Entrepreneurial Finance Seminar
Online-Workshop 14/04/2021 - 10:00 to 11:45

10:00 Introduction by Prof. Dr. Jörn Block (Trier University) and Dr. Helmut Krämer-Eis (EIF)

10:15 Presentation: „Differences in Venture Capital screening criteria" (Trier University)

10:45 Presentation: „The impact of VC on the exit and innovation outcomes of EIF-backed start-ups" (EIF)

11:15 Discussion and avenues for future research from a practitioner's and researcher's perspective

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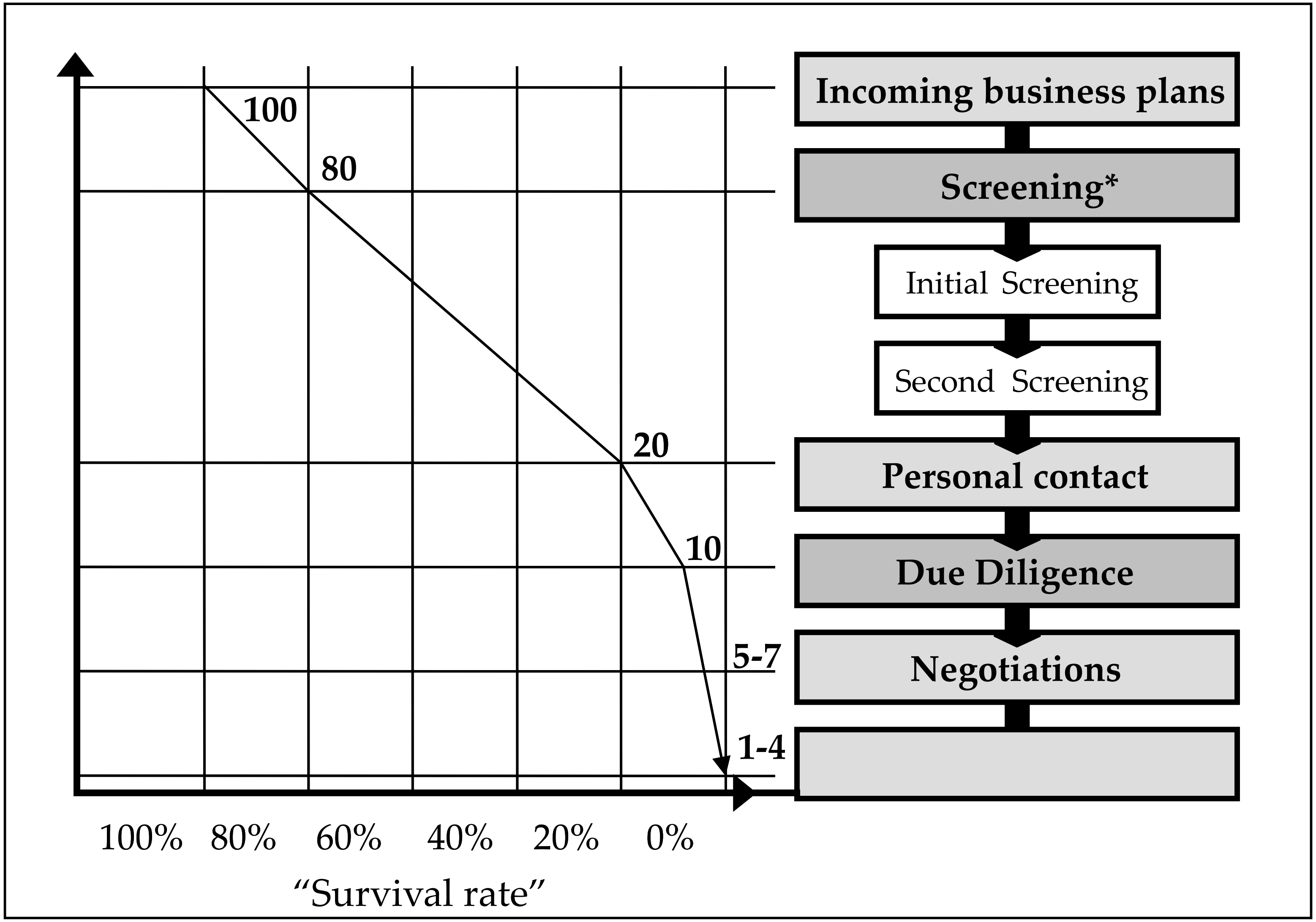
VC and PE screening criteria: Results from several studies

Prof. Dr. Jörn Block

08.03.2022

Steps of a VC evaluation process



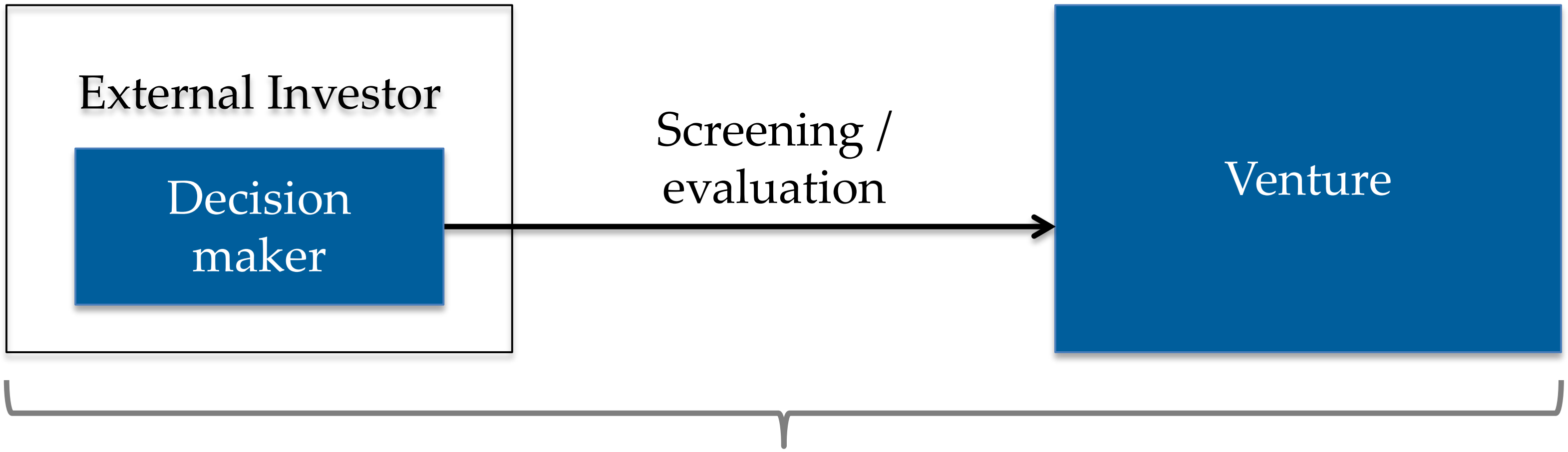
* 20% do not even enter the screening phase due to poor formal quality of the business plan.

Investor’s decision criteria

Screening criteria

- Track record
- Management team
- Market growth
- Valuation
- Product
- Marketing strategy
- …
- CEO experience
- Market potential
- Exit options
- Financial data
- Image
- IPP
- Potential ROI
- Layout of the business plan
- Education of founder

Research questions



1. What are **important criteria** that investors use to screen growth ventures?
2. What is the **relative importance** of each of the criteria?
3. How do **characteristics of the individual decision maker** (e.g., age, experience or education) influence the screening decision?
4. How do **characteristics of the investor company** (e.g., investor type or country) influence the decision making?
5. Can we observe differences between EU and the US in the importance of criteria?

Mixed-methods approach

1.) Literature review and expert interviews to find most relevant criteria

2.) Conduction of conjoint experiment

3.) Further expert interviews to interpret results

Only third study

Identified criteria

- Our **literature review** and **expert interviews** resulted in **seven important screening criteria for later-stage ventures**

Characteristic	Possible levels
Value added for customers	*Low; Medium; High*
Business model	*Low cost; Innovation-centered; Lock-in; Complementary*
International scalability	*Difficult; Moderate; Easy*
Current profitability	*Not profitable; Break even; Profitable*
Current revenue growth	*10%; 20%; 50%; 100%*
Current investors	*No external; Unfamiliar external; Tier 1 external*
Management team (track record)	*No team members; Some team members; All team members*

Choice experiment

- **Two potential companies were presented**, differing in seven characteristics, decision of which one is more attractive:

Characteristics of the venture	Growth venture A	Growth venture B
Value added for customers:	Low	Medium
Business model:	Low cost	Lock-in
International scalability:	Moderate	Easy
Current profitability:	Not profitable	Break even
Current revenue growth:	20%	10%
Current investors:	No external investors	External investors - Tier 1
Management team (track record):	*No* team member with relevant track record	*All* team members with relevant track record
More attractive:	ChoiceExperiment_Random1=1	ChoiceExperiment_Random1=2

- Task had to be completed 13 times
- Conjoint tasks were followed by a questionnaire that delivered us detailed information on the participant (e.g., headquarter, investor type)

The sample

The participants

N = 798 investors

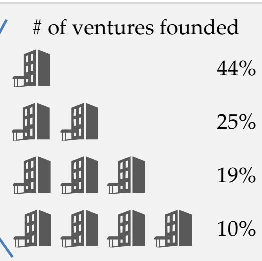
Investor type	%	N
VC fund	43%	324
CVC fund	9%	66
Family offices	8%	60
Growth equity fund	25%	181
Buyout fund	10%	71
Other	5%	42

Gender	Total	*Partner level*
Male	87%	*92%*
Female	13%	*8%*

Type of prev. experience	%	N	
Startup *(mainly)*	25%	*195*	
Corporate *(mainly)*	40%	*304*	Majority
Mixed	35%	*262*	

	Age	%	N
	< 25	2%	20
	25-34	28%	225
Ø age	35-44	26%	209
	45-54	28%	226
	55-64	10%	83
	> 64	4%	35

Entrepreneurial background	%
Yes	51%
No	49%



Educational background	Law	Business / Economics (Majority)	Engineering	Natural science
%	7%	77%	23%	11%
N	52	617	185	85

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Private equity investment criteria: An experimental conjoint analysis of venture capital, business angels, and family offices

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ARTICLE INFO ABSTRACT

(1)
Different importance of screening criteria depending on
Investor type

VC investors' venture screening:

the role of the decision maker's education and experience

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* These authors contributed equally.

(2)
Different importance of screening criteria depending on
Investor education and experience

Differences in the importance of screening criteria between US and continental European VC investors

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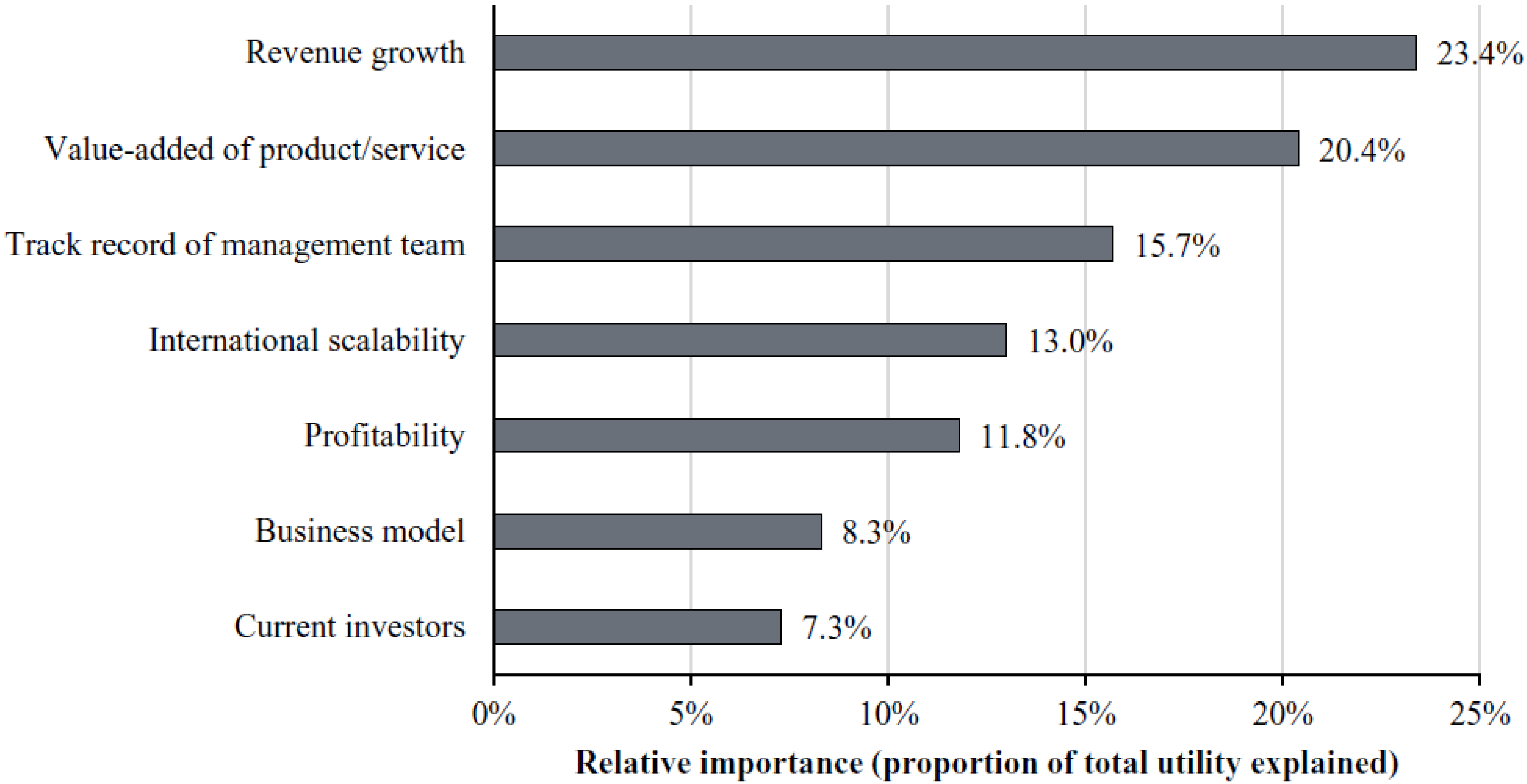
Abstract

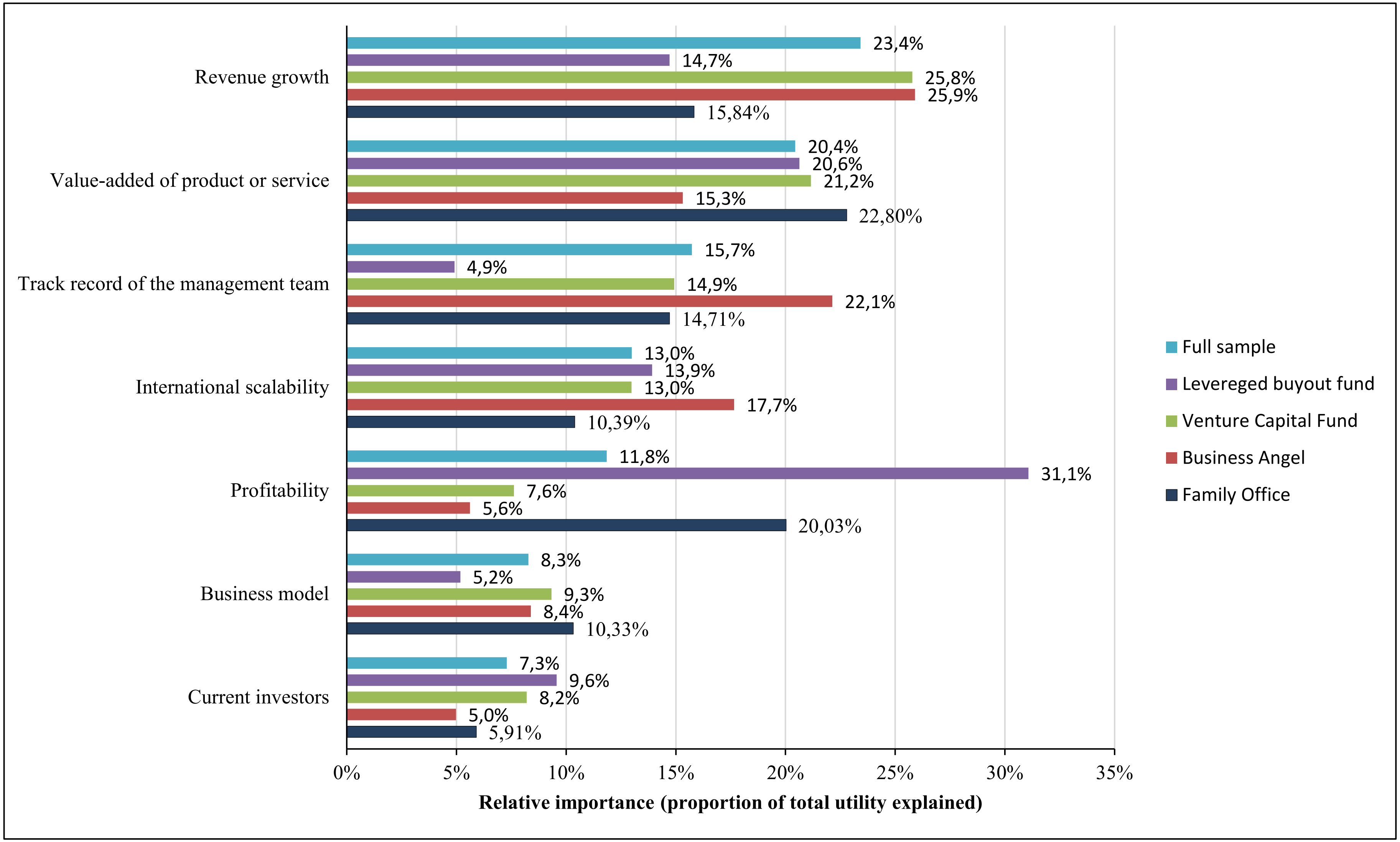
Decision-making research in venture capital (VC) tends to study investors solely in particular countries or regions and lacks studies that directly compare the importance of screening

(3)
Different importance of screening criteria depending on
Investor location (US vs EU)

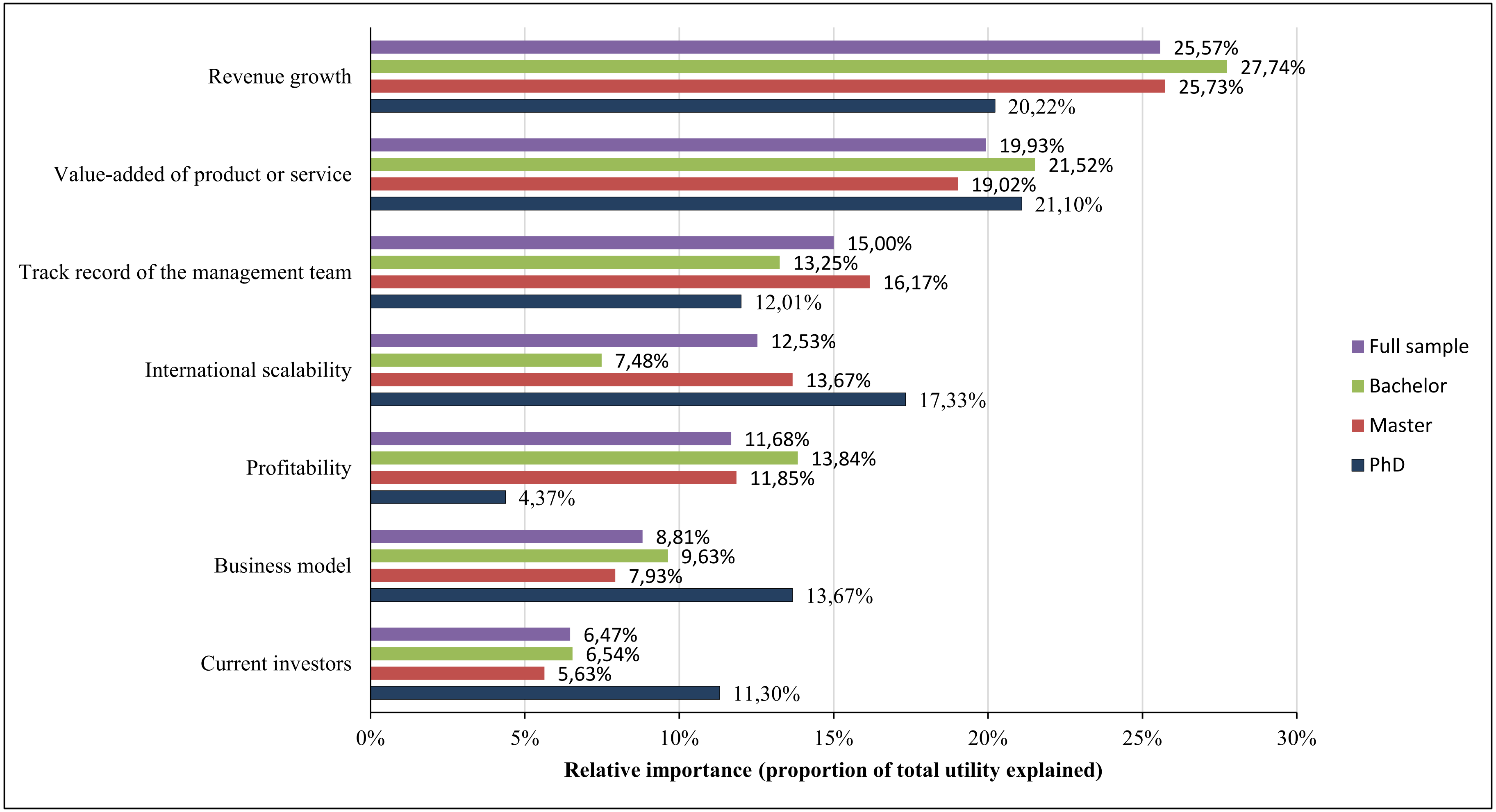
Relative importance of screening criteria



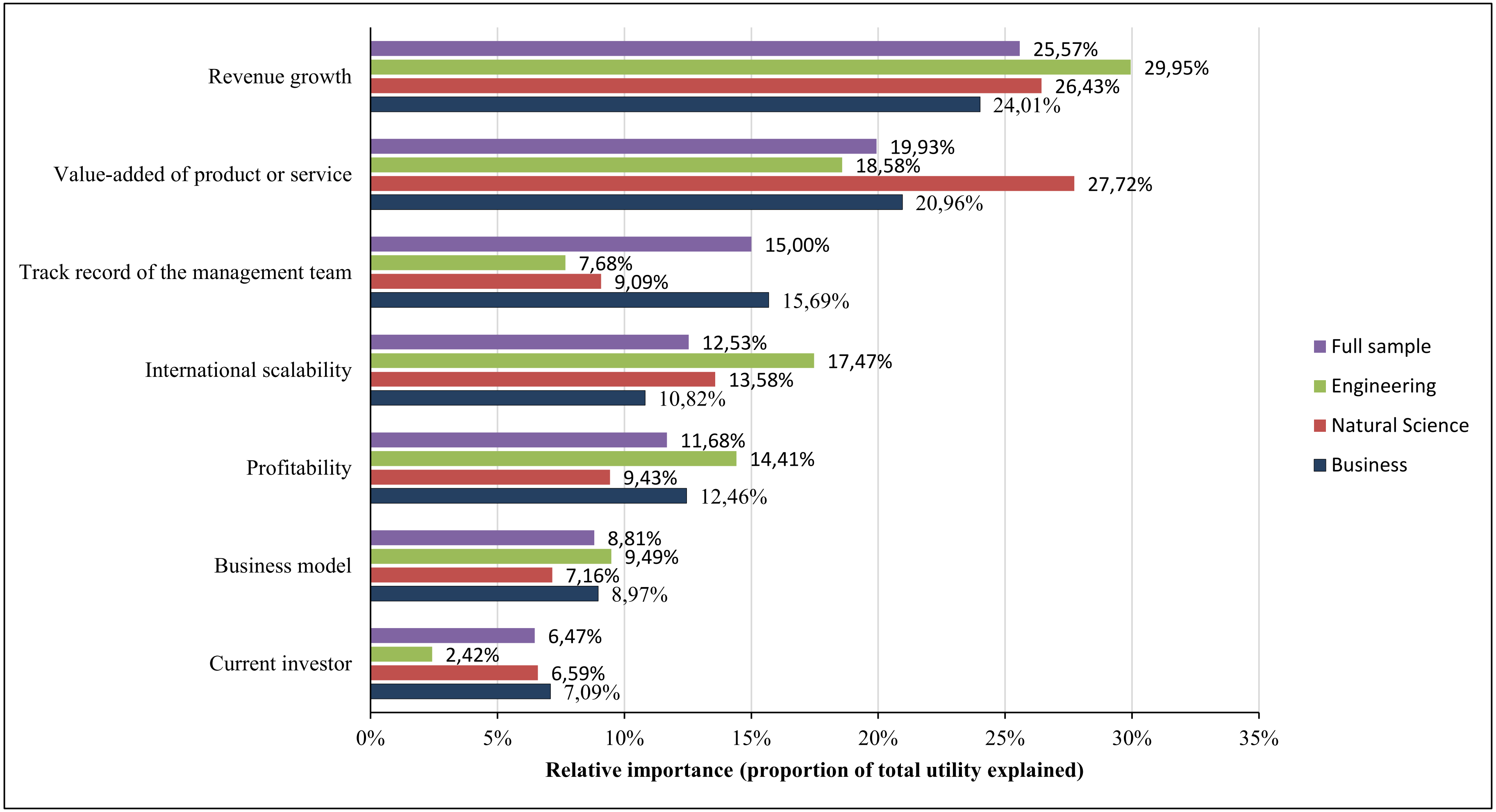
… by investor type



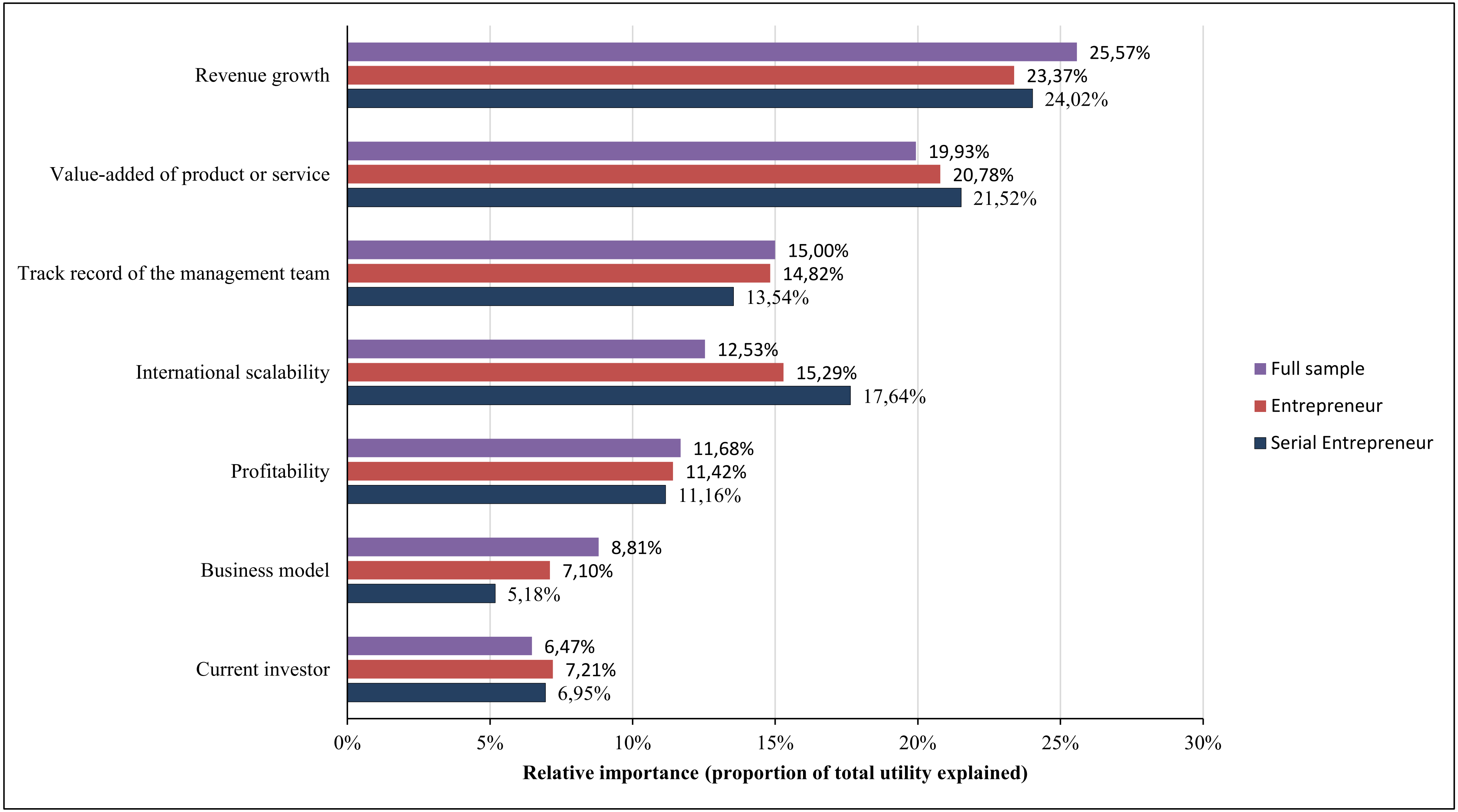
… by level of education



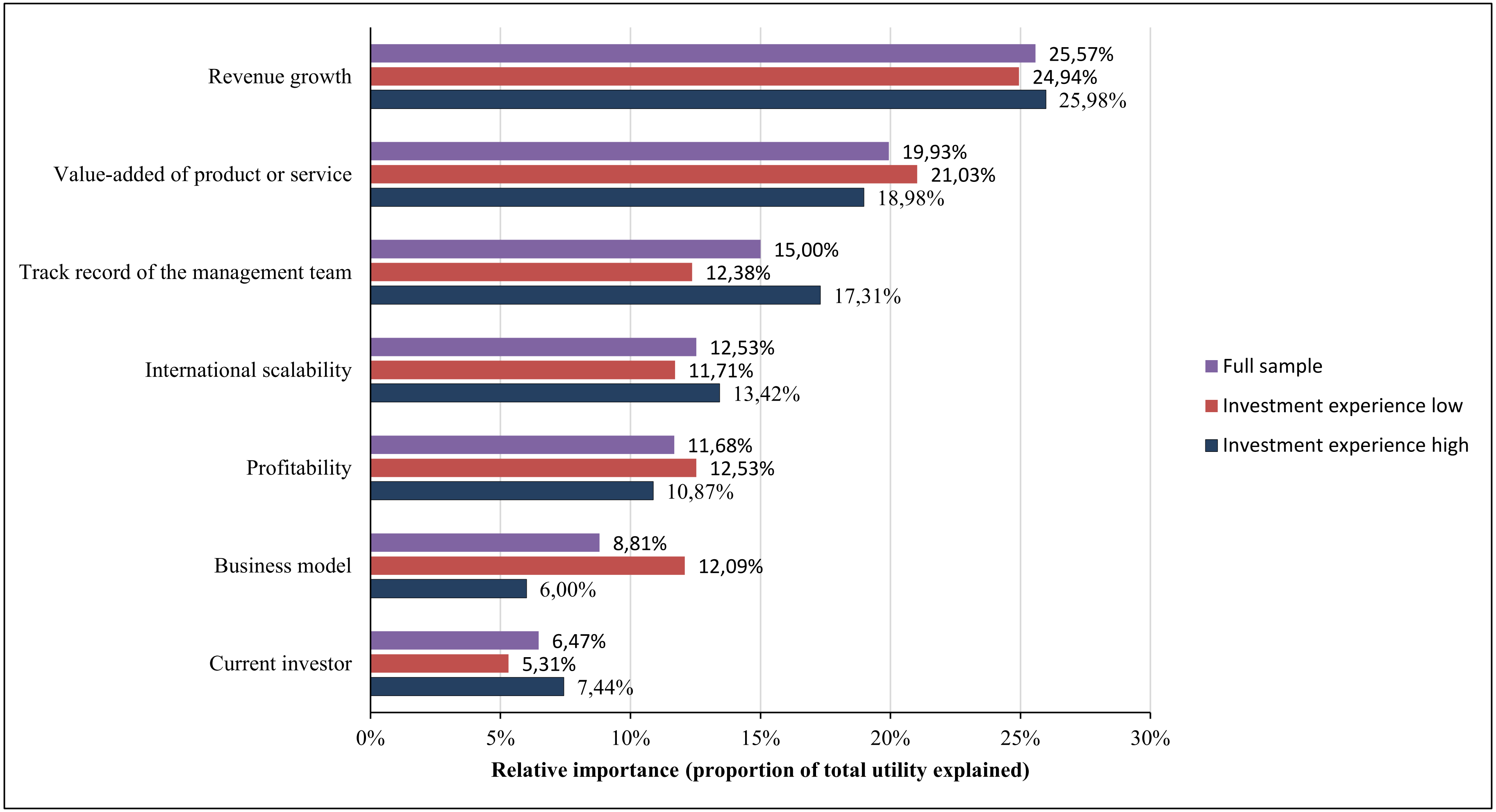
… by field of education



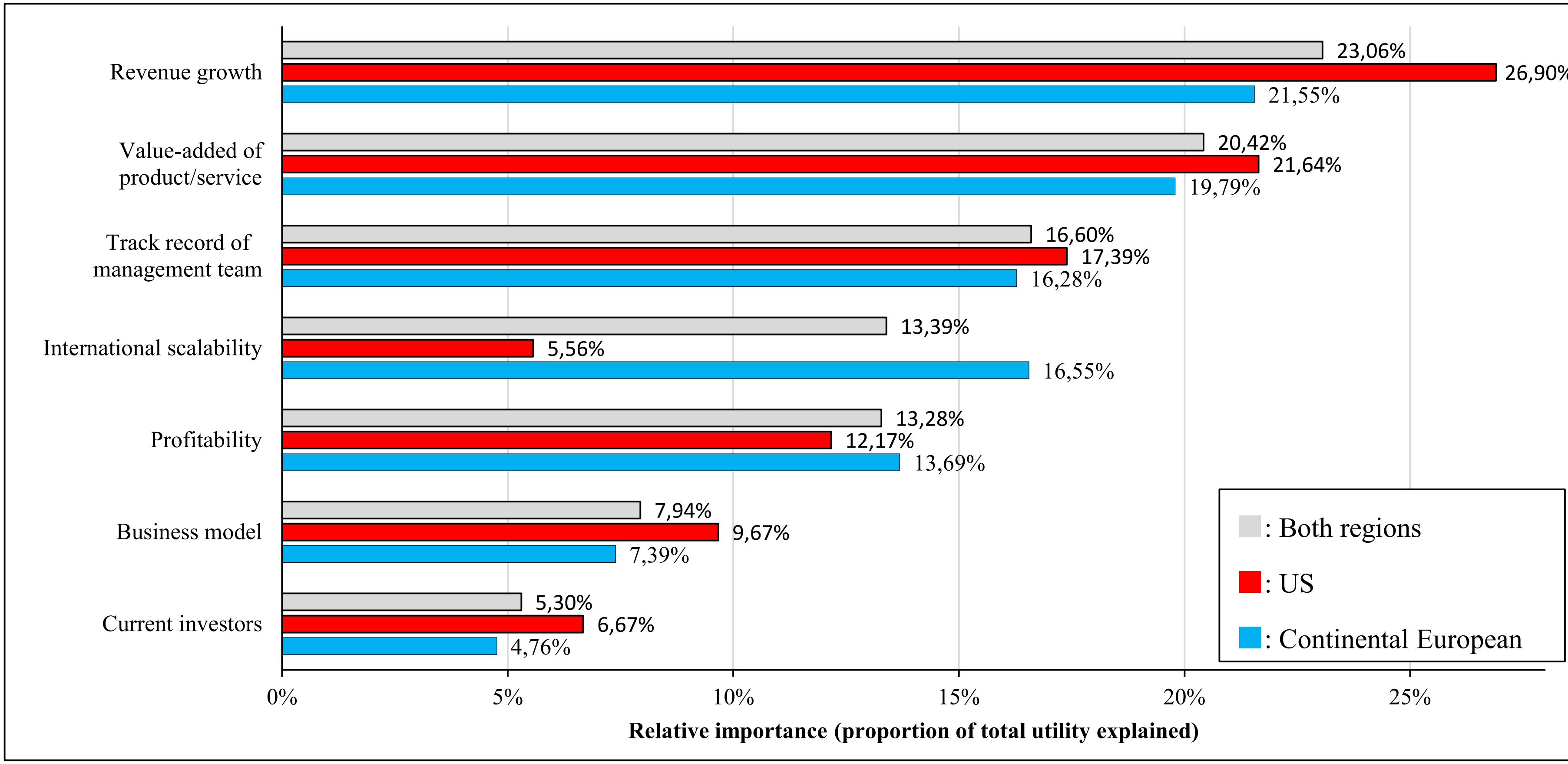
… by entrepreneurial experience



… by investment experience



US vs. continental European investors



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Which criteria matter when impact investors screen social enterprises?

Joern H. Block [a, b, c], Mirko Hirschmann [a], Christian Fisch [a, b]

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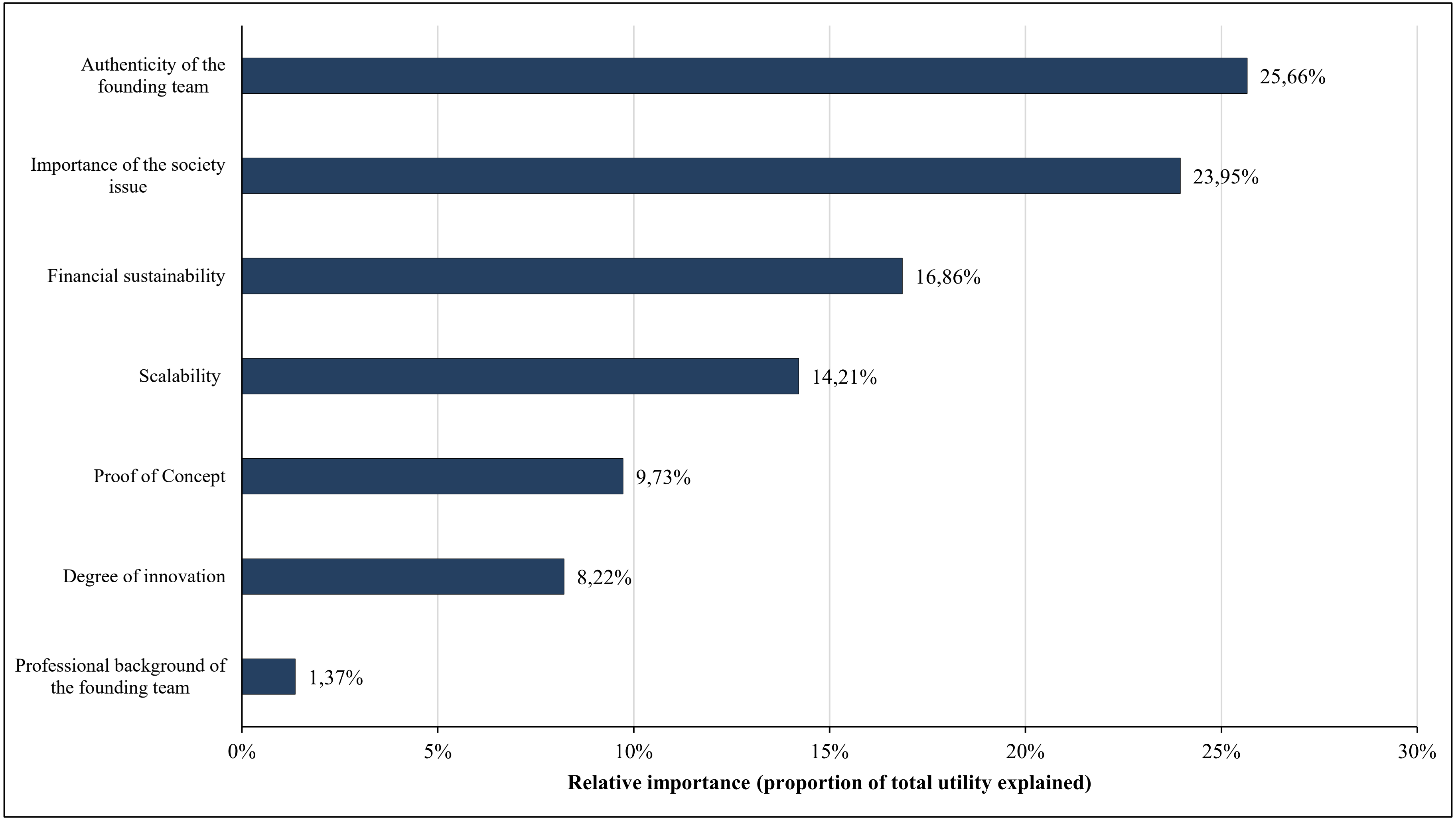
https://doi.org/10.1016/j.jcorpfin.2020.101813

Screening criteria of impact investors



Outlook

Does a Schumpeterian founder impression increases the chances of getting funded by a VC?

- The effect of a founders Twitter behavior on resource acquisition
- **3,313 founders**
- **> 2 million Tweets**
- **Algorithm-based text analysis („Linguistic inquiry word count“)**

- **Main findings:**
  - **Entrepreneurial vision** and **optimism** displayed via Twitter significantly increase the chances for a second funding
  - Displaying an **achievement motive** via Twitter significantly decreases the chances for a second funding

The European Venture Capital Landscape: an EIF Perspective

The impact of VC on the exit and innovation outcomes of EIF-backed start-ups

Elitsa Pavlova Simone Signore

European Investment Fund (EIF)

Entrepreneurial Finance Seminar – 14 April 2021, Online Workshop

Disclaimer

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Outline

The paper in a nutshell (1/2)

Research question and empirical approach

- We assess the impact of venture capital (VC) on the exit and innovation outcomes of young and innovative firms supported by the EIF in the years 2007–2014;
- We create a counterfactual group of non-VC-backed firms through a combination of exact and propensity score matching;
- We estimate treatment propensity using a series of innovative measures based on machine learning, network theory, and satellite imagery analysis;
- We investigate exit and innovation outcomes of start-ups using competing risks methods. Competing risks analysis measures the occurrence over time of exit events that are mutually exclusive.

The paper in a nutshell (2/2)

Key results

- EIF VC-invested start-ups are about three times more likely to participate in an M&A deal and experience an IPO compared to similar, non-VC-backed firms;
- EIF VC has a strong effect on the likelihood to experience horizontal, vertical and international M&A integration;
- EIF VC has no significant effect on other forms of buy-outs or on bankruptcy rates (though this might be due in part to the low statistical power of the empirical estimations);
- Start-ups supported by the EIF experienced a doubling of their patenting rate, compared to counterfactuals.

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Introduction

- Venture capital (VC) financing has been linked to positive effects in new industry creation and growth of industrial innovation (Sorenson and Stuart, 2001; Kortum and Lerner, 2000),
- but a variety of factors may limit access to venture capital for young innovative companies (Gompers and Lerner, 1999):
  - *uncertainty, asymmetric information, the nature of firm assets, and the conditions in the relevant financial and product markets.*

> *"European official documents [...] tend to focus on the supply of funds and on the creation of favorable structural conditions for entrepreneurship. However, it is far from evident which policy measures would be most appropriate to nurture venture capital in Europe. Here the lack of rigorous investigation is felt most."*
> (Bottazzi and Da Rin, 2002)

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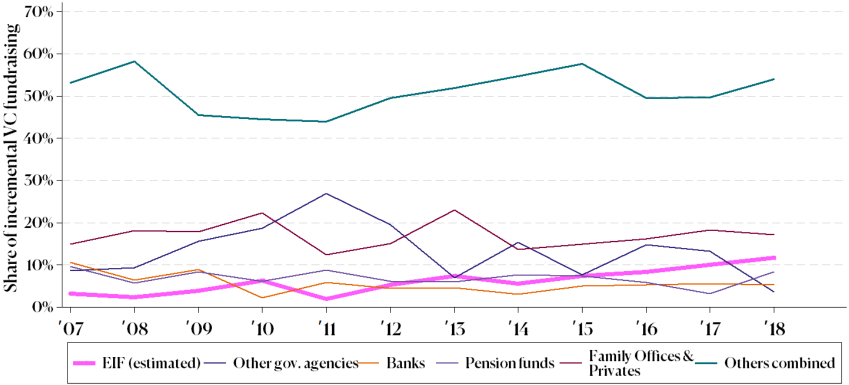
Has the increased public support brought its intended effects?

Figure 1: Incremental VC fundraising in the EU27 and UK, by investor type



Source: Kraemer-Eis et al.*, 2016 and Kraemer-Eis* et al.*, 2019, based on data from Invest Europe*

VC market development

Data Sources

▸ Data collection

- **Company data (incl. corporate group)** – Bureau van Dijk's (BvD) Orbis database, which covers about 300m companies in 90+ countries.
  - Orbis is an aggregator of firm-level data from various national IPs and offers harmonised data, collected from official business registers, national banks, annual reports, *etc.*
- **Exit data** – BvD's Zephyr database, which as of December 2020 contains information on over 2.1m worldwide M&A, IPO, private equity and VC deals.
  - Zephyr assigns every deal to one or more participating legal entities in the Orbis database. A deal might be directly assigned to a legal entity and/or indirectly assigned to a controlling entity allowing to account for the (time-varying) structure of start-ups' corporate groups.
- **Patent data** – also in Orbis, originating from the PATSTAT database, maintained by the European Patent Office (EPO).

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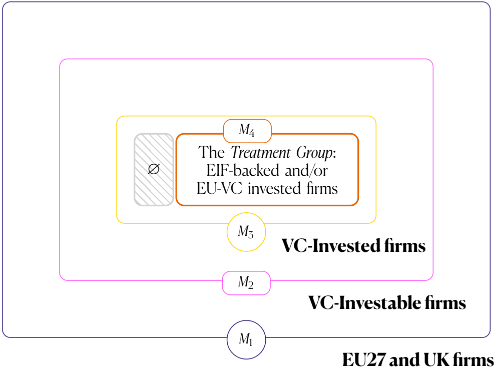
Treatment group

Selection of appropriate time period

- We partnered with Invest Europe, the association representing Europe's VC/PE industry, covering over 90% of AUM in 2007-2014.
- The joint exercise allowed us to map the population of 11,577 VC-backed start-ups in Europe in the 2007-2014 period.
- Jeng and Wells (2000) recommend separating between early stage and later stage VC financing, both for purposes of analysis and policy implications.
- We define strict(er) criteria for early stage companies, Criteria then focus on 782 EIF-supported early stage start-ups in the years 2007–2014. Breakdown

Identification strategy



For firm i and input mix $\mathbf{X}_i = \{\mathbf{H}_j, \mathbf{Z}_j\}$:

$$Pr\{i \in O | i \in M_1\} = \rho \tag{1}$$

$$\mathbb{1}_{M_2,i} = h(\mathbf{H}_i) \tag{2}$$

$$Pr\{W_i | i \in M_2\} = e(\mathbf{X}_i) \tag{3}$$

$$Pr\{i \in M_3 | i \notin M_4\} \approx 0 \tag{4}$$

where $M_4 \subseteq M_3 \subset M_2 \subset M_1$.

- Under unconfoundedness and overlap, we estimate the average treatment effect for the treated (ATT) with a matching estimator based on the propensity score $e(\mathbf{X}_i)$ (Rosenbaum and Rubin, 1983). Rubin's causal Model

The assignment mechanism (1/2)

Stylised VC demand & supply model

VC Firm

Start-up team

VC contract?

Manigart *et al.* (2002); Petty and Gruber (2011)

Bertoni *et al.* (2016)

Valuation

- Human capital (*e.g.* CV of start-up team)
- **Innovative potential**
- Projected cashflow (growth prospects)
- *Financial statements*

Required IRR

- Investment stage
- Degree of innovation
- Investment window
- Economic cycle
- Size of proposal
- **Accessibility (Bernstein *et al.*, 2015)**

Alternative credit channels

- Own capital
- Insider's capital (*e.g.* family, friends, fools)
- **Value of collateral (Saiz, 2010)**

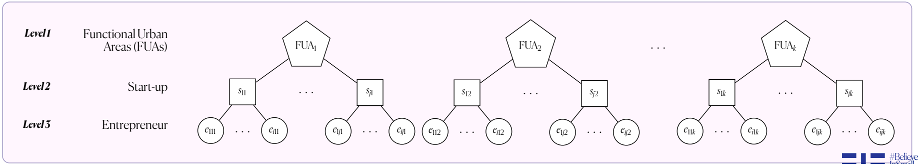
Endowment/ compl. assets

- Founding experience
- **Corporate structure**
- Network of contacts
- Search costs

The assignment mechanism (2/2)

Empirical measures and model set-up

- **Innovative potential**: we trained a deep learning algorithm to identify start-ups with a high risk/return profile and high reliance on R&D; ▸ Innovative potential
- **Corporate structure**: we included a count of start-ups' controlling firms; an indicator of their independence (i.e. power to autonomously set strategic direction) and their level of ownership concentration; ▸ Corporate structure
- **Location-based measures**: accessibility ▸ Start-up accessibility, value of collateral ▸ Collateral;
- **Unobserved heterogeneity**: multi-level set-up, as per our data structure ▸ Multi-level:



Propensity Score Model Results (odds ratios)

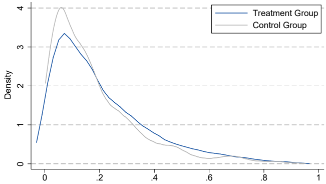
	Pr (treatment = 1)
	MULTI-LEVEL ME LOGIT
Founding team size‡	1.8622*** (0.086)
Age of founding team‡	0.9531*** (0.010)
Previous founding experience‡	3.9512*** (1.360)
Foreign-born entrepreneurs‡	0.9081** (0.030)
Female entrepreneurs‡	0.1326*** (0.033)
Firm's age at investment year	0.8908*** (0.014)
Firm holds patent at investment year	3.2436*** (0.425)
Predicted degree of innovativeness	1.8180** (0.359)
Firm's accessibility	1.2528 (0.175)
ln (Firm's distance from closest FUA's centroid)	0.8817*** (0.011)
ln (FUA's undevelopable land)	0.3755 (0.232)
Number of shareholders	0.4899*** (0.068)
Independence Indicator:* (omitted: A)	
B	1.0518 (0.114)
C	0.1708*** (0.078)
D	0.3593*** (0.038)
Unknown	1.8455*** (0.169)
Group ownership type: (omitted: No shareholders)	
Corporate majority shareholder	1.7970*** (0.150)
Corporate plurality shareholder	1.3108** (0.136)
Non-corporate majority/plurality shareholder	0.6000 (0.334)
...	
Investment Year FEs	Yes
Start-up macro-industry FEs	Yes
Start-up macro-region FEs	Yes
Log-likelihood	-6167.16
Obs.	31,989
Pseudo-R^2 (McKelvey and Zavoina, 1975)	0.41
Area under the ROC curve	0.872

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡ Founder-level characteristic; Exponentiated coefficients (odds-ratios).

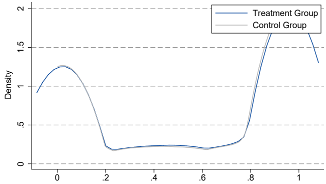
- Most hypotheses about the assignment mechanism are verified in the data.
  - Innovative potential, team composition, start-up age and corporate structure are all strong predictors of early stage VC.
- We note the significant role of previous founding experience (positive), gender and nationality diversity (negative).
- Following the literature, we saturate our propensity score model using a variety of non-linear effects and interactions.

Covariate balancing ability

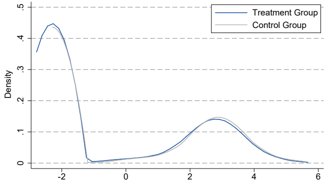
Figure 2: Kernel density estimates of select matching covariates, by treatment status



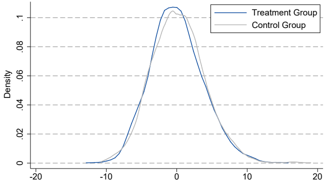
(a) Estimated propensity score



(b) Innovativeness score



(c) ln (Distance from the FUA's centroid)



(d) Age of founding team (FE)

Descriptive statistics after matching

	Obs. (1)		Mean (2)		Median (3)		St. dev. (4)		P-value (5)
	T	C	T	C	T	C	T	C	T/C
Average team age at founding	274	274	40.81	41.90	40.29	42.34	8.446	8.226	0.126
Share of female team members	274	274	0.10	0.11	0.00	0.00	0.193	0.199	0.531
Share of foreign team members	274	274	0.17	0.15	0.00	0.00	0.275	0.310	0.606
Average team prev. experience	274	274	42.04	22.08	1.88	1.00	434.9	227.5	0.501
Team size	274	274	4.28	4.19	3.00	3.00	3	3	0.741
Company age at inv. year	274	274	2.07	2.02	1.36	1.36	1.868	1.817	0.776
Patent at investment year	274	274	0.20	0.20	0.00	0.00	0.404	0.404	1.000[φ]
Innovativeness score	274	274	0.59	0.59	0.91	0.92	0.436	0.434	0.975
Company accessibility score	274	274	1.24	1.15	0.45	0.38	1.644	1.654	0.536
ln (distance from FUA's centroid)	274	274	-0.78	-0.84	-2.30	-2.30	2.308	2.352	0.767
ln (undevelopable land)	274	274	-2.95	-2.97	-3.43	-3.39	1.023	1.083	0.792
Number of shareholders	274	274	0.19	0.19	0.00	0.00	0.521	0.600	1.000[φ]
Investment period:									
2007-08[‡]	274	274	0.19	0.19	0.00	0.00	0.390	0.390	1.000[φ]
2009-11[‡]	274	274	0.23	0.23	0.00	0.00	0.424	0.424	1.000[φ]
2012-14[‡]	274	274	0.58	0.58	1.00	1.00	0.494	0.494	1.000[φ]
Macro-sector:									
ICT[‡]	274	274	0.50	0.50	0.50	0.50	0.501	0.501	1.000[φ]
Life Sciences[‡]	274	274	0.20	0.20	0.00	0.00	0.399	0.399	1.000[φ]
Services[‡]	274	274	0.17	0.17	0.00	0.00	0.374	0.374	1.000[φ]
Other[‡]	274	274	0.14	0.14	0.00	0.00	0.342	0.342	1.000[φ]
Macro-region:									
DACH[‡]	274	274	0.28	0.28	0.00	0.00	0.452	0.452	1.000[φ]
Nordics[‡]	274	274	0.12	0.12	0.00	0.00	0.322	0.322	1.000[φ]
France & Benelux[‡]	274	274	0.09	0.09	0.00	0.00	0.283	0.283	1.000[φ]
South & CESEE[‡]	274	274	0.06	0.06	0.00	0.00	0.242	0.242	1.000[φ]
UK & Ireand[‡]	274	274	0.45	0.45	0.00	0.00	0.498	0.498	1.000[φ]
Independence indicator									
A[‡]	274	274	0.19	0.14	0.00	0.00	0.390	0.346	0.133
B[‡]	274	274	0.15	0.10	0.00	0.00	0.361	0.303	0.073
C[‡]	274	274	0.31	0.32	0.00	0.00	0.465	0.469	0.784
D[‡]	274	274	0.01	0.01	0.00	0.00	0.104	0.104	1.000
Group ownership type									
No shareholders[‡]	274	274	0.22	0.20	0.00	0.00	0.414	0.399	0.529
Corp. majority shareholder[‡]	274	274	0.57	0.57	1.00	1.00	0.496	0.496	0.931
Corp. plurality shareholder[‡]	274	274	0.21	0.23	0.00	0.00	0.407	0.422	0.536
Non-corp. maj./plur. sh.[‡]	274	274	0.00	0.00	0.00	0.00	0.060	0.000	0.318

[‡] dichotomic variable; [‡‡] exactly matched.

Competing risks model

- Competing risks methods suitable to model start-ups' exit outcomes:
  - exit events are mutually exclusive,
  - an exit's timing is a key element contributing to its success.

- Under competing risks, only the earliest exit event is observed (and its time-to-exit). Until then, each exit option has some probability to occur.

Competing risks methods

- How to assess treatment effects under competing risks? Austin and Fine (2019):
  - Fit a Cox (1972) model to estimate the **relative treatment effect**, regressing the cause-specific hazard (i.e. the instantaneous rate of a given exit route occurring) on the treatment status.
  - Fit a Fine and Gray (1999) model to estimate the **absolute treatment effect**, i.e. the percentage points change in the incidence of a given exit outcome due to the treatment status, in the presence of competing risks.

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Primary exit outcomes: relative treatment effects

Descriptives

Table 1: Estimated odds ratios for the Cox proportional hazard model (PHM)

	M&A		IPO		Other Buy-out		Bankruptcy$^{\alpha}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	PHM	PHM	PHM	PHM	PHM	PHM	PHM	PHM
VC-invested	3.220***	2.934***	3.254†	3.327†	0.891	1.001	1.183	1.266
	(0.849)	(0.796)	(2.207)	(2.385)	(0.544)	(0.655)	(0.185)	(0.219)
Firm age at inv. year		1.058		0.995		0.921		0.994
		(0.070)		(0.153)		(0.155)		(0.048)
Predicted degree of innovativ.		1.061		3.184		0.463		0.408***
		(0.344)		(2.918)		(0.448)		(0.086)
Patent at inv. year		0.583		4.062*		1.950		0.989
		(0.222)		(2.789)		(2.461)		(0.217)
Propensity score		4.930*		1.412		0.036		0.579
		(3.448)		(1.955)		(0.075)		(0.301)
Corp. group covariates‡	No	Yes	No	Yes	No	Yes	No	Yes
Log-Likelihood	-434.94	-411.97	-69.28	-64.01	-52.84	-48.39	-809.22	-790.81
N° of observations	548	548	548	548	548	548	548	548
N° of exit events	75	75	12	12	9	9	137	137
Tot. time at risk (quarters)	14,351	14,351	14,351	14,351	14,351	14,351	15,835	15,835

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡n° of shareholders, Independence indicator; cluster-robust std errors in brackets.
$^{\alpha}$ Estimated under the assumption of no competing risks.

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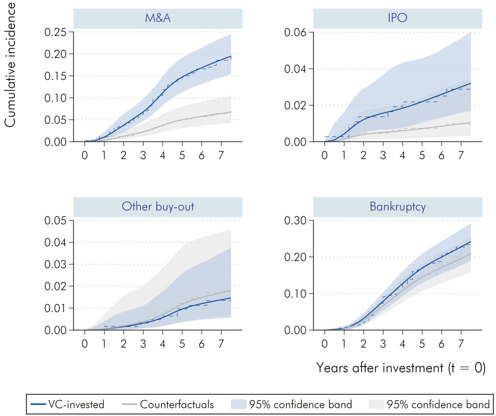
Primary exit outcomes: absolute treatment effects

Figure 4: Changes in the cumulative incidence function (CIF) due to treatment, by exit route



Secondary M&A outcomes: relative treatment effects (1/2)

Descriptives

Table 2: Estimated odds ratios for the Cox proportional hazard model (PHM)

	Horizontal integration		Vertical integration		Diversification	
	(1)	(2)	(3)	(4)	(5)	(6)
	PHM	PHM	PHM	PHM	PHM	PHM
VC-invested	3.779**	3.329**	6.259***	6.150***	1.217	1.157
	(1.568)	(1.494)	(3.339)	(3.387)	(0.606)	(0.602)
Firm age at inv. year		1.185†		0.815		1.161†
		(0.113)		(0.106)		(0.104)
Predicted degree of innovativ.		0.669		3.733†		0.575
		(0.315)		(2.642)		(0.372)
Patent at inv. year		0.078*		0.781		1.926
		(0.078)		(0.465)		(1.030)
Propensity score		12.161*		3.245		2.849
		(13.110)		(3.176)		(4.124)
Corp. group covariates‡	No	Yes	No	Yes	No	Yes
Log-Likelihood	-179.26	-165.24	-151.80	-141.75	-101.04	-92.75
N° of observations	548	548	548	548	548	548
N° of exit events	31	31	27	27	17	17
Tot. time at risk (quarters)	14,351	14,351	14,351	14,351	14,351	14,351

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

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Secondary M&A outcomes: relative treatment effects (2/2)

Descriptives

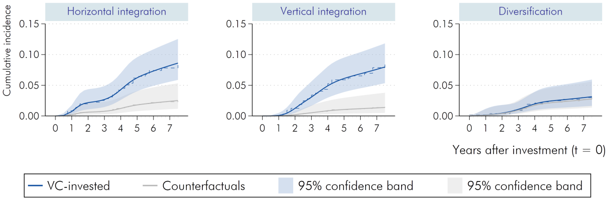
Table 3: Estimated odds ratios for the Cox proportional hazard model (PHM)

	Foreign		National	
	(1)	(2)	(3)	(4)
	PHM	PHM	PHM	PHM
VC-invested	5.995***	5.456***	1.612	1.634
	(2.418)	(2.432)	(0.621)	(0.656)
Firm age at inv. year		1.037		1.109
		(0.092)		(0.088)
Predicted degree of innovativ.		1.231		0.964
		(0.509)		(0.494)
Patent at inv. year		0.320*		1.146
		(0.176)		(0.548)
Propensity score		9.703**		1.653
		(8.160)		(1.849)
Corp. group covariates‡	No	Yes	No	Yes
Log-Likelihood	-252.97	-238.82	-179.05	-168.35
N° of observations	548	548	548	548
N° of exit events	45	45	30	30
Tot. time at risk (quarters)	14,351	14,351	14,351	14,351

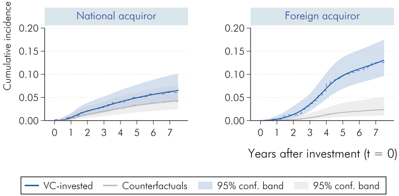
† 0.10 * 0.05 ** 0.01 *** 0.001; ‡n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

Secondary M&A outcomes: absolute treatment effects

Figure 5: Changes in the cumulative incidence function (CIF), by M&A route



(a) M&A integration type



(b) Location of M&A buyer(s)

Patenting activity: relative treatment effects

Descriptives

Table 4: Estimated odds ratios for the Cox proportional hazard model (PHM)

	Patenting	
	(1)	(2)
	PHM	PHM
VC-invested	1.901***	2.172***
	(0.261)	(0.349)
Firm age at inv. year		0.927
		(0.046)
Predicted degree of innovativ.		1.914*
		(0.506)
Patent at inv. year		7.275***
		(1.699)
Propensity score		2.105†
		(0.924)
Corp. group covariates‡	No	Yes
Log-Likelihood	-805.06	-727.82
N° of observations	548	548
N° of exit events	133	133
Tot. time at risk (quarters)	11,378	11,378

† 0.10 * 0.05 ** 0.01 *** 0.001; ‡n° of shareholders, Independence indicator; cluster-robust std errors in brackets.

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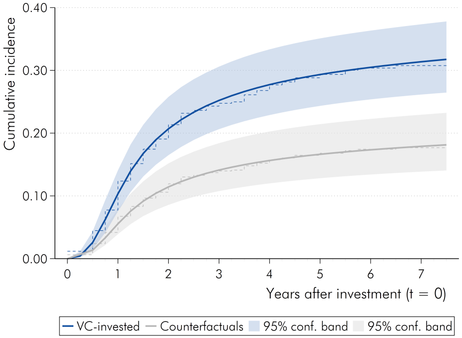
Patenting activity: absolute treatment effects

Descriptives

Figure 7: Changes in the cumulative incidence function (CIF) for patenting due to treatment



Moderating effects

Table 5: Observed *vs* expected events ratio and log-rank test for treated firms, by moderator.

	M&A (1)	IPO (2)	Other Buy-out (3)	Bankruptcy (4)	Patenting (5)
	LOG-RANK	LOG-RANK	LOG-RANK	LOG-RANK	LOG-RANK
Investment period:					
2007-08	1.770**	1.005	1.010	0.889	1.439**
	(7.802)	(0.000)	(0.000)	(0.433)	(7.257)
2009-11	1.449†	2.020	1.000	1.216	1.509**
	(3.795)	(2.055)	(0.000)	(1.549)	(6.855)
2012-14	1.497**	1.678†	0.800	1.121	1.217
	(9.747)	(2.714)	(0.203)	(1.018)	(2.608)
Macro-sector:					
ICT	1.746***	0.000	0.500	1.089	1.569**
	(24.601)	(2.007)	(1.008)	(0.479)	(10.047)
Life Sciences	1.200	1.775*	1.887	0.738	1.354**
	(0.404)	(3.923)	(0.898)	(1.565)	(7.217)
Services	1.121	1.961	0.000	1.144	1.154
	(0.128)	(1.921)	(2.022)	(0.767)	(0.370)
Other	1.272	2.083	2.020	1.365	1.291
	(0.580)	(1.093)	(2.057)	(2.314)	(1.123)
Predicted degree of innovativ.:$^{\chi}$					
Below 30%	1.506*	1.000	0.797	0.985	1.330†
	(6.291)	(0.000)	(0.206)	(0.017)	(2.896)
Between 30% and 70%	0.938	–$^{\varphi}$	0.000	0.942	1.433
	(0.026)		(1.042)	(0.054)	(1.315)
Above 70%	1.628***	1.610†	1.299	1.235†	1.331**
	(16.116)	(3.683)	(0.285)	(2.816)	(9.668)
Firm age at inv. year:$^{\chi}$					
Less than 2 yrs	1.696***	1.661	1.181	1.104	1.235*
	(22.185)	(2.642)	(0.169)	(0.917)	(4.415)
2 to 5 yrs	1.190	1.606	0.498	1.009	1.546**
	(0.741)	(1.831)	(1.025)	(0.003)	(9.802)
5 or more yrs	1.481	0.000	–$^{\varphi}$	1.215	1.308
	(1.166)	(1.048)		(0.459)	(1.002)
Macro-region:					
DACH	1.912***	–$^{\varphi}$	1.307	1.433	1.739***
	(16.762)		(0.293)	(2.287)	(13.165)
Nordics	1.170	1.195	0.000	0.995	1.429†
	(0.303)	(0.193)	(1.000)	(0.000)	(3.689)
France & Benelux	1.471	2.041†	2.000	1.343	1.127
	(1.477)	(3.133)	(1.000)	(1.528)	(0.200)
South & CESEE	2.066*	1.887	0.000	0.713	1.445
	(5.354)	(0.873)	(1.000)	(0.982)	(1.370)
UK & Ireland	1.297†	1.325	0.662	1.047	1.148
	(2.720)	(0.321)	(0.342)	(0.208)	(1.317)
N° of observations	548	548	548	548	548
N° of exit events	75	12	9	137	133
Tot. time at risk (quarters)	14,351	14,351	14,351	15,835	11,378

† 0.10 * 0.05 ** 0.01 *** 0.001; log-rank χ^2-statistic in brackets; $^{\varphi}$ no exit events in the respective sub-sample;

- The log-rank test compares the observed number of outcomes in each group against an expected number of outcomes.
  - **Note:** the log-rank statistic only provides qualitative (as opposed to quantitative) evidence that the difference between duration curves is statistically significant.
- Our findings do not support the argument that the effects of EIF VC are highly heterogeneous.
- Most often, statistically significant differences between the exit duration curves only reflect the larger sample sizes of groupings.

Robustness tests

- **Model misspecification**:
  - Rosenbaum sensitivity analysis `mhbounds`
  - Multinomial logit competing risks analysis Multinomial logit
  - OLS method applied to patenting activity OLS
- **Representativeness of main results**:
  - Alternative matching strategies Alternative matching
  - Alternative model specifications Alternative model specifications

Conclusion

- We estimate the economic effects of EIF VC activities by:
  - applying an established econometric framework for causal inference
  - using ML and other data-driven techniques to model VC assignment
  - exploiting the European VC ecosystem heterogeneity.
- Overall, our work provides meaningful evidence towards the positive effects of EIF's VC activity on the exit prospects and innovative capacity of young and innovative businesses in Europe.
- Full paper at http://www.eif.org/news_centre/research/index.htm:
  - Read, send us feedback and subscribe to our research ☺ .

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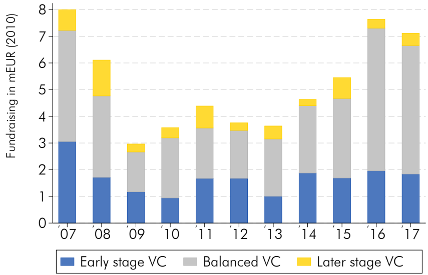
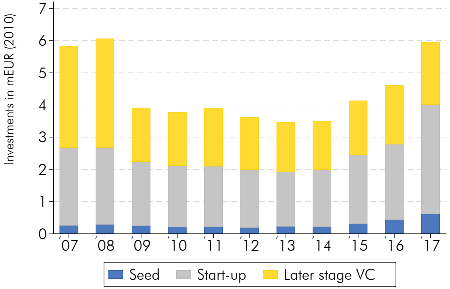
VC Market development

Figure A1: Incremental fundraising of Europe-based VC firms, EUR 2010 million



Source: Invest Europe (2017).

Figure A2: Investments into Europe-based VC start-ups, EUR 2010 million



Source: Invest Europe (2017).

Rubin's Causal Model (Rubin, 1974)

- Y_i outcome of interest. Two potential outcomes given treatment W_i:

$$Y_i(W_i) = Y_i(0) \cdot (1 - W_i) + Y_i(1) \cdot W_i = \begin{cases} Y_i(0) & \text{if} \quad W_i = 0 \\ Y_i(1) & \text{if} \quad W_i = 1 \end{cases}$$

- We are interested in the average treatment effect for the treated (ATT):

$$\tau^t = \mathbb{E}\left[Y_i(1) - Y_i(0) \mid W_i = 1\right]$$

- The quantity τ^t is identified from the distribution of $(Y, W, \mathbf{X})$ *iff*:

$$\underbrace{W_i \perp\!\!\!\perp (Y_i(0), Y_i(1)) \mid \mathbf{X}_i}_{\text{Unconfoundedness}} \qquad \text{and} \qquad \underbrace{0 < Pr(W_i \mid \mathbf{X}_i = \mathbf{x}) < 1, \quad \forall \mathbf{x}}_{\text{Overlap}}$$

- Under the same assumptions, we can consistently estimate the ATT with a matching estimator based on the propensity score $e(\mathbf{X}_i)$ (Rosenbaum and Rubin, 1983).

Data collection process

- The exercise consists in tracking of legal entities *(= private limited companies)* within corporate groups *(= collections of legal entities featuring an ownership chain)*. We analyse 54,543 legal entities and their time-varying corporate groups.
- We assign an exit deal to a given start-up if:
  a) the legal entity code of the start-up is reported in the Zephyr deal description, OR
  b) the legal entity code of any start-up's shareholder with 50% or higher ownership stake (either directly or indirectly) is reported in the deal description.
- Our final dataset provides 2,760 exit events, half of which associated to the start-ups' legal entities and the other half to their shareholders'. Data thoroughly checked to discard deals not entailing an exit outcome for the respective start-up.
- The classification of exit events is mainly based on the Zephyr deal descriptions, with *ad-hoc* data cleaning to ensure consistency. We further partition M&As into *vertical, horizontal* integrations, or *diversifications,* based on the approach in Alfaro and Charlton (2009).
- Corporate group data collected in this phase feeds into our propensity score matching model. Corporate structure

Identification criteria for early stage companies

Table A1: Early stage identification criteria

#	Criterion	Source
1	Early stage investments reach firms that have been operating for 10 years at most.	Bertoni and Martí (2011)
2	Early stage investments target companies reporting no positive turnover in the 2 years preceding investment date.	Leslie and Wells (2000, p. 243)
3	Early stage investments target companies with less than 250 employees at investment date.	Davila *et al.* (e.g., 2003, p. 696)

Source: Kraemer-Eis *et al.* (2016).

Full treatment sample breakdown

Table A2: VC-invested firms breakdown

Sample	Investees
Full European VC-backed population	27,044
- of which invested in 2007-2014	11,577
- of which identified in Orbis	8,943
- of which early stage	6,695
- of which early stage (stricter criteria)	4,945
- of which EIF	782

Note: The "full" population of VC-backed European start-ups is estimated from Invest Europe time series and the assumption that both domestic-to-foreign and initial-to-follow-on ratios, only available for the entire private equity segment, are also representative of the VC industry (i.e. seed, start-up, later stage venture). For aggregates prior to 2007, we further assume that foreign investments were distributed proportionally to the (domestic) market size of the target country.

Innovative potential

Classifying business models using ML techniques

- We manually classify 23,044 treatment and control start-ups (from an initial dataset of 222,684) into *highly innovative* or *less/non-innovative* start-ups.
- The classification is based on business descriptions and the taxonomy of Pavitt (1984). We aim at identifying *science based* and *information-intensive* business models, linked to the emergence of disruptive innovation.
- We translate business descriptions into *vectorial representations* (word embeddings) using a pre-trained neural network (Mikolov *et al.*, 2017). We use these to train a *residual LSTM* model (Jaeyoung *et al.*, 2017).
- The model achieves 87% accuracy. The area under the ROC curve is 95.3%. The false positive (negative) rate is 14% (10%).

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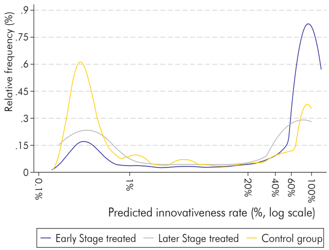
Innovative potential

Pre-matching statistics

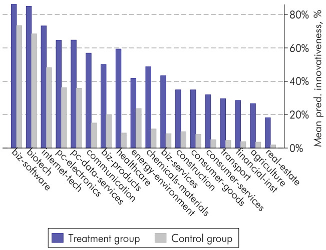
Table A3: Examples of business descriptions innovation score assignment

Innovation score	Trade description text
0.25%	"Crushing of concrete and stone."
54.28%	"Engaged in the operation of a medical laboratory."
98.37%	"Online mortgages and insurance comparison website operator."

Figure A3: Distributional features of the predicted innovativeness rate



(a) Innovativeness distribution by evaluation group



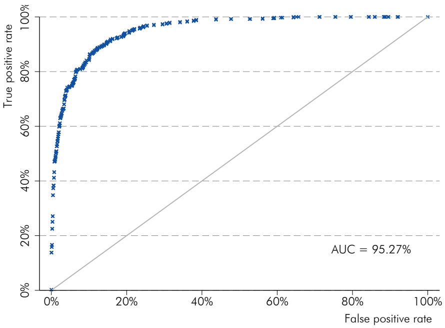
(b) Average innovativeness by industry

Innovative potential

Model performance

Figure A5: Training and validation performance

Figure A6: Receiver Operating Characteristic (ROC) curve



Corporate structure

Main variables and definitions

- Number of start-up's shareholders
- Ownership type:
  a) Corporate majority shareholder, i.e. a single corporation holds a controlling share in the start-up
  b) Corporate plurality shareholders, i.e. a group of corporations hold a controlling participation in the start-up;
  c) Non-corporate majority/plurality shareholder/s, i.e. one or more natural persons hold a controlling share in the start-up
- Orbis independence indicator:
  A: no known recorded shareholder having more than 25% of direct/indirect ownership;
  B: one or more shareholders with an ownership percentage above 25%, but no known shareholder with more than 50% of direct/indirect ownership;
  C: a shareholder with more than 50% of indirect ownership;
  D: a shareholder with more than 50% of direct ownership;
  Unknown: none of the above.

Start-up accessibility (Bernstein *et al.*, 2015)

Motivation

- Lerner (1995) discusses VCs' inclination for geographic proximity. Bernstein *et al.* (2015) show that reduced travel time raises VCs' involvement in portfolio firms.
- We create a *network of flight routes* using the OpenFlights database. The *nodes* of the network are 716 European FUAs. *Edges* are the existing flight route(s) between two FUAs in a given year. A FUA is served by any airport in a radius of 120km.
- We exploit the location of VC/PE firms to weigh edges. The *effective distance* between FUA k and m is:

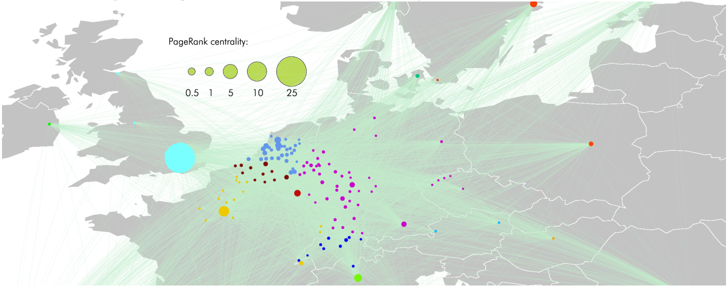
$$\Delta_{km} = \begin{cases} \frac{d_{km}}{f_k \cdot r_{km}} & \text{if} \quad f_k > 0, r_{km} > 0 \\ \infty & \text{otherwise} \end{cases}$$

where d_{km} is the geodetic distance, f_k the number of investors in the source FUA and r_{km} the number of connecting flight routes.

Start-up accessibility (Bernstein *et al.*, 2015)

Measure

Figure A7: Accessibility by plane: PageRank centrality by FUA (only top 20% shown)



- Start-up j's accessibility is measured from the centrality of its closest FUA:

$$\alpha_j = \sqrt{\rho_k} \cdot e^{-\frac{\sigma_{jk}}{c}}$$

where ρ_k is the PageRank centrality (Page *et al.*, 1998) for FUA k, σ_{jk} is the distance of start-up j from FUA k *access point*. $c = 50$ is a normalizing constant.

FUA accessibility

Table A4: Centrality measures for top 20 FUAs by PageRank (ranking in brackets)

Functional Urban Area	PageRank	Katz-Centrality	Eigen-Rank	Degree centrality
LONDON, UK	**26.245** (1)	**0.235** (1)	**69.538** (1)	**0.784** (14)
PARIS, FR	**3.155** (2)	**0.059** (2)	**7.610** (27)	**0.741** (66)
MILANO, IT	**1.703** (3)	**0.047** (17)	**4.778** (46)	**0.735** (79)
STOCKHOLM, SE	**1.444** (4)	**0.042** (33)	**3.119** (91)	**0.613** (254)
AMSTERDAM, NL	**1.240** (5)	**0.049** (8)	**9.252** (24)	**0.734** (84)
LUXEMBOURG, LU	**1.212** (6)	**0.042** (32)	**3.009** (95)	**0.645** (224)
DACORUM, UK	**1.145** (7)	**0.037** (81)	**1.495** (181)	**0.797** (1)
HILVERSUM, NL	**1.113** (8)	**0.049** (9)	**10.067** (16)	**0.755** (50)
MÜNCHEN, DE	**0.787** (9)	**0.040** (41)	**3.242** (86)	**0.708** (120)
FRANKFURT AM MAIN, DE	**0.786** (10)	**0.040** (40)	**3.433** (81)	**0.714** (109)
LEIDEN, NL	**0.781** (11)	**0.049** (14)	**10.848** (12)	**0.734** (84)
CAMBRIDGE, UK	**0.731** (12)	**0.037** (92)	**1.700** (163)	**0.780** (24)
OSLO, NO	**0.623** (13)	**0.036** (100)	**1.883** (148)	**0.621** (243)
ROTTERDAM, NL	**0.620** (14)	**0.050** (6)	**12.728** (7)	**0.743** (63)
S' GRAVENHAGE, NL	**0.616** (15)	**0.047** (16)	**10.512** (14)	**0.734** (84)
ANTWERPEN, BE	**0.606** (16)	**0.050** (5)	**12.702** (8)	**0.761** (36)
WARSZAWA, PL	**0.596** (17)	**0.037** (90)	**1.730** (159)	**0.572** (314)
UTRECHT, NL	**0.592** (18)	**0.046** (20)	**9.429** (22)	**0.755** (50)
LIÈGE, BE	**0.588** (19)	**0.046** (18)	**9.288** (23)	**0.780** (24)
MANNHEIM-LUDWIGSHAFEN, DE	**0.578** (20)	**0.040** (42)	**4.227** (53)	**0.735** (79)

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Value of collateral (Saiz, 2010)

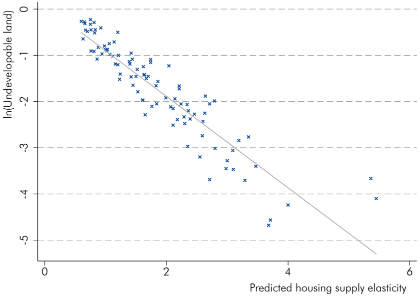
- Robb and Robinson (2014) show that an increase in housing supply elasticity positively affects start-ups' likelihood of obtaining bank credit. This is due to supply elasticity stabilising the value of home equity as collateral.
- We introduce a similar measure to test for the availability of alternative credit channels for European start-ups, replicating the work of Saiz (2010) for the US.
- Using satellite-generated data on terrain elevation and presence of water bodies, we estimate the share of land lost to sea, elevation and other water bodies within a 35km radius from the centroid of 687 European FUAs (the "*undevelopable land*").
- Saiz (2010) used this measure to estimate housing supply elasticities. Since we lack comprehensive data on housing prices for European FUAs, we opt for the direct use of this variable. Saiz (2010) shows that the relationship between ln (undevelopable land) and housing supply elasticity is negative and quasi-linear.

Value of collateral

Table A5: Functional Urban Areas (FUAs) by share of undevelopable land (top and bottom 10)

Functional Urban Area	Undevelopable land (%)
Valletta, MT	95.52948
Thanet, UK	79.07122
Messina, IT	63.42009
Melilla, ES	62.95040
Cherbourg, FR	59.11571
Great Yarmouth, UK	59.03460
Ceuta, ES	58.56501
Reggio di Calabria, IT	57.28986
Middelburg, NL	57.25204
Siracusa, IT	56.95813
. . .	. . .
Koblenz, DE	0.22809
Plock, PL	0.22595
Hradec Králové, CZ	0.16452
Jastrzebie-Zdrój, PL	0.13054
Tübingen, DE	0.10102
Rybnik, PL	0.09868
Charleroi, BE	0.05481
Lódz, PL	0.01037
Bielsko-Biala, PL	0.00399
Kraków, PL	0.00006

Figure A8: Relationship between housing supply elasticity estimates and ln (undevelopable land) in Saiz (2010)



Source: Authors, based on Saiz (2010)

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Multi-level modelling

- Let k represent the FUA, j the start-up and i the entrepreneur. We rearrange our predictors of VC financing to account for the hierarchical nature of our data:
- The resulting input mix is $\mathbf{X}_{ijk} = \{\mathbf{H}_{jk}, \mathbf{r}_k, \mathbf{w}_{jk}, \mathbf{z}_{ijk}\}$. We fit a two-stage mixed effects logit: the first stage accounts for the *micro*→*macro* design (Steele *et al.*, 2016):

$$\begin{cases} z_{v,(ijk)} = \delta_0 + \delta' \mathbf{z}_{-v,ijk} + \upsilon_{v,k} + \omega_{v,jk} + \varepsilon_{ijk} \quad \forall v = 1, 2, \ldots, V \\ \text{logit}\left(e\left(\mathbf{X}_{jk}\right)\right) = \underbrace{\gamma_{00} + \beta' \mathbf{H}_{jk} + \gamma_0' \mathbf{r}_k + \theta' \mathbf{w}_{jk} + \varphi' \left(\widehat{\boldsymbol{\upsilon}}_k + \widehat{\boldsymbol{\omega}}_{jk}\right)}_{\text{fixed effects (FEs)}} + \underbrace{\zeta_{0k} + \eta_{jk}}_{\text{random effects (REs)}} \end{cases}$$

where $\widehat{\boldsymbol{\upsilon}}_k$ and $\widehat{\boldsymbol{\omega}}_{jk}$ are the empirical Bayes estimates of the FUA and start-up random effects for the entrepreneurial characteristics.

- The random effects ζ_{0k} and η_{jk} capture unobserved heterogeneity associated with the FUA and the start-up. We add group-level covariate means to control for the potential endogeneity of REs (Hausman, 1978).

Competing risks methods (1/3)

- Consider k potential exit events occurring at time $E_1, E_2, \ldots, E_k$ respectively.
- For a given start-up, we cannot observe $(E_1, E_2, \ldots, E_k)$. Instead, we have exit time $T = \min(E_1, E_2, \ldots, E_k)$ and exit status $\delta(T) = k$ if $\min(E_1, E_2, \ldots, E_k) = E_k$.
- *(Right censoring)* let θ be some cutoff time. If $T > \theta$, then no exit event and $\delta(\theta) = 0$.
- Two key measures in competing risks analysis:
  - The cumulative incidence function (CIF) for exit event k, i.e. the probability that a start-up will experience the exit outcome k by time u:

$$C_k(u) = Pr(t \leq u, \delta(t) = k) \tag{1}$$

  - The cause-specific hazard rate $h_k(t)$, i.e. the instantaneous risk of experiencing exit outcome k at time t, given that the start-up still has not faced any exit event by then:

$$h_k(t) = \lim_{dt \longrightarrow 0} \frac{Pr(\delta(t + dt) = k \,|\, \delta(t) = 0)}{dt} \tag{2}$$

  - (1) can be expressed in terms of (2):

$$C_k(t) = \int_0^t h_k(u) S(u)\, du \tag{3}$$

- $S(t) = 1 - C_1(t) - C_2(t) - \ldots - C_k(t)$ is the survival function, i.e. the probability that no exit event has ever occurred by time t.

Competing risks methods (2/3)

Estimation strategies in the presence of competing risks:

- Cox (1972) cause-specific proportional hazard model (PHM). Models (2) as follows:

$$h_k(t|X) = h_{k0}(t) \exp\{\beta' X\}$$

where h_{k0} represents the baseline hazard function for exit type k.

  - The Cox model is unable to draw a direct relationship between X and the CIF, because the CIF is a function of all cause-specific hazards.

- Fine and Gray (1999) proportional hazards model for the sub-distribution. Models (3) as follows:

$$C_k(t|X) = 1 - \exp\left\{\int_0^t \lambda_{k0}(t) \exp\{\beta' X\}\, du\right\}$$

where $\lambda_{k0}(t)$ represents the baseline sub-hazard function for exit type k.

  - The coefficients of the Fine and Gray model do not have a straightforward quantitative meaning, because the sub-hazard function itself does not have an intuitive interpretation.

Competing risks methods (3/3)

- Recently, Geskus (2011) proved that the Fine and Gray (1999) model can also be estimated using a weighted version of standard survival estimators for e.g., the Cox proportional hazard model.

- In this framework, we can estimate confidence bounds for the survival/incidence curve and carry out auxiliary statistical tests, e.g. the one discussed in Gray (1988).

- In addition, Lambert (2017) discusses a series of estimators based on the Royston and Parmar (2002) flexible parametric survival model. These allow fitting survival data and generate smooth versions of the traditional non-parametric Kaplan–Meier survival curves, which still account for competing risks.

Descriptive statistics on primary exit outcomes

Table A6: Distribution of primary exit outcomes, by treatment status

Treatment status	No exit	M&A		IPO		Other Buy-out		Bankruptcy		Total
	Nº (%)†	Nº (%)†	TTE‡ avg (sd)	Nº (%)†	TTE‡ avg (sd)	Nº (%)†	TTE‡ avg (sd)	Nº (%)†	TTE‡ avg (sd)	Nº (%)†
VC-invested	139	56	4.5	9	4.1	4	6.2	66	4.6	274
	(50.7%)	(20.4%)	(2.3)	(3.3%)	(3)	(1.5%)	(2.6)	(24.1%)	(2.5)	(100%)
Counterfactuals	189	19	3	3	2.9	5	3.4	58	4.8	274
	(69%)	(6.9%)	(2)	(1.1%)	(2.5)	(1.8%)	(1.7)	(21.2%)	(2.9)	(100%)
Total	328	75	4.1	12	3.8	9	4.6	124	4.7	548
	(59.9%)	(13.7%)	(2.3)	(2.2%)	(2.8)	(1.6%)	(2.5)	(22.6%)	(2.7)	(100%)

† **Note:** numbers and percentages sum up horizontally (aggregates are in the Total column). ‡ TTE: time-to-exit (in years).

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Descriptive statistics on secondary M&A outcomes

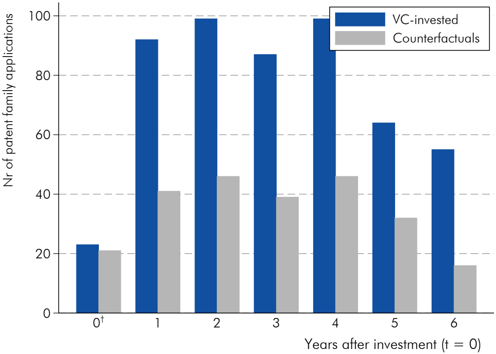
Table A7: Distribution of secondary M&A outcomes, by treatment status

Treatment status	M&A integration type			Location of M&A buyer(s)‡		
	Horizontal (Nº/%)†	Vertical (Nº/%)†	Diversified (Nº/%)†	National (Nº/%)†	EU or UK (Nº/%)†	Extra-EU (Nº/%)†
VC-Invested	24 (8.8%)	23 (8.4%)	9 (3.3%)	18 (6.6%)	14 (5.1%)	24 (8.8%)
Counterfactuals	7 (2.6%)	4 (1.5%)	8 (2.9%)	13 (4.7%)	1 (0.4%)	5 (1.8%)
Total	31 (5.7%)	27 (4.9%)	17 (3.1%)	31 (5.7%)	15 (2.7%)	29 (5.3%)

† Figures sum up horizontally. ‡ In case of multiple buyers, we classify deals with at least one foreign buyer as non-national M&A. Most deals with a foreign buyer have exclusively non-national buyers.

Descriptive statistics on patenting activity

Figure A9: Aggregate patenting activity, by treatment status



† Patenting activity at investment year is comparable by construction. We assume that VC firms can detect the presence of patentable technologies prior to the time of the investment: as such, patent applications submitted in the investment year are considered to be factored in the appraisal process. See also Pavlova and Signore (2019).

Robustness to model misspecification (1/3)

Rosenbaum sensitivity analysis

Table A8: Rosenbaum sensitivity analysis estimates

Γ	*P*-value M&A	*P*-value IPO	*P*-value Patenting
1.0	0.000	0.072	0.000
1.1	0.000	0.097	0.002
1.2	0.000	0.125	0.007
1.3	0.000	0.154	0.019
1.4	0.001	0.184	0.043
1.5	0.002	0.215	0.084
1.6	0.004	0.247	0.144
1.7	0.008	0.278	0.222
1.8	0.013	0.309	0.314
1.9	0.022	0.340	0.413
2.0	0.034	0.370	0.512
2.1	0.050	0.399	0.475
2.2	0.070	0.427	0.386
2.3	0.094	0.455	0.307

Note: The *P*-value on the Patenting estimates rises first and then falls. This is the case since Γ becomes so large that the estimated average treatment effect on the treated switches sign and becomes more significant again.

Robustness to model misspecification (2/3)

Discrete time analysis

Table A9: Multinomial logit competing risks analysis: estimated odds ratios

	M&A (1)	IPO (2)	Other Buy-out (3)	Bankruptcy (4)
VC-invested	3.099***	3.234†	1.038	1.369†
	(4.15)	(1.74)	(0.05)	(1.71)
Firm age at inv. year	1.080	0.976	0.941	0.998
	(1.19)	(-0.15)	(-0.31)	(-0.05)
Predicted degree of innovativ.	1.218	2.963	0.515	0.442***
	(0.65)	(1.17)	(-0.77)	(-3.70)
Patent at inv. year	0.505†	3.943*	2.019	1.140
	(-1.86)	(1.99)	(0.76)	(0.51)
Probability of treatment	4.602*	1.412	0.0337	0.400
	(2.49)	(0.25)	(-1.31)	(-1.59)
Corporate group	Yes	Yes	Yes	Yes
Nr of Observations	14,895	14,895	14,895	14,895
Log-Likelihood	-1282.60	-1282.60	-1282.60	-1282.60
LR Chi-Sq.	157.15	157.15	157.15	157.15
Chi-Square (p-value)	0.000	0.000	0.000	0.000
Pseudo-R-squared	0.06	0.06	0.06	0.06
Mc-Fadden R-squared	0.06	0.06	0.06	0.06
Adj. Mc-Fadden R-squared	0.03	0.03	0.03	0.03
AIC	2637	2637	2637	2637

†0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets;

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Robustness to model misspecification (3/3)

OLS method applied to patenting activity

Table A10: Patenting activity: estimated ATTs, by post-treatment period

	ln(Number of annual patent applications)
ATT (Period 1)	0.1161***
	(0.033)
ATT (Period 2)	0.1038**
	(0.039)
ATT (Period 3)	0.1324***
	(0.039)
ATT (Period 4)	0.1383**
	(0.042)
ATT (Period 5)	0.0948*
	(0.042)
ATT (Period 6)	0.1613**
	(0.054)
Nr of Observations	4,393

†0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets;

Alternative matching strategies

Table A11: Primary outcomes: estimated odds ratios for the Cox proportional hazard model

	M&A			IPO			Other Buy-out		
	Baseline	NN	Rank 3	Baseline	NN	Rank 3	Baseline	NN	Rank 3
VC-invested	2.934***	2.079**	3.602***	3.327†	4.504*	5.719**	1.001	1.300	1.834
	(0.796)	(0.510)	(0.839)	(2.385)	(3.190)	(3.632)	(0.655)	(0.880)	(1.200)
Firm age at inv. year	1.058	1.071	1.081	0.995	0.961	1.028	0.921	0.982	0.889
	(0.070)	(0.062)	(0.059)	(0.153)	(0.156)	(0.131)	(0.155)	(0.158)	(0.146)
Predicted degree of innovativ.	1.061	1.081	0.981	3.184	2.142	3.614	0.463	0.433	0.500
	(0.344)	(0.282)	(0.273)	(2.918)	(1.592)	(3.285)	(0.448)	(0.364)	(0.439)
Patent at inv. year	0.583	0.553*	0.673	4.062*	1.863	3.340†	1.950	0.906	2.698
	(0.222)	(0.151)	(0.219)	(2.789)	(1.095)	(2.250)	(2.461)	(1.158)	(2.895)
Propensity score	4.930*	4.438***	7.772**	1.412	3.434	1.922	0.036	1.155	0.129
	(3.448)	(1.985)	(4.894)	(1.955)	(3.631)	(2.663)	(0.075)	(2.517)	(0.261)
Corp. group covariates‡	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-411.97	-595.04	-539.20	-64.01	-96.38	-74.03	-48.39	-62.24	-65.42
N° of observations	548	696	982	548	696	982	548	696	982
N° of exit events	75	103	91	12	17	13	9	11	11
Tot. time at risk (quarters)	14,351	18,056	26,027	14,351	18,056	26,027	14,351	18,056	26,027

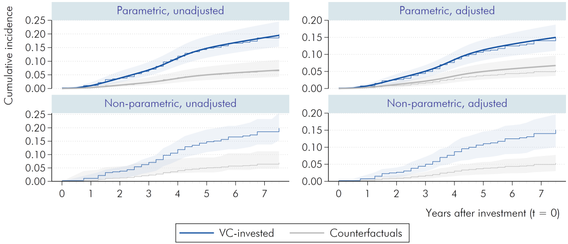
† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets; NN: 1:1 nearest neighbour, no calliper; Rank 3: 3:1 nearest neighbour, with calliper.

	Bankruptcy			Patenting		
	Baseline	NN	Rank 3	Baseline	NN	Rank 3
VC-invested	1.266	1.170	1.156	2.172***	2.062***	2.154***
	(0.219)	(0.174)	(0.159)	(0.349)	(0.313)	(0.305)
Firm age at inv. year	0.994	0.982	1.021	0.927	0.902†	0.917*
	(0.048)	(0.046)	(0.037)	(0.046)	(0.047)	(0.033)
Predicted degree of innovativ.	0.408***	0.431***	0.324***	1.914*	1.932**	1.874**
	(0.086)	(0.080)	(0.056)	(0.506)	(0.431)	(0.397)
Patent at inv. year	0.989	0.991	1.149	7.275***	7.089***	9.491***
	(0.217)	(0.194)	(0.224)	(1.699)	(1.337)	(1.918)
Propensity score	0.579	0.417*	0.488	2.105†	1.906†	2.319*
	(0.301)	(0.156)	(0.230)	(0.924)	(0.660)	(0.893)
Corp. group covariates‡	Yes	Yes	Yes	Yes	Yes	Yes
Log-Likelihood	-790.81	-1077.80	-1576.14	-727.82	-967.80	-1149.18
N° of observations	548	696	982	548	696	982
N° of exit events	137	180	249	133	169	194
Tot. time at risk (quarters)	15,835	20,038	27,744	11,378	14,471	21,117

† 0.10 * 0.05 ** 0.01 *** 0.001; cluster-robust standard errors in brackets; NN: 1:1 nearest neighbour, no calliper; Rank 3: 3:1 nearest neighbour, with calliper.

Alternative model specifications (1/2)

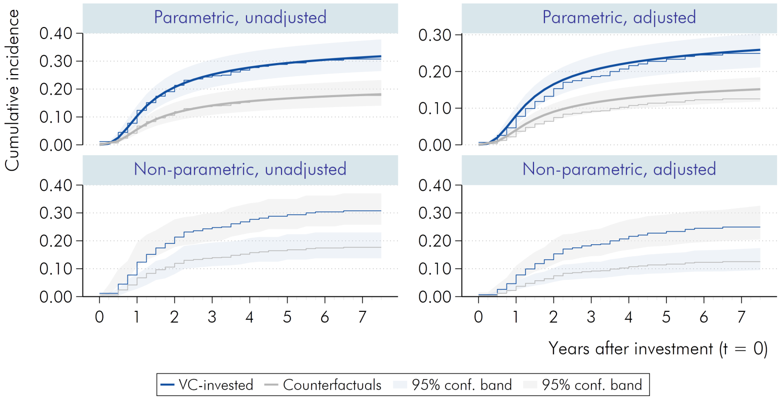
Figure A10: M&A: changes in the CIF due to treatment



- Baseline estimates of the CIF a) do not control for potential covariate imbalance and b) based on the Royston and Parmar (2002) model — interpolates the CIF via natural cubic splines. Alternatives:
  - Prentice *et al.* (1978) provide the traditional, non-parametric approach to estimating the CIF.
  - Add further controls (but mind the over-fitting).
- Four alternative model choices:
  1. parametric w/o covariate adjustment (baseline)
  2. parametric w/ covariate adjustment
  3. non-parametric w/o covariate adjustment
  4. non-parametric w/ covariate adjustment

Alternative model specifications (2/2)

Figure A11: Patenting: changes in the CIF due to treatment



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Chief Economist

14.04.2021

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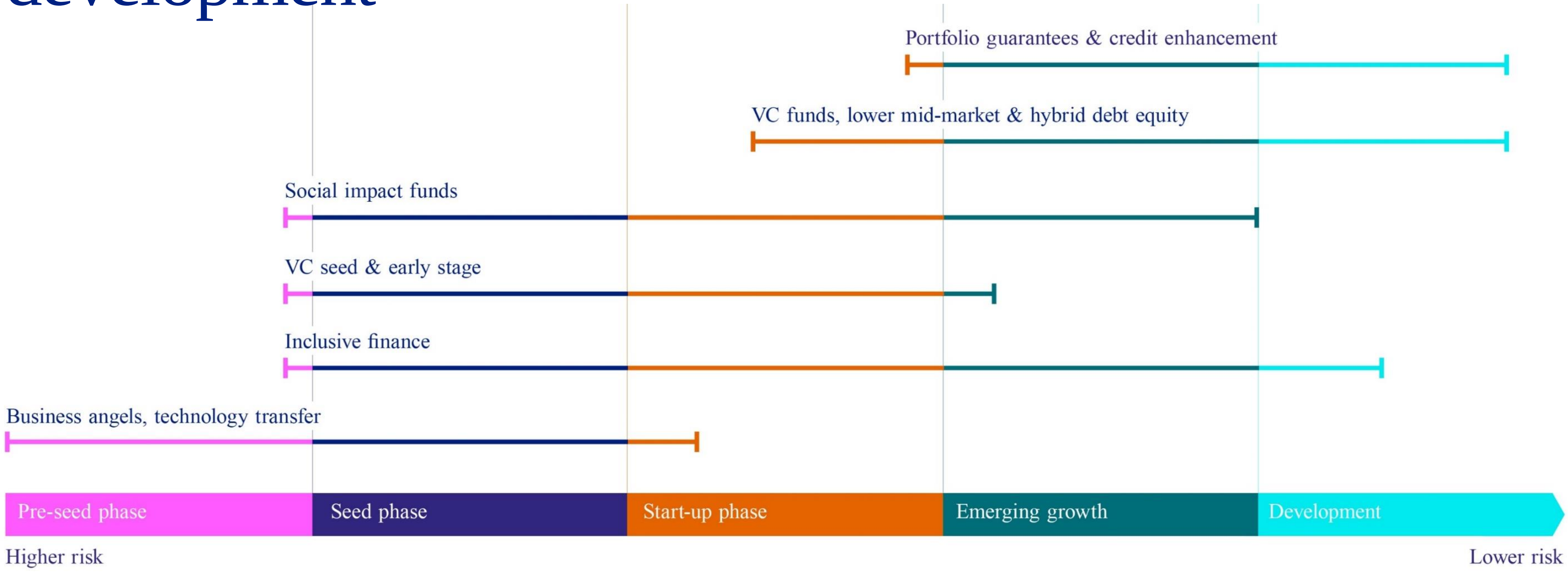

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Quantitative Economic impact assessment (ex-post)

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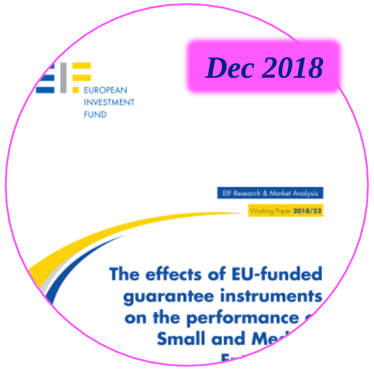
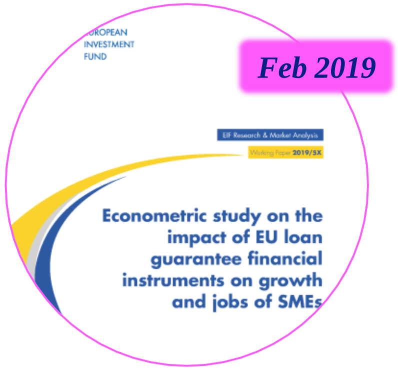
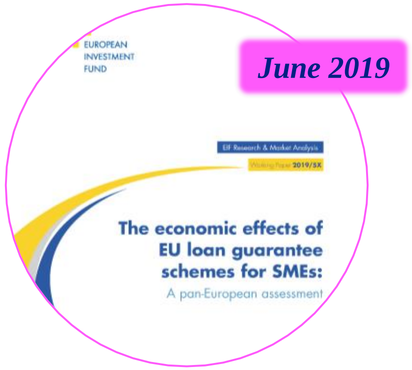
In the last five years, RMA analysed the real effects of its guarantee instruments, via four different publications:

Central, Eastern and South-Eastern Europe (CESEE)	*France*	*Italy, Benelux and the Nordics*	*Pan-European assessment*
			

Impact Assessment - EIF VC activities (1/2)

The European VC ecosystem

"EIF had a positive significant crowding-in impact on European VC in the aftermath of the recent economic crisis"

Financial growth and cluster analysis

"20% of EIF-backed companies grew more than fourfold the first 5 years after investment"

Exits, IPOs and unicorns backed by EIF

"EIF supported 50% of currently existing European unicorns"

EIF-supported innovation

"In 1996-2012 EIF supported returns from patented innovations for a total estimated volume of EUR 22.3bn – 28.3bn"

Impact Assessment - EIF VC activities (2/2)

Apr 2019

Dec 2019

Feb 2021

The economic impact of VC supported by the EIF

"Higher capitalisation levels, higher revenues and higher job creation of start-ups supported by the EIF compared to non-VC-backed firms."

The VC Factor

"Almost half of high-growth start-ups would have experienced significantly lower growth or defaulted without VC"

Exit and innovation outcomes

"EIF VC-invested start-ups were three times more likely to participate in an M&A deal and/or experience an IPO"

#BelieveInSmall

If we believe in small big things can happen

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