dummies for each investment focus. The dummy switches on when the VC fund invests with that focus (e.g. technology transfer).
logdist	Fund Distance	Continuous	log	Log of geodetic distance between VC firm and investee company.
logfirstinv	First Investment	Continuous	log of real value (EUR 2005)	Log of the first investment amount of the fund into the company.
logfundsize	Fund Size	Continuous	log of real value (EUR 2005)	Log of the VC fund's total amount raised.
logportsize	Portfolio Size	Continuous	log	Log of the total number of investments made by the VC fund.
unicorn	Unicorn	Indicator (dummy)	none	Dummy equal to 1 if the investee company has reached valuation greater or equal than EUR 1 bn while staying private.
age_at_inv	Age@investment	Continuous	none	Age (in years) of the company when invested by the VC fund.

Note: Source: BvD Orbis (2016), EIF internal data (2016).

F Robustness checks

To ensure the robustness of our results, we compare the estimates of the methodology in Fine and Gray (1999) with results from the *destination-specific* hazard. Specifically, we seek to test whether our results are sensitive to the *continuous-time* assumption of Fine and Gray (1999). To do so, we revert to a *discrete-time* setting, following the approach outlined in Jenkins (2004). In particular, we estimate a *multinomial logit model*, [58] assuming independent risks and proportional hazards. Table F1 shows the estimation output.

The results are qualitatively the same, let alone for the coefficients of VC firm distance and portfolio size, which become significant. In particular, under this specification, an increase in the geographic distance between the fund and the portfolio company is linked to lower probabilities of both liquidation and acquisition, suggesting a common finding in the venture capital literature: longer-distance investments tend to be performed more conservatively than those with higher proximity (see, for instance, Kraemer-Eis *et al.*, 2016b).

An interesting result pertains to the size of the portfolio. In this second specification, it is linked to a higher incidence of both write-offs and IPOs. While the obvious *caveat* relates to its non-significance in the Fine and Gray (1999) model, it might otherwise indicate that larger portfolios have a greater propensity to write-off — a finding consistent with faster VC human capital reallocation in large portfolios (Fulghieri and Sevilir, 2009) — but also a higher chance of exiting through IPO. This last result is non-trivial, because it promotes the idea that, in the presence of power law return distributions (see section 4), expanding the portfolio size may increase the likelihood of reaching the *outlier* that can potentially return the entire fund.

[58] The approach is justified by the theoretical results discussed in Allison (1982).

Table F1: Multinomial Logit Competing Risks Model Estimates

	Write-off	Liquidation	Acquisition	IPO
Age at investment	0.994	0.978	1.007	0.948
	(-0.28)	(-1.16)	(0.29)	(-1.05)
First Investment	0.919*	0.823***	1.032	1.509***
	(-1.93)	(-5.15)	(0.56)	(2.60)
Fund Distance	1.003	0.969**	0.964*	1.023
	(0.18)	(-2.01)	(-1.81)	(0.51)
Vintage Year	0.948***	0.984	1.031**	0.879***
	(-3.64)	(-1.18)	(1.98)	(-2.90)
Unicorn status	0.000	2.388	15.358***	8.997**
	(-0.00)	(1.19)	(6.55)	(2.11)
First-time VC teams	1.043	0.985	0.933	1.194
	(0.36)	(-0.12)	(-0.45)	(0.51)
Fund Size	0.927	1.119*	0.933	0.818
	(-1.13)	(1.76)	(-0.82)	(-0.98)
Portfolio Size	1.159*	1.079	0.985	2.198***
	(1.77)	(0.96)	(-0.15)	(2.84)
Funds raised by VC firm	0.817***	1.017	1.095**	0.935
	(-4.04)	(0.45)	(2.09)	(-0.72)
Investee macro-sector (omitted: ICT)				
Life Sciences	0.553***	0.608***	0.738**	3.109***
	(-5.37)	(-4.87)	(-2.35)	(4.97)
Manufacturing	1.233	0.971	1.158	0.000
	(0.99)	(-0.13)	(0.53)	(-0.01)
Services	0.924	1.211	1.585**	0.000
	(-0.39)	(1.16)	(2.51)	(-0.02)
Green Technologies	0.843	0.328*	1.217	0.000
	(-0.40)	(-1.90)	(0.52)	(-0.01)
Fund macro-region (omitted: DACH)				
NORDICS	2.377**	2.034**	0.952	0.521
	(2.46)	(2.10)	(-0.13)	(-0.76)
FR&BENELUX	1.051	0.927	1.373	0.985
	(0.22)	(-0.41)	(1.41)	(-0.04)
SOUTH	1.246	1.373	1.353	0.142*
	(0.67)	(1.00)	(0.75)	(-1.71)
UK&IRELAND	0.974	0.925	2.073***	2.478**
	(-0.10)	(-0.35)	(2.95)	(2.02)
CESEE	0.426	1.226	0.844	0.004
	(-1.02)	(0.32)	(-0.22)	(-0.00)
Observations	63971			
Log-Likelihood	-9100.96			
LR Chi-Sq.	1175.45			
Chi-Square (p-value)	0.000			
Pseudo-R-squared	0.06			
Mc-Fadden R-squared	0.06			
Adj. Mc-Fadden R-squared	0.05			
AIC	18450			
Geographic macro-region	Yes			
Fund investment focus	Yes			

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Exponentiated coefficients; t statistics in parentheses

Note: based on 63,971 quarterly observations from 2,823 EIF-backed VC investments. Estimated coefficients reported are exponentiated coefficients, *i.e.* relative risk ratios, which are equivalent to hazard ratios in a destination-specific hazard framework for competing risks. A hazard ratio above (below) one means that the effect of increasing the covariate is to increase (decrease) the probability of the exit outcome modelled. Multinomial logit estimation based on Jenkins (2004).

G Current EIF-supported Unicorns

The seminal contribution of Aileen (2013) on Techcrunch has introduced for the first time the concept of *Unicorn*. In the corporate finance and VC jargon, a Unicorn is a *privately held start-up company with current valuation of USD 1 bn or more*. Despite the 1 bn threshold being void of practical meaning, the concept summarizes well the surging phenomenon of VC-backed technology companies scaling up to unprecedented levels of revenues, innovation and employment creation. Although the rise of Unicorns has been so far mainly a US fact, more and more Unicorns are emerging in Europe, alongside the development of its tech start-ups ecosystem.

As of today, CBInsights tracks 186 Unicorn companies worldwide. Collectively, these companies are worth approximately USD 650 bn and have raised about USD 125 bn. We have used CBInsights data to identify the European Unicorns and, by matching them with EIF internal records, those upheld by EIF. As Table G1 shows, out of 21 European Unicorns, almost 50% of them have been financed by EIF-supported VC funds (marked in **bold**).

Table G1: List of the current European Unicorns

Company	Valuation (USD bn)	Country	Industry
Spotify	**8.53**	**Sweden**	**Software & Services**
Global Switch	6.02	United Kingdom	Hardware
Delivery Hero	**3.1**	**Germany**	**eCommerce/Marketplace**
Adyen	2.3	Netherlands	Fintech
Klarna	**2.25**	**Sweden**	**Fintech**
Hellofresh	2.09	Germany	eCommerce/Marketplace
CureVac	1.65	Germany	Healthcare
BlaBlaCar	**1.6**	**France**	**On-Demand**
Oxford Nanopore Tech.	**1.55**	**United Kingdom**	**Healthcare**
Farfetch	**1.5**	**United Kingdom**	**eCommerce/Marketplace**
ironSource	1.5	Israel	Software & Services
Auto1 Group	**1.2**	**Germany**	**eCommerce/Marketplace**
Infinidat	1.2	Israel	Hardware
Global Fashion Group	**1.1**	**Luxembourg**	**eCommerce/Marketplace**
TransferWise	1.1	United Kingdom	Fintech
OVH	1.1	France	Big Data
Shazam	**1**	**United Kingdom**	**Software & Services**
Funding Circle	**1**	**United Kingdom**	**Fintech**
AVAST Software	1	Czech Republic	Cybersecurity
MindMaze	1	Switzerland	VR/AR
benevolent.ai	1	United Kingdom	Healthcare

Note: a Unicorn is a *privately held technology company worth 1 USD bn or more*. EIF-supported Unicorns are outlined in **bold**. Source: CBInsights (2017).

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The European Investment Fund (EIF) is Europe's leading risk finance provider for small and medium-sized enterprises (SMEs) and midcaps, with a central mission to facilitate their access to finance. As part of the European Investment Bank (EIB) Group, EIF designs, promotes and implements equity and debt financial instruments which specifically target the needs of these market segments.

In this role, EIF fosters EU objectives in support of innovation, research and development, entrepreneurship, growth, and employment. EIF manages resources on behalf of the EIB, the European Commission, national and regional authorities and other third parties. EIF support to enterprises is provided through a wide range of selected financial intermediaries across Europe. Since its inception in 1994, EIF has supported over 1.8 million SMEs.

EIF is a public-private partnership whose tripartite shareholding structure includes the EIB, the European Union represented by the European Commission and various public and private financial institutions from European Union Member States and Turkey. For further information, please visit www.eif.org.

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