The European Venture Capital Landscape: an EIF Perspective

The economic impact of EIF-backed VC investments

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Outline

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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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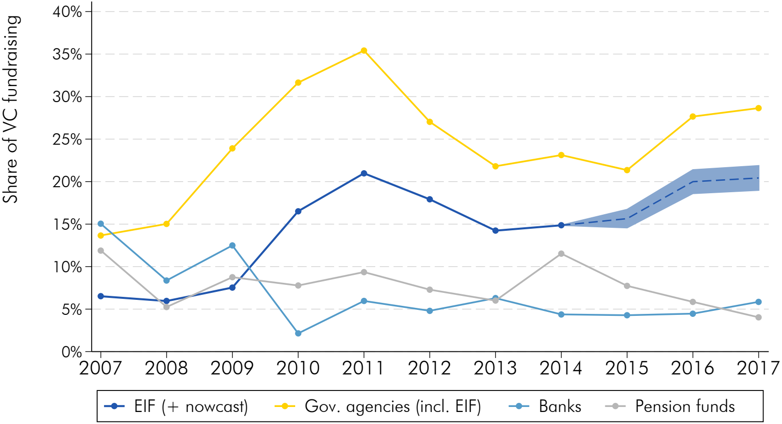
EIF's role in the VC market

Figure 1: VC fundraising in Europe, by selected investor types



Source: Kraemer-Eis et al., *2016 and Kraemer-Eis* et al., *2018, based on data from Invest Europe*

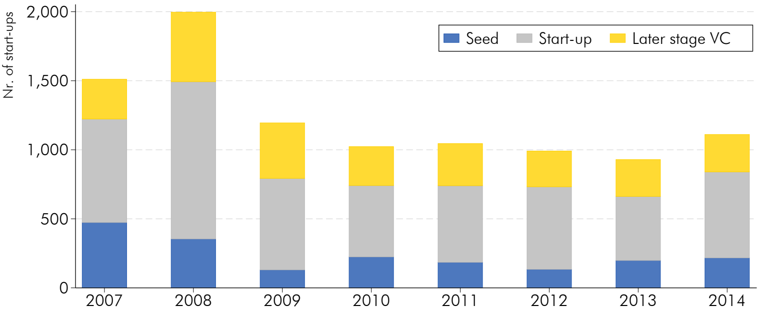
This paper (Pavlova and Signore, forthcoming)

- Models the assignment mechanism of European venture capital investments, incorporating machine learning and recent developments in the VC literature.
- Carries a propensity score-based analysis of EIF-supported start-ups, against a counterfactual group of non-VC-supported innovative firms.
- Provides a comprehensive evaluation of the economic effects of EIF-supported VC investments, following the recent economic crisis.

Treatment group

- 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 7,842 VC-backed start-ups in Europe in the 2007-2014 period.

Figure 2: Population of European VC-backed firms by year of first investment and stage



ORBIS Financial and Production Data

- ORBIS database provided by Bureau van Dijk (BvD) (2005–), covering almost 300 million companies in 90+ countries.
- ORBIS is an aggregator of firm-level data from various national IPs. It offers harmonised data, collected from official business registers, national banks, annual reports, *etc.*

Five main features of the data:

- Balance sheets and profit and loss accounts (advantage over Census)
- Good coverage relative to Census *iff* one merges across different vintages of data/across different disks
- Covers many of small and private firms (advantage over Compustat/Worldscope). Listed firms are 1% of the sample
- Detailed industry classification (4-digit)
- Mimics official size distribution for most European countries (maybe others)

(Kalemli-Ozcan *et al.*, 2015)

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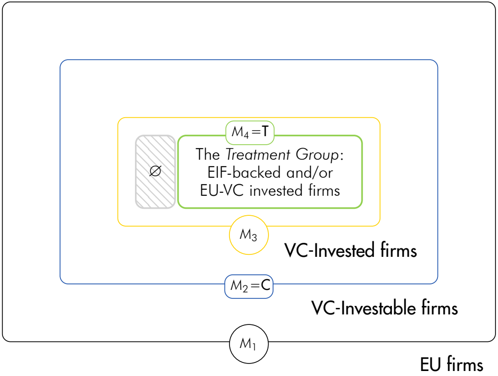
Conceptual framework



Given firm i and input mix $\mathbf{X}_i = \begin{bmatrix} \lambda_i \\ Z_i \end{bmatrix}$:

$$Pr\left\{i \in O_{RBIS} | i \in M_1\right\} = \rho \tag{1}$$

$$\mathbb{1}_{M_2,i} = H\left(\lambda_i\right) \tag{2}$$

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

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

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

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*:

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

- 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).

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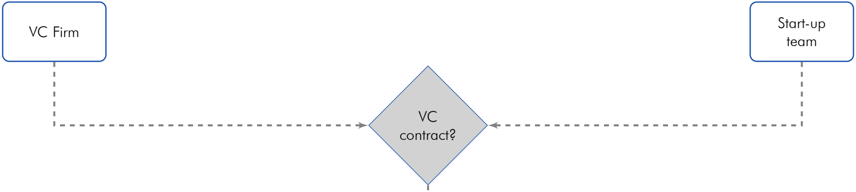
The propensity score model

The assignment mechanism



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

Bertoni *et al.* (2016)

Valuation

- Human capital (*e.g.* CV of start-up team)
- Product/technical/ marketing info
- 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

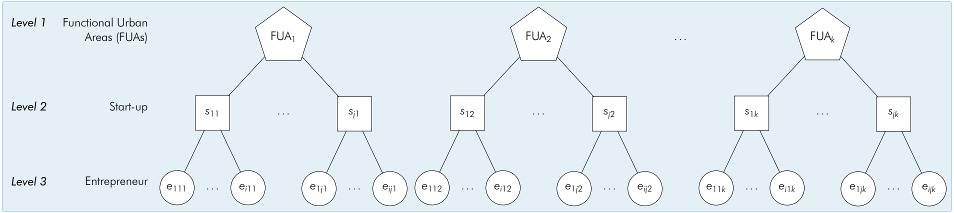
- Own capital
- Insider's capital (*e.g.* family, friends, fools)
- Value of collateral (Saiz, 2010)

Endowment compl. assets

- Founding experience
- Reputation
- Network of contacts
- Search costs

The propensity score model

Modelling unobserved heterogeneity



Given input mix $X_{ijk}^{\intercal} = \left[\; \theta_{ijk}^{\intercal} \; \middle| \; \varphi_{jk}^{\intercal} \; \middle| \; \mu_{k}^{\intercal} \; \right]$, we fit a two-stage mixed effects logit model. The first step accounts for the *micro-macro* design (Steele *et al.*, 2016):

$$\begin{cases} \theta_{h,(ijk)} = \delta_0 + \delta^{\intercal}\theta_{-h,ijk} + v_{h,k} + u_{h,jk} + \zeta_k + \eta_{jk} + \varepsilon_{ijk} \quad \forall h = 1, 2, \ldots, H \\ \text{logit}\left(e\left(X_{jk}\right)\right) = \underbrace{\gamma_{00} + \gamma_0^{\intercal}\mu_k + \beta^{\intercal}\varphi_{jk} + \rho^{\intercal}\left(\mathbf{v}_k + \mathbf{u}_{jk}\right)}_{\text{fixed effects (FEs)}} + \underbrace{\zeta_{0k} + \eta_{jk}}_{\text{random effects (REs)}} \end{cases}$$

we add group-level covariate means to control for endogeneity of REs (Hausman, 1978).

Degree of innovation

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% validation accuracy. The area under the ROC curve is 95.3%. The false positive (negative) rate is 14% (10%).
- We use the model's predicted scores (0% to 100%) to assess the innovation potential of each firm's business model.

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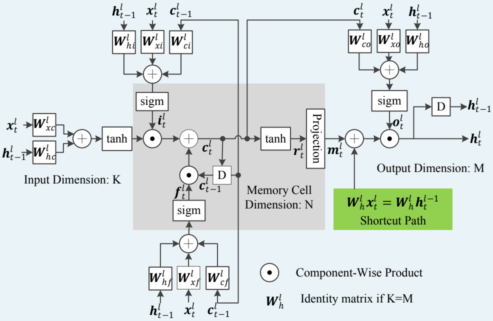
Degree of innovation

Long-short term memory neural network

Figure 3: Residual LSTM architecture



$$
\begin{cases}
i_t^\ell = \sigma(W_{xi}^\ell x_t^\ell + W_{hi}^\ell h_{t-1}^\ell + w_{ci}^\ell c_{t-1}^\ell + b_i^\ell) \\
f_t^\ell = \sigma(W_{xf}^\ell x_t^\ell + W_{hf}^\ell h_{t-1}^\ell + w_{cf}^\ell c_{t-1}^\ell + b_f^\ell) \\
c_t^\ell = f_t^\ell \cdot c_{t-1}^\ell + i_t^\ell \cdot \tanh(W_{xc}^\ell x_t^\ell + W_{hc}^\ell h_{t-1}^\ell + b_c^\ell) \\
o_t^\ell = \sigma(W_{xo}^\ell x_t^\ell + W_{ho}^\ell h_{t-1}^\ell + W_{co}^\ell c_t^\ell + b_o^\ell) \\
r_t^\ell = \tanh(c_t^\ell) \\
m_t^\ell = W_p^l \cdot r_t^\ell \\
h_t^\ell = o_t^l \cdot \left(m_t^\ell + W_h^\ell x_t^\ell\right)
\end{cases}
$$

ℓ represents layer index and i_t^ℓ, f_t^ℓ and o_t^ℓ are input, forget and output gates respectively. x_t^ℓ is an input from $(\ell-1)^{th}$ layer (or an input to a network when ℓ is 1), h_{t-1}^ℓ is a ℓ^{th} output layer at time $t-1$ and c_{t-1}^ℓ is an internal cell state at $t-1$. W_p^ℓ is a projection matrix to reduce dimension of r_t^ℓ.

(*Jaeyoung* et al., *2017, pp. 2-3*)

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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.

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

Measure

- 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.

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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 "*unusable 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 *unusable land* and housing supply elasticity is positive and quasi-linear.

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Propensity Score Model Results (odds ratios)

	Early Stage (1)	Later Stage (2)
Age of founding team †	0.9941 (0.007)	0.9498** (0.015)
Previous founding experience †	10.9261*** (3.638)	3.2369** (1.181)
Immigrant entrepreneurs †	0.1220*** (0.068)	0.0370** (0.038)
Female entrepreneurs †	0.0423*** (0.009)	0.3993*** (0.083)
Firm's age at inv. year	0.9178*** (0.013)	0.9317*** (0.011)
Firm holds patent at inv. year	2.9844*** (0.451)	3.7316*** (1.175)
Predicted degree of innovation	2.3295*** (0.421)	1.9324 (0.650)
Firm's accessibility	1.6796** (0.271)	1.7042 (0.519)
Firm's distance from closest FUA's centroid	0.1340*** (0.027)	0.2642** (0.109)
FUA's unusable land	529.1725** (1172.535)	4931.4549* (19405.521)
Neg-log transform of Curr. liab.		1.7443*** (0.097)
Log transform of Capital		1.2742*** (0.034)
Constant	0.0073*** (0.003)	0.0432** (0.052)
Log-likelihood	-6631.30	-1607.53
Obs.	26,946	8,886
Pseudo-R^2 (McKelvey&Zavoina)	0.34	0.43
Area under the ROC curve	0.812	0.872

* $p<0.05$, ** $p<0.01$, *** $p<0.001$; † founder-level variable; Regressions include investment year, macro-industry and macro-region FEs, interations and non-linear effects.

- Our hypotheses about the assignment mechanism are all verified for early stage companies, and at least partially for later stage.
  - Innovative potential, accessibility and alternative fin. channels are strong predictors of early stage VC.
  - For later stage, much of the predictive ability is captured by pre-treatment characteristics.
- 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.

Preliminary results ahead

Regression Results - Early Stage only

	ln (Total Assets) (1)	ln (Curr. Liab) (2)	ln (Innov. Nr.) (3)
Treatment = ATT (Period 0)	3.2123***	0.7723***	0.0140
	(0.357)	(0.131)	(0.040)
Period 1	0.5493*	0.1513**	-0.0358
	(0.261)	(0.057)	(0.026)
Period 2	0.7404*	0.1938**	-0.0381
	(0.315)	(0.074)	(0.021)
Period 3	0.7269	0.3185**	-0.0704*
	(0.389)	(0.108)	(0.030)
Period 4	0.8413	0.3563*	-0.0129
	(0.467)	(0.152)	(0.031)
Period 5	0.8528	0.4413*	-0.0376
	(0.562)	(0.196)	(0.033)
Period 6	1.3813*	0.5997*	0.0213
	(0.664)	(0.233)	(0.042)
Constant	-1.2601***	0.4922***	0.1220***
	(0.307)	(0.057)	(0.029)
ATT (Period 1)	2.9809***	1.0165***	0.1033**
	(0.325)	(0.133)	(0.037)
ATT (Period 2)	3.1301***	1.1406***	0.0794*
	(0.392)	(0.164)	(0.038)
ATT (Period 3)	3.2840***	1.2736***	0.1203**
	(0.521)	(0.216)	(0.040)
ATT (Period 4)	3.7010***	1.7422***	0.0719
	(0.586)	(0.276)	(0.051)
ATT (Period 5)	3.1777***	1.6130***	0.0841
	(0.773)	(0.348)	(0.053)
ATT (Period 6)	2.3982*	1.6524***	0.0293
	(1.034)	(0.461)	(0.072)
Obs.	1,164	1,174	2,466
Firms	346	344	472
Treated	173	172	236

* p<0.05, ** p<0.01, *** p<0.001; † founder-level variable; interaction terms not shown;

- On average, early stage VC-backed start-ups grow significantly more than their counterfactuals in terms of size.
- Significant average treatment effects on current liabilities (but also long term debt) hint that VC facilitates start-ups' access to bank financing.
- On average, we see a significant treatment effect on innovation, although counterfactuals catch-up by the fourth post-investment year.

Conclusion

- We estimate the economic effects of EIF VC activities by:
  - applying established econometric methods
  - using ML and other data-driven techniques to model VC assignment
  - exploiting the EU VC ecosystem heterogeneity.

- Preliminary results seem in line with the relevant literature and show that EIF has positively affected young and creative European start-ups, contributing to innovation and development across the EU.

- The full publication is planned for end of 2018 and will be freely available on the EIF website (http://www.eif.org/news_centre/research/index.htm).

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